Part 5

Crisis and contagion

Time

March 8th, 14:00～17:00

Contents

Multinational banks

SUMMARY

This paper examines whether multinational banks have a stabilizing or a destabilizing role during times of financial distress. With a focus on Europe, it looks at how these banks' foreign affiliates have been faring during the recent financial crisis. It finds that retail and corporate lending of these foreign affiliates has been stable and even increasing between 2007 and 2009. This pattern is related to the functioning of the internal capital market through which these banks funnel funds across their units. The internal capital market has been an effective tool to support foreign affiliates in distress and to isolate their lending from the local availability of financial resources, notwithstanding the systemic nature of the recent crisis. This effect has been particularly large within the EU integrated financial market and for the EMU countries, thus showing complementarity between economic integration and multinational banks' internal capital markets. In light of these findings, this paper supports the call for an integration of the European supervisory and regulatory framework overseeing multinational banks. The analysis is based on an analytical framework which derives the main conditions under which the internal capital market can perform this support function under idiosyncratic and systemic stresses. The empirical evidence uses both aggregate evidence on foreign claims worldwide, and firm-level evidence on the behaviour of banking groups' affiliates, compared to stand-alone national banks.

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Multinational banking in Europe – financial stability and regulatory implications: lessons from the financial crisis

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1. INTRODUCTION

Multinational banks (MNBs) have been growing fast, especially within the EU. The size and the global interconnectedness of their activities have raised serious concerns about their potential systemic effects. They have been considered as being among the main culprits of the present financial crisis. Many of the financial institutions that had to be bailed out or supported with public funds in 2008 and 2009 in Europe and in the United States were MNBs.[1] Special supervisory mechanisms and prudential requirements for these banks are at the core of most reform proposals of regulation and supervision of financial markets.[2]

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The Managing Editor in charge of this paper was Philippe Martin.

[1] For example, the Royal Bank of Scotland, Lloyds, ING, Fortis, Dexia, Merril Lynch, Citigroup and several others.

[2] See, for example, the proposal for the European Banking Authority by the EU and Turner (2009).

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However, these concerns often rest on a superficial assessment of the role and the activities of MNBs. The aim of this paper is to provide a comprehensive assessment of the behaviour of MNBs in the last decade and during the recent crisis. The analysis will be based on an in-depth theoretical evaluation of the functioning of the *internal capital market* (ICM), through which MNBs funnel funds across their global operations, and on macro and firm level evidence. We will address the question of whether MNBs have a stabilizing or destabilizing role during times of financial distress. There are several well-grounded economic arguments supporting the claim that this type of bank can rather have a stabilizing effect on global financial markets and on the economies of the host countries where they operate. Also, the empirical evidence, including the period of the recent financial crisis, shows that these banks have kept being a substantial and stable source of financial resources for host economies.

The analysis is especially focused on the operations that MNBs carry out in the host countries, where they have foreign affiliates. Indeed, these banks have increasingly been competing with domestic institutions in activities which are to a large extent non-tradable, like retail banking and corporate loans to small businesses, and which imply a high degree of local intermediation of funds through affiliates based in host countries (McCauley *et al.*, 2010). Their role has been growing especially fast within the integrated financial market of the EU and in emerging economies, where domestic institutions are weak. The financial claims towards residents in host countries held by MNBs through their affiliates account today for more than half of the total foreign claims of the banking system worldwide (which also include the cross-country operations of national, stand-alone banks).

This type of banking is of course similar to what domestic institutions do and inherently less volatile and more intertwined with the real economy than wholesale cross-border activities. However, it is also quite clear that MNBs have greater ease than domestic banks in channelling funds across their units world-wide, because of their role in the wholesale market and through internal transfers of liquidity and assets, indeed the ICM. In this respect, their deep involvement in the retail and corporate market of local economies, associated with a high potential for mobilizing activities cross border, has raised concerns that these financial institutions might be a cause of volatility and instability in the countries where they operate.[3]

The availability of a global ICM can indeed affect stability in both directions: MNBs can either support foreign affiliates in distress or, rather, funnel resources away, thereby creating potential distress. The theoretical framework we develop here, though, shows that it is possible to identify clearly the conditions under which the bright side of ICMs (i.e. their ability to support affiliates in distress and to allocate resources efficiently on the basis of global returns) is more likely to emerge.

[3] For example Ostry *et al.* (2010) have recently argued that FDI in the financial sector in emerging economies may be disguising a build-up of intragroup debt in the financial sector and increase the riskiness of local financial systems.

The empirical analysis we carry out on a large panel of banks in the EU27 countries between 2000 and 2008 provides robust evidence that foreign affiliates of MNBs, compared to stand-alone domestic banks and domestic banking groups, actively use the ICM to isolate the rate of growth of loans in host countries from available local resources (measured by the rate of growth of local deposits). During this period ICMs have indeed been functioning so as to isolate lending activities of foreign affiliates from *idiosyncratic* shocks in the local availability of funding. But our evidence of the limited volatility of aggregate claims during the recent financial crisis supports the view that MNBs can enhance financial stability also in times of *systemic* financial distress. Indeed, even in 2007 and 2008 ICMs helped to isolate lending activities of foreign affiliates from the local availability of funding.

Both the analytical framework and the empirical analyses developed in this paper are consistent with the claim that the activities carried out by MNBs through their affiliates have not been a source of financial instability in host economies. Rather, they have enhanced the supply of resources in those local markets.

Although it provides a general framework for analysis and evidence on worldwide trends in multinational banking, this paper focuses mostly on the EU. Our results show that the ICM is particularly effective when banks operate within the integrated EU financial market. This is not surprising, since retail activities and corporate lending and support to local businesses are non-tradable and in this domain market integration can only be fostered through the activities of MNBs. To this extent the ICMs and the external capital markets are to some degree *complementary*. When the external capital markets are less integrated, for regulations or because they involve different currencies, then the ICMs of MNBs are *de facto* operating to a very limited extent or even inactive, with no differences with respect to domestic banks. Consequently, even though some of the top MNBs in the world are non-European, the largest share of multinational banking activities are carried out within the EU and by European banks.

Within an integrated financial market our results also imply that there is a special urgency for reforming regulations and supervision, so as to deal with groups operating cross-border. Based on our analysis on the working of ICMs, in the final section we then discuss how a reformed European regulatory framework could enhance the stabilizing role of MNBs. We support the call for an integrated European supervision of MNBs and for an increased harmonization of national regulatory frameworks.

European countries should contemplate a new and specific framework for European MNBs that would allow these banks to set up truly integrated organizations with well-functioning ICMs. This framework would define the responsibilities and the powers of the parent company and its foreign affiliates, providing due protections to minorities and creditors. A specific treatment for MNBs in terms of regulation and supervision should be contemplated, along the lines of the proposals that have already been discussed in Europe (i.e., enhancing coordination among countries through strengthened colleges of supervisors overseen by a newly created

European Banking Authority and also possibly defining rules for the allocation of the costs of rescuing those banks in case of distress). A sensible revision of the current framework should seriously keep into account the organizational format that MNBs adopt for their ICMs. And also that the effectiveness of any regulatory reform strictly depends on the level of financial integration between the countries where the bank is active.

Several other works have been looking at the functioning of the ICM for global corporations in general and specifically for banks (see, for example, Houston *et al.*, 1997; Houston and James, 1998; Morgan *et al.*, 2004; Kroszner and Strahan, 2006; Kroszner, 2008; de Haas and van Lelyveld, 2010). These works are discussed in Sections 3 and 4. Also, a very large number of recent contributions have discussed regulatory and supervisory reforms to deal with MNBs (see, for example, Eisenbeis and Kaufman, 2006; Dermine, 2005; Freixas, 2009). The novelty of this paper is combining the analytical insights on the functioning of the ICM with empirical evidence which compares the performance of MNBs to the one of stand-alone national banks, and thus delivering some insights for policy reforms.

The remainder of this paper is organized as follows. The next section sets the scene and provides aggregate descriptive evidence on worldwide trends in multinational banking. Section 3 outlines an analytical framework for the functioning of the ICM, highlighting several testable implications on the conditions under which the 'bright side' of ICMs (e.g., their ability to support affiliates in distress) is more likely to emerge and taking them to the data. Section 4 is devoted to the assessment of the effects of the crisis on the behaviour of MNBs with particular reference (although not only) to Europe. Finally, Section 5 concludes and develops some policy implications of our analysis that may be useful in particular for the current debate in Europe.

2. KEY FACTS ON MULTINATIONAL BANKS

This section examines the key facts of the main global trends in the activities of MNBs since 2000, as emerging from aggregate statistics. It sets the scene for the subsequent analysis of the behaviour of these banks during the crisis. We examine how large these activities are with respect to the size of host countries' economies and how fast they have been growing in the last decade. In particular, we look at the patterns of the assets and liabilities of foreign affiliates (for a precise definition see n. 9), as these are the distinctive activities of MNBs, those likely to have a larger long-term impact on the economies of the host countries. We defer to Section 4 the assessment of how these activities have been faring since the outset of the financial crisis.

Two key facts emerge from the data. First, total claims of foreign affiliates[4] of banks have been rising worldwide, in absolute terms and with respect to the total

[4] See Box 1 for a definition.

banking assets and the GDP of host economies. Second, the rise has been especially large in the EU and particularly within the euro area.

2.1. The rise of multinational banking

The activities of MNBs' affiliates in host countries differ from cross-border financial transactions, which could also be undertaken by non-MNBs. These activities are mostly non-tradable, as they include retail banking and loans towards local businesses. As argued by McCauley *et al.* (2010), international banking has evolved for many countries from a model essentially based on centralized patterns of resource allocation (involving a large share of cross-border transactions), whereby headquarters pool funds and then reallocate them within the group, to a more decentralized pattern, where affiliates are allowed to raise funds locally to finance assets in each location. As we will discuss extensively in the next section, both models of multinational banking can be more or less efficiently supported by an ICM channelling funds across countries within the group. However, the decentralized model implies that a larger share of funds is directly intermediated by foreign affiliates.

The increasing role of foreign affiliates in local markets indeed emerges from the aggregate cross-country data provided by the Bank for International Settlements' (BIS) Banking Statistics, discussed in detail in Box 1. These statistics provide data on the claims of foreign affiliates in *host countries* vis-à-vis local residents (families, firms and other financial institutions) – defined as local claims – denominated in local and foreign currency.[5] These include loans, but also securities such as stocks and bonds. BIS statistics also provide data on total foreign claims, which include all the foreign assets held abroad by banks (domestic and MNBs), that is, summing up the local claims held through local affiliates with those held through cross-border transactions.

Trends in local and foreign claims are reported in Figure 1. Local claims in local currency (measured in current US dollars) rose in absolute terms to a value of more than \$10 trillion and almost doubled between 2000 and 2009 with respect to world GDP (from roughly 10% to 20%). Also local claims in foreign currency followed a similar pattern, although they can only be estimated as of March 2005. Both types of local claims summed up to \$17 trillion in 2009, accounting for more than 55% of total foreign claims, also reported. Notice that in the last two years (December 2007–December 2009) total foreign claims experienced a more pronounced decline compared to local claims. We will further discuss this point in Section 4, which deals specifically with the crisis.

[5] The BIS Banking Statistics report separate statistics for local claims in local currency only, whereas local claims in foreign currency are summed up with cross-border claims, and thus are not immediately identifiable. Following McCauley *et al.* (2010) they can be estimated starting from March 2005 as the difference between total international claims on an immediate borrower basis and cross-border claims on an ultimate risk basis (further details and a discussion on the bias introduced by this estimation are in Box 1).

Box 1. The banking statistics of the Bank for International Settlements (BIS)

The BIS Banking Statistics report financial claims and liabilities of banks towards the rest of the world.

Data are compiled on a consolidated (*Consolidated Statistics*) and on an unconsolidated basis (*Locational Statistics*).

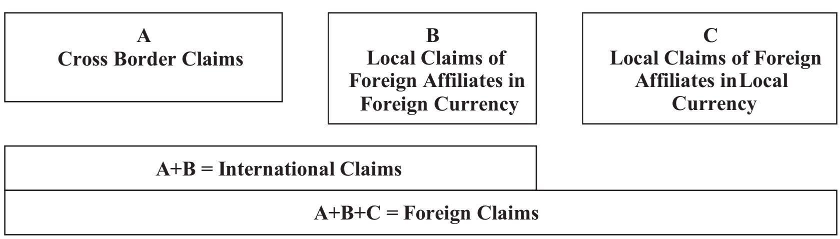
The *Consolidated Statistics* report banks' on-balance sheet financial claims on the rest of the world and thereby provide a measure of the risk exposures of lenders' national banking systems. The quarterly data cover contractual lending by the head office and all its branches and subsidiaries on a worldwide consolidated basis, that is, net of inter-office accounts. Total claims are broken down by maturity, sector (banks, non-bank private sector and public sector) as well as vis-à-vis country. It is therefore possible to construct statistics on total foreign claims by destination (vis-à-vis) country. These statistics also provide separate data on claims and liabilities of foreign affiliates (branches and subsidiaries, see note 9 for a discussion of these two types of foreign affiliates), located outside the reporting countries, towards residents of the host country, on an unconsolidated basis (defined as '*Local Claims*', see below).

The *Locational Statistics* report the aggregate international claims and liabilities of all banks resident in the 41 reporting countries broken down by instrument, currency, sector, country of residence of counterparty, and nationality of reporting banks. In this system, both domestic and foreign-owned banking offices in the reporting countries record their positions on a gross basis (except for derivative contracts for which a master netting agreement is in place) and on an unconsolidated basis, including those vis-à-vis own affiliates, which is consistent with the principles of national accounts, money and banking, balance of payments and external debt statistics. As locational statistics combine foreign activities of both national and multinational banks, it is not possible to disentangle separate data for foreign affiliates.

From a risk reallocation perspective, BIS provides information either on an *immediate borrower basis* or on an *ultimate risk basis*. Within the former, the claim is allocated directly to the country of immediate risk; the latter reallocates claims to the country of ultimate risk which is defined as the country where the guarantor of a claim resides. The use of derivative transactions, for instance, often implies a mismatch between risk allocated on a borrower or on an ultimate risk basis: suppose an Italian bank acquires a bond issued by a German issuer but guaranteed by a US insurance company on the basis of a derivative transaction written on the top of the bond; in this case, Germany is the country of the immediate guarantor, while the United States is the country where the ultimate risk resides.

Most of the data used in Section 2 are derived from the Consolidated Statistics and expressed on an immediate borrower basis, as per the following definitions:

- *Foreign Claims* are the sum of cross-border claims of banks (domestic and multinationals) plus the local claims in all currencies of banks' foreign affiliates. Claims comprise financial assets (items reported on balance sheets only) including, as a minimum, deposits and balances with other banks, loans and advances to other banks and non-banks, and holdings of debt securities. It excludes derivatives and off balance sheet transactions. In the BIS statistics foreign claims are reported as the sum of international claims (A + B) and local claims in local currency (C).
- *International Claims* (A + B) are banks' cross-border claims (A) plus local claims of foreign affiliates in foreign currencies (B).
- *Local Claims* (C) are the claims denominated in local currency of foreign affiliates on the residents of the host country (i.e., country of residence of affiliates).



Local Claims of foreign affiliates is the key variable used in the analysis of this paper, as it measures the claims of foreign affiliates towards residents in the host country. However, consolidated statistics on an immediate borrower basis provide separate data only on local claims in local currency and not on local claims in foreign currencies. Therefore, local claims in foreign currency are estimated as the difference between total international claims on an immediate borrower basis (Table 9AA BIS Statistics) and cross-border claims on an ultimate risk basis (Table 9CT BIS Statistics; see McCauley *et al.*, 2010). Estimates for local claims in foreign currency at the country level therefore include a bias which is larger, the larger the ultimate transfer risk.

Local Liabilities refer to liabilities of foreign affiliates of domestic banks in local currency vis-à-vis local residents.

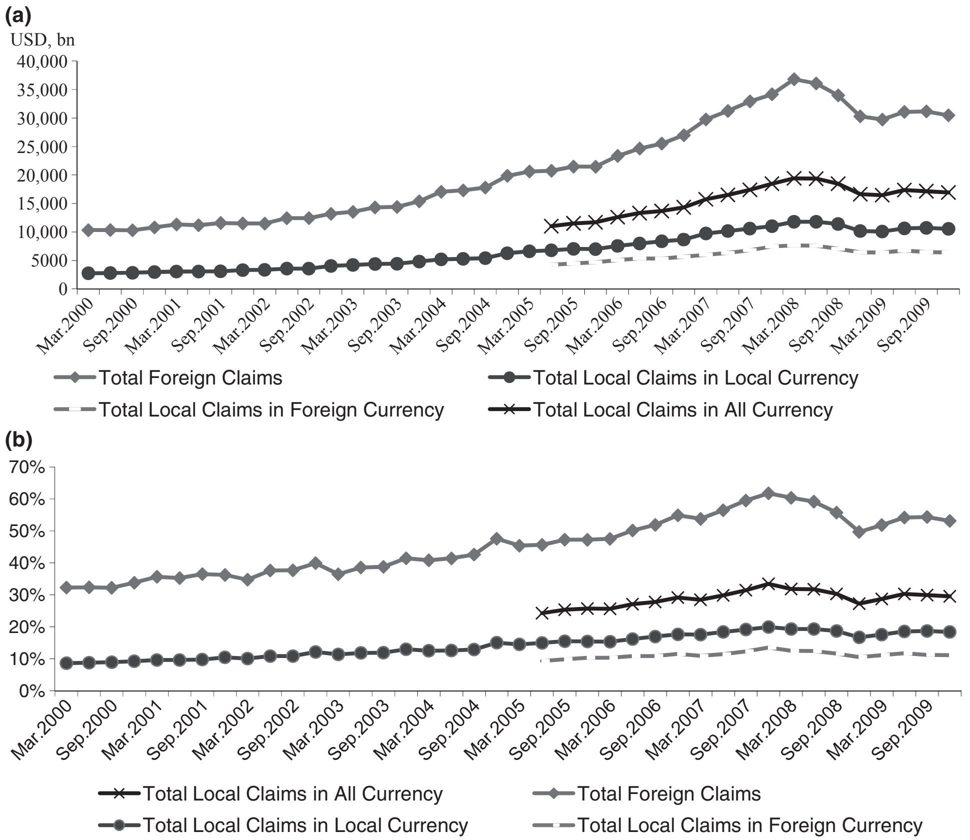


Figure 1. Total foreign and local claims in (a) nominal values and (b) percentage of GDP

Source: BIS Consolidated Statistics for claims and World Bank Statistics for GDP.

2.2. The rise of multinational banking within the EU single market

Decomposing the BIS data by regions of destination, we notice that the value of local claims of foreign affiliates denominated in local currency (converted in current US dollars in the BIS statistics) have been rising especially fast in the EU, particularly among the EMU12 countries (Figure 2), reaching the other advanced economies, including the United States and Japan, by the end of the period.[6]

These trends are also the outcome of severe exchange rate fluctuations in the period analysed. The yen roughly devalued by 30% with respect to the euro between 2000 and 2009 and the dollar by almost 50%. To better gauge the

[6] Here we restrict our analysis to claims denominated in local currency, as the bias in the estimates of those in foreign currency is particularly severe at the level of a country or a group of countries.

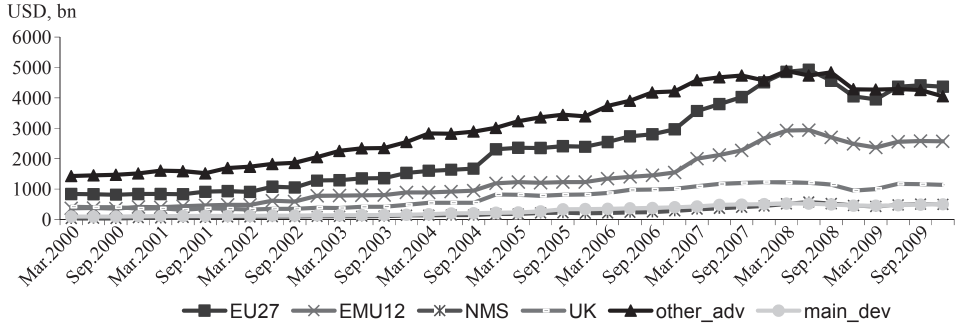


Figure 2. Nominal total local claims of foreign affiliates by host region

Note: Other advanced: United States, Canada, Japan, Australia, New Zealand, Switzerland. NMS: Bulgaria, Cyprus, Czech Republic, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia, Slovenia. Main Developing: China, India, Malaysia, South Korea, South Africa, Singapore, United Arab Emirates.

Source: BIS Consolidated Statistics.

Table 1. Total local claims in local currency on total assets (%)

	avg 2001–2003	avg 2004–2006	2007	2008-I	2008-II	2008-III	2008-IV	2009-I	2009-II
EU27	9.8	13.3	17.9	17.8	17.7	17.8	16.4	16.6	16.9
EMU12	7.5	9.9	15.1	15.4	15.2	15.2	14.1	13.8	13.8
UK	16.5	21.7	23.0	21.7	21.3	21.5	21.0	22.9	23.4
NMS	35.7	43.1	50.2	49.4	50.6	48.9	44.7	46.6	47.4
other_adv	4.1	5.1	6.0	6.3	6.0	6.3	5.6	5.9	5.9

Notes: Other advanced: United States, Canada, Japan, Australia, New Zealand, Switzerland. NMS: Bulgaria, Cyprus, Czech Republic, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia, Slovenia.

Source: BIS Consolidated Statistics for Local Claims. IMF, International Financial Statistics for Total Assets.

increasing role of multinational banking it is therefore necessary to relate local claims to the value of total banking assets in the countries of destination. This is done in Table 1.

The especially important role of foreign affiliates in the EU stands out clearly when the size of their assets is normalized with the total banking assets of each country. By mid-2009 these were 16.9% with respect to total assets, compared to a mere 5.9% for the other industrialized economies. The ratio for the EU has also risen considerably (and at a faster pace than for other advanced economies) from early 2000, when it was lower than 10%. The picture is fairly heterogeneous within the Union. Foreign affiliates have an especially large role in the United Kingdom and in the new member states (NMSs), particularly in those that have adopted the euro, where they account for a very large share of total assets. These particularly high shares reflect of course the role of the United Kingdom as an international financial centre and, for the NMSs, their relatively weak local financial institutions which were acquired by large European banks during the transition years. As for the EMU12, the share of assets held by foreign banks is lower than for the EU average. However, given the size of this area, in nominal values the EMU12 countries account collectively for the largest amount of local claims held by foreign affiliates.

The evidence that MNBs have become increasingly active within the EU, particularly through mergers and acquisitions, requires some qualifications.[7] In principle, an integrated financial market should provide an ideal ground for cross-border market transactions, reducing the need to rely on the ICM to move resources across countries, as it would be the case with MNBs. Yet, we know that retail activities are non-tradable even within integrated markets. Therefore, tapping the European retail market requires having local operations in foreign countries anyway. But within an integrated financial area and particularly with a single currency, those local operations can likely benefit from easier and smoother intra-bank cross-border transactions, taking place through the ICM. We will discuss extensively these results in Sections 3 and 4.

The argument that the ICM is likely to work more smoothly within integrated financial areas is also supported by the evidence that most foreign banking activity in the Union is intra-European. This can be gauged by ECB data, where total banking assets of member countries are decomposed by the nationality of ownership of the bank and by whether foreign affiliates are independent subsidiaries or branches.[8] As we will further discuss below, the distinction between subsidiaries and branches is important both from the point of view of the organization of the internal capital market and of the regulatory framework in the EU (see Calzolari and Loranth, 2010, for an analysis of regulation of MNBs in terms of their organization).[9] This decomposition is reported in Figure 3. Differences in definitions of

[7] M&A activity within the EU banking sector experienced a boom at the beginning of the new century. In 2000 there were approximately 140 M&A transactions in the EU, of which intra EU 25 M&A deals involving a non-domestic acquirer represented almost 30% of the total (European Central Bank, 2006).

[8] Assets of credit institutions under the ECB definition comprise any asset that is (i) cash; or (ii) a contractual right to receive cash or another financial instrument from another enterprise; or (iii) a contractual right to exchange financial instruments with another enterprise under conditions that are potentially favourable; or (iv) an equity instrument of another enterprise. Total assets are calculated on a residential basis, meaning that for each Member State the credit institutions under the law of that Member State are included (regardless of whether or not they are a subsidiary of a foreign bank). However, the activity of the foreign branches of these credit institutions is not included, as this is reported by the host country. Credit institutions include any institution covered by the definition contained in Article 4(1) of Directive 2006/48/EC (recast). Accordingly, a credit institution is '(i) an undertaking whose business is to receive deposits or other repayable funds from the public and to grant credits for its own account; or (ii) an electronic money institution within the meaning of Directive 2000/46/EC. The most common types of credit institutions are banks and savings banks'.

[9] Foreign affiliates set up as subsidiaries are stand-alone companies, where local management has a high degree of decisional autonomy within the group. In the current European regulatory framework they are subject to host country supervisory authorities. Branches instead are part of the foreign group and not stand-alone companies, normally with less decisional autonomy than subsidiaries. They are subject to the home country supervisory authorities. Branches are used more frequently by MNBs to carry out wholesale activities. Subsidiaries are normally used to carry out retail activities, given that they collect deposits and that a large part of their transactions have to be carried out face to face with local customers. The largest share of foreign assets is held by EU banks through subsidiaries. This reflects the recent spur of cross-border acquisitions, where acquired banks become autonomous foreign subsidiaries and also the fact that within Europe foreign affiliates are generally used to carry out non-tradable activities like retail.

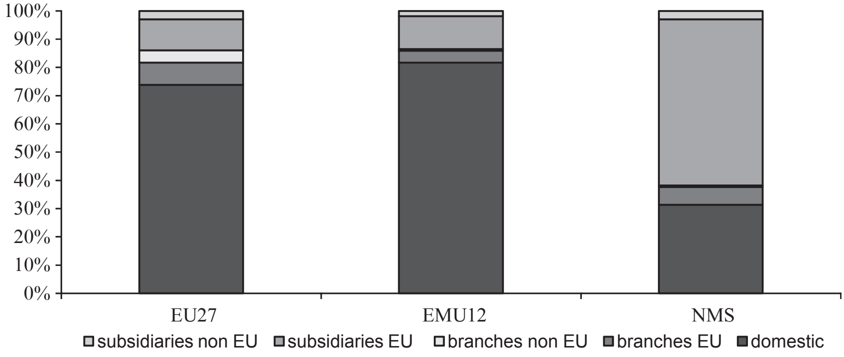


Figure 3. Distribution of total banking assets EU27 (2008)

Note: NMS: Bulgaria, Cyprus, Czech Republic, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia, Slovenia.

Source: ECB Statistics.

asset categories explain why the ECB figures do not match precisely the BIS figures reported above.[10]

If we consider the aggregate of the EU countries, we notice that foreign banks account for roughly 29% of total assets, held through either subsidiaries or branches. Foreign banks' assets can further be decomposed into EU and extra-EU institutions. Notice that by far the largest share of these assets are owned by EU banks. This share is especially large within the EMU aggregate.

The EU is therefore an especially interesting case to look at for assessing the role of MNBs and the functioning of their ICMs, particularly during the financial crisis. This justifies our focus on the EU in the micro analysis of the following sections.

3. MULTINATIONAL BANKS AND INTERNAL CAPITAL MARKETS: IMPLICATION FOR EFFICIENCY AND FINANCIAL STABILITY

This section examines how the availability of an ICM affects the behaviour of MNBs, and their possible reactions during a crisis. It is indeed the ICM that makes the activities of foreign affiliates in host economies distinctly different from those of stand-alone national banks. Large corporations can establish ICMs that allocate scarce capital, liquidity and risk across the many units belonging to the holding (Box 2 briefly describes the functioning of ICMs and summarizes the literature in finance and economics that have analysed their working, both theoretically and empirically).

[10] Note that the share of the assets held by foreign banks (29%) is larger than the share of local claims on total assets (15%) and smaller than the share of foreign claims (60%) reported in Table 1. The reason is that the definitions of assets are different for the two institutions. Foreign assets under the ECB include claims towards residents and non-residents in the host country held by foreign subsidiaries and branches based in a given EU host country (but not those held through other foreign subsidiaries or branches based abroad). Local claims under the BIS have a strictly host country perspective and only include claims of foreign branches and subsidiaries vis-à-vis residents in the host country. Foreign claims in BIS statistics also include cross-border transactions.

Box 2. Internal capital markets: the bright and the dark side

Financial and non-financial institutions are often organized in divisions or affiliated units, by product or by location. Consider, for example, a bank with its parent company P and two affiliates A1 and A2, each with some internal funding, collaterals, pledgeable income and investment opportunities (see Figure 4 for a graphical representation). A1 can be financed as a stand-alone entity using funds internal to A1 or raised directly by A1 in the external credit market. Alternatively, in the absence of constraining regulation, A1 can be financed in an ICM in which A1 approaches P for funding. The parent P in turn can directly raise external funds against its own and the combined collateral of affiliates A1 and A2, centralize the funds individually raised by the affiliates and, finally, allocate them to A1, A2 and P according to some criteria. In the end, this allocation is similar to the task performed by the credit market, although it takes place within the 'internal' capital market of the bank. The central question for ICMs is whether this internal process is more or less efficient and profitable for the bank than an external market for credit. Clearly, if the capital market were fully efficient, ICMs would be irrelevant, but we know this is almost never the case. First, raising external funds in a centralized way may allow increasing the total amount of funds (the '*more-money effect*' of ICMs). Second, funds may be allocated more efficiently and profitably to all investment opportunities when the process is centralized and information asymmetries are overcome (the '*smarter-money effect*' of ICMs). Clearly the two effects, which are known as the '*bright side*' of ICMs, are related (smarter money may lead to more money) and depend on the ICM's organization. In particular, more money may take place since the control power attributed to the internal capital market should induce more screening and monitoring of the projects to be financed. Furthermore, an ICM may create value in financially constrained firms, since affiliates' projects compete for scarce internal funds and are jointly screened within the ICM. However, badly organized ICMs may show up with a '*dark side*': competition for funding may turn out to be wasteful rent-seeking, funds may be spread among affiliates with no reference to relative merit, thus dampening incentives and with the affiliates' manager feeling expropriated. The empirical literature has shown that ICMs do operate in large corporations since one observes that shocks in one affiliate affect investments in other affiliates and investments in small units are positively related to cash flow of other units. ICMs have also been shown to deliver more and smarter money when the external capital market is less developed (e.g. for weak legal enforcement, inadequate accounting and disclosure practices); when divisions have not sharply divergent investment prospects; when the firm is able to control the agency issues intrinsic to ICMs using high-powered incentives such as management ownership. These results have been shown by a significant theoretical and empirical academic literature while that on ICMs for banks is instead less developed and that on MNBs even less so, as discussed in the main text.

Some relevant theoretical papers related to the more-money and smarter-money effects are Williamson (1975), Gertner *et al.* (1994), Stein (1997, 2002), and Carletti *et al.* (2007). Scharfstein and Stein (2000), Rajan *et al.* (2000), Hart and Holmstrom (2010), and Brusco and Panunzi (2005) have studied the dark side of ICMs. For empirical analyses see, among others, Lamont (1997), Scharfstein (1998), Shin and Stulz (1998), Rajan *et al.* (2000), Chevalier (2004), Khanna and Tice (2001), Whited (2001), Billett and Mauer (2003), Ozbas and Scharfstein (2008).

This analysis is important to our aims since MNBs have the possibility to diversify risk internationally, to optimally allocate funds across their network of international affiliates in search of higher returns, and to efficiently share liquidity. We are also particularly interested in understanding whether ICMs in cross-border banks have stabilizing or destabilizing effects in home and host countries, in normal times and in times of crisis. In particular, as for the effects of shocks affecting banks and host countries, in this section we will deal with *idiosyncratic* ones, while the next section will be devoted to the *systemic* shocks of the present crisis. Here we will develop a theoretical framework for MNBs and their ICMs which will deliver a number of 'claims'. Considering the set of all these claims, we will then derive some testable implications that will be explicitly verified with the empirical analysis in the next section.

Affiliates of an MNB located in different countries may well face different costs of external funds. These banks may thus collect deposits, say in country 1 and 2, and finance a project in country 2 by pooling deposits in an ICM. In addition, by pooling liquidity from affiliates in different countries, when affiliates' liquidity shocks are not positively correlated, an MNB may then be able to keep lower liquidity to take care of the duration mismatch of assets and liabilities typical of the transformation activity of banks. For given regulatory constraints that national authorities impose to banks on liquidity, this possibility allows an MNB to reduce overall costs. Although diversification can also be obtained in a large national group, it is clear that cross-border activities may well increase diversification. On the other hand, one should also consider that the functioning of an ICM operating across countries may be hindered by factors such as limited economic and regulatory integration, differences in (business) culture, in languages and by distance among the units belonging to the ICM, as we will further illustrate.

From these arguments it is possible to derive some important consequences of an ICM in a banking group and, in particular, for an MNB. As explained in Box 2,

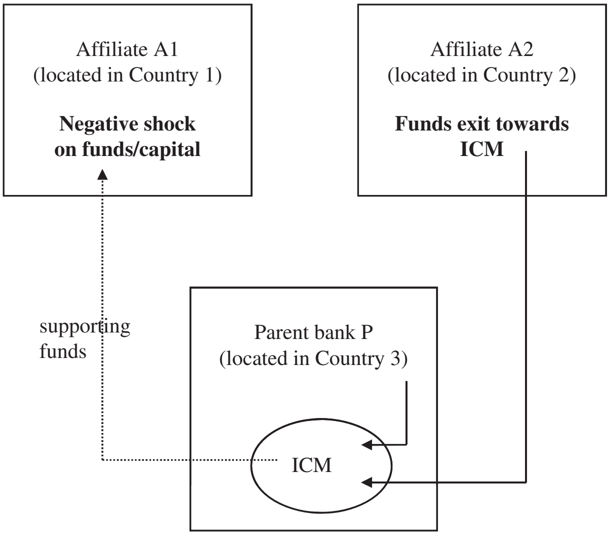


Figure 4. Functioning of ICM of an MNB when affiliate A1 is hit by shock on capital

the organization of an ICM and its functioning are responsible for the possible realization of 'smarter money', according to which funds, risk and liquidity are allocated to the MNB's affiliates that are better at managing them. This process of relocation leads to a *support* effect and a *substitution* effect which are described next (this useful taxonomy is due to Morgan *et al.*, 2004).

Consider Figure 4 and a shock that is local in country 1, deteriorating capital (assets or loans) or reducing funds availability (with a reduction of deposits) of affiliate A1 of the MNB. This negative shock may force the affiliate either to obtain new equity, to satisfy its capital adequacy ratio and/or its strategies, or to reduce its loans. This would certainly be the case were the bank a single entity. When belonging to an MNB, instead, the shock may be reduced by the capital and the liquidity provided by home or other affiliates in foreign countries, through the ICM. An MNB may then be able and willing to *support* its affiliates in cases of country-specific shocks, thus watering down the effect of these local shocks: *the support effect makes an affiliate's lending capacity less responsive to local shocks on capital and deposits*, *i.e. on the availability of local funds* (*Claim 1*).

In addition to the support effect, an ICM determines capital and liquidity movements looking for the best remuneration within the MNB (the 'smarter money'), that might lead to a *substitution* effect. Consider now a real shock hitting the economy in the country of an affiliate (say country 1 in the previous figure), thus reducing the returns of investments in that country. Then, the ICM would substitute the activities of that affiliate relocating funds towards the parent bank and other affiliates with better investment opportunities. This makes an affiliate's lending in a banking group more responsive to shocks affecting the returns of its investments. *Hence, the substitution effect weakens the link between funds availability and lending. This is more so for banking groups operating in countries with little correlated real shocks and it is definitely less relevant for domestic banking groups operating in a single country* (*Claim 2*).

The support and substitution effects emerge from the 'smarter money' of an ICM (which ultimately may enhance efficiency and profitability of an MNB). We are now interested to see the role of 'more money' that a banking group may generate if its ICM works properly (see again Box 2). If this is the case, then an ICM has much more information and control on a troubled affiliate than the external capital market which, instead, may be completely impaired due to lack of information. On a similar vein, the functioning and the effects of ICMs are closely related to the organization and the incentives that are used in setting up an MNB's ICM. On the one hand, affiliates may be tightly integrated to form a unique ICM, such as for branches of a bank which are *de facto* (and *de jure*) parts of the holding company. Alternatively, even though they take part in an ICM, affiliates may keep some independence and responsibility in their decisions, as it is often the case for MNBs' subsidiaries (which are *de jure* independent legal entities controlled by the holding). We are mainly interested in the organization of groups with subsidiaries, which are the predominant form of foreign affiliates in Europe (with the exception of the United Kingdom), also because, as explained in the sequel, data on single affiliates are only available for subsidiaries. It has been emphasized (Shah and Thakor, 1987; Kahn and Winton, 2004; Boot and Schmeits, 2000) that a subsidiary structure may allow external investors to better evaluate the different projects in the holding by clearly associating projects to single units so that higher transparency translates into smaller cost for external funding. Hence, *a well-organized ICM of domestic and international banking groups may generate 'more money' available to address any kind of shock, thus smoothening the link between funds and lending* (*Claim 3*).

Overall, Claims 1–3 all point to a reduction of correlation between available funds and a bank's lending capacity.

As explained in Box 2, however, an ICM can deliver its desirable properties that lead to Claims 1–3 when showing its bright side. Support/substitution is strictly related to the information that is made available within the organization, since an ICM involves a decision process that requires information.[11] Hence, a more integrated ICM with intense information sharing may lead to more substitution and support effects. However, for an ICM to work smoothly there must not be impediments which can emerge as external constraints. These constraints may

[11] A decentralized MNB with more independent units still belonging to the ICM (i.e. a flatter organization) is most likely to be an attractive option when information about individual projects is 'soft' and cannot be easily and credibly transmitted upstream through the hierarchy. In contrast, a large and hierarchical MNB with multiple layers composed of units of limited independence and a strongly integrated ICM is best when information can be 'hardened' and passed along the hierarchy.

emerge because of an inadequate organization and incentive mechanism of the ICM, but also by the regulatory and economic environment. Pooling resources into an ICM and relocating internationally to the affiliate in need of support requires that the MNB satisfies a set of rules imposed by possibly many different countries (since a fully harmonized or integrated regulatory authority is still missing in the international banking sector) thus leading to a 'regulatory risk'. Pooling resources also exposes the MNB to a 'transfer risk', for example associated with the exchange rate swings of the currencies in use in the different countries. On a similar vein, the literature on the ICM has shown that this should operate better when the participating units have not sharply divergent investment prospects, as it is the case in related economies. Thus, *MNBs operating in an integrated area, both in terms of regulations and in terms of currencies, may make a more intense use of their ICMs* (*Claim 4*). Furthermore, one may expect that *units that are located in distant countries with different languages or different cultural environments may find it difficult to actively take part into a cross-border ICM of an MNB* (*Claim 5*).

In light of Claims 2, 4 and 5, it will be particularly interesting to understand whether the ICMs are substitutes or complements of the process of market integration taking place at different stages in Europe. On the one hand, as illustrated above, the need for an ICM may be limited in very well-integrated economies with correlated real shocks, since the external and the integrated internal capital markets may function as substitutes and the scope for the substitution effect is limited. On the other hand, differences in terms of cultures, languages, banks' regulations and currencies may obstruct the kind of integration within the MNB that is needed for an ICM to work smoothly.

That ICMs operate in large banks is a documented fact. It has been shown that loan growth of an affiliate of domestic holdings is more sensitive to the parent's cash flow and capital than the affiliate's own capital (Houston *et al.*, 1997; Houston and James, 1998; Morgan *et al.*, 2004; Kroszner and Strahan, 2006; Kroszner, 2008; Carlson and Mitchener, 2009).[12] As for cross-border banks, De Haas and van Lelyveld (2010) have recently documented the functioning of ICMs in the top 45 MNBs around the world (see also Chan-Lau *et al.*, 2008), showing that they are more active (in terms of support and substitution effects) in foreign units that are less independent (e.g. that have been established with green field investment instead of takeover).[13] In this case, they find evidence that the substitution effect is at play, since foreign lending is negatively related to the business cycle of the home country of the parent holding, and that the support effect shows up mainly for dependent

[12] Carletti *et al.* (2007) set up a theoretical model of banks merging in different regions and explicitly account for their liquidity decisions. They show that merged banks have lower liquidity risk and financing costs and are more efficient but also that merges may have adverse macro effects reducing liquidity of the interbank market.

[13] Havrylchyk and Jurzyk (2006) show that greenfield banks are much more embedded in an MNB group's internal capital market, whereas acquired banks within the group seem to be organized as rather independent capital units.

units of MNBs that reduce lending less than independent banks when the foreign economy is hit by a negative shock.[14]

3.1. Empirical evidence on the functioning of internal capital markets: a European perspective

Following the five claims we identified above, we now turn to an empirical analysis of the effects of ICMs on the link between bank lending and funds availability in Europe. To do so, we consider how, in a given bank, deposits co-vary with loans, focusing therefore on one specific effect of the availability of an ICM, its impact on the correlation between funding and the use of resources. The advantage of using this simple index is that it requires no assumptions on the direction of causality between deposit and loan growth. We focus instead on the possible differences in their correlation between banks that do have internal capital markets and banks that do not. Clearly, this exercise is only possible by retaining a control group of stand-alone units, which represents our benchmark for banks that have no access to ICMs.

The existing empirical literature has not explicitly considered domestic banks and domestic banking groups as controls for a direct comparison for the effects of national and international ICMs. Our strategy is therefore complementary to that of De Haas and van Lelyveld (2010), who show that the lending behaviour of bank affiliates is affected by their parents' financial conditions, but only control for the contemporaneous behaviour of very large stand-alone units, that might not be fully comparable with typically smaller foreign affiliates.

Comparing the correlation between loans and deposit of MNBs and a counterfactual of national banks is also justified by the fact that we are focusing our analysis on Europe, where the number of country-specific crises is very limited. Consequently, in our case, contrary to De Haas and van Lelyveld (2010), we cannot test for the existence of the ICM by looking at how national banking crises affect the lending strategies of affiliates based in other countries.[15]

Finally, since we will concentrate on banks operating in Europe, we have the possibility to consider banks active in an economic area with a significant level of integration both for the real economy, thus being characterized by correlated real shocks, and for the financial sector. We will then study the interplay between international integration and the functioning of ICMs. As explained above, *a priori*

[14] On anecdotal evidence, during the 2003 crisis of Norwegian banks, it has been observed that Noredea Norway, although hit by significant losses (accounting for 1.17% of its gross lending in 2003), was able to limit the reduction of its capital by borrowing from the Nordea Group. Looking at the crisis of Japanese banks in the early 1990s, units in the United States experienced reduction of lending where they were units more dependent on the parent banks but they were almost unaffected when they were more independent (Peek and Rosengren, 1997).

[15] According to the reliable and updated dataset on banking crises by Laeven and Valencia (2008) – the one used, for example, in De Haas and van Lelyveld (2010) – there are no national crises in our sample, except for the crisis hitting the United Kingdom in 2007, which is however the first year of a global crisis.

the relationship could be one of complements or substitutes. Discriminating between the two cases is critical in particular in the current period of revision of the European environment for supervision and regulation of MNBs.

Our analysis is based on balance sheet information of a large sample of European banks, collected by the commercial data provider Bureau Van Dijk, in its Bankscope data base. We started by considering all affiliates in the EU27 countries of the 100 largest European banks (that are likely to be those that will be more directly supervised by European colleges of supervisors) between 2000 and 2008, distinguishing between domestic and foreign affiliates (i.e. dependent subsidiary banks that operate, respectively, in the same country and in a different one from that of incorporation of the parent bank), on the basis of their ownership structure.[16] In addition, we have checked the shareholding structure of all other banks in our sample, that includes all institutions in EU27 countries with total assets above US$100 million, to identify additional affiliates of domestic or foreign institutions. Summary statistics for our sample are presented in Table 2.

We have 7,326 banks, 637 affiliates of which 529 foreign, and 213 parent banks of which 148 MNBs.[17] The average size of the banks in our sample, measured by their total assets, is US$17 billion, while the median is less than US$1 billion, suggesting a significant skewness, as it is quite common when using company data. Affiliates and parent banks are larger (US$31.3 billion and US$204.0 billion, respectively). The average yearly rate of growth of nominal customer loans in our sample period is 20%, and it is smaller than average for parent banks (18%) and larger for affiliates (26%). Similarly, the average rate of growth of demand deposits is 19% (22% for affiliates and 15% for parent banks). Affiliates are also more profitable and are more leveraged than both parents and stand-alones. Finally, foreign affiliates within EMU and EU15 are larger than average, less leveraged and less profitable.

As a preliminary step, we have calculated the total correlations between the rate of growth of customer loans and of deposits, distinguishing between stand-alone banks, domestic and multinational parent banks and domestic and foreign affiliates. Table 3 shows that the average correlation between the loan and deposit growth is 0.54, and it is statistically significant at the 1% level. Consistent with our Claim 1 (*the support effect makes an affiliate's lending capacity less responsive to local shocks on capital and deposits*, *i.e. on the availability of local funds*) and Claim 2 (*the substitution effect weakens the link between funds availability and lending. This is more so for banking groups operating in countries with little correlated real shocks and definitely less relevant for domestic banking groups operating in a single country*), the correlation is slightly smaller than average for

[16] As it is common in this literature, we have not been able to extend our analysis to the behaviour of foreign branches, because with very few exceptions their activities are recorded only in confidential supervisory data, and not by all countries.

[17] The largest number of banks in our sample is from Germany, Italy and France; the largest number of affiliates is from Luxemburg, Poland and Spain.

Table 2. Summary statistics

Variables	Observations	Mean	Coefficient of variation	Median
Full sample				
Total assets (US$ bn)	7326	17.00	5.76	0.79
Customer loans (%)	6732	0.20	1.61	0.18
Demand deposits (%)	6584	0.19	1.53	0.17
Bank total assets – Country (%)	9239	0.17	0.44	0.18
Returns on assets (%)	7311	0.58	4.05	0.47
Customer loans/total assets	7263	0.58	0.38	0.62
Bank deposits/total assets	7058	0.18	1.08	0.12
Equity/total assets (%)	7316	10.27	1.51	7.26
Loan loss prov./Net int. margin	7311	0.58	4.05	0.47
Net interest margin (%)	6862	0.17	4.91	0.14
GDP (%)	7201	2.85	1.99	2.70
Stand-alones				
Total assets	6535	11.00	5.59	0.66
Customer loans (%)	6026	0.20	1.66	0.18
Demand deposits (%)	5893	0.19	1.54	0.17
Bank total assets – Country (%)	8445	0.17	0.40	0.18
Returns on assets (%)	6523	0.57	4.26	0.45
Customer loans/total assets	6479	0.58	0.36	0.63
Bank deposits/total assets	6285	0.17	1.12	0.11
Equity/total assets (%)	6525	10.33	1.56	7.27
Loan loss prov./Net int. margin	6137	0.17	5.17	0.14
Net interest margin (%)	6433	2.87	2.06	2.73
Affiliates				
Total assets	637	31.30	4.29	32.79
Customer loans (%)	570	0.26	1.28	0.25
Demand deposits (%)	556	0.22	1.43	−0.22
Bank total assets – Country (%)	633	0.23	0.53	−0.21
Returns on assets (%)	634	0.70	2.76	0.69
Customer loans/total assets	630	0.50	0.50	0.53
Bank deposits/total assets	621	0.29	0.79	0.23
Equity/total assets (%)	637	10.53	0.96	7.64
Loan loss prov./Net int. margin	634	0.70	2.76	0.69
Net interest margin (%)	574	0.17	1.97	−0.12
Parent banks				
Total assets	213	204.00	2.00	37.70
Customer loans (%)	192	0.18	1.11	0.18
Demand deposits (%)	191	0.15	1.67	0.13
Bank total assets – Country (%)	219	0.19	0.64	0.18
Returns on assets (%)	213	0.66	1.04	0.57
Customer loans/total assets	213	0.53	0.40	0.57
Bank deposits/total assets	211	0.20	0.80	0.16
Equity/total assets (%)	213	7.04	0.98	5.85
Loan loss prov./Net int. margin	213	0.66	1.04	0.57
Net interest margin (%)	210	0.16	1.14	0.14
Foreign affiliates				
Total assets	529	21.40	5.08	2.95
Customer loans (Δ%)	483	0.26	1.27	0.27
Demand deposits (Δ%)	471	0.22	1.45	0.23
Bank total assets – Country (Δ%)	530	0.24	0.52	0.23
Returns on assets (%)	527	0.67	2.52	0.67
Customer loans/total assets	522	0.50	0.49	0.53

Table 2. (Continued)

Variables	Observations	Mean	Coefficient of variation	Median
Bank deposits/total assets	520	0.29	0.80	0.23
Equity/total assets (%)	529	10.76	1.00	7.60
Loan loss prov./Net int. margin	527	0.67	2.52	0.67
Net interest margin (%)	475	0.17	2.07	0.12
Foreign parent banks				
Total assets	148	251.00	1.80	52.30
Customer loans (Δ%)	135	0.16	1.11	0.17
Demand deposits (Δ%)	134	0.13	1.68	0.13
Bank total assets – Country (Δ%)	153	0.18	0.70	0.18
Returns on assets (%)	148	0.66	1.04	0.56
Customer loans/total assets	148	0.51	0.41	0.54
Bank deposits/total assets	148	0.22	0.77	0.17
Equity/total assets (%)	148	6.37	0.78	5.50
Loan loss prov./Net int. margin	148	0.66	1.04	0.56
Net interest margin (%)	146	0.16	1.12	0.14
Banks chartered in EMU				
Total assets	6087	15.40	6.05	0.74
Customer loans (Δ%)	5614	0.19	1.59	0.18
Demand deposits (Δ%)	5515	0.18	1.52	0.17
Bank total assets – Country (Δ%)	7629	0.16	0.34	0.18
Returns on assets (%)	6082	0.53	3.82	0.43
Customer loans/total assets	6040	0.58	0.37	0.62
Bank deposits/total assets	5914	0.18	1.08	0.12
Equity/total assets (%)	6077	10.07	1.12	6.97
Loan loss prov./Net int. margin	6082	0.53	3.82	0.43
Net interest margin (%)	5826	0.18	4.93	0.15
Banks chartered in EU15				
Total assets	6826	18.10	5.62	0.78
Customer loans (Δ%)	6283	0.19	1.66	0.18
Demand deposits (Δ%)	6142	0.18	1.55	0.17
Bank total assets – Country (Δ%)	8654	0.16	0.35	0.18
Returns on assets (%)	6812	0.58	3.58	0.45
Customer loans/total assets	6764	0.58	0.38	0.63
Bank deposits/total assets	6576	0.18	1.09	0.12
Equity/total assets (%)	6816	10.11	1.57	7.05
Loan loss prov./Net int. margin	6812	0.58	3.58	0.45
Net interest margin (%)	6406	0.17	4.99	0.14
Foreign subsidiaries in EMU				
Total assets	283	33.00	4.41	5.49
Customer loans (Δ%)	258	0.22	1.57	0.22
Demand deposits (Δ%)	247	0.19	1.71	0.19
Bank total assets – Country (Δ%)	291	0.20	0.52	0.20
Returns on assets (%)	282	0.49	2.83	0.51
Customer loans/total assets	278	0.48	0.59	0.50
Bank deposits/total assets	281	0.34	0.74	0.28
Equity/total assets (%)	283	9.01	1.14	5.94
Loan loss prov./Net int. margin	282	0.49	2.83	0.51
Net interest margin (%)	256	0.19	2.30	0.13
Foreign subsidiaries in EU15				
Total assets	314	33.40	4.19	5.28
Customer loans (Δ%)	284	0.21	1.62	0.21
Demand deposits (Δ%)	274	0.18	1.91	0.18
Bank total assets – Country (Δ%)	325	0.19	0.55	0.19

Table 2. (Continued)

Variables	Observations	Mean	Coefficient of variation	Median
Returns on assets (%)	312	0.52	2.55	0.53
Customer loans/total assets	308	0.46	0.61	0.47
Bank deposits/total assets	309	0.33	0.74	0.28
Equity/total assets (%)	314	9.52	1.17	5.94
Loan loss prov./Net int. margin	312	0.52	2.55	0.53
Net interest margin (%)	275	0.18	2.39	0.12

Source: Data are from Bankscope.

Table 3. Correlations between the rate of growth of customer loans and of demand deposits

Sample	Correlations
All banks	0.54
Stand-alones	0.54
Affiliates	0.42
Domestic affiliates	0.46
Foreign affiliates	0.42
Foreign affiliates (EMU)	0.26
Foreign affiliates (EU15)	0.26
Foreign affiliates (non-EU15)	0.66
Parent companies	0.82
Domestic parent companies	0.83
Multinational parent companies	0.82

Note: EMU and EU15 foreign affiliates are defined as those with their parent company within EMU and EU15, respectively. Non-EU15 foreign affiliates can have their parent company in any other EU27 country. All correlations are statistically significant at the 99% level.

Source: Data are from Bankscope.

affiliates, and it is even smaller for foreign affiliates. Further, the correlation is even smaller for foreign affiliates located within more integrated areas, such as EMU and EU15, providing convincing evidence to Claim 4 (*MNBs operating in an integrated area, both in terms of regulations and in terms of currencies, may make a more intense use of their ICMs*). Only in the case of foreign affiliates located in the NMSs of Central and Eastern Europe and of the few foreign banks in Malta and Cyprus (non-EU15 countries), the correlation is significantly higher, consistent with the hypothesis that regulatory and monetary integration is an important ingredient fostering the functioning of ICMs. The correlation is higher than average also for parents, both domestic and MNBs. A possible explanation is that parents are themselves very large banks composed with several dependent units (e.g. branches) and since they normally organize the ICM of the group, they smooth out the balance between loans and deposit of their affiliates, but on average keep stable their own relation between loans and deposits.

The indications of the simple correlations are that banks that may use ICMs can afford a more independent management of their assets and liabilities, thus smoothing the effects of potential idiosyncratic shocks. Furthermore, this is even more the case for those banks operating an ICM internationally.[18] To strengthen this preliminary evidence, in the following we will present the results of a more robust econometric analysis, capable of providing further support of our previous claims.

Our econometric framework exploits thoroughly the information contained in the correlations between each bank's growth of deposits and customer loans, using a two-step procedure. First, we estimate the time series correlation between each bank's rates of growth of deposits and of customer loans. Due to the frictions in our data set, we lose information for about 2,000 banks, obtaining a sample of 5,665 bank specific correlations. Second, we use the bank specific correlations as a dependent variable in a standard regression model, where the explanatory variables are: a set of dummies for foreign affiliates, in some specifications distinguishing those located within EMU and EU15; a set of bank specific characteristics; and country dummies.[19] In practice, our most general specification is the following:

$$\begin{aligned}\Delta Correl_{ij} = {} & a_1 + a_2 DUM\_DomS_{ij} + a_3 DUM\_ForS_{ij} \\ & + a_4 DUM\_ForS\_EMU_{ij} + a_5 DUM\_For\_EU15_{ij} \\ & + a_6 DUM\_For\_EU15nEMU_{ij} + a_7 Char_{ij} + a_8 Country_j + \varepsilon_{ij}\end{aligned} \tag{1}$$

where: $\Delta Correl_{ij}$ is the correlation between the rate of growth (calculated as the annual change of the natural logarithm) of customer loans and of customer deposits of bank i in country j between 2000 and 2008; DUM_DomS_{ij} is a dummy variable for domestic affiliates; DUM_ForS_{ij} is a dummy variable for foreign affiliates; $DUM\_ForS\_EMU_{ij}$, $DUM\_For\_EU15_{ij}$, and $DUM\_For\_EU15nEMU_{ij}$ are dummies for foreign affiliates operating in EMU, in EU15 and in EU15 countries that are not EMU members, respectively;[20] $Char_{ij}$ are average characteristics of bank i of country j between 2000 and 2008; $Country_j$ is a set of country dummies; and ε_{ij} is a standard error term. The model is estimated using weighted least squares, to account for the different time span over which bank specific correlations have been calculated. As bank characteristics we have considered a measure of specialization (the share of customer loans over total assets), since banks active in traditional activities are more likely to have a strong matching between retail funding and lending; a measure of interbank liquidity (the share of bank deposits over total assets),

[18] It might be argued that MNBs are better at insuring idiosyncratic shocks because they are more efficient than domestic banks. Indeed, our results can be interpreted as showing that MNBs are more efficient precisely in the sense that they have an organization that allows them to make a better use of ICMs.

[19] We have chosen to focus on affiliates because, in a number of unreported regressions we have verified that the behavior of holding companies is not too dissimilar from that of average standalones, giving insignificant coefficients of the associated dummies.

[20] We considered banks that changed their status during the sample period as different institutions.

because easier access to the interbank market reduces the need for a strict matching of customer deposits and loans; leverage (the equity to total assets ratio), because more leveraged banks are typically those with better access to funding in capital markets; and size (the logarithm of total assets). To limit the effect of outliers we have run the estimates excluding observations below the 1st and above the 99th percentile of the sample distribution.[21]

The tests of our earlier claims are based on the signs and significance of the coefficients a_2 to a_5, associated with the dummies for the domestic affiliates and for the foreign affiliates in the different groups of countries. In particular, Claims 1–3 are generically consistent with a negative coefficient for the dummies of domestic and of foreign affiliates (a_2 and a_3); Claims 4 and 5 imply negative coefficients of the dummies for EMU and possibly non-EMU-EU15 affiliates (a_4 and a_5), consistent with an even lower correlation in the case of foreign affiliates, the more so if they operate within more integrated areas.

Table 4 presents the results of different specifications of model (1).

In column 1 we have included among the explanatory variables only the dummies for domestic and foreign affiliates, and the country dummies. As expected, both coefficients are negative, although only the coefficient of foreign affiliates, that is larger in absolute value, is statistically significant. Although the difference between the two is statistically insignificant, this provides some evidence consistent with the hypothesis of stronger incentives to use ICMs within a multinational group. Indeed, the aggregate result is likely to be the outcome of two opposing forces. In the case of domestic affiliates, ICMs may operate more smoothly, but they are used only when support is needed, since substitution is much less relevant within banks operating in the same country. In the case of foreign affiliates, both the support and the substitution effects are at work. Recall that both effects when at work should reduce the correlation between deposits and loans. But their relative magnitude is likely to vary, depending on the degree of market integration. Among highly integrated economies, on the one hand funds can be transferred more smoothly, but on the other hand business cycles are more correlated. Depending which of the two forces prevail, the support and the substitution functions are stronger or weaker within integrated areas. Columns 2 to 4 test precisely this hypothesis.

In column 2 we have included an additional dummy for MNBs operating within EMU. Consistent with Claim 4, we find strong evidence that foreign affiliates of EMU holding companies operating in another EMU country have an economic and statistically significant lower correlation between the rates of growth of deposits and of customer loans, with a coefficient of –0.197. Controlling for this effect, the coefficient of foreign affiliates becomes positive (0.007), although not statistically significant. For EMU foreign subsidiaries, the cumulative effect obtained summing

[21] Our results hold in unreported regressions where we use other trimming strategies.

Table 4. Correlation between loan and deposit growth – baseline specification

	(1)	(2)	(3)	(4)	(5)	(6)
Domestic affiliate (dummy)	−0.035	−0.036	−0.037	−0.037	−0.037	0.018
	0.038	0.038	0.038	0.038	0.038	0.035
Foreign affiliate (dummy)	−0.070***	0.007	0.067**	0.067**	0.067**	0.084**
	0.021	0.027	0.03	0.031	0.031	0.029
EMU foreign affiliate (dummy)		−0.197***		−0.264***	−0.258***	−0.193***
		0.042		0.045	0.045	0.042
EU15 foreign affiliate (dummy)			−0.266***			
			0.042			
EU15 non-EMU foreign affiliate (dummy)				−0.265***		
				0.064		
EU15 non-EMU non-UK foreign affiliate (dummy)					−0.091	−0.083
					0.101	0.093
UK foreign affiliate (dummy)					−0.355***	−0.233***
					0.076	0.07
Loans / total assets						0.364***
						0.018
Interbank deposits						−0.462***
						0.022
Leverage						−0.006***
						0.001
Total assets (log)						0.006**
						0.002
Observations	5665	5665	5665	5665	5665	5539
R^2	0.12	0.12	0.12	0.12	0.13	0.26

Notes: The dependent variable is the correlation between the annual percentage change of loans to customers and demand deposits at the bank level. Estimates are made using weighted least squares, using the number of years used to calculate the correlations as weights. All regressions include country dummies. Standard errors are reported in parentheses. The symbol *** indicates a significance level of 1% or less; ** between 1 and 5%; * between 5 and 10%.

Source: Data for balance sheet information is from Bankscope.

the two coefficients of the dummy for foreign subsidiaries and of the interaction term is negative and it is statistically significant at the 1% level.

This first evidence is further strengthened by the results reported in column 3, showing that MNBs operating within the larger group of EU15 countries (that includes EMU members) also benefit significantly from the functioning of ICMs. The coefficient for the dummy of EU15 foreign affiliates is −0.266 and it is statistically significant at the 1% level; as in the case of EMU, the cumulative effect obtained summing the two coefficients of the dummy for EU15 foreign subsidiaries and of the interaction term is negative and statistically significant. The coefficient of foreign affiliates remains positive (0.067) and it becomes statistically significant, suggesting that for the foreign affiliates operating in countries outside the EU15, mainly the NMSs of Central and Eastern Europe, the correlation between the rates of growth of deposits and of customer loans is even stronger than that of stand-alones. In this case, therefore, ICMs do work less smoothly, dampening the impact of potential support and substitution effects. This is not entirely surprising, since non-EU15 countries in our sample include mostly those recently admitted to the EU, that have typically higher cultural, linguistic and institutional barriers, as well as less-developed financial markets.

In column 4 we have distinguished between affiliates within EMU and affiliates within other EU15 countries, but outside EMU, with the aim of verifying the role of the monetary union in facilitating the functioning of internal capital markets for MNBs. On the one hand, sharing a common monetary policy and a common currency should facilitate intra-group fund transfers; on the other hand, it is possible that the support and substitution effects are in this case less relevant, due to the higher synchronization of the business cycles within EMU. The evidence of column 4 suggests that the two effects compensate each other, and the coefficients of the dummies for foreign affiliates in EMU and in the other EU15 countries are both economically and statistically significant, and very similar in size (−0.264 and −0.265, respectively). Again, the cumulative effects obtained summing the two coefficients of the dummy for foreign subsidiaries and of the interaction terms are economically and statistically significant.

In column 5 we have further distinguished between foreign affiliates operating in the United Kingdom and those operating in the other EU15 countries that are not members of EMU. The United Kingdom has a key role as a major financial centre, and its financial institutions have a large share of transactions denominated in the common European currency. Fund transfers with foreign affiliates operating in the United Kingdom might therefore be much smoother than with other non-EMU European countries, and therefore be the drivers of the coefficient of the dummy for the non-EMU-EU15 countries in the previous specification. Indeed, the results provide evidence in favour of this: the coefficient of the dummy for UK affiliates is negative and larger than that for EMU in absolute size (–0.355), while that for the other non-EMU-EU15 affiliates remains negative, but it becomes statistically insignificant.[22]

Finally, in column 6 we have added some bank specific controls to our previous specification. Our previous findings on the smoothness of the functioning of ICMs for foreign affiliates operating in different economic areas are substantially confirmed. As expected, we also find that the correlation between the rate of growth of deposits and of customer loans is on average higher for banks specialized in traditional lending activities, less leveraged, and less active in interbank markets. Bank size has a positive but negligible effect.

The evidence presented in Table 4 provides strong support to our claims on the functioning of ICMs for MNBs operating within well-integrated areas. In Table 5 we have further analysed the role of integration, including among the explanatory variables some measures of economic and institutional proximity, to test our earlier

[22] Indeed, our sample includes very few instances of foreign affiliates operating in non-EMU-EU15 countries other than the United Kingdom. In unreported regressions we have also analysed separately the role of Luxemburg, another important banking centre, finding that it also has no significant impact on our results.

Table 5. Correlation between loan and deposit growth – the role of proximity

	(1)	(2)	(3)	(4)
Domestic affiliate (dummy)	0.018	0.018	0.018	0.018
	0.035	0.035	0.035	0.035
Foreign affiliate (dummy)	0.060*	0.084**	0.038	0.111***
	0.031	0.029	0.033	0.032
EMU foreign affiliate (dummy)	−0.210***	−0.206***	−0.197***	−0.207***
	0.043	0.043	0.042	0.043
EU15 non-EMU non-UK affiliate (dummy)	−0.056	−0.087	−0.057	−0.108
	0.094	0.093	0.094	0.094
UK foreign affiliate (dummy)	−0.226***	−0.277***	−0.246***	−0.261***
	0.07	0.076	0.070	0.072
Loans / total assets	0.363***	0.363***	0.362***	0.363***
	0.018	0.018	0.018	0.018
Interbank deposits	−0.462***	−0.461***	−0.462***	−0.462***
	0.022	0.022	0.022	0.022
Leverage	−0.006***	−0.006***	−0.006***	−0.006***
	0.001	0.001	0.001	0.001
Total assets (log)	0.006**	0.006**	0.006**	0.006**
	0.002	0.002	0.002	0.002
Common border (dummy)	0.072*			
	0.037			
Common language (dummy)		0.121		
		0.079		
Low distance countries (dummy)			0.094*	
			0.035	
Low GDP correlation (dummy)				−0.086*
				0.046
Observations	5539	5539	5539	5539
R^2	0.26	0.26	0.26	0.26

Notes: The dependent variable is the correlation between the annual percentage change of loans to customers and demand deposits at the bank level. Estimates are obtained from weighted least squares, using the number of years used to calculate the correlations as weights. Low distance and low GDP correlation is defined as below the median of the sample distribution. All regressions include country dummies. Standard errors are reported in parentheses. The symbol *** indicates a significance level of 1% or less; ** between 1 and 5%; * between 5 and 10%.

Source: Data for balance sheet information is from Bankscope and data for GDP growth is from IFS.

Claim 5, that *units that are located in distant countries with different languages or different cultural environment may find more difficulties in actively taking part into a cross-border ICM of an MNB.*

In columns 1 and 2 we have included a dummy for foreign affiliates operating in countries sharing a border with that of the holding company (column 1), or where the same language is spoken (column 2). In both cases the estimated coefficient is positive, suggesting that stronger proximity has mainly the effect of reducing the impact of the substitution effect, but this result is only significant in the case of countries sharing a border and not for those with a common language.

In column 3 we have disentangled the effect for foreign affiliates operating in the countries that have a distance from that of the holding company that is below the median of the sample distribution. Closer countries are typically more integrated and have more synchronous business cycles, therefore reducing the scope for the substitution effect, but they are also more likely to permit a smoother working of

ICMs, for example by facilitating personal contacts. It turns out that the first effect prevails, since foreign affiliates operating in geographically closer countries have a higher correlation between the rates of growth of deposits and of customer loans.

Finally, to test the second part of our earlier Claim 2, that the substitution effect weakens the link between funds availability and lending especially for banking groups operating in countries with less correlated real shocks, in column 4 we have analysed the effect of the synchronization of the business cycles, disentangling the average effect of ICMs for affiliates operating in countries that have a bilateral correlation of the rate of growth of GDP with the country of the holding company that is below the first quartile of the sample distribution. Consistent with our expectation, the larger scope for the substitution effect in the case of less synchronized countries increases the role of ICMs, determining a reduction in the correlation between the rates of growth of deposits and of customer loans. Reassuringly, even when we include these controls, the EMU and EU dummies, which capture the degree of integration of financial markets, keep their negative and significant sign.[23]

4. MNBs AND THE SYSTEMIC CRISIS

In the previous section we have analysed how ICMs are expected to function under idiosyncratic financial distress and we have shown empirically that they have indeed been functioning so as to isolate lending activities of foreign affiliates from the local availability of funding. This finding is in line with the claim that ICMs may be used to support and stabilize financial markets, but it is not a direct test of how they have functioned in times of distress. Of particular concern is how they behaved during the current crisis, given its pervasiveness and that it impacted all players in the financial sector in Europe and all over the world.

In this section we turn precisely to the assessment of the effects of the recent crisis. We first discuss how the claims outlined in Section 3 hold in the case of a systemic crisis and then analyse empirically how the lending policies of foreign affiliates have been faring during the crisis. We do so first by using aggregate BIS world data and then our sample of European banks. Clearly, in this setting it is not our intention to provide an interpretation of the causes and consequences of the crisis itself, that have been and are being extensively analysed elsewhere (see, e.g., Acharya and Richardson, 2009).

Previous studies have shown that the presence of MNBs tend to increase stability in host developing countries during times of financial distress since domestic lending dropped during crises much more for domestic banks than for affiliates of MNBs

[23] Following the suggestion of one of the panellists, Martin Brown, we have also verified if the correlation between customer deposits and loans diminishes when a previously independent bank is acquired and becomes a foreign affiliate. Unfortunately, there are only few such operations in our sample with a time span before and after the acquisition sufficiently long to allow for the estimation of the correlations. Despite some weak evidence in favour of our hypothesis of a reduction in the correlation, we were unable to detect any statistically significant effect.

(see, for example, Clarke *et al.*, 2003, Detragiache *et al.*, 2006). Referring to the United States, Morgan *et al.* (2004) and Kroszner and Strahan (2006) have shown that when in a state there is a significant activity of a banking group that operates across states, then important macro variables in the state (e.g. growth and employment) tend to be less volatile, the size of the business cycle tends to be reduced and at the micro level loan availability becomes less related to the local banks' capital.

But all that these works do is show that banking groups seem to have a stabilizing role during *idiosyncratic* shocks. Our aim in this section is instead to verify the behaviour of MNBs in the current *systemic* crisis, in which the shocks are highly correlated among the countries in which the MNBs are active. To our knowledge, only two papers have focused on the behaviour of MNBs during the recent crisis. Using aggregate BIS and IMF data, Cetorelli and Goldberg (2010) show that foreign banks reduced the rate of growth of loans with respect to the pre-crisis period more than domestic banks. However, since their lending activity was much more buoyant than that of domestic intermediaries, their evidence confirms that the rate of growth of loans granted by foreign banks remained positive and stronger than that of domestic banks also after the crisis. Popov and Udell (2010) analyse instead a sample of medium and small firms in Eastern European countries, showing that firms that are located in provinces with a stronger presence of foreign intermediaries have a higher probability of being denied credit or to have renounced applying for bank loans because they feared to be denied. However, their data (based on a questionnaire) do not allow linking each firm to a potential lender, and the results are also consistent with the alternative hypothesis that MNBs are more efficient to screen troubled borrowers than domestic banks (thus relating to the 'smarter money' effect discussed above).

Despite the lack of analytical research, a well-shared perception during the crisis was that MNBs were heavily contributing to a credit crunch. The argument was that, by operating across borders, MNBs had quickly created a dramatic drop in lending in all countries where they were active, notwithstanding (substantially) stable deposits.

However, a deeper investigation of the functioning of ICMs reveals that this is a simplistic view. Two contradictory claims can emerge here. First, *if the shock is systemic, then one may expect that being an MNB may not help that much since the ICM cannot activate the support and substitution effect* (*Claim 6*). Second, if ICMs are well organized and functioning, they may attract more external funds relatively to stand-alone banks (i.e., the 'more money' effect described in Box 2). Depositors, for example, may behave differently when the bank belongs to an MNB: the 'more money' effect may significantly reduce the negative impact of the shock since the MNB may still be considered a safe harbour.[24] Hence, *if ICMs make the allocation of resources more*

[24] Indeed, De Haas and van Lelyveld (2010) illustrate this effect showing that in a crisis affecting a national banking system, foreign subsidiaries increase their deposits, contrary to domestic banks.

efficient within MNBs, they may help relaxing the nexus between local lending and funds also during a systemic crisis. MNBs would then have a stabilizing effect (*Claim 7*).

4.1. Aggregate evidence on the effects of the crisis on the activities of MNBs

A first test of Claims 6 and 7 can be performed by extending the analysis of Section 2 and looking at the aggregate trends in the activities of MNBs. Specifically, we focus on how local claims of these banks have behaved during the recent financial crisis, from the last term of 2007 to the fourth term of 2009. The key question is whether during the crisis MNBs have been unwinding their assets held through their foreign affiliates in host countries, or, in contrast, whether they have been channelling liquidity to their subsidiaries to support them.

We argued in Section 2 that local claims had been more stable than total foreign claims in 2008 and 2009. If we consider the EU27, the total value of local claims denominated in local currency, once converted in US dollars (as reported above in Figure 2 of Section 2) amounted roughly to $4.500 billion at the end of 2007, it declined by about $450 billion by the end of 2008, but was already at $4.370 billion dllars by the end of 2009. This pattern is consistent in all subgroups of EU countries, including the United Kingdom. In the NMS the absolute value of local claims by mid-2009 is even larger than at the end of 2007. This trend is also similar in the non-EU advanced economies like the United States.

The stability of local claims stands out even more clearly if we adjust for exchange rate fluctuations, by constructing index numbers measured in national currencies for the EMU12 aggregate and for the most significant NMS in terms of absolute values of foreign claims (Figure 5a). In all the country groups the value of local claims measured in local currency was higher at the end of 2009 than at the beginning of 2007. This is also true for Hungary and Poland, countries where foreign banks were the major players in the financial crisis and which have been through a particularly severe recession in 2008 and 2009.

In Figure 5b we also report local claims denominated in foreign currency. These figures should be taken as proxies for likely trends, because, as mentioned above, they are estimated and their allocation to individual countries is likely to be biased. Moreover, since the currency basket of these claims is not reported, we keep them in current US dollars (as BIS does). Also in this case, claims are higher at the end of 2009 than at the beginning of 2007 in the EMU12 countries, Hungary and Poland.[25]

To better understand investment policies of foreign banks during the crisis, and particularly whether these banks have been instrumental in channelling financial resources towards host countries rather than the opposite, it is useful to relate

[25] Figures for the Czech Republic are negligible and therefore have not been reported.

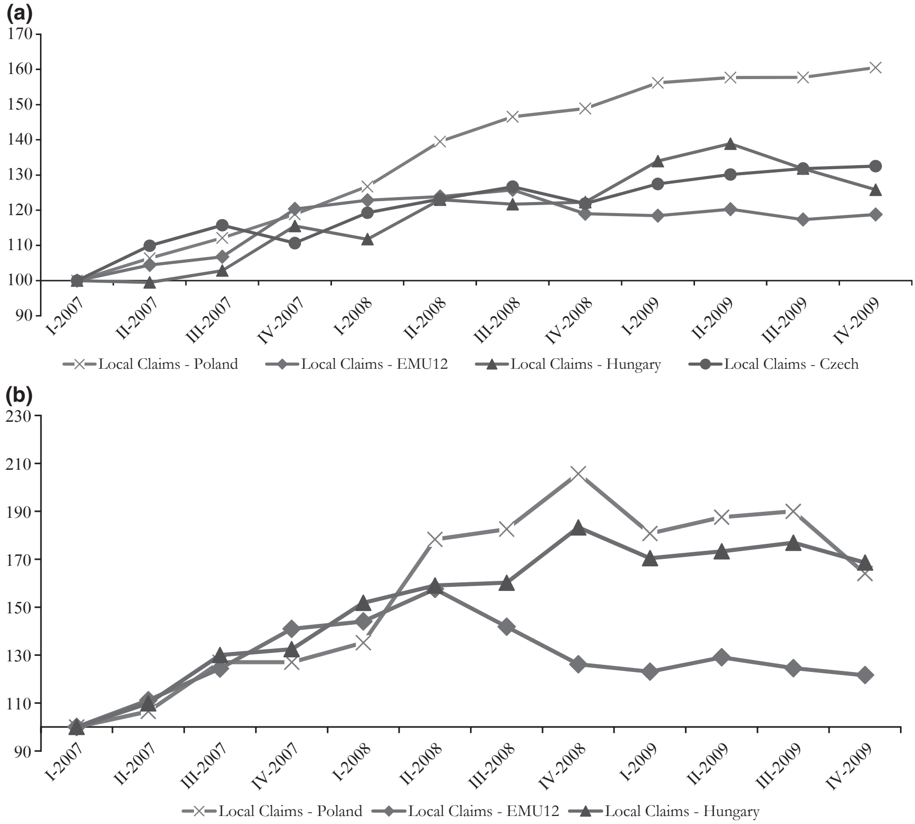


Figure 5. Total local claims in (a) local currency expressed in national currencies, and (b) foreign currency

Note: EMU12 and specific countries. I-2007 = 100

Source: BIS Consolidated Statistics.

trends in assets to trends in liabilities in local currency towards local residents (see Box 1 above for the definitions). The issue here is understanding, first, how much claims in local currency are strictly funded by local deposits and other liabilities and, second, whether during the crisis resources acquired in a given country have been transferred to affiliates based in other countries or to headquarters. Figure 6 reports the ratio between these assets and liabilities for the EMU12 and the other countries reported in Figure 5 from the first term of 2007 to the fourth term of 2009. The evidence is particularly interesting and in line with the hypothesis that foreign banks have been supporting local assets through cross-border funding.

Indeed it stands out that this ratio is always larger than one. In Hungary it is the highest, almost at 1.8. Also, this ratio is stable and even increasing for most countries. Now local assets not funded by local liabilities in local currency can either be funded by local liabilities in foreign currency (not reported in the BIS statistics but

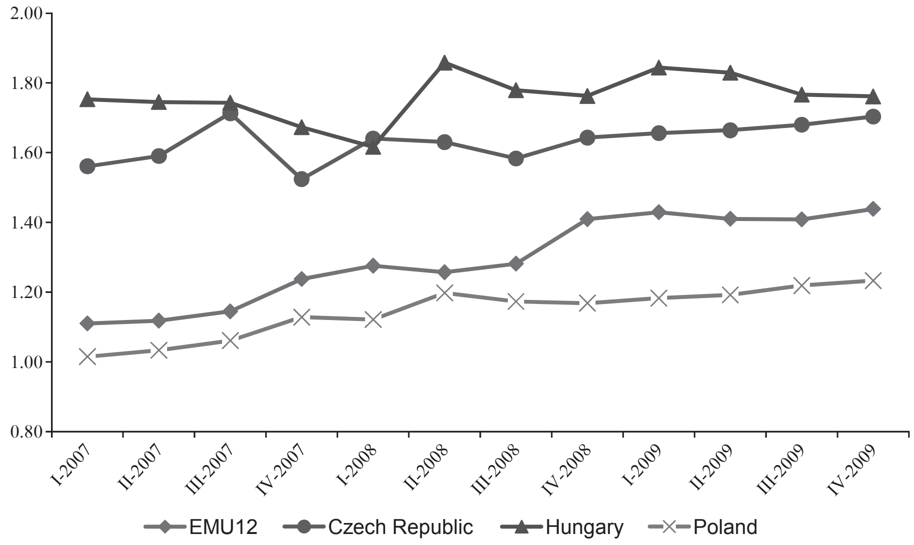


Figure 6. Ratio total claims over total liabilities in local currency

Source: BIS Consolidated Statistics.

likely to be pretty small) or by cross-border funds, channelled either through the global market or through the ICM. In other words, during the crisis an increasing share of the local assets of foreign subsidiaries have been funded by cross-border financial flows.

This preliminary descriptive evidence that lending and investment policies of MNBs have been stable, if not rising, during the period of the crisis is now tested econometrically. Using the same quarterly data described above for the period between 1999 and 2009 and for a sample of 49 developed and developing countries, we look at whether the time trends of local claims denominated in domestic currencies of foreign affiliates is affected by the crisis, taking them as a ratio of local liabilities denominated in domestic currencies, or of total financial assets in the country, obtained from IMF data.

The results are reported in Table 6. Since both ratios show a high cross-country dispersion, we used a quantile regression technique evaluated at the median, also including country fixed effects. Column 1 shows that on average the ratio of local claims to local liabilities has increased since 1999, as shown by the positive and significant coefficient of a linear time trend. Moreover, the growth has accelerated in the post-crisis period, as shown by the positive and statistically significant coefficient of the post crisis dummy, that takes the value of one from the fourth quarter of 2007 (column 2). In column 3 we have further specialized our analysis, interacting the post-crisis dummy with a set of dummies for different groupings of countries, to see if the effect of the crisis has been heterogeneous across regions. The results show that the ratio of local claims to local liabilities has increased in all geographic

Table 6. Claims-liabilities ratio: the effect of the crisis

	Claims/total liabilities			Claims/total assets		
	(1)	(2)	(3)	(4)	(5)	(6)
Time trend	0.004***	0.003***		0.004***	0.004***	
	0.001	0.001		0.000	0.000	
Post crisis (dummy)		0.058*			−0.003	
		0.022			0.006	
Time trend * EMU countries			−0.004**			0.007***
			0.001			0.000
Time trend * EU-no-EMU-no-NMS countries			0.003			0.003***
			0.002			0.000
Time trend * NMS countries			0.008***			0.003***
			0.002			0.000
Time trend * CEECs-no-NMS countries			0.038***			
			0.002			
Time trend * Main developing countries			0.001			0.001***
			0.002			0.000
Time trend * Other countries			−0.004**			0.002***
			0.002			0.000
Post crisis * EMU countries			0.129***			0.013*
			0.037			0.008
Post crisis * EU-no-EMU-no-NMS countries			0.027			−0.010
			0.060			0.011
Post crisis * NMS countries			0.116***			−0.011
			0.045			0.009
Post crisis * CEECs-no-NMS countries			−0.614***			
			0.042			
Post crisis * Main developing countries			0.159***			0.060***
			0.044			0.011
Post crisis * Other countries			0.047			0.047***
			0.054			0.011
Observations	2074	2074	2074	1471	1471	1471
Pseudo R^2	0.27	0.27	0.28	0.63	0.63	0.63

Notes: In columns 1–3, the dependent variable is the ratio between total claims and total liabilities denominated in local currencies, of foreign affiliates; in columns 4–7 it is the ratio between total claims by foreign affiliates and total credit to the private sector in the country. All estimates are conducted using quantile regression technique, evaluated at the median, and include country dummies. EMU countries include: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Slovenia; NMS countries include Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania and Slovakia; CEEC countries excluding NMSs include: Albania, Armenia, Bosnia and Herzegovina, Croatia, Georgia, Kazakhstan, Moldova, Montenegro, Russia, Serbia, Turkey, Ukraine, Uzbekistan; Main developing countries include China, India, Malaysia, South Korea, South Africa, Singapore, United Arab Emirates; other countries are Australia, Canada, Japan, New Zealand, Switzerland, USA. Since data on total financial assets in the post-crisis period for Central and Eastern European countries outside EU are available only for Turkey, in Column 6 it is included in the group of NMSs. The symbol *** indicates a significance level of 1% or less; ** between 1 and 5%; * between 5 and 10%.

Source: Data for claims and liabilities is from BIS, and data for private credit is from IMF.

areas, with the only exception of Central and Eastern European countries (CEECs) that are not members of EU. The effect has been stronger in the NMSs and in the EMU countries, smaller and not statistically significant in the EU countries that are not EMU members, neither NMSs and in the other main developed countries.

The results are broadly confirmed by the analysis of the evolution of the local claims of foreign affiliates as a ratio of total financial assets in the country. Also this ratio has been increasing since 1999, as shown by the positive and statistically significant nature of the coefficient of the time trend, in column 4. However, the crisis has not significantly altered its evolution, as shown by the insignificant coefficient of the post-crisis dummy in column 5. Finally, analysing separately the effect of the crisis across different groups of countries shows that this ratio has significantly risen within affiliates in EMU and in the other main developed and developing countries outside the EU. It has not changed significantly in the group including NMSs and Turkey.[26]

The role played by MNBs in NMSs during the recent crisis, and in particular the decisions of the parent companies to support their foreign affiliates, might have been influenced by the international initiatives of financial support decided at the multilateral level and by the ring-fencing policies that some of these countries might have put in place. Indeed, it is legitimate to question whether foreign parent companies have stabilized and even increased local lending because of: (a) ring fencing policies decided by host governments; (b) indirect resources provided by multilateral institutions to some NMSs. However, the evidence is controversial. On the one hand, there is no evidence of a tightening of formal regulatory ring fencing in NMSs during the crisis. On the other hand, it is true that a coordinated international effort to financially support the regions provided resources to banks with a local presence.[27] But although these interventions had effects that cannot be disentangled in our data, a number of facts suggest that they cannot be the sole explanation of our findings. First, they do not explain the increase in the lending to deposit ratio of foreign affiliates relative to that of domestic banks, which were all the same entitled to receive part of the financial resources provided on the basis of these multilateral agreements. Second, the financial support only became operative in the first quarter of 2009, and our evidence does not show a substantial reduction in the lending to the deposit ratio in the previous quarters. Third, all the main support measures undertaken in favour of Central and Eastern European countries are not legally binding agreements, but they are made on a voluntary basis, including

[26] Since data on total financial assets in the post-crisis period for Central and Eastern European countries outside EU are available only for Turkey, we have included it in the group of NMSs.

[27] During the crisis the IMF and the EU committed to extensive balance of payments support packages of over €50 billion (the commitment was sealed at the end of March 2009). In addition, on the basis of a joint agreement (the so-called IFI Action Plan) the European Bank for Reconstruction and Development, the European Investment Bank and the World Bank committed to make available up to $25 billion on a 2-year horizon programme to support banking sector stability and lending to the real economy; $19 billion have been already delivered (the commitment was sealed in February 2009).

the so-called Vienna Initiative.[28] Finally, our data show that also in other European markets, where such measures were not implemented, foreign banks have neither reduced lending nor behaved differently from domestic banks.

4.2. Micro effects of the crisis

Since our bank specific micro-data cover the period from 2000 to 2008, we have also investigated the effects of the financial crisis on the relationship between deposits and customer loans. Unfortunately, the empirical model of Equation (1) is unsuitable to analyse the effects of the crisis, because it is impossible to calculate the correlation between the rates of growth of deposits and loans at the bank level, with only two years' observations since the summer of 2007. For this reason, we have chosen a specification similar to the one adopted for the analysis at the aggregate level, verifying if the bank specific ratio of customer loans to deposits has changed significantly during the crisis, and in particular if these changes have been different for foreign affiliates operating in different areas (which we couldn't test with aggregate data). In practice, we have estimated the following specification of a difference in difference model around the event of the crisis:

$$\begin{aligned} Ratio_{ijt} = a_1 &+ a_2 DUM\_Crisis * DUM\_ForS\_EMU_{ij} \\ &+ a_3 DUM\_Crisis * DUM\_For\_EU15nEMU_{ij} \\ &+ a_4 DUM\_Crisis * DUM\_For\_nEU15_{ij} \\ &+ a_5 DUM\_ForS\_EMU_{ij} + a_6 DUM\_For\_EU15nEMU_{ij} \\ &+ a_7 DUM\_For\_nEU15_{ij} + a_8 Char_{ijt-1} + a_9 Year_t + a_{10} Country_j + \varepsilon_{ijt} \end{aligned} \tag{2}$$

where $ratio_{ijt}$ is the ratio between customer loans and customer deposits of bank i in country j at time t; *DUM_Crisis* is a dummy taking the value of one in 2007 and 2008; $DUM\_ForS\_EMU_{ij}$, $DUM\_For\_EU15nEMU_{ij}$ and $DUM\_For\_nEU15_{ij}$ are dummy variables that take the value of one if bank i of country j at time t is a foreign subsidiary of a holding company located, respectively, in EMU, in EU15 countries that are not EMU members, and in the remaining EU27 countries; $Char_{ijt-1}$ are characteristics of bank i of country j at time $t-1$ (the logarithm of total assets and leverage); $Year_t$ is a yearly time dummy; $Country_j$ is a country dummy; and ε_{ijt} is a standard error term. Due to the extremely high kurtosis of the dependent variable, we have run the estimates excluding observations below the 10th and above the 90th percentile of the sample distribution.

[28] Following the IFI Action Plan (see previous footnote), country-based policy coordination has evolved in voluntary agreements (known as the Vienna Initiative) according to which the parent banks of affiliates operating in countries that have received support from IMF programmes (co-financed by the EC in the case of EU members) committed to maintain constant their exposures in the host nations and to recapitalize their subsidiaries as long as IMF/EC programmes are on track. So far, such agreements have been reached in Romania, Hungary, Serbia, Bosnia Herzegovina, and most recently in Latvia.

The test of the effect of the financial crisis on the functioning of ICMs for cross-border groups is based on the sign and significance of coefficients a_2 to a_4. A positive and significant value would imply that foreign banks with access to ICMs reduced their loans-deposits ratio less than the control group of banks, and therefore had a stabilizing effect after the shock induced by the financial crisis. Clearly, a negative coefficient would imply the opposite.

Table 7 presents the results of the estimation of Equation (2). Column 1 presents the estimates obtained using an OLS specification, including unreported country dummies. The negative values of the coefficients for the year dummies in 2007 and 2008 show that the ratio between customer loans and customer deposits have been shrinking on average since the beginning of the crisis. However, all the coefficients of the interaction terms between the crisis and foreign affiliates are positive, and those for affiliates located in EU15-non-EMU countries and in the NMSs of Central and Eastern Europe, Malta and Cyprus (non-EU15) are statistically significant at the 1% level, showing that the impact of the crisis has been in these areas lower for foreign affiliates than for domestic banks.

Since, despite the trimming, our data might be affected by the presence of outliers, in column 2 we report the results obtained using a more robust quantile regression technique, evaluated at the median. The results substantially confirm the previous findings: the coefficient of the dummy for foreign affiliates located in EU15 is negative but statistically insignificant, while that of the dummies for the EU15-non-EMU countries and for the NMSs are positive and statistically significant, respectively at the 10% and at the 1% level. The only remarkable difference with respect to column 1 is that the dummy for affiliates located in EMU becomes negative, although it remains statistically insignificant. Finally, in column 3 we have estimated a model with fixed bank effects, which once again confirms the robustness of the previous findings.[29]

These results can be interpreted in light of Claims 6 and 7 above. Foreign banks had a stabilizing effect during the crisis in Eastern Europe's NMSs and in EU15-non-EMU countries, which is in line with Claim 7 that these banks can be effective providers of funds locally even during a systemic distress. This result is also probably driven by the fact that in the NMSs, MNBs are by far the dominant players, and domestic banking is extremely weak. However, in other areas these banks have essentially been behaving like national banks, showing that they had been equally affected by the pervasiveness of the crisis. This is in line with Claim 6.[30]

[29] Moreover, in the specifications of Panels 2 and 3, the average value of the coefficients of the year dummies before the crisis is significantly higher than that after the crisis.

[30] Indeed, an increase in the ratio of claims to deposits is not necessarily evidence of the functioning of ICMs. For a fixed level of loans, such a ratio would increase also in case customers withdraw their deposits and the bank matches such reduction in its aggregate liabilities by selling bonds. However, in an unreported regression we found no evidence of a reduction in customer deposits for the sample of banks analysed above. We thank Nicola Cetorelli for pointing this out to us.

Table 7. Loan-deposit ratio at the bank level: the effect of the crisis

	OLS	Median regression	Fixed effects
	(1)	(2)	(3)
Post crisis * EMU subsidiaries	0.008	−0.053	−0.007
	0.044	0.05	0.026
Post crisis * EU15-non-EMU subsidiaries	0.223***	0.264*	0.058
	0.037	0.114	0.049
Post crisis * non-EU15 subsidiaries	0.248***	0.308***	0.202***
	0.078	0.039	0.018
EMU subsidiaries (dummy)	0.191***	0.206***	
	0.061	0.032	
EU15-non-EMU subsidiaries (dummy)	0.081***	0.048	
	0.007	0.064	
Non-EU15 subsidiaries (dummy)	0.066	0.036	
	0.070	0.027	
Lagged leverage	0.055***	0.051***	0.167***
	0.006	0.001	0.006
Lagged total assets (ln)	0.399***	0.493***	−1.233***
	0.105	0.058	0.076
Year 2002	0.001	−0.004	0.007*
	0.009	0.008	0.003
Year 2003	−0.003	−0.013	−0.020***
	0.016	0.008	0.004
Year 2004	−0.018	−0.025***	−0.052***
	0.022	0.008	0.004
Year 2005	−0.015	−0.021**	−0.075***
	0.032	0.009	0.005
Year 2006	−0.002	−0.011	−0.075***
	0.039	0.008	0.005
Year 2007	−0.007	−0.024***	−0.097***
	0.050	0.008	0.005
Year 2008	−0.024	−0.039***	−0.131***
	0.057	0.009	0.006
Observations	23595	23595	23595
R^2 (Pseudo R^2 in column 2)	0.30	0.14	0.06

Notes: The dependent variable is the ratio between customer loans and deposits. EMU countries include: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Slovenia; EU15-non-EMU countries include Cyprus, Denmark, Malta, Sweden and United Kingdom; non-EU15 countries include Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania and Slovakia. All regressions include time dummies; the regression in column 3 includes bank specific fixed effects. Column 1 reports estimates obtained using OLS; column 2 reports estimates obtained using quantile regression methods, evaluated at the median; column 3 is a fixed effect panel. In column 1, robust standard errors adjusted for clustering at the bank level are reported in parentheses; standard errors in columns 2 and 3 are unadjusted. The symbol *** indicates a significance level of 1% or less; ** between 1 and 5%; * between 5 and 10%.

Source: Bankscope.

In summary, these results based on bank specific data during the crisis show that foreign affiliates certainly did not have a destabilizing effect, since their loan-deposit ratio has either remained constant or increased. Contrary to a diffused misperception, we find no evidence that these banks have been funnelling resources away from any of their host countries. That the working of ICMs did not allow foreign affiliates to have a significant stabilizing effect within EMU is not entirely surprising, due to the systemic nature of the recent crisis, which has made it nearly impossible to smooth the shocks within a group of similar economies. If all banks are simultaneously hit by an identical shock, there is no benefit in transferring funds from one unit to the other. In fact, we find that ICMs indeed had a stabilizing effect precisely in the case of affiliates located in NMSs, where the impact of the shock was more diverse, because of the lower economic integration.[31]

5. CONCLUDING REMARKS: INSIGHTS FOR A BETTER REGULATORY DESIGN OF MNBs IN EUROPE

We conclude this paper by answering the following question: What are the policy implications that can be delivered by our results?

In Europe, multiple national authorities are involved in the supervision of a single MNB, often in an uncoordinated way and operating with often dissimilar regulatory frameworks. This current regime has several shortcomings. Supervisors tend to operate only in the interest of their own country, without taking into account the cross-border spill-over implications of their own decisions. Under several scenarios, this framework is unable to produce the relevant and timely information for prompt supervision and regulation. The shortfalls of the current regulatory and supervisory frameworks are already evident in ordinary times, but they become even more compelling in times of distress. As highlighted by the recent crisis, cooperation and coordination between national supervisors often proved ineffective, since the impact of the crisis was assessed mainly at the national level, and remedial actions were defined almost exclusively at the country level.

Given this suboptimal environment for regulation of MBNs in Europe, in this concluding section we illustrate a number of policy implications stemming from our findings, which may help fine-tuning regulatory reforms.

5.1. Multinational banks are not a source of instability

In the aftermath of the financial crisis, MNBs have been perceived as an important cause for systemic risk and a source of global volatility. However, we have shown that these conclusions are driven by an inadequate understanding of what these banks do and how they function, particularly concerning retail banking activities.

As shown by the econometric results of Section 3.1, affiliates of MNBs use extensively their ICMs, and this has a significant impact on the correlation between the rates of growth of customer loans and deposits. In normal times (before 2007), MNBs

[31] As pointed out by our discussant at the Panel Meeting in Madrid, Dalia Marin, this result for NMSs contrasts with the evidence that during the 1990s foreign affiliates in East European countries did not rely on parental liquidity to finance their activities. Indeed, we also showed in Section 3.1 that the correlation between customer deposits and loans for affiliates in NMSs have been particularly high even during the last decade. Taken together, these results suggest that MNBs might indeed have changed their behaviour during the recent financial crisis.

have been able to use the ICM to isolate local lending from the availability of local funds. In fact, the correlation of the rate of growth of local loans and deposits is lower for foreign subsidiaries of MNBs than for stand-alone domestic banks. Hence, MNBs through their ICMs can exert a stabilizing role in the presence of idiosyncratic shocks.

In times of systemic distress the evidence of Section 4 supports the view that MNBs did not weaken financial stability in local markets. During the crisis the ratio of local bank claims to liabilities did not decline, and it even increased in some groups of countries (for example the NMSs, where foreign banks account for the dominant share of total banking activities). This aggregate pattern is further confirmed by the micro-evidence based on the sample of the largest European banks, showing that, compared to self stand-alone domestic banks and domestic banking groups, subsidiaries of MNBs have been able to isolate their lending activities from fluctuations in funds, and that they have been better able to profit from positive upswings in lending conditions. The evidence also supports the view that this has been done through the ICM.

We can therefore conclude that our results do not provide support to the argument that a world with only small and domestic banks is safer. Rather, we show that the size and the global extensions of the activities of MNBs contributed positively to hedging the downturns of the crisis, even in transition economies like the NMSs.

5.2. ICMs are especially effective within integrated financial markets

We have also shown that the degree of market integration between the countries where foreign activities of MNBs are based influences the functioning of the ICM. In fact, ICMs appear to be especially at work within better integrated financial areas, like the EU, and less so across markets with severe regulatory and market barriers. In particular, our empirical findings of Section 3.1, based on bank level data, clearly illustrate that also in normal times the correlation between the rates of growth of loans and deposits of foreign affiliates is lower than that of domestic banks, especially for those affiliates that belong either to EMU or to the restricted set of countries that are more integrated in Europe (i.e., the EU15 group). To this extent, our evidence shows that ICMs and the external capital markets are by and large complementary. When the external capital markets are less integrated, due to regulatory constraints or because they involve different currencies, then MNBs' affiliates are *de facto* using the ICMs to a very limited extent, and therefore show no relevant differences with respect to domestic banks.[32]

[32] Although further scrutiny on the causes of this effect is needed, since the effect related to the euro seems to be stronger, a possible interpretation is that an ICM that operates across countries with different currencies incurs in the additional cost of exchange rate risk. Indeed, anecdotal evidence illustrates that activities of ICMs across countries almost always involve currency swaps. Furthermore, transfers of liquid assets within ICMs are often used in the country of destination as collaterals with the local central bank to obtain liquidity. Since the central banks tend to associate lower volatility to local treasury bills, limited integration (e.g. outside EU15) may involve significant impediments to ICMs.

At first sight this is not fully intuitive, as market integration imposes a trade-off on the ICM: easier movement of resources (due to more harmonized regulations and common currency), but highly correlated business cycles and returns, that reduce the scope for the global diversification of investments. The evidence supports the view that the first component of the trade-off prevails: ICMs function better if markets are more integrated. Indeed the fast rise of multinational banking in the last 10 years has taken place mostly within the EU, even though there are still considerable regulatory barriers between member countries.

5.3. Harmonizing the European regulatory framework

Since the ICM functions well especially within integrated markets, reducing the inconsistencies and differences in the regulatory framework across member states and coordinating bank supervision within the EU would provide better supervision on global activities of MNBs. This should be a priority, since it would be instrumental in fostering the efficiency of the ICM and market integration in retail and corporate banking.

5.4. Neutrality of rules with respect to the organizational mode

In Section 3 we illustrated that different types of foreign incorporation (branches and subsidiaries) give rise to different liability structures between the bank's units within the group, and hence different incentives to the functioning of ICMs. We have seen that an ICM works well and shows its 'bright side' if: (a) liquidity and capital are really free to flow among units, (b) the information is free to flow within the organization without impediments, and (c) the incentives within the organization and its units are well designed.

Although the 'single banking licence scheme' was introduced in Europe with the purpose of facilitating free access within the Single European Market and of ensuring a level playing field, the current regulatory framework in Europe shows a bias in favour of structuring MNBs with branches (with the single passport). In particular, regulatory approaches strongly differ if banks are organized with independently incorporated subsidiaries or with foreign branches.[33] However, branches may not be the best organization to address the internal incentive issues of point (c). In principle, with subsidiaries one could identify clear responsibilities of local managers and units and thus give them the right incentives.[34] Independent local managers

[33] The single licence applies to branches of an MNB that are subject to the regulation and supervision of the authority regulating the parent company. Subsidiaries instead are considered independent despite their being part of a group and each of them is under the regime of the authority of the country in which they are based. Thus, rules applied to affiliates of the same group often differ and conflict.

[34] It is also worth mentioning that a subsidiary structure may be preferred and rewarded by markets in time of distress since it naturally allows identifying units and cross-liabilities among them.

are in a better position to make use of 'soft information' that would instead be very difficult, if not impossible, to transmit for the functioning of a fully centralized ICM.[35] With an organization based on branches, instead, local managers in foreign countries may be exposed to and feel that the ICM actually expropriates the capital and liquidity that has been produced locally by their branches.

Clearly, one could argue that in the current environment branches are to be preferred since, to some extent, they allow a consolidated supervision of the MNB. However, it is also clear that this is simply the suboptimal consequence of the current state of affairs in regulation and supervision of MNBs. Along the same line of reasoning, reform proposals aimed at ring fencing subsidiaries in host countries and forcing systemically relevant branches to be transformed into subsidiaries, like those put forward within the FSB Standing Committee on Supervision and Regulatory Cooperation (Turner, 2009), may restrict considerably the optimal functioning of the ICM.

The reform of the European regulatory and supervisory framework should not ignore these organizational issues and introduce a neutral regime between branches and subsidiaries. Choosing the best organization for banks is the task of managers, and regulation should not impose a preference.

5.5. The 28th regime

Finally, we think that to achieve a coordinated and neutral regulatory framework, European countries should contemplate a new and specific framework for European MNBs, allowing these banks to set up a truly integrated organization with its well-functioning ICM, as illustrated in the previous pages. This framework would define the responsibilities and the powers of the parent company, the branches and independent subsidiaries, provided due protections to minorities and creditors are granted. In this respect, some commentators have referred to this proposal as a 28th regime for MNBs, in addition to those available to banks in the 27 Member States belonging to the EU. This regime should contemplate a specific treatment for MNBs in terms of regulation and supervision, along the line of the proposals that have already been discussed in Europe (i.e., enhancing coordination among countries through strengthened colleges of supervisors overseen by a newly created European Banking Authority, and possibly defining rules for the allocation of the costs of rescuing those banks in case of distress).[36] Banks should be then left free to

[35] Currently, national regulations on privacy limit the possibility for units to exchange information on their activities with their partners that are independent entities of the same group. This is another undesirable bias of regulation that affects the internal organization of MNBs.

[36] To some extent this new regime for truly European players is close to the dual system that is in place in the United States according to which banks active at the level of the entire nation are under the federal scrutiny (with a federal charter, associated federal laws and a federal supervisor).

choose whether to opt for this regime, which would guarantee the best functioning of ICMs.

Discussion

Gianmarco I.P. Ottaviano

Bocconi University and CEPR

The aim of this paper is to examine the behaviour of multinational banks (MNBs) during times of financial distress with a focus on Europe. In particular, it asks whether MNBs have a stabilizing or a destabilizing role in those times of trouble. The answer of the paper stresses their stabilizing role due to the support that the internal capital market (ICM) has given to foreign affiliates in distress, isolating their lending from the local availability of financial resources. This has happened notwithstanding the systemic nature of the recent crisis.

The paper argues that stabilization by MNBs has been particularly pronounced within the EU integrated financial market, and for the EMU countries. This finding is interpreted as showing complementarity between economic integration and the ICM of MNBs. Such complementarity naturally leads to a call for more integration of the European supervisory and regulatory frameworks overseeing multinational banks.

Overall, this is a timely well-written paper. Its contribution is accurately placed into context. It carefully builds on the existing literature while trying to systematize it. Several findings are interesting and convincing. Among them, two stand out. First, the ICM has a stabilizing role in the presence of idiosyncratic shocks across countries. Second, the ICM is neutral in the presence of systemic shocks in integrated areas where the impact of systemic shocks is symmetric.

At the same time, however, the discussion of the policy implications of these findings is sometimes confusing and blurs the actual results of the paper. Specifically, the paper provides a theoretical discussion of the possible pros and cons of the ICM, usefully highlighting a series of *ceteris paribus* and sometimes opposing effects (called 'claims' by the authors). The empirical analysis is then presented as a 'test' of the relative importance of these claims. Alternatively, it could also be seen as a rationalization of what the data show.

Since the empirical analysis is not structural, it would be important to better tie the policy implications to the empirical findings. In particular, the paper calls for two broad areas of policy intervention: the harmonization of regulation on MNBs; and the neutrality of regulation with respect to the organizational structures of MNBs. In the discussion, however, the distinction between harmonization and neutrality is blurred and sometimes confusing. The discussion of the policy implications could be improved by stressing the pros and cons of harmonization on the one hand, and those of neutrality on the other hand, linking both hands to specific findings, especially to the two key findings highlighted above.

Finally, multinational manufacturing firms are among the main actors in the world economy. It would be interesting to have some additional comment on whether the interests of those firms are better served by MNBs.

Dalia Marin

University of Munich

Why look at multinational banks?

Since 1990 most countries undertook financial integration by reducing impediments to cross-border financial transactions and an increased participation of foreign banks in the local banking system. This trend was particularly pronounced for Eastern Europe and the New Member States (NMS) where foreign multinational banks have become the dominant players in the local banking system in these markets. So the question arises whether the participation of multinational banks has been good or bad. This is a timely paper of high policy relevance.

In their paper the authors ask two questions: First, do foreign banks behave differently than domestic banks? Second, do multinational banks (MNBs) amplify or stabilize external financial shocks? What is their role in the financial crisis? I want to comment on these two questions and add some evidence on Austrian and German multinational banks in Eastern Europe. Let me start with the first question.

Do MNBs behave differently?

The authors argue yes. MNBs behave differently because they have an internal capital market (ICM). Why should the availability of an ICM make a difference? MNBs with an ICM can support affiliates in distress with liquidity or they may reallocate resources away from affiliates creating distress. This way ICMs may stabilize or destabilize local banking systems.

A Feldstein–Horioka approach

In their empirical analysis the authors do not provide direct evidence on ICMs. Rather they pursue an approach similar to that used by Feldstein and Horioka (1980) in their famous saving-investment puzzle. Feldstein and Horioka demonstrated that across OECD countries long period averages of national saving rates are highly correlated with similar averages of domestic investment rates. A cross-section regression of investment on saving covering 1960 through the mid-1970s yielded slope coefficients near unity. Later studies for the 1990s found similar but somewhat smaller coefficients. Surprisingly, in highly integrated financial markets domestic investment is predominantly financed out of national savings. Thus, the high correlation between investment and saving across countries suggests a small role for international capital flows.

Similar to Feldstein and Horioka, the authors test with a large panel of bank firm level data of 5,500 European banks whether or not the bank specific correlation between the rate of growth of bank lending and of local bank deposits is lower for multinational affiliate banks compared to stand-alone banks. A low correlation between bank lending and local deposits indicates that multinational affiliates are getting capital inflows from parent firms while stand-alone banks base their lending mainly on the availability of local deposits. The authors indeed find that the correlation between lending and deposits is lower in foreign affiliates of multinational banks in particular within the EMU and the EU15. In order to avoid endogeneity issues, the authors proceed to estimate whether the correlation between the growth rate of lending with the growth rate of deposits as the dependent variable is indeed lower for affiliates of banks in particular within the EU15 after controlling for a number of bank and country characteristics. They indeed find this. They also find that affiliates that are operating in geographically closer countries and in countries with less synchronized business cycles can count on more liquidity from parent firms enabling them to provide lending beyond available local deposits. The authors conclude from this evidence that affiliate banks have been a source of financial stability in host countries.

Direct evidence on internal capital markets

I want to turn now to some direct evidence on ICMs of Austrian and German multinational banks in Eastern Europe based on original firm level survey data of 2,200 direct investments in Eastern Europe of the Chair of International Economics of the University of Munich.[37] The data are a full population survey of Austrian and German foreign direct investment in Eastern Europe in the period 1990 to 2001. Austrian and German affiliate banks account for more than 50% of all banks in some of the NMSs. Does the direct evidence on ICM support the author's stability enhancing view of MNBs?

From Table 8 we can see that the internal capital market is by far the most important source of finance of Austrian and German multinational banks investing in Eastern Europe. On the side of parent banks in Austria and Germany, 87% of the parent banks said that they financed the investment of the affiliate bank in Eastern Europe internally rather than externally or in a mixed finance package. External financing is practically zero. Among the internal types of finance by far the most

[37] For more details on the data see Marin (2010).

Table 8. Internal versus external capital markets in investments to Eastern Europe[a]

Type of finance	Parent firm		Affiliate firm	
	Banks	Non-banks	Banks	Non-banks
	In % of total investment			
External financing	0.9	10.7	50.0	49.6
Internal financing	87.2	50.5	50.0	25.5
Internal and external financing	11.9	38.8	0	24.9
Total	*100*	*100*	*100*	*100*
External financing				
Credit raising in parent country	0	63.5	0	0.0
Credit raising in host country	0	15.8	33.3	47.3
Capital increase via issue of stocks in parent country	100	18.3	33.3	25.7
Capital increase via issue of stocks in host country	0	1.7	33.3	25.7
Supplier credit	0	0.8	0	1.2
Total	*100*	*100*	*100*	*100*
Internal financing				
Financing from profits and cashflows	72.2	68.6	100	93.0
Intracompany reallocation of funds	27.8	31.4	0	7.0
Total	*100*	*100*	*100*	*100*

[a] Eastern Europe includes the New Member States, South-East Europe, the former Yugoslavia as well as Russia and the Ukraine.

Source: Sample of 2,200 Austrian and German FDI projects in Eastern Europe, Chair of International Economics, University of Munich.

important source of finance is out of cash flow and profits (72%), while funds out of intra-firm reallocation from other units account for 28% of the bank investments in Eastern Europe. These numbers suggest that parent banks in Austria and Germany do from time to time reallocate funds away from some units in order to finance other (in this case Eastern European) units.

On the side of affiliate banks in Eastern Europe, the picture looks somewhat different: 50% of affiliate banks said that they finance their activity internally out of cash flow, while the other 50% come from external financing out of loans by other local banks, by raising capital through the issuing of stocks in either the parent or the host country. Surprisingly, however, the financing pattern of multinational non-banks does not appear to be that much different from that of multinational banks. Both bank as well as non-bank affiliates rely heavily on internal cash flow and loans raised from local banks.[38]

These numbers suggest that affiliate banks in Eastern Europe, once they are established, function autonomously and do not depend on parent banks to provide liquidity. Their activity is financed out of cash flow or by raising capital mostly locally. Taken together these data suggest that affiliate banks do not appear to be

[38] See also Marin *et al.* (2003), and Marin and Schnitzer (2006).

supported by an internal capital market of parent banks, while their original establishment is almost exclusively financed by internal funds of parent bank firms.[39]

Multinational banks and the financial crisis

I turn now to the second question raised by the authors on the role of MNBs in the recent financial crisis. Financial integration has been the subject of much debate following the emerging market crisis in the late 1990s with different opinions about capital account liberalization policies. The current global financial crisis poses similar questions in the face of international financial volatility. Therefore, it is important to understand whether foreign banks contribute or not to credit volatility in host countries. Foreign banks may play a stabilizing role by being better able to diversify risk and by being able to rely on parental liquidity when a host country shock hits. But at the same time foreign banks may act as a transmission mechanism of parent country shocks on host country lending.

Similar to de Haas and van Lelyveld (2006) this paper shows that the ICM has been used in the current financial crisis to stabilize financial markets in host countries. In order to test this, the authors do not look directly at how the ICM works in times of distress but rather they estimate a regression of the ratio of claims to liabilities in local currency of foreign affiliates in a panel of 49 developed and developing countries for the period between 1999 and 2009. They find that on average the ratio of local claims to local liabilities has increased since 1999 and has accelerated in the post-crisis period. They also show that this ratio has increased in all geographic regions in particular in the NMS. They also run a regression on the bank specific ratio of loans to deposits to investigate whether this ratio has changed significantly during the crisis and in particular for foreign affiliates in different European regions such as EU15 and the NMS. They find that foreign affiliates did not have a destabilizing role, since their loan-deposit ratio has remained constant. In sum, they find that foreign affiliate banks have been essentially behaving like national banks in all regions with the exception of the NMS in Eastern Europe where foreign banks had a stabilizing effect.

At a closer look at the direct evidence on ICM for Eastern Europe given in Table 8, I find the results of the authors for the NMS somewhat surprising. Clearly, affiliate banks in Eastern Europe do not rely on parental liquidity to finance their host activities. Therefore, the fall in cash flow in parent banks appears to have an effect only on new foreign investment activity in the banking sector rather than on already established affiliates in Eastern Europe. This way, the financial crisis in parent countries is less likely to have been translated to host countries. So far so good. But the financial crisis also led to a drop in profits in affiliate banks in Eastern

[39] The data are consistent with the findings of Goldberg (2005) who shows that international activities of foreign banks headquartered in the United States are not influenced by host country economic conditions.

Europe and this should have clearly shown up in the results of the empirical analysis. One caveat is that the data of Table 8 are from the pre-crisis period and the behaviour of parent and affiliate banks may have changed during the crisis. Another is that the Vienna Initiative, a forum which was created in early 2009 to coordinate the responses of major stakeholders to the financial crisis has already shown an effect in the empirical analysis.

Panel discussion

Athanasios Vamvakidis believed the questions raised in the paper were particularly relevant for the many emerging European countries where the share of foreign banks is very high. He noted the concentration of foreign-owned banks by origin varies across the region (e.g. Swedish banks are mainly located in the Baltics, southern Europe consists of a large share of Italian banks), and suggested this may partly explain the different behaviour of foreign-owned banks during the crisis especially when one takes into account policy coordination actions such as the Vienna initiative or IMF discussions held with particular parent banks and their subsidiaries.

Silvana Tenreyro remarked that during the Argentine crisis in 2001 affiliates received no support from their foreign partners despite demands to do so. The consequence of which was a greater decline in lending and in turn added to the perception that MNBs had a destabilizing effect on the economy. She suggested that this event also highlighted that greater integration of foreign banks may be crucial in reducing the potential destabilizing effects of MNEs. She also noted that although the recent crisis was a systemic one, countries experienced very different outcomes and suggested the authors could exploit this variation to further examine the role of ICMs.

Refet Gürkaynak found it difficult to accept the authors' assertion that MNBs limited fluctuations during the crisis and asked them to give a more detailed explanation in the paper as to how MNBs did so. He wondered how the capacity of MNBs to limit fluctuations differed between affiliates and subsidiaries. He commented it was unlikely that the British or the Dutch who were adversely affected by the branches of the Icelandic banks would accept the view that MNBs limited fluctuations.

Samuel Bentolila considered all the variables in the analysis to be endogenous and believed the authors should attempt to identify idiosyncratic country shocks to examine the role of ICM in a country's adjustment process. He noted an important avenue of research would be to investigate how MNBs differed in their dealings with households and business.

Rafael Repullo noted that although the paper focused on subsidiaries, he believed the results were likely to be stronger for branches because they are not incorporated in the host countries. Given that many affiliates were established only in the recent past, he worried that some of the estimates might be capturing a transition affect where new affiliates temporarily pursue an unbalanced strategy upon entry into a new market before adjusting over time. It is therefore important to distinguish between greenfield and buyout type entry of affiliates.

Georges de Ménil remarked the analysis is based solely on European data and it is important to highlight that multinational banking is relatively underdeveloped in Europe. Augustin Landier emphasized the importance of indentifying how MNBs and national banks serve the local market. He wondered was it the case that MNBs deal with large companies in hard information industries while national banks deal with small companies in soft information industries.

Richard Portes suggested there is likely to be a move towards subsidiaries away from branches in the future. He noted that many factors will contribute to this shift including gains in tax efficiency and also stronger macro prudential regulation which will be applied on a national basis.

In response to Gianmarco Ottaviano's comment on the importance of distinguishing between the impact of systemic and idiosyncratic shocks on MNB behaviour, Giorgio Barba Navaretti noted there is evidence to suggest that even during a systemic shock MNBs are better funded and able to support their branches. He agreed with the discussants that the lack of harmonization in the regulatory framework complicated the management of the banking crisis. Also from an MNB viewpoint, asymmetric national regulation probably inhibits the efficient functioning of these banks.

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Moral hazard and adverse selection in the originate-to-distribute model of bank credit[☆,☆☆]

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ABSTRACT

Bank credit has evolved from the traditional relationship banking model to an originate-to-distribute model. We show that the borrowers whose loans are sold in the secondary market underperform their peers by about 9% per year (risk-adjusted) over the three-year period following the initial sale of their loans. Therefore, either banks are originating and selling loans of lower quality borrowers based on unobservable private information (adverse selection), and/or loan sales lead to diminished bank monitoring that affects borrowers negatively (moral hazard). We propose regulatory restrictions on loan sales, increased disclosure, and a loan trading exchange/clearinghouse as mechanisms to alleviate these problems.

1. Introduction

The historic credit crisis of 2007–2008 brought an important question sharply into focus—to what extent should bank credit be allowed to evolve from its traditional relationship banking model to the transaction-oriented model that has largely emerged over the last two decades? This fundamental shift in banking has been due to the explosive growth in the secondary syndicated loan market.[1] The presence of this market transforms bank credit to an "originate-to-distribute" model, where banks can originate loans, earn their fees, and then distribute them to other investors in a largely opaque manner.

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[1] From 1997 to 2007, the secondary syndicated loan market has grown from $60b to $342b in annual trading volume, fueled by securitization and the tremendous growth in collateralized debt obligation (CDO) and collateralized loan obligation (CLO) funds.

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This shift to the originate-to-distribute model of bank credit has important implications for all market participants, including the originating banks, the participating loan investors, the borrowing firms and the regulators. The banks' superior information about their borrowers gives rise to concerns about adverse selection—are the banks selling off loans about which they have negative private (unobservable) information? In a perfect market, this should lead to a breakdown of the secondary loan market due to the classic ''lemons'' problem. The issue of adverse selection is important from the perspective of the participating loan investors as well—can they trust that the bank selling the loan is doing so due to legitimate motives (like capital relief and risk management) rather than due to negative private information? Alternatively, does it lead to moral hazard in terms of an impairment in the monitoring function of banks, thereby having a negative effect on the borrowers?

There are several policy questions that arise from this debate. Should the regulatory authorities restrict the originate-to-distribute activities of banks? Should they enforce enhanced disclosure of the banks' activities in the loan sales market? How are the borrowing firms being affected, in the long run, by banks moving from relationship banking to the originate-to-distribute model of credit? Does this shift lead to value creation or value reduction in the corporate sector? These questions are, ultimately, empirical ones. Using extensive data from the syndicated loan market, this paper is the first empirical investigation of these important but as yet unanswered questions.[2]

Banks could sell loans in the secondary market due to negative private information about the borrower, or for legitimate reasons such as capital relief, risk diversification, improving balance-sheet liquidity, and reducing financing frictions and their cost of capital. The positive effects of loan sales on banks have led to a point of view that the originate-to-distribute model of bank credit is ''socially desirable''.[3] There is also a vast literature on banks being ''special'', since they generate proprietary information about the borrowers in the course of lending to them.[4] The loan buyers who do not have a lending relationship with the borrowers are then likely to be at an information disadvantage when buying a loan originated by a relationship bank. This could lead to moral hazard and adverse selection problems (Gorton and Pennacchi, 1988; Pennacchi, 1988). Banks that sell loans would have a reduced incentive to engage in costly screening and monitoring of the borrowers. In addition, they would have an incentive to sell the loans of the borrowers about whom they have negative private information. Duffee and Zhou (2001) examined these issues in a theoretical setting with bank loans and the presence of credit risk mitigation via the default swap market or the loan sales market.

From a borrower's perspective, there are potentially positive as well as negative consequences of their loans being sold in the secondary market. The positive effects include a lower cost of capital (Gupta et al., 2008), increased access to debt capital (Drucker and Puri, 2008), and information effects (Gande and Saunders, 2008). The negative effects include a breakdown of lending relationships, reduced monitoring which could lead to suboptimal investment and operating decisions, harsher covenants (Drucker and Puri, 2008), and difficulties in renegotiation (Carey et al., 1993).[5] Parlour and Plantin (2008) presented a theoretical model which embeds some of the bank and borrower incentives and effects outlined above. However, from an empirical standpoint, it is not clear which of these effects dominate. Furthermore, if the originate-to-distribute model of credit creates incentives for banks to originate bad loans and then sell them off in the secondary market, such borrowers should underperform their peers in the long run. Since theoretical arguments on this issue can go either way, it needs to be resolved empirically. Our paper is the first one in the literature to empirically examine the long-run performance of borrowers with and without an active secondary market for their loans.

The existing empirical literature has largely focused on the impact of bank loan *announcements* on the borrowers' stock returns. Most studies have shown that loans are ''special''—their announcements elicit positive short-term abnormal returns for borrowers, in contrast to the announcement effect of most other forms of corporate financing such as common stock, preferred stock, straight debt and convertible debt.[6] This result has been somewhat reversed by Billett et al. (2006), who show that firms announcing bank loans suffer negative abnormal returns in the long run. The literature on the effects of loan sales on the borrower's stock price is rather sparse. While Dahiya et al. (2003) documented a negative *announcement* effect of the sale of a borrower's loans by its lending bank, Gande and Saunders (2008) documented the opposite (positive) announcement effect. However, none of these studies has measured the long-run performance of the borrowers whose loans trade in the secondary loan market.

We study a large sample of 1054 borrowers, the largest sample analyzed in this literature thus far. Our results show that borrowers with an active secondary market for loans significantly underperform their peers by about 9% per year on a risk-adjusted basis over the three-year period subsequent to their loans first being traded in the secondary market. This result is robust to most techniques of measuring long-run abnormal returns. The underperformance is stronger for small, high-leverage, speculative-grade (SG) borrowers, which is intuitive since these are precisely the firms where moral hazard

[2] The risk of these loans can also be distributed via the credit default swap (CDS) market. During our sample period, the CDS market was liquid primarily for investment-grade obligors, while more than 75% of the syndicated loan market activity has been concentrated in the speculative-grade segment. Therefore, the overlapping sample between the syndicated loan market and the CDS market is statistically too small to analyze.

[3] These concepts have been explored in prior literature, for example, Stein (1998), Kashyap and Stein (2000), Greenspan (2004), Schuermann (2004), and Diamond and Rajan (2006).

[4] See Diamond (1984), Ramakrishnan and Thakor (1984), Fama (1985), Rajan (1992), and others.

[5] Lending relationships have been shown to be valuable for borrowers since they enhance the availability of credit, reduce the requirement for collateral, and reduce the costs of financial distress, as shown by Hoshi et al. (1990, 1991), Petersen and Rajan (1994), Berger and Udell (1995), etc.

[6] See, for example, James (1987), Lummer and McConnell (1989), Best and Zhang (1993), Billett et al. (1995), etc.

and adverse selection problems may be more severe. For the borrowers that have an active secondary loan market, using Tobin's q we find a significant reduction in value (as a percentage of total assets) of about 14% over three years when compared to their peers.

The significant long-run underperformance and value reduction of borrowers with an active secondary loan market is a striking result, for which we offer two possible explanations. First, banks may be cherry picking by preferentially selling loans of the borrowers about whom they have negative private information that is unobservable to outsiders. Alternatively, banks may be knowingly originating some lemons, primarily to expand their origination fee based income, since they are able to sell these loans in the secondary market to outside investors (mostly non-bank financial institutions and hedge funds).[7] In a perfect market, reputation concerns should prevent a bank from cherry picking and/or selling lemons on a systematic basis. If it is still happening, it is perhaps an indication of a market failure, where the investors have not (yet) recognized the adverse selection that they are facing in the secondary syndicated loan market.

Our second explanation is based on the moral hazard argument. When borrowers lose the discipline of bank monitoring, they may be more prone to making suboptimal investment and operating decisions, which may lead to a negative long-run performance and value reduction.[8] Based on our tests and results, it is not possible to clearly distinguish which one of the two explanations dominates. It is likely that both these mechanisms play some role in explaining our results. In addition, despite our extensive robustness tests, there is always a possibility that some of the abnormal returns that we observe may be partly due to inadequate risk adjustments.

While the borrowers with an active loan market underperform their peers, those without an active loan market do not show any significant long-run underperformance. Our findings refine the results of Billett et al. (2006), who claim that bank loans are not special. This is especially interesting in light of the results of Gande and Saunders (2008) who claim that banks are "special" even in the presence of a secondary market for loans.[9] *Our paper shows that bank loans are still "special", but only if the bankers do not sell them.*

Our results have important policy implications for regulators. Whether the underperformance and value reduction of borrowers with an active secondary loan market is due to banks originating and selling lemons, or due to diminished monitoring, it raises serious questions about the extent to which the originate-to-distribute model of bank credit is "socially desirable". While there are clear benefits of enhancing the liquidity of the secondary syndicated loan market, we demonstrate some of its long-term undesirable consequences. It is likely that one of the major reasons for the latter is the highly deregulated nature of the secondary syndicated loan market. Should the regulators impose restrictions on the sales of bank loans by originating banks? Perhaps. At the minimum, they could require the originating banks to retain a certain proportion of the loans on their balance sheet to limit the moral hazard and adverse selection problems. Also, there must be additional disclosure requirements about the loans being traded in the secondary market, along with disclosure about the market participants that are trading them. A loan trading exchange with a clearinghouse could be a possible solution. It is certainly clear that the originate-to-distribute model of bank credit needs to be modified, and the transactions made more transparent.

The rest of our paper is organized as follows. In Section 2, we provide information about our data along with some descriptive statistics. In Section 3, we explain the different methods used in this paper for examining the long-run performance of the borrowing firms. We describe and interpret our results in Section 4. Section 5 concludes.

2. Data

The data for this study are drawn from all U.S. publicly listed firms that borrowed in the syndicated loan market from January 1, 2000 until December 31, 2004.[10] We obtain the loan origination data from the DealScan database maintained by the Loan Pricing Corporation. We focus on borrowers with syndicated term loans originated during this period, excluding borrowers that only obtained other forms of financing such as revolvers and lines of credit.[11]

To classify borrowers into the two groups, those with and without an active secondary loan market, we rely on the secondary loan market database from the Loan Syndication and Trading Association (LSTA). LSTA provides an independent,

[7] This is similar to the recent events in the subprime mortgage crisis, where banks have been originating mortgages of questionable quality just because there was an active secondary market for such loans.

[8] There is a large literature that has examined the special role that banks play in monitoring their borrowers. These papers show that monitoring banks participate in the borrowers' internal decision making, limit their excessive risk taking, help enforce and renegotiate written and unwritten covenants, serve a corporate governance role, constrain managers' opportunistic behaviors, etc., that leads to positive wealth effects for borrowers. See Diamond (1984, 1991), Fama (1985), Pennacchi (1988), Shleifer and Vishny (1997), Datta et al. (1999), Byers et al. (2008), Ahn and Choi (2009) and others for these discussions.

[9] The differing results in Gande and Saunders (2008) are due to their inferences being based on the announcement effect of bank loan sales, while our results are based on the long-run performance over the subsequent three-year period. Our sample of 1054 borrowers is also significantly larger than those examined in prior studies.

[10] We consider loans originated only until 2004 so that we can use stock-return data up to 2007 to analyze the long-run performance of all borrowers over a three-year period.

[11] In the case of revolvers and lines of credit, only the drawn portion trades in the secondary market—the undrawn portion remains with the original lenders. Since we do not have any information on the drawdown schedule of these lines of credit, the moral hazard and adverse selection issues are not clear when these lines of credit trade in the secondary market.

daily mark-to-market pricing service on several thousand syndicated loans to numerous institutions that manage bank loan portfolios. LSTA receives bid and ask price quotes, every day, on nearly 5000 syndicated loan tranches, from over 35 dealers that represent the loan trading desks of virtually every major commercial and investment bank. Our conversations with market participants indicate that these dealers and their quoted loans represent over 80% of the secondary market trading in syndicated loans. Therefore, these loan price quotes provide an adequate representation of the secondary syndicated loan market. LSTA aggregates these price quotes and provides the average of all bids and all asks for all loans that have at least two bid quotes. (Generally, about two-thirds of all loans quoted in the market have at least two bid quotes.) They also provide the number of quotes on the bid and the ask side. Many loans have quotes from three or more dealers, sometimes from as many as 17 dealers. In addition, LSTA provides some identifying information about the borrower and the loan tranche, which is used to hand-match this sample to the loan origination data from DealScan. The hand-matching is necessary since there is no common identifier between DealScan and the LSTA secondary pricing database.

Following Gupta et al. (2008), we classify borrowers into those that have loans with an active secondary market (*LIQ*), and those without loans with an active secondary market (*noLIQ*). If a borrower's term loans are quoted in our secondary market database by at least two dealers, and the first quoted bid price is greater than 98 (i.e., it is a "par" loan), we classify the borrower as *LIQ*. If there were at least two dealers that quoted bid prices for a loan, it is reasonable to infer that it was possible to trade the loan on that day. Further, if the loan is first quoted at par, it implies that it was not a distress sale, since the loan did not have to be discounted for it to be sold in the secondary market. Therefore, we classify a borrower as *LIQ* only if its loans had an active interest from secondary market dealers without initiating "fire sales" by discounting them. Our results are robust to alternative ways of defining the two categories of firms. Nevertheless, any errors due to misclassification will only bias our tests against finding any results.

Next, we match these loan databases to CRSP and Compustat, in order to obtain firm-level stock return and accounting data. Again, there is no common identifier between the loan databases and CRSP/Compustat, so the borrowers have to be carefully hand-matched. Our CRSP and Compustat data covers the period 2000–2007. However, following Cornett et al. (1998), we impose the requirement that all firms have CRSP/Compustat data at least two years prior, i.e., from 1998 onwards, to avoid the new listing bias. This leaves us with a large sample of 1054 borrowers.

Table 1 presents descriptive statistics for our sample of borrowers. Based on the definition of *LIQ*, we find that 309 of the 1054 borrowers have an active secondary market for their syndicated term loans. The remaining 745 firms have syndicated term loans originated during the 2000–2004 period, but they are never liquid as per our definition. Our total sample of 1054 borrowers represents a large proportion of firms in the corporate universe—they have, in the aggregate, about \$3.3 trillion in market capitalization, \$5.1 trillion in total assets, and over \$800 billion in net sales. Average firm statistics are fairly similar for the groups of borrowers with and without an active secondary loan market. However, the distribution across market capitalization, total assets and net sales is much wider for the latter group. The median size of the borrowers

Table 1
Descriptive statistics: this presents the descriptive statistics for firms with bank loans originated between 2000 and 2004.

	LIQ		*noLIQ*		All borrowers	
Number of firms	309		745		1054	
	Mean	Median	Mean	Median	Mean	Median
Size (\$m)	3275.48	1130.11	3099.98	388.11	3148.33	579.71
Total assets (\$m)	5564.35	1944.32	4618.46	479.40	4878.49	793.81
Sales (\$m)	884.47	362.77	716.77	110.77	762.87	164.23
Leverage	0.68	0.69	0.55	0.56	0.58	0.60
ROA (%)	0.37	0.66	0.45	0.91	0.43	0.83
Profit margin (%)	−9.77	3.24	−5.47	3.63	−6.67	3.52
	Distribution of borrowers across industry and credit quality					
Consumer		0.19		0.27		0.24
Manufacturing		0.26		0.22		0.23
Technology		0.21		0.19		0.20
Healthcare		0.08		0.09		0.09
Other industries		0.26		0.24		0.25
IG		0.11		0.34		0.24
SG		0.89		0.66		0.76

The first two columns, identified as *LIQ*, refer to the subset of borrowers with an active secondary loan market, columns three and four refer to the subset of borrowers without an active secondary loan market, and the last two columns refer to the set of all borrowers. We report the number of firms in each category; firm characteristics such as size (market value of equity), total assets, net sales, book leverage, the ratio of net income to total assets (ROA) and the ratio of net income to revenue (profit margin); and the distribution of borrowers across industry and median credit quality. All summary statistics are computed over the sample period from 2000 to 2007.

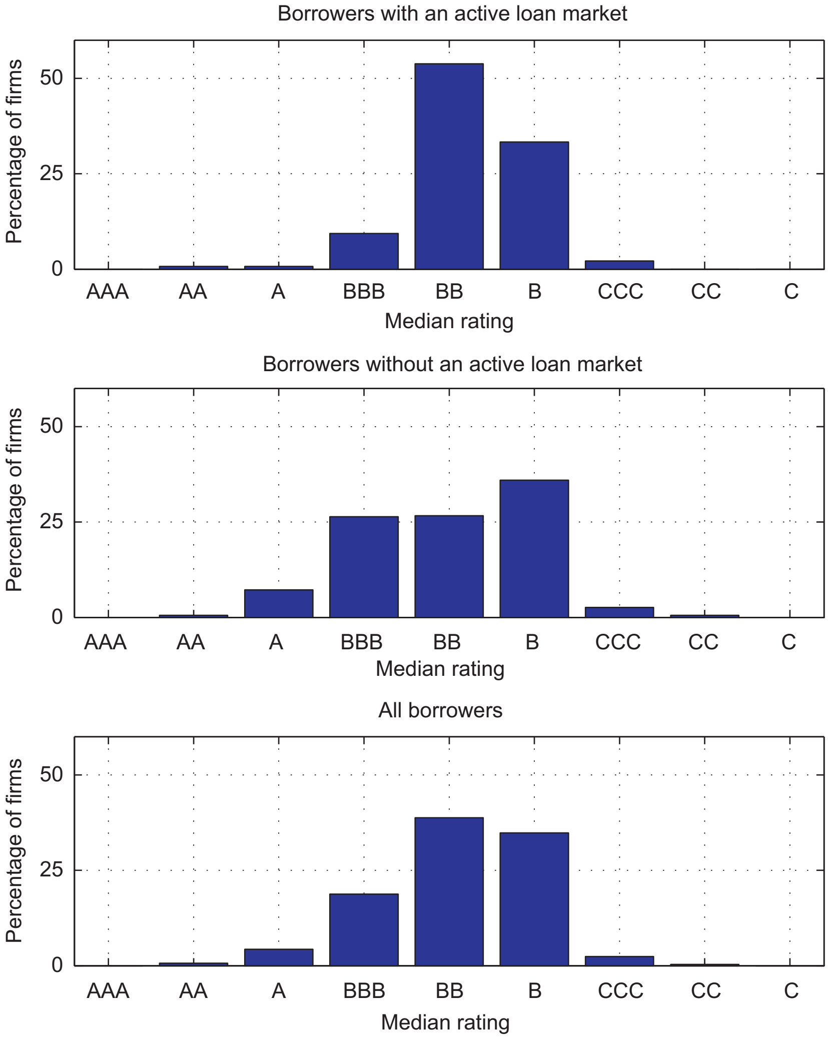

Fig. 1. Distribution of the median long-term S&P credit rating for borrowers with an active secondary loan market (*LIQ*), for borrowers without an active secondary loan market (*noLIQ*) and for all borrowers, over the sample period from 2000 to 2007.

in the *LIQ* group is about $1.1 billion in market capitalization, $1.9 billion in total assets, and $363 million in net sales, while the median borrower in the *noLIQ* category is about one-third to one-fourth in size on these parameters.[12] This is not surprising, since there is more public information (including greater analysts following) available for larger firms, which would help investors in the secondary loan market in evaluating these borrowers. Prima facie, one would expect this comparison to point to an indirect mechanism for loan investors to guard against moral hazard and adverse selection issues, since smaller firms should be more susceptible to these problems. Hence if we still find evidence of moral hazard and adverse selection in the loan market, despite the fact that it is generally the larger borrowers whose loans are actively traded, it would be an even more striking result.

We also observe that borrowers that have an active secondary loan market are more levered and less profitable than those without actively traded loans. About 89% of borrowers in the *LIQ* group are speculative-grade, while this percentage is lower at 66% among the borrowers in the *noLIQ* category. Fig. 1 provides more details on the distribution of borrowers by credit rating. Most of the syndicated term loan market is concentrated on BBB, BB, and B rated borrowers—higher rated borrowers are able to issue equity, bond or commercial paper directly to investors, thus avoiding the costs of intermediation. The lower rated borrowers often do not have any choice but to approach a financial institution for a loan. However, most of the actively traded loans are concentrated within the BB and B rating categories, and there is very little trading activity in the investment-grade (IG) segment. This is primarily due to demand-side reasons. Loans originated by

[12] Note that we only consider publicly listed borrowers with sufficient CRSP/Compustat data, so many of the smaller syndicated loan borrowers are already excluded from our sample.

speculative-grade borrowers are high-yield credits with spreads over LIBOR that are upwards of several hundred basis points. These are precisely the loans that investors (including CDO/CLO hedge funds) are interested in buying due to their higher expected returns. The return on investment-grade loans is generally not high enough to entice loan investors to participate in this market.

3. Long-run performance and valuation analysis

The existing literature on measuring long-run abnormal performance dates back to Ritter (1991) and often focuses on testing IPO and SEO performance.[13] Adapting and suitably modifying that methodology for firms with bank loans, we estimate the risk-adjusted long-run abnormal stock returns for the two portfolios: borrowers with and without an active secondary loan market.

There are two widely used approaches for measuring long-term abnormal returns: (i) calendar-time methods proposed by Fama (1998) and Brav et al. (2000) that allow the simulation of investment strategies that could be implemented by a portfolio manager and (ii) event-time studies, recently applied in Cornett et al. (1998) and Ergungor et al. (2009), that focus on the aftermarket performance of event firms. Fama (1998) and Mitchell and Stafford (2000) pointed out that the event-time approach may overstate the long-run performance since it can grow with the return horizon even when there is no abnormal return after the first period. Moreover, since event-time measures are computed over a long horizon, time-period overlap can introduce cross-sectional correlations. This cross-sectional dependence in sample observations can lead to poorly specified test statistics (see, e.g., Fama, 1998; Lyon et al., 1999; Brav, 2000). We therefore rely on the calendar-time analysis to measure long-run abnormal returns, and use the event-time approach as a robustness check.

3.1. Calendar-time analysis

Our primary abnormal return measure is the alpha coefficient from the monthly time-series regression of excess returns on the three Fama and French (1993) factors *MKT*, *SMB* and *HML*, and on the momentum factor, *UMD*, introduced by Jegadeesh and Titman (1993):

$$R^j(t) - R_f(t) = \alpha + \beta_{MKT} MKT(t) + \beta_{SMB} SMB(t) + \beta_{HML} HML(t) + \beta_{UMD} UMD(t) + \varepsilon(t), \quad j \in \{LIQ, noLIQ\}, \tag{1}$$

where R_f is the one-month T-bill rate. $R^{LIQ}(t)$ denotes the monthly return on the portfolio of borrowers whose loans first became liquid in the secondary market in the q months prior to t, where $q = 12, 24$, or 36 months, depending on the long-run return horizon being analyzed. $R^{noLIQ}(t)$ denotes the monthly return on the portfolio of borrowers that did not have an active secondary loan market in the q months prior to t. We distinguish between equally-weighted (EW) and value-weighted (VW) portfolio returns $R^j(t)$. If in a particular calendar month t there are no firms in the portfolio, Lyon et al. (1999) dropped that month from estimating Eq. (1). Since the number of our test firms is generally large enough, we are able to run the regressions under the stricter requirement that portfolios need to consist of at least 30 firms for any month.[14]

We also compare the abnormal returns on the *LIQ* portfolio to that on the *noLIQ* portfolio by replacing $R^j(t) - R_f(t)$ in (1) with $R^{noLIQ}(t) - R^{LIQ}(t)$. Such a regression yields the alpha estimate for a portfolio that is long in borrowers with no active loan market and short in borrowers that have an active loan market. An estimate for alpha that is significantly less than zero is evidence of underperformance in the long run of borrowers with an active loan market relative to those without an active loan market.

To understand if the performance of borrowers with and without an active secondary loan market is uniform throughout the sample, or if there are certain types of firms that exhibit a stronger or a weaker effect, we stratify borrowers along different dimensions. We repeat the regression analysis in (1) after stratifying the set of all borrowers by size, S&P long-term credit rating, book leverage, and industry. The cutoff point between small and large firms, for example, is computed at the beginning of each month as the median size of all NYSE-traded stocks in our reference set (firms that did not issue bank loans between 2000 and 2004). Similarly, we distinguish between low-leverage and high-leverage borrowers. The industry groups considered are consumer industries, manufacturing, technology, healthcare, and other industries.[15]

An alternative calendar-time portfolio method computes mean calendar-time abnormal returns (MCTARs). For each month t and borrower i, the calendar-time abnormal return of firm i is calculated relative to the return on its reference portfolio, $R^{i,ref}(t)$:

$$CTAR^i(t) = R^i(t) - R^{i,ref}(t), \tag{2}$$

where $R^i(t)$ denotes the return on firm i in month t.

[13] For recent applications see, for example, Kooli et al. (2004), Chan et al. (2008), and Ergungor et al. (2009).

[14] When stratifying the sample, we reduce that requirement to 10 or more firms for large, IG or low-leverage borrowers, and for all industry portfolios.

[15] For more details, including the distribution of SIC codes across industries, see Kenneth French's website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

We follow the procedure of Daniel et al. (1997), Cornett et al. (1998) and Lyon et al. (1999) in constructing 125 reference portfolios based on size (market value of equity (ME)), book-to-market ratio (B/M), and momentum characteristics. Our reference portfolios include all firms listed on the NYSE, AMEX, and Nasdaq exchanges from 2000 to 2007, provided that the following three requirements are met: (i) Compustat data are available for the firm at least two years prior to the inclusion of the firm into the portfolio, (ii) the firm has market value data available in CRSP both one year and six months prior to the inclusion, and (iii) in the 12 months prior to the inclusion, at least 6 monthly returns are available in CRSP. Reference firms exclude firms that issued bank loans between 2000 and 2004. This leaves us with a reference sample of 7324 firms.[16]

First, all NYSE firms in our reference sample are sorted into quintiles according to their market value of equity, calculated at the beginning of each month. Within each quintile, we further sort firms into five portfolios according to their book-to-market ratios.[17] Finally, for each size and book-to-market sorted portfolio, we sort the firms into quintiles according to their preceding 12-month return. This process gives us a total of 125 NYSE-based portfolios to which any AMEX and Nasdaq firms in the reference sample are added. For a particular month t, we match each borrower to a benchmark portfolio according to its size, book-to-market ratio, and momentum rank at the beginning of that month. The reference portfolio return is the equally-weighted or the value-weighted return on the portfolio of reference stocks.

Each calendar month t, a weighted abnormal return across borrowers is calculated as

$$\overline{CTAR^j}(t) = \sum_i w^i(t) CTAR^i(t), \quad j \in \{LIQ, noLIQ\}. \tag{3}$$

$\overline{CTAR^{LIQ}}(t)$ denotes the weighted calendar-time abnormal return on the portfolio of borrowers whose secondary loan market first became liquid in the q months prior to t, where $q = 12, 24$, or 36 months. $\overline{CTAR^{noLIQ}}(t)$ denotes the return on the portfolio of borrowers that had bank loans originated prior to time t, but did not have an active secondary loan market in the q months prior to time t. The weights $w^i(t)$ are all equal when reference portfolios and abnormal returns are equally weighted. When they are value-weighted, $w^i(t)$ is equal to the size of firm i at the beginning of month t relative to the total size across all firms. A grand mean abnormal monthly return is calculated as

$$MCTAR^j = \frac{1}{T} \sum_{t=1}^{T} \overline{CTAR^j}(t), \quad j \in \{LIQ, noLIQ\}. \tag{4}$$

To directly compare the abnormal returns on the LIQ portfolio to those on the $noLIQ$ portfolio, we estimate the average difference in weighted calendar-time abnormal returns by replacing $\overline{CTAR^j}(t)$ in (4) with $\overline{CTAR^{noLIQ}}(t) - \overline{CTAR^{LIQ}}(t)$.

3.2. Event-time analysis

Our event-time tests examine the cumulative abnormal returns (CARs) and the buy-and-hold abnormal returns (BHARs) for the portfolios of borrowers with and without an active secondary loan market. The analysis of CARs answers the question whether borrowers in one of these categories persistently earn abnormal monthly returns.

The weighted abnormal return at s months after the event is calculated as

$$\overline{AR^j}(s) = \sum_i w^i(s)(R^i(s) - R^{i,ref}(s)), \quad j \in \{LIQ, noLIQ\}, \tag{5}$$

where $\overline{AR^{LIQ}}(s)$ denotes the weighted event-time abnormal return on the portfolio of borrowers whose secondary loan market first became liquid s months ago, and $\overline{AR^{noLIQ}}(s)$ denotes the return on the portfolio of borrowers that do not have an active loan market. For each borrower that does not have an active loan market during our sample period, we randomly assign an "event month" on or after that firm's first loan origination date. We use 1000 simulations, and $\overline{AR^{noLIQ}}(s)$ is stored for each. The weights $w^i(s)$ are all equal when reference portfolios and abnormal returns are equally weighted. When they are value-weighted, $w^i(s)$ is equal to the size of firm i relative to the total size across all firms. Reference portfolios are formed as in the previous section. We distinguish between continuously rebalanced reference portfolios and reference portfolios that are not allowed to update.

The q-month cumulative abnormal portfolio return is calculated as

$$CAR^j = \sum_{s=1}^{q} \overline{AR^j}(s), \quad j \in \{LIQ, noLIQ\}, \tag{6}$$

where $q = 12, 24$, or 36 months. To account for potential skewness in cumulative abnormal returns, we rely on skewness-adjusted t-statistics as discussed in Barber and Lyon (1997). We also report the median, across the 1000 simulations, of the

[16] The requirement to exclude all firms that issued bank loans between 2000 and 2004 from the reference portfolios may introduce a small look-ahead bias in (2) that can be avoided by only excluding borrower i when computing $R^{i,ref}(t)$. We have implemented the latter version as well. It yields similar results, which is not surprising given the large number of firms in our reference set.

[17] Following Fama and French (1993), we do not use negative book equity values when calculating these cutoff points.

difference in cumulative abnormal returns between the portfolios of borrowers with and without an active secondary loan market, as well as the median of the associated two-sample t-test statistics with unpooled variances.

Another measure of long-run stock returns is the buy-and-hold abnormal return, which represents the compounded returns that a long-horizon investor would earn (see, e.g., Barber and Lyon, 1997; Kothari and Warner, 2007). The weighted abnormal return from a buy-and-hold strategy over a q-month period is computed as

$$\overline{BHAR^j} = \sum_i w^i BHAR^i, \quad j \in \{LIQ, noLIQ\}, \tag{7}$$

where

$$BHAR^i = \left(\prod_{s=1}^{q} (1 + R^i(s)) - \prod_{s=1}^{q} (1 + R^{i,ref}(s)) \right), \tag{8}$$

for $q = 12, 24$, or 36 months. $\overline{BHAR^{LIQ}}$ denotes the weighted buy-and-hold abnormal return on the portfolio of borrowers with an active secondary loan market, whereas $BHAR^{noLIQ}$ is the buy-and-hold abnormal return on the portfolio of borrowers with no actively traded loans. Since long-run buy-and-hold abnormal returns are often positively skewed, we use skewness-adjusted t-statistics as discussed in Barber and Lyon (1997). As we did for CAR, for each borrower that does not have an active loan market during our sample period, we randomly assign an "event month" on or after that firm's first loan origination date. We use 1000 simulations and report the median $BHAR^{noLIQ}$. As before, we distinguish between equal and value-weighting, and between reference portfolios with continuous rebalancing and those without rebalancing.

We also compute the median, across the 1000 simulations, of the difference in the buy-and-hold abnormal returns between the portfolios of borrowers with and without an active secondary loan market, as well as the median of the associated two-sample t-test statistics with unpooled variances.

3.3. Valuation analysis

To complement our study of long-run stock returns, we examine a widely used measure of long-run changes in borrower valuation, the Tobin's q. It is defined as the ratio of the sum of the market value of equity plus the book value of debt to total assets.[18]

Our measure of changes in Tobin's q is match-adjusted: the long-run change in a borrower's valuation is measured relative to that of a matched sample of non-borrowers. Using the methodology of Barber and Lyon (1996), for each borrower and a given month t, we consider a list of two-digit SIC code and valuation-matched (Tobin's q within 90% and 110% of the issuer at beginning of month) firms that did not originate bank loans between 2000 and 2004. For firms with an active secondary loan market, t denotes the month during which the loan market first became liquid. For borrowers without an active loan market, we randomly sample t from the months of or after the firm's first loan origination date. Note that we winsorize all firm valuation measures at the 1% and 99% levels to avoid our results being driven by outliers.

The reference 36-month-ahead Tobin's q for borrower i, $TQ^{i,ref}(t+36)$, is computed as the median Tobin's q at the end of month $t+36$, across all firms in borrower i's reference group. One drawback of using the *level* of the reference group's firm valuation measure is that it ignores the history of the borrower's valuation measure relative to that of the reference group. An alternative reference 36-month-ahead Tobin's q for borrower i is equal to its past valuation measure plus the change in the reference portfolio's valuation measure.

For borrower i, the 36-month-ahead difference in Tobin's q relative to the reference group firms using *levels* is defined as

$$\text{I:} \quad TQ^i(t+36) - TQ^{i,ref}(t+36).$$

Similarly, the 36-month-ahead difference in Tobin's q relative to the reference group firms using *changes in levels* is given as

$$\text{II:} \quad TQ^i(t+36) - [TQ^i(t) + (TQ^{i,ref}(t+36) - TQ^{i,ref}(t))].$$

We use both methods I and II to compute the average, across all borrowers with and without an active secondary loan market, of the 36-month-ahead difference in Tobin's q relative to the reference group firms. For the latter set of borrowers, we report the median across the 1000 simulations of event-times.

4. Results

We now present the results from the calendar-time, event-time and valuation analysis.

[18] For a recent application, see Roll et al. (2008).

Table 2
Factor regressions: this shows the four-factor calendar-time risk-adjusted long-run abnormal stock returns for two portfolios, borrowers with an active loan market and borrowers without an active loan market.

12 months		24 months		36 months	
EW	VW	EW	VW	EW	VW
		Active loan market			
−0.73	−1.09	−0.93	−1.06	−0.75	−0.74
(−1.57)	(−2.29)	(−2.62)	(−2.27)	(−2.79)	(−1.93)
50	50	67	67	80	79
		No active loan market			
0.30	−0.21	0.39	−0.18	0.40	−0.19
(1.87)	(−1.10)	(2.37)	(−0.89)	(2.32)	(−0.92)
93	93	93	93	93	93
		No active loan market − active loan market			
1.19	0.99	1.36	0.97	1.18	0.67
(2.34)	(2.06)	(3.47)	(2.05)	(3.81)	(1.79)
50	50	67	67	80	79

We report estimates for alpha in the monthly time-series regression of excess returns on the three Fama–French factors *MKT*, *SMB* and *HML*, and momentum, *UMD*: $R^j(t) - R_f(t) = \alpha + \beta_{MKT}MKT(t) + \beta_{SMB}SMB(t) + \beta_{HML}HML(t) + \beta_{UMD}UMD(t) + \varepsilon(t)$, $j \in \{LIQ, noLIQ\}$. $R^{LIQ}(t)$ is the return on the equally-weighted (EW) or value-weighted (VW) portfolio of borrowers whose secondary loan market first became liquid in the q months prior to t, $q \in \{12, 24, 36\}$. $R^{noLIQ}(t)$ is the return on the portfolio of borrowers that did not have an active secondary loan market in the q months prior to t. R_f denotes the one-month T-bill rate. We also report the alpha of a portfolio that is long in borrowers with no active loan market and short in borrowers that have an active loan market, by replacing $R^j(t) - R_f(t)$ with $R^{noLIQ}(t) - R^{LIQ}(t)$. For each regression, we report the estimate for alpha (in percent), Newey–West t-statistics with three lags (in parentheses), and the number of monthly observations during the 2000–2007 sample period.

4.1. Calendar-time analysis

In Table 2, we report the intercept terms (alphas) from regressing the portfolio returns for borrowers with and without an active secondary loan market on the three Fama–French and the momentum factors. Each alpha can be interpreted as the average abnormal monthly return of its respective portfolio. We also report the alpha for a portfolio that is long in borrowers with no active loan market and short in borrowers that have an active loan market, which is indicative of the abnormal return of an admissible trading strategy based on the liquidity of the borrowers' loans in the secondary market.

The results show that the borrowers whose loans are sold in the secondary market underperform their peers by an economically large magnitude of about 9% annually, on a risk-adjusted basis, over the three-year period following the initial sale of their loans. For borrowers with an active loan market, the abnormal monthly return is on average about −0.75% ($t = -2.79$) using equally-weighted portfolios. The result is very similar using value-weighted portfolios, with an estimated alpha of −0.74% ($t = -1.93$). On the other hand, the borrowers that do not have an active loan market do not underperform in the long run. The long–short portfolio performance indicates that the strategy would yield an abnormal monthly return of 1.18% ($t = 3.81$) using equally-weighted portfolios and of 0.67% ($t = 1.79$) using value-weighted portfolios.

This is clear evidence of underperformance of firms whose loans are sold in the secondary market. These results are somewhat different from, but intuitively consistent with, those reported by Billett et al. (2006), who report that firms announcing bank loans suffer negative abnormal stock returns over the subsequent three years. We find this negative risk-adjusted excess return *only* for firms whose loans are sold. Borrowers whose loans are not sold do not suffer negative abnormal returns. Perhaps the pooling of these two types of firms with different long-run performance patterns gives rise to their results. In fact, if we average the alphas for the two types of firms in our sample, we obtain average alphas that are close to the ones these authors report. This distinction is important—our results support prior studies that find bank loan financing to be "special" and different from other forms of corporate financing such as IPOs, SEOs, public and convertible debt, since it does not lead to a negative long-run performance of the borrowers, *except for firms whose loans are being sold by the lending banks.*

As with all studies using risk-factor models, there is always a concern whether the alphas simply represent a poor risk adjustment.[19] The ideal experiment would be to compare the stock returns of borrowers that are identical to outsiders, with one set having actively traded loans and the other set with no actively traded loans. In this case, there would be no need for a risk-factor adjustment. Unfortunately, given the median firm characteristics reported in Table 1, this ideal experiment is nearly impossible to conduct. A match on size, B/M, momentum and rating is feasible only for 20 borrowers with actively traded loans. For this set of firms, however, the monthly MCTAR relative to reference groups of borrowers

[19] We thank our referee for diligently pressing us to refine our analysis on this point.

Table 3
Robustness of factor regressions: this shows the calendar-time risk-adjusted long-run abnormal stock returns for two portfolios, borrowers with an active loan market and borrowers without an active loan market.

12 months		24 months		36 months	
EW	VW	EW	VW	EW	VW
		8 factors Active loan market			
−0.76	−1.10	−0.97	−1.10	−0.81	−0.84
(−1.83)	(−2.66)	(−2.66)	(−2.49)	(−3.07)	(−2.25)
50	50	67	67	80	79
		No active loan market			
0.27	−0.21	0.36	−0.17	0.37	−0.18
(1.47)	(−0.96)	(1.99)	(−0.77)	(1.95)	(−0.79)
88	88	88	88	88	88
		4 factors, censored Active loan market			
−0.32	−0.96	−0.64	−1.17	−0.56	−0.87
(−0.73)	(−1.72)	(−1.78)	(−2.62)	(−2.00)	(−2.29)
43	43	63	63	75	75
		No active loan market			
0.12	−0.33	0.22	−0.30	0.24	−0.30
(0.71)	(−1.32)	(1.44)	(−1.16)	(1.52)	(−1.18)
92	92	92	92	92	92
		8 factors, censored Active loan market			
−0.35	−0.92	−0.70	−1.21	−0.66	−0.98
(−1.04)	(−2.23)	(−2.00)	(−2.96)	(−2.39)	(−2.77)
43	43	63	63	75	75
		No active loan market			
−0.03	−0.21	0.10	−0.18	0.12	−0.18
(−0.16)	(−0.98)	(0.57)	(−0.78)	(0.68)	(−0.81)
88	88	88	88	88	88

The first panel reports estimates for alpha in the monthly time-series regression of $R^j - R_f$, $j \in \{LIQ, noLIQ\}$, on the three Fama–French factors, momentum, and four additional factors: innovations in market illiquidity (Acharya and Pedersen, 2005), the Fama–French factors *TERM* and *DEF*, and changes in the S&P500 volatility index (Ang et al., 2006). $R^{LIQ}(t)$ is the return on the equally-weighted (EW) or value-weighted (VW) portfolio of borrowers whose secondary loan market first became liquid in the q months prior to t, $q \in \{12, 24, 36\}$. $R^{noLIQ}(t)$ is the return on the portfolio of borrowers that did not have an active secondary loan market in the q months prior to t. R_f denotes the one-month T-bill rate. Panels labeled "4 factors, censored" and "8 factors, censored" report alphas from the four-factor and eight-factor regressions, after removing the smallest quintile of firms. Size (ME) quintiles are computed each month based on all NYSE-traded firms that did not issue bank loans between 2000 and 2004. For each regression, we report the estimate for alpha (in percent), Newey–West t-statistics with three lags (in parentheses), and the number of monthly observations during the 2000–2007 sample period.

without an active secondary loan market is still significantly negative at −1.77% ($t = -2.13$). (The CAR and BHAR measures are also negative and of economic significance, but are not statistically significant due to the small sample size.) Since the matching exercise shows that it is not feasible to conduct the ideal experiment in a statistically robust manner, we are forced to adopt the risk-factor adjustments.

To examine the robustness of our risk-factor adjustment, we expand the four-factor model to eight factors by including liquidity, term, default, and volatility factors. The results for the full eight-factor model are reported in Table 3.[20] The abnormal monthly return for borrowers with an active loan market is −0.81% ($t = -3.07$) for equally-weighted and −0.84% ($t = -2.25$) for value-weighted portfolios, reinforcing our inference regarding the underperformance of this set of firms. In this table, we also report censored results for the four-factor and eight-factor models where we remove the smallest quintile of firms, in order to test whether any of our results are driven by the smallest firms in the sample. Once again, we obtain negative abnormal returns of similar magnitude and significance for the set of borrowers that have an active secondary loan market.[21]

[20] Results using various five-, six-, and seven-factor models are similar, but we do not report them due to space constraints. We thank Viral Acharya for data on innovations in market illiquidity.

[21] We also perform the four-factor and eight-factor regressions after removing the lowest and the highest percentile of return observations, and obtain similar results.

Table 4
Factor regressions by size: this shows the four-factor calendar-time risk-adjusted long-run abnormal stock returns for two portfolios, small borrowers with an active loan market and small borrowers without an active loan market.

12 months		24 months		36 months	
EW	VW	EW	VW	EW	VW
		Small borrowers			
		Active loan market			
0.29	0.71	−0.65	−0.37	−0.53	−0.42
(0.46)	(1.24)	(−1.91)	(−0.98)	(−2.37)	(−1.57)
22	22	53	53	65	65
		No active loan market			
0.36	0.31	0.44	0.43	0.45	0.45
(1.84)	(1.08)	(2.18)	(1.52)	(2.15)	(1.57)
93	93	93	93	93	93
		Large borrowers			
		Active loan market			
–	–	0.14	−0.04	0.29	−0.01
		(0.76)	(−0.20)	(1.54)	(−0.03)
		23	23	45	45
		No active loan market			
−0.01	−0.17	0.10	−0.15	0.11	−0.16
(−0.08)	(−0.96)	(0.69)	(−0.76)	(0.81)	(−0.81)
88	88	88	88	88	88

We report estimates for alpha in the monthly time-series regression of excess returns on the three Fama–French factors *MKT*, *SMB* and *HML*, and momentum, *UMD*: $R^j(t) - R_f(t) = \alpha + \beta_{MKT}MKT(t) + \beta_{SMB}SMB(t) + \beta_{HML}HML(t) + \beta_{UMD}UMD(t) + \varepsilon(t)$, $j \in \{LIQ, noLIQ\}$. $R^{LIQ}(t)$ is the return on the equally-weighted (EW) or value-weighted (VW) portfolio of borrowers whose secondary loan market first became liquid in the q months prior to t, $q \in \{12, 24, 36\}$. $R^{noLIQ}(t)$ is the return on the portfolio of borrowers that did not have an active secondary loan market in the q months prior to t. R_f denotes the one-month T-bill rate. For each regression, we report the estimate for alpha (in percent), Newey–West t-statistics with three lags (in parentheses), and the number of monthly observations during the 2000–2007 sample period. The second panel shows the results for similar portfolios of large firms. The cutoff point between small and large firms is computed each month as the median market value of equity of all NYSE-traded firms that did not issue bank loans between 2000 and 2004.

To further assess the effectiveness of the four-factor risk-adjustment model during our 2000–2007 sample period, we compute alphas for the 25 Fama–French portfolios sorted on size and book-to-market ratio. The alphas are significantly negative only for one portfolio using value-weighting and two portfolios using equal-weighting, with magnitudes of half or less of those found for the *LIQ* group. Therefore, our results do not appear to be driven by the inadequacy of the four-factor risk adjustment. Nevertheless, while we have performed an extensive sensitivity analysis of our risk-adjustment model, we acknowledge that the possibility remains that a portion of our abnormal returns may be due to some other missing risk factor.[22]

Next, we drill down into our sample of borrowing firms to understand if the underperformance of firms with an active secondary loan market is uniform throughout the sample, or if there are some types of firms that exhibit a stronger or a weaker effect. Table 4 reports the four-factor alphas for our sample stratified by size. We find that the relative underperformance is present only in the smaller firms. The smaller firms with an active loan market have an average abnormal monthly return of -0.53% ($t = -2.37$) using equally-weighted portfolios and -0.42% ($t = -1.57$) using value-weighted portfolios, while the alphas are insignificant for large firms. The smaller firms are more likely to be more opaque, with less public information about them. In this case the private information advantage of the bank is likely to be greater, resulting in a greater ability of the banks to sell the loans of firms that they *internally* believe will perform poorly in the future. Alternatively, the smaller firms are more likely to benefit from the discipline of the lending banks monitoring them closely, since they may not have sophisticated corporate governance systems in place, or as much public scrutiny as the larger firms. In this case, the weakening of their relationship with their lenders could affect them negatively.

The second stratification is based on the credit rating of the borrowing firms. The four-factor alphas for this stratification are reported in Table 5. The speculative-grade firms with an active loan market have an average abnormal monthly return of -0.78% ($t = -2.64$) using equally-weighted and -1.11% ($t = -2.38$) using value-weighted portfolios. This is not

[22] The subset of actively traded syndicated loan borrowers has specific firm attributes. It does not represent the entire cross-section of firms in the corporate universe, since not all firms borrow in the syndicated loan market, and only some of those borrowers have actively traded loans. These attributes may be plausibly related to risk, hence a risk-based explanation for our alphas may be possible.

Table 5
Factor regressions by rating: this shows the four-factor calendar-time risk-adjusted long-run abnormal stock returns for two portfolios, IG borrowers with an active loan market and IG borrowers without an active loan market.

12 months		24 months		36 months	
EW	VW	EW	VW	EW	VW
		IG borrowers			
		Active loan market			
–	–	0.24	−0.17	0.29	−0.28
		(0.49)	(−0.31)	(1.23)	(−0.91)
		25	25	52	52
		No active loan market			
0.36	0.03	0.37	0.04	0.36	0.03
(2.63)	(0.16)	(2.75)	(0.23)	(2.62)	(0.18)
90	90	90	90	90	90
		SG borrowers			
		Active loan market			
−0.12	−0.34	−0.92	−1.41	−0.78	−1.11
(−0.17)	(−0.53)	(−2.30)	(−2.47)	(−2.64)	(−2.38)
29	29	62	62	74	74
		No active loan market			
−0.11	−0.38	0.17	−0.19	0.22	−0.18
(−0.54)	(−1.18)	(0.88)	(−0.54)	(0.97)	(−0.48)
84	84	82	82	82	82

We report estimates for alpha in the monthly time-series regression of excess returns on the three Fama–French factors *MKT*, *SMB* and *HML*, and momentum, *UMD*: $R^j(t) - R_f(t) = \alpha + \beta_{MKT}MKT(t) + \beta_{SMB}SMB(t) + \beta_{HML}HML(t) + \beta_{UMD}UMD(t) + \varepsilon(t)$, $j \in \{LIQ, noLIQ\}$. $R^{LIQ}(t)$ is the return on the equally-weighted (EW) or value-weighted (VW) portfolio of borrowers whose secondary loan market first became liquid in the q months prior to t, $q \in \{12, 24, 36\}$. $R^{noLIQ}(t)$ is the return on the portfolio of borrowers that did not have an active secondary loan market in the q months prior to t. R_f denotes the one-month T-bill rate. For each regression, we report the estimate for alpha (in percent), Newey–West t-statistics with three lags (in parentheses), and the number of monthly observations during the 2000–2007 sample period. The second panel shows the results for similar portfolios of SG firms.

surprising, since the speculative-grade firms are riskier firms where the lemons problem is more likely to be present. These are also the firms that could benefit the most from the discipline imposed by bank monitoring.

We next classify borrowers into high-leverage and low-leverage borrowers based on the median book leverage of all NYSE traded stocks in our reference set of non-borrowers. These results are presented in Table 6. The high-leverage firms with an active loan market have an average abnormal monthly return of -0.89% ($t = -3.34$) using equally-weighted and -0.97% ($t = -2.46$) using value-weighted portfolios. In light of our results for stratifications by size and credit rating this is again intuitive, given that these two variables are generally correlated with leverage.

Overall, our results lead to two important inferences. First, the borrowers whose loans are sold in the secondary market suffer a negative abnormal return, on a risk-adjusted basis, of about 9% per year over the three years following the initial sale of their loans. These negative abnormal returns are concentrated within small, high-leverage, speculative-grade firms.[23] Second, we find that the borrowers that have no active secondary loan market do not have any negative abnormal returns over a three-year horizon, which is different from the results of underperformance of firms raising capital through other means such as equity or public debt issuance.

We next examine the MCTARs based on calendar-time portfolios, as an alternative to the alphas obtained from factor regressions. The results for the full sample are presented in Table 7. These results clearly show that the borrowing firms with actively traded loans significantly underperform relative to their peers. Over a three-year horizon, the firms with an active loan market experience an average abnormal monthly return of -0.85% ($t = -3.17$) using equally-weighted and -0.73% ($t = -2.50$) using value-weighted portfolios, which translates to an annual abnormal return between 8.8% and 10.2% over a three-year period, very similar to the results obtained using the four-factor model. These results are both economically and statistically significant. The stratifications by size, leverage and credit rating yield results similar to those reported for the factor regressions earlier, that this effect is mostly due to small, high-leverage, speculative-grade firms.

[23] Stratification on the five Fama–French industries shows negative abnormal returns for the "consumer" and "other" industries. The latter include firms in business services, entertainment, finance and hotels.

Table 6
Factor regressions by leverage: this shows the four-factor calendar-time risk-adjusted long-run abnormal stock returns for two portfolios, low-leverage borrowers with an active loan market and low-leverage borrowers without an active loan market.

12 months		24 months		36 months	
EW	VW	EW	VW	EW	VW
Low leverage					
Active loan market					
0.29	−0.53	−0.25	−0.56	−0.01	−0.16
(0.49)	(−0.88)	(−0.55)	(−0.92)	(−0.02)	(−0.31)
33	33	67	67	78	78
No active loan market					
0.41	−0.32	0.45	−0.29	0.43	−0.32
(1.68)	(−0.85)	(1.84)	(−0.76)	(1.75)	(−0.83)
94	94	94	94	94	94
High leverage					
Active loan market					
0.10	−0.22	−0.94	−1.12	−0.89	−0.97
(0.24)	(−0.49)	(−3.05)	(−2.41)	(−3.34)	(−2.46)
26	26	61	61	73	73
No active loan market					
0.28	−0.01	0.40	0.03	0.44	0.05
(1.44)	(−0.03)	(1.99)	(0.15)	(2.15)	(0.21)
92	92	92	92	92	92

We report estimates for alpha in the monthly time-series regression of excess returns on the three Fama–French factors *MKT*, *SMB* and *HML*, and momentum, *UMD*: $R^j(t) - R_f(t) = \alpha + \beta_{MKT}MKT(t) + \beta_{SMB}SMB(t) + \beta_{HML}HML(t) + \beta_{UMD}UMD(t) + \varepsilon(t)$, $j \in \{LIQ, noLIQ\}$. $R^{LIQ}(t)$ is the return on the equally-weighted (EW) or value-weighted (VW) portfolio of borrowers whose secondary loan market first became liquid in the q months prior to t, $q \in \{12, 24, 36\}$. $R^{noLIQ}(t)$ is the return on the portfolio of borrowers that did not have an active secondary loan market in the q months prior to t. R_f denotes the one-month T-bill rate. For each regression, we report the estimate for alpha (in percent), Newey–West t-statistics with three lags (in parentheses), and the number of monthly observations during the 2000–2007 sample period. The second panel shows the results for similar portfolios of high-leverage firms. The cutoff point between low-leverage and high-leverage firms is computed each month as the median book leverage of all NYSE-traded firms that did not issue bank loans between 2000 and 2004.

Table 7
Mean calendar-time abnormal returns: this shows the long-run mean calendar-time abnormal stock returns (MCTARs) for two portfolios, borrowers with an active loan market and borrowers without an active loan market.

12 months		24 months		36 months	
EW	VW	EW	VW	EW	VW
Active loan market					
−0.85	−1.37	−0.87	−0.99	−0.85	−0.73
(−1.69)	(−2.62)	(−2.55)	(−2.80)	(−3.17)	(−2.50)
37	37	64	64	76	76
No active loan market					
−0.15	−0.07	−0.10	−0.05	−0.08	−0.06
(−0.95)	(−0.26)	(−0.63)	(−0.20)	(−0.50)	(−0.21)
93	93	93	93	93	93
No active loan market − active loan market					
0.47	1.16	0.67	0.91	0.76	0.70
(1.11)	(2.71)	(2.05)	(2.67)	(2.91)	(2.46)
37	37	64	64	76	76

For each calendar month, the abnormal return for each borrower is calculated relative to the returns on the 125 reference portfolios based on size (market value of equity), book-to-market ratio, and momentum: $CTAR^i(t) = R^i(t) - R^{i,ref}(t)$. The reference portfolio return is the equally-weighted (EW) or value-weighted (VW) return on the portfolio of reference stocks. Reference portfolio stocks must have entered the Compustat database at least two years prior to the inclusion of the firm into the portfolio, and exclude firms that issued bank loans between 2000 and 2004. In each calendar month t, a weighted abnormal return is calculated as $\overline{CTAR}^j(t) = \sum_i w^i(t) CTAR^i(t)$, $j \in \{LIQ, noLIQ\}$. $\overline{CTAR}^{LIQ}(t)$ denotes the weighted calendar-time abnormal return on the portfolio of borrowers whose secondary loan market first became liquid in the q months prior to t, $q \in \{12, 24, 36\}$. $\overline{CTAR}^{noLIQ}(t)$ is the return on the portfolio of borrowers that did not have an active secondary loan market in the q months prior to t. A grand mean abnormal monthly return is calculated as $MCTAR^j = 1/T \sum_{t=1}^{T} \overline{CTAR}^j(t)$. T-statistics (in parentheses) and the number of monthly observations during the 2000–2007 sample period are provided with each estimate. The last three rows report the results for the average difference in calendar-time abnormal returns between the portfolio of borrowers without an active loan market and the portfolio of borrowers that have an active loan market, by replacing $\overline{CTAR}^j(t)$ with $\overline{CTAR}^{noLIQ}(t) - \overline{CTAR}^{LIQ}(t)$.

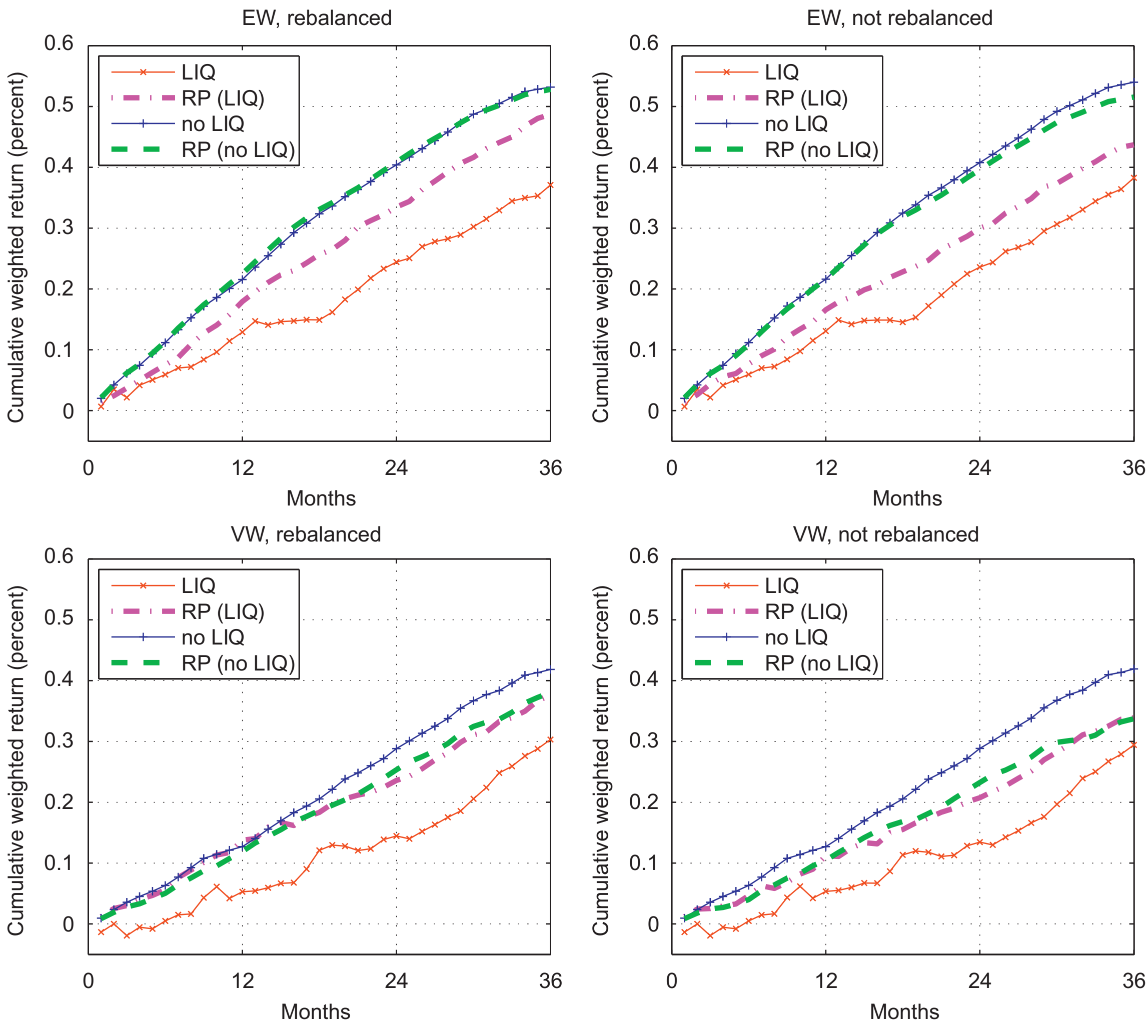

Fig. 2. Event-time cumulative weighted returns for borrowers with an active loan market (*LIQ*), their reference portfolios (RP (*LIQ*)), for borrowers without an active loan market (*noLIQ*), and their reference portfolios (RP (*noLIQ*)). The latter two are computed as the median cumulative weighted returns across 1000 simulations of event dates on or after the firm's first loan origination date.

4.2. *Event-time analysis*

In Fig. 2, we present the event-time CARs for borrowers with and without an active loan market and their respective reference portfolios, both equally- and value-weighted, for portfolios that are rebalanced as well as for those that are not rebalanced. Consistent with prior results, the borrowers with an active loan market have the lowest CARs in all four plots, as shown by the bottom graph line in these figures. Even visually, this group of borrowers clearly and consistently underperforms the other borrowers as well as the reference portfolio firms over the three-year period subsequent to the sale of their loans.

In Table 8 we present the CARs for firms with and without an active secondary loan market, as well as for the long–short strategy. The first panel presents the results when the reference portfolios are rebalanced every month, while the second panel presents the results without rebalancing the reference portfolios. Our results show, using rebalanced reference portfolios, that the borrowers with an active loan market have a three-year CAR of -11.62% ($t = -2.21$) using equally-weighted portfolios and -7.36% ($t = -1.95$) using value-weighted portfolios. These firms appear to be experiencing negative returns relative to the returns on the reference portfolios matched based on size, book-to-market ratio and momentum. On the other hand, the borrowers with no active loan market do not underperform in the long run. As reported in the second panel, the results using reference portfolios that are not rebalanced are similar (though not statistically significant in some cases). These findings are consistent with our results in the previous subsection, which show that borrowers whose loans are being sold appear to underperform their peers, and that the magnitude of this

Table 8
Cumulative abnormal returns: this shows the 12-, 24- and 36-month cumulative abnormal stock returns (CARs) for two portfolios, borrowers with an active loan market and borrowers without an active loan market.

12 months		24 months		36 months	
EW	VW	EW	VW	EW	VW
		Rebalanced reference portfolios			
		Active loan market			
−4.70	−8.42	−8.89	−10.44	−11.62	−7.36
(−1.30)	(−3.22)	(−1.93)	(−3.23)	(−2.21)	(−1.95)
187	187	187	187	182	182
		No active loan market			
−0.73	1.09	−0.64	2.43	0.50	3.80
(−0.39)	(0.98)	(−0.25)	(1.60)	(0.17)	(2.09)
507	507	515	515	524	524
		No active loan market − active loan market			
3.97	9.51	8.25	12.87	12.12	11.15
(0.98)	(3.35)	(1.57)	(3.60)	(2.00)	(2.67)
		Reference portfolios not rebalanced			
		Active loan market			
−3.14	−5.53	−6.15	−7.74	−5.43	−4.44
(−0.87)	(−2.09)	(−1.31)	(−2.33)	(−0.99)	(−1.15)
187	187	187	187	182	182
		No active loan market			
0.07	2.13	0.82	5.10	2.46	8.18
(0.04)	(1.91)	(0.31)	(3.32)	(0.80)	(4.44)
507	507	515	515	524	524
		No active loan market − active loan market			
3.21	7.66	6.97	12.85	7.89	12.62
(0.79)	(2.67)	(1.30)	(3.52)	(1.26)	(2.95)

CAR is computed using the Lyon et al. (1999) reference portfolio method, with 125 reference portfolios based on size (market value of equity), book-to-market ratio, and momentum. The reference portfolio return is the equally-weighted (EW) or value-weighted (VW) return on the portfolio of reference stocks. Reference portfolio stocks must have entered the Compustat database at least two years prior to the inclusion of the firm into the portfolio, and exclude firms that issued bank loans between 2000 and 2004. The first panel reports results for continuously rebalanced reference portfolios, whereas in the second panel reference portfolios are not allowed to update. For each portfolio, we report the estimate for CAR (in percent), its skewness-adjusted t-statistic (in parentheses) as discussed in Barber and Lyon (1997), and the number of firms in the portfolio. For borrowers without an active loan market, we randomly draw 1000 samples of event dates on or after the firm's first loan origination date, and show the median of the statistics. The last two rows of each panel report the median, across the 1000 simulations, of the difference in the cumulative abnormal returns between the portfolios of borrowers without an active loan market and the portfolio of borrowers that have an active loan market, as well as the median of the associated two-sample t-test statistics with unpooled variances.

underperformance is statistically and economically significant. When we stratify our sample based on size, credit rating or leverage we get similar results as before. However, we lose statistical significance in some of the tests due to the small sample sizes in each of the strata.

In Table 9, we present the BHARs as an alternative measure of returns aggregated based on event-time. The sign of these abnormal returns is similar, but we do not find statistical significance using this measure. In both panels, using reference portfolios that are either rebalanced monthly or not rebalanced at all, we find that the borrowers with an active secondary loan market have lower BHARs, and that the long–short strategy has a positive BHAR, though they are not statistically significant. Stratification by size, credit rating or leverage yields results similar to the ones reported before.

4.3. *Borrower valuation*

One of the inferences of the literature on the loan sales market has been that it is "socially desirable", given all the benefits of loans sales that accrue to the borrowers as well as to the banks. Some papers (such as Arping, 2004) have even suggested that the presence of this market could lead to "value creation" in the corporate sector. Our results so far suggest that the borrowers whose loans are sold underperform their peers, over a three-year period following the loan sale. What is the long-run impact of the loan sales market on the valuation of such borrowers? We answer this question by analyzing the changes in Tobin's q, which is a widely used proxy for firm valuation.

Table 9
Buy-and-hold abnormal returns: this shows the 12-, 24- and 36-month buy-and-hold abnormal stock returns (BHARs) for two portfolios, borrowers with an active loan market and borrowers without an active loan market.

12 months		24 months		36 months	
EW	VW	EW	VW	EW	VW
		Rebalanced reference portfolios			
		Active loan market			
−3.60	−6.96	−3.92	−9.45	−13.63	−9.64
(−0.93)	(−0.60)	(−0.65)	(−0.64)	(−1.34)	(−0.39)
187	187	187	187	182	182
		No active loan market			
−1.40	1.18	−3.40	2.89	−4.19	4.86
(−0.49)	(0.32)	(−0.69)	(0.45)	(−0.53)	(0.53)
507	507	515	515	524	524
		No active loan market – active loan market			
2.20	8.14	0.52	12.34	9.44	14.50
(0.47)	(0.84)	(0.07)	(0.92)	(0.74)	(0.71)
		Reference portfolios not rebalanced			
		Active loan market			
−0.92	−2.79	2.82	−2.72	4.80	0.13
(−0.25)	(−0.17)	(0.54)	(−0.07)	(0.63)	(0.13)
187	187	187	187	182	182
		No active loan market			
0.82	2.34	3.78	6.69	8.29	11.28
(0.35)	(0.62)	(0.94)	(1.11)	(1.40)	(1.36)
507	507	515	515	524	524
		No active loan market – active loan market			
1.74	5.13	0.96	9.41	3.49	11.15
(0.40)	(0.52)	(0.14)	(0.69)	(0.33)	(0.56)

BHAR is computed using the Lyon et al. (1999) reference portfolio method, with 125 reference portfolios based on size (market value of equity), book-to-market ratio, and momentum. The reference portfolio return is the equally-weighted (EW) or value-weighted (VW) return on the portfolio of reference stocks. Reference portfolio stocks must have entered the Compustat database at least two years prior to the inclusion of the firm into the portfolio, and exclude firms that issued bank loans between 2000 and 2004. The first panel reports results for continuously rebalanced reference portfolios, whereas in the second panel reference portfolios are not allowed to update. For each portfolio, we report the estimate for BHAR (in percent), its skewness-adjusted *t*-statistic (in parentheses) as discussed in Barber and Lyon (1997), and the number of firms in the portfolio. For borrowers without an active loan market, we randomly draw 1000 samples of event dates on or after the firm's first loan origination date, and show the median of the statistics. The last two rows of each panel report the median, across the 1000 simulations, of the difference in the buy-and-hold abnormal returns between the portfolio of borrowers without an active loan market and the portfolio of borrowers with an active loan market, as well as the median of the associated two-sample *t*-test statistics with unpooled variances.

In Table 10 we report the long-run changes in Tobin's q for the two groups of borrowers relative to their two-digit SIC code and valuation-matched reference group firms, as recommended by Barber and Lyon (1996). We report the average and median differences in 36-month-ahead Tobin's q using two benchmarks for the "expected" Tobin's q. The first one uses the level of Tobin's q for the reference group and the second one relies on the change in Tobin's q for the reference group. As Barber and Lyon (1996) showed, these two models are the most reliable in detecting the differences between the test and the reference portfolios. The results are striking—we find that, on average, borrowers with an active secondary loan market lose between 11.5% and 14% of their value (as a percentage of their total assets) when compared to their reference group firms, over the three-year period subsequent to the initial sale of their loans. This result is significant for both average and median long-run changes in Tobin's q. In addition, the borrowers without an active loan market do not show any abnormal changes in Tobin's q, when compared to their reference firms. This again reaffirms our earlier conclusion that bank loan financing has no negative long-run effects on the borrowers, except for the ones whose loans are being sold in the secondary market.

Perhaps the weakening of the bank–borrower relationship due to the sale of the loan induces moral hazard on the part of the bank, leading to diminished monitoring of the borrower. Syndicated loans are renegotiated quite often, the covenants are often adjusted, and unwritten covenants enforced in response to the borrowers' actions. The lead banks keep close tabs on the borrowers in whom they have substantial financial interest. As shown in prior studies, they play an important corporate governance role, restrict excessive risk-taking and opportunistic managerial behavior on the part of the borrowers, and thus have a positive wealth effect on them. It is possible that diminished monitoring could cause value

Table 10
Valuation analysis: we report results for two models of long-run changes in firm valuation: (I) the 36-month-ahead difference in Tobin's q of borrowers relative to a reference group using *levels* of firm valuation and (II) the 36-month-ahead difference in Tobin's q of borrowers relative to a reference group using *changes* in firm valuation.

12 months		24 months		36 months	
I	II	I	II	I	II
		Active loan market			
−2.80	−2.98	−1.02	−1.43	−11.49	−14.02
(−1.01)	(−0.88)	(−0.25)	(−0.35)	(−2.50)	(−2.84)
−2.11	−3.83	−0.27	−2.17	−6.56	−7.43
[0.09]	[0.04]	[0.89]	[0.52]	[0.02]	[0.01]
187	187	169	169	151	151
		No active loan market			
2.07	0.86	2.45	1.28	3.06	1.63
(0.69)	(0.29)	(0.71)	(0.37)	(0.74)	(0.38)
−1.02	−1.13	−1.52	−1.93	−1.83	−2.32
[0.54]	[0.45]	[0.55]	[0.39]	[0.53]	[0.36]
458	458	429	429	396	396
		No active loan market − active loan market			
4.88	3.85	3.46	2.71	14.55	15.64
(1.20)	(0.86)	(0.66)	(0.50)	(2.35)	(2.40)

Besides 36 months, we also report results for 12-month-ahead and 24-month-ahead differences. For both models, the reference group is two-digit SIC code and valuation matched. The table is divided into three panels. The first panel shows results for firms with an active loan market, whereas the second panel reports the results for borrowers without an active loan market. For each of these two panels, the first and second rows show the average difference in 36-month-ahead Tobin's q (in percent) and the associated *t*-statistic, respectively. Rows three and four report the median difference in 36-month-ahead Tobin's q (in percent) and the *p*-value of the associated Wilcoxon signed rank test statistic. Row five reports the number of firms in the test sample. For the second panel, we report the median statistics over 1000 simulations of event dates on or after the firm's first loan origination date. The third panel of the table reports the median, over the 1000 simulations, of the difference between the abnormal valuation estimate for the no-active-loan-market group minus that of the active-loan-market group (in percent), as well as the median of the associated two-sample *t*-test statistics with unpooled variances.

reduction due to an impairment of any of these roles of the lead banks. However, it is equally plausible that this value loss is a result of adverse selection, not moral hazard. Our empirical tests cannot distinguish between the two. Nevertheless, it does not appear that, in the long run, the presence of an active secondary market for syndicated loans is entirely "socially desirable", at least from the perspective of the borrowing firms.

5. Concluding remarks

We investigate the effects of the transition in bank credit from the relationship banking model to the "originate-to-distribute" model, on a large sample of borrowers in the syndicated loan market. This shift has mainly been due to the growth in the secondary market for syndicated loans, which has allowed banks to sell loans to participating investors in a largely opaque manner. While the prior literature has documented several benefits of the loan sales market for the banks as well as the borrowers, the long-run effects of the existence of this market on the borrowing firms have never been examined. This is precisely what we study in this paper.

When banks sell syndicated loans in the secondary market, it raises moral hazard and adverse selection questions. Are the banks selling lemons, i.e., the loans of borrowers about whom they have negative private information that is unobservable to outside investors? Are they deliberately originating bad loans to enhance their fee income, just because there is an active secondary market where they can sell these loans? How does this affect the incentives of the bank to monitor their borrowers? Is the severance of their lending relationship harmful for borrowers? What is the consequent impact on the long-run valuation of the borrowers? Theory alone is insufficient to answer these questions, as there are both positive and negative effects of the secondary market for syndicated loans. Ultimately, these issues must be resolved empirically, which is the focus of our paper.

We find that borrowers with an active secondary market for their loans underperform their peers by about 9% per year in terms of annual risk-adjusted abnormal returns, over the three-year period subsequent to the initial sale of their loans. These abnormal returns are largely concentrated among small, high-leverage, speculative-grade borrowers. In addition, the borrowers with an active loan market suffer a valuation loss of about 11–14% of the value of their total assets over a three-year period when compared to their peers.

We offer two explanations for our results. First, banks may indeed be selling lemons based on their unobservable private information about the borrower. This would be an indication of a market failure, since, in an efficient market, reputation concerns should inhibit such actions on the part of banks. It bears a remarkable resemblance to the events that have unfolded in the monumental subprime mortgage crisis that began in 2007. Second, borrowers might suffer due to their diminished relationship with banks, since selling the loans removes the discipline of bank monitoring. This might diminish firm value in the long run. Our tests cannot conclusively confirm one or the other explanation. In addition, there is always the possibility that the abnormal returns that we find in our paper are, at least partly, due to inadequate risk adjustment in our factor models. We try and alleviate these concerns by estimating an array of alternative factor models and abnormal return calculations. Our results are robust across the different model specifications and approaches that we use in this paper.

We also find that the borrowers without an active secondary loan market do not suffer any negative long-run effects after obtaining syndicated bank loans. This reaffirms the inference that, for some borrowers, bank loans are indeed "special" when compared to other forms of corporate financing such as equity or public debt, all of which result in a negative long-run performance of the firms raising capital. Our results refine the findings of Billett et al. (2006) who documented a negative long-run performance for all firms that borrow in the syndicated loan market. We show that this negative long-run performance is limited to the borrowers that have an active secondary market for their loans. This is especially interesting in light of the results in Gande and Saunders (2008), who inferred that banks continue to be special even in the presence of a secondary market for loans. Gande and Saunders also suggested that secondary market loan trading is valuable to equity investors. Their inferences are based just on the announcement effect of loan sales on the borrowers' stock price, whereas we examine the long-run performance of the borrowing firms. Our results suggest that bank loans are "special", but only for the subset of borrowers that do not have secondary market trading in their loans.

We show that the originate-to-distribute model of bank credit may not entirely be "socially desirable", since we document some of the negative effects of this model on the long-run performance and valuation of borrowers. Our results have important policy implications for regulators. The highly deregulated nature of the secondary loan market is perhaps one of the reasons for the moral hazard and adverse selection problems that we detect. One solution could be to impose restrictions on the sale of the loans that the banks originate, in terms of requiring them to hold at least a certain percentage of those loans on their books. This would hinder banks from originating bad loans as well as preserve some of the benefits of bank monitoring of borrowers. There should of course be additional disclosure requirements on all participants in the loan sales market, in order to reduce the occurrence of adverse selection. Lastly, the establishment of a loan trading exchange with a clearinghouse could benefit all market participants by way of greater transparency and regulatory oversight.

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Working Paper

Global banks and international shock transmission: Evidence from the crisis

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Abstract

Global banks played a significant role in transmitting the 2007-09 financial crisis to emerging-market economies. We examine adverse liquidity shocks on main developed-country banking systems and their relationships to emerging markets across Europe, Asia, and Latin America, isolating loan supply from loan demand effects. Loan supply in emerging markets across Europe, Asia, and Latin America was affected significantly through three separate channels: 1) a contraction in direct, cross-border lending by foreign banks; 2) a contraction in local lending by foreign banks' affiliates in emerging markets; and 3) a contraction in loan supply by domestic banks, resulting from the funding shock to their balance sheets induced by the decline in interbank, cross-border lending. Policy interventions, such as the Vienna Initiative introduced in Europe, influenced the lending-channel effects on emerging markets of shocks to head-office balance sheets.

Key words: bank, global, liquidity, transmission, capital markets, cross-border lending, emerging market

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I. Introduction

Global banks expanded their international activities over their past decade, with this expansion interrupted by the Great Recession. The consequences of this increased internationalization of banking have been debated. One dimension of the debate focuses on the advantages and disadvantages of banks from more developed financial systems having expanded and sometimes dominant positions in emerging market economies. Banking globalization can lead to institutional and regulatory or supervisory improvements, which promote "strong property rights and a financial system that directs capital to its most productive uses [which] are crucial to achieving high economic growth and the eradication of poverty" (Mishkin 2009). [1] When shocks originate within the emerging markets, foreign bank entry into local banking systems is a stabilizing force. It also results in more efficient allocation of productive resources in globalized economies [see survey by Goldberg (2009)].

Yet, international banking linkages are viewed as having spread the profound difficulties from the financial crisis that began in industrialized countries in 2007. The dramatic changes in capital flows to emerging markets are cited as evidence for such concerns (Chart 1). After a period of strong growth through 2007, capital inflows contracted across Emerging Asia, Latin America, and Emerging Europe. The initial boom was across multiple forms of private international capital flows (Chart 2), covering foreign direct investment, bank loans, portfolio equity, and net debt securities. While the subsequent reversal was in all broad categories of inflows, by far the sharpest decline in activity was in international bank loans. After rising to over $500 billion in 2007, international bank loans dropped to slightly above $100 billion in 2008. Such observations prompted the International Monetary Fund's April 2009 *World Economic Outlook* (WEO) to argue that global bank linkages "fuel the fire" of the current crisis to emerging markets (page 149).

In this paper we provide a conceptual and econometric examination of the international transmission of the balance sheet shocks that pummeled industrialized-country banks. We conjecture the existence of multiple channels of transmission of the original shock through the

[1] See also the discussion by Crystal, Dages, and Goldberg (2001) and by Calomiris and Powell (2001). Additionally, globalization of banking weakens the lending channel for monetary policy within the United States, while extending the transmission of U.S. policy and liquidity shocks to foreign markets (Cetorelli and Goldberg, 2008). The home market shocks are transmitted into the lending of foreign affiliates. At the same time, such internal capital markets mean that foreign bank subsidiaries do not need to rein in their credit supply during a (local) financial crisis at the same time that domestically-owned banks need to (De Haas and van Lelyveld, 2009). .

operations of global banks. Using bilateral lending data covering cross-border lending and local claims between countries, as well as data from destination emerging markets, we identify the magnitude and consequences of respective channels of transmission through international banks. To achieve this goal, we isolate loan demand from loan supply shocks, both of which contributed to the patterns shown in Chart 2, adapting an econometric methodology recently utilized by Khwaja and Mian (2008). Controlling for loan demand shocks is important, since the crisis also induced declines in home investment, home consumption, and international trade.[2]

In Section II we use the heuristic of T-accounts for bank balance sheets to show that the loan supply effects through global banks and international capital markets take three different forms. The intuition begins with the observation that changes in the sources of funds available to banks initiate a lending supply response (Kashyap and Stein 2000). The sources differ for global banks and domestically-owned banks in emerging markets. The *external capital market* of all banks in emerging markets includes local deposits, other host market sources, and cross-border interbank borrowing. Banks that are part of a broader organization, for example a global bank holding company, may also receive funding from related affiliates, with such resources falling under the heading of *internal capital market* funding.[3] Both external and internal capital markets play roles in the international transmission of shocks.

In a crisis, a foreign-owned bank hit by an adverse liquidity shock may reduce its cross-border lending. If this bank has overseas affiliates, it may also activate an internal capital market channel, reducing funding to affiliates abroad or actively transferring foreign funds in support to the head office balance sheet. The foreign-owned banks are not the only entities that may reduce lending in emerging markets. *Domestically*-owned banks may rely on external capital markets

[2] The dramatic collapse of global trade in goods and services during the crisis has spawned a debate about the reasons for this collapse. Comparative facts on the downturn are provided by Imbs (2010). Some studies posit that banking and trade credit disruptions played a key role (Amiti and Weinstein, 2009; Chor and Manova 2009). Other studies dispute the central role of trade credit, instead arguing that global demand and the expanded role of vertically integrated production account for most of the observed collapse of trade (Eaton, Kortum et al. 2009, Yi, Bems, and Johnson 2010, Levchenko, Lewis, and Tesar 2009), or that the collapse was a manifestation of an inventory adjustment (Alessandria, Kaboski, and Midrigan 2010).

[3] Internal capital markets have received earlier attention in domestic banking contexts. For example, Houston, Marcus, and James (1997) emphasize active internal capital markets in banking organizations, with banks relying on related entities in a bank holding company to get insulation from localized shocks within the United States. Likewise, Ashcraft (2008) shows that bank holding companies are a source of strength to their affiliates, while Campello (2002) shows that parent bank insulation from access to external capital markets extends to small affiliated banks, leaving them less vulnerable to shocks than other small banks that are unaffiliated. See also Ashcraft and Campello (2007). The application to global banks by Cetorelli and Goldberg (2008, 2009) argues that there is often internal borrowing and lending between parent organizations and their overseas affiliates. Correa and Murry (2009) consider the cross-border lending dynamics.

for funding local activities, with cross-border interbank borrowing being one of these external sources. Hence, domestically-owned banks also could end up with a balance sheet shock that reduces their own lending capacity. Indeed, the external capital markets of small host country banks can be quite volatile, leading to lending activity that is hostage to the boom and bust features of cross-border lending. Ex ante, however, it cannot be concluded that domestically-owned banks operating in emerging markets will necessarily be more stable or effective lenders in those markets than the foreign banks that have entered over the past decades. Which of these respective channels are larger in emerging markets is an empirical question.

In Section III we provide the econometric analysis of the bank lending channel in emerging markets, focusing on mechanics at work during the financial crisis of 2007 to 2009. Our methodology, an adaptation of Khwaja and Mian (2008), uses a difference-in-difference approach to isolate loan demand from loan supply in a matrix of lending between 17 developed source and 94 emerging market destination countries across Asia, Latin America, and Europe. Three types of lending are considered: cross-border loans, local loans extended by foreign-owned banks, and local loans extended by domestically-owned banks.

We find evidence of substantial lending supply shocks to emerging markets through all three balance sheet channels conjectured ex ante. Foreign banks that were particularly affected by the original liquidity shock to their balance sheet, cut both cross-border lending and local lending growth to emerging markets. Transmission through external capital markets was strong for both foreign-owned and domestically-owned banks. The loan supply contraction by domestically-owned banks was not attributable to their reliance on cross-border funding sources per se. Instead, the contraction was greater for those countries that had more cross-border funding from banking systems that were ex ante more imbalanced.[4]

Section IV concludes with a discussion of related policy themes. We argue that cross-border lending and internal capital markets are both conduits for international shock transmission, both positive and negative. However, these features do not imply that closed or reduced access to international capital markets is welfare-improving for emerging markets.

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[4] Our approach focuses on transmission channels as a result of existing bilateral ties between source and destination countries. A complementary take is to look at potential "contagion" effects, so that transmission occurs also through "third" country channels. van Rijckeghem and Weder (2003) find evidence of significant transmission of shocks through such channels.

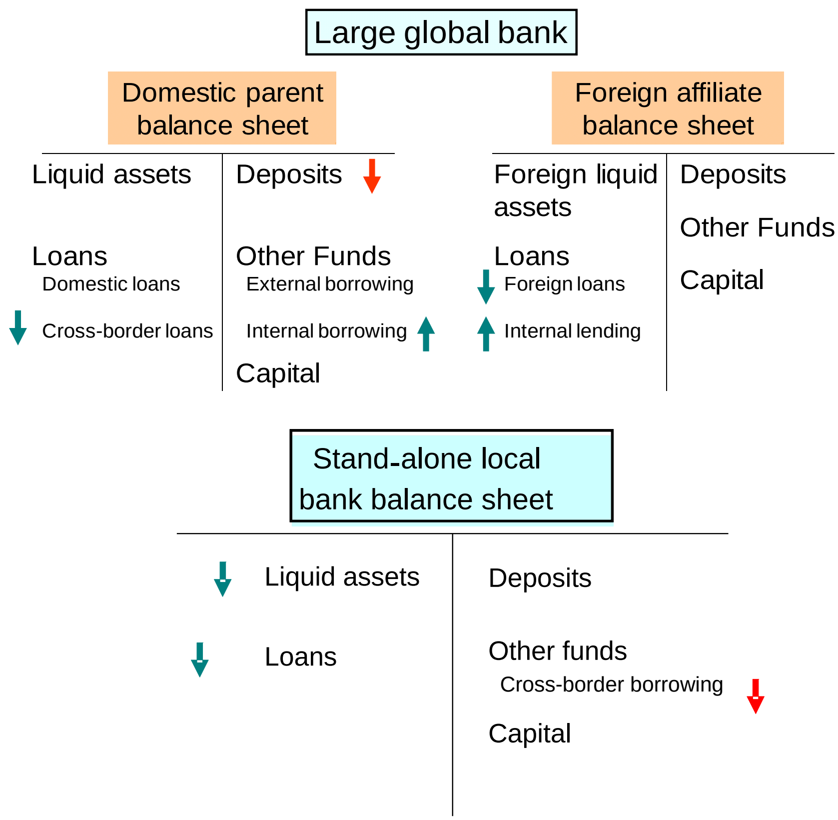
II. A Brief Primer on Internal and External Capital Markets and Bank Balance Sheets

What can a bank do when confronted with a shock to its balance sheet? Alternative responses to a liquidity shock can be illustrated using a simplified version of bank balance sheets. The generic bank T-account has bank assets on the left side of the T and bank liabilities on the right side. In broad terms, bank liabilities are divided into deposits, other funds, and bank capital; bank assets are divided into liquid assets and less liquid assets such as loans extended to bank customers.

Prior research describes how a contraction in available liquidity, for example through a decline in a bank's reservable deposits, has distinct consequences across types of banks, such as small stand-alone banks, small banks affiliated with larger bank holding companies, and larger banks (Kashyap and Stein 2000; Campello 2002). A contractionary monetary policy that reduces the amount of reservable deposits (or other shock to bank funds) can translate into a reduction in bank lending activity when banks are unable to replace each dollar of lost deposits with other liabilities. The reduced liabilities will lead to a combination of reduced liquid assets and reduced lending. Larger banks or bank holding companies can either be domestically oriented or have operations spread across global markets. In the international context, balance sheet effects incorporate international transmission through internal capital markets and are statistically and economically important (Cetorelli and Goldberg 2008). International transmission also occurs through cross-border flows by global banks, even those without overseas branches and affiliates. The transmission of policy and liquidity shocks through U.S. bank cross-border flows has been statistically and economically significant: a significant reduction in the level of cross-border claims occurs during periods of U.S. monetary tightening, pointing to the existence of a cross-border lending channel (Correa and Murry 2009).

These themes are illustrated in Box 1 using the T-account framework applied to banks lending to emerging markets. Consider two types of banks: a global bank with an affiliate operating within an emerging market and a domestically-owned bank. The top panel presents the global bank balance sheets, distinguishing between those of the parent bank balance sheet and the affiliate. The parent bank has assets divided into liquid assets, loans in the home market, and cross-border loans. Given an initial adverse shock to liabilities through deposits or other sources of funds, the global bank can respond by trying to replace this liquidity in external capital markets. If this is not sufficient (or desirable), the bank can engage in some form of lending contraction, reducing loan issuance at home or cross-border flows to foreign markets. Some balance sheet pressures can be alleviated if the parent organization borrows liquidity from overseas affiliates, i.e., through internal capital markets. Such borrowing may mitigate the liquidity shock consequences in the home market of the parent bank (Cetorelli and Goldberg 2008) or even cross-border loans. However, the internal capital market transfer changes the balance sheet of the affiliate firm, leading to adjustments that might lead to a reduction of local lending by that affiliate if other adjustments to affiliate bank assets or liabilities are not forthcoming. The cross-border loan supply contraction and the contraction in affiliate lending are two possible forms of parent bank transmission to emerging markets.

Box 1: Global Balance Transmission through Different Channels



By contrast, the initial transmission channel to the domestically-owned, stand-alone banks may come from a drop in cross-border interbank borrowing, used by these banks as a source of funds. It is possible that deposits move between the domestically-owned banks and the foreign affiliates, but the direction of these flows is not straight-forward to predict. Without access to offsetting alternative funding sources, the loans extended by the domestically-owned bank might contract in line with the reduced availability of cross-border funds. This illustrates a third channel through which there can be international transmission of shocks into the loan supply to emerging markets.

III. Bank Funding and Lending Volatility in the Financial Crisis

The econometric analysis explores the scale and existence of these three channels of transmission of global bank shocks to emerging market economies in the crisis beginning in 2007. A priority in this analysis is isolating contractions in loan supply from those in loan demand. Below, we present the econometric methodology, discuss the main data sources, and conclude with the empirical findings.

III. 1 The econometric methodology

Our goal is to assess to what extent the balance sheet shocks suffered by banks in many developed countries during the financial crisis determined a corresponding shock to their supply of 1) cross-border loans to emerging economies and 2) local loans from their offices located in emerging market countries. Additionally, we want to assess the potential impact on the supply of loans by *domestic* banks in emerging markets, and the extent that the retreat in cross-border lending corresponded to a shock to domestic bank funding sources.

The empirical implementation presents important and well known identification challenges. In particular, it requires showing that if banks are affected by a shock to their funding sources, their ultimate response is to accommodate such shock with an equivalent adjustment in their lending activity. However, as our section II exposition of bank balance sheets shows, this accommodation of lending does not need to occur: banks may be able to substitute away from adversely shocked funding sources into other, more readily available ones. Moreover, even in the presence of imperfect substitution on the liability side of the balance sheet, banks may still be able to insulate lending activity by absorbing the liability shock with a corresponding change in available liquid asset buffers.

Moreover, establishing the existence of a bank lending channel also requires the identification of an effective lending *supply* shock, separate from potential contamination by concomitant changes in credit *demand* conditions. Recall from Chart 2 the substantial drop in international bank lending to emerging markets in the aftermath of the crisis. This decline in lending is not evidence *per se* of a loan supply shock. The same decline could have also been observed if banks had been able to insulate their lending books from the original liquidity shock – either through funding substitution and/or utilization of existing liquid asset buffers – and yet firms, simultaneously hit on current product demand or on their future investment opportunities, may have simply reduced overall loan demand. Given the extent of the crisis and the after-the-fact impact on global GDP growth, we cannot exclude a priori this alternative explanation.

In a recent paper, Khwaja and Mian (2008) propose a simple but elegant identification strategy that very effectively isolates a lending supply shock around a well-defined funding shock on banks' balance sheets.[5] The authors focused their attention on bank lending activity in Pakistan around the time of an exogenous macroeconomic shock that occurred in 1998 as a result of nuclear testing by India and Pakistan. In this episode, capital controls were imposed in response, generating a shock on dollar-denominated deposits and a resulting *quasi* natural experiment that Khwaja and Mian (2008) exploited to assess the extent of both the bank lending channel and the ultimate impact on firm borrowings.[6] The authors relied heavily on the fact that the liquidity shock was *not* felt homogeneously across banks, since ex ante not all Pakistani banks had built similar levels of dollar-denominated liabilities. Moreover, the authors took advantage of the fact that many firms had been borrowing simultaneously from more than one bank; hence, firm funding sources were heterogeneously affected. In light of this set of

[5] Schnabl (2009) provides another recent example of loan supply shock identification. He uses the 1998 Russian default as a negative credit supply shock to international banks and analyzes its impact on bank lending in Peru. With data on individual firms, he controls for credit demand by examining firms that borrow from several banks.

[6] In retaliation to unanticipated nuclear tests in India in May 2008, Pakistan followed through in a matter of days with their own nuclear tests. As a result of such tests, both countries were promptly sanctioned by the international community, with the suspension of exchange rate support to the Pakistani rupee as part of the sanction package. This chain of events, unrelated to the functioning of the Pakistani banking industry, ultimately resulted in a severe bank liquidity crunch, since many Pakistani banks had a substantial deposit base in dollar-denominated accounts. The dollars collected through these bank deposits, however, had to be transferred to the government, which upon withdrawal requests from bank clients would eventually release such dollars at the exchange rate at the time of the original deposit. In essence, the government bore all the currency risk on bank deposits. In response to the financial sanctions cited above, the Pakistani government announced the suspension of this convertibility agreement, releasing instead dollars at the current, much devalued exchange rate, effectively imposing a partial default on this liability. Despite the much less favorable conditions, a substantial amount of dollars were withdrawn by depositors, thus determining a severe funding crisis for the Pakistani banking system.

conditions, Khwaja and Mian (2008) modeled the change in the growth of lending supply by an array of individual banks vis-à-vis an array of firms to which they make loans. This informative difference-in-difference approach facilitates isolation of loan supply versus loan demand effects.

At least from the perspective of a natural experiment design, the characteristics of our empirical study have strong similarities to those in Khawja and Mian (2008). The recent financial crisis mainly originated as a sudden and exceptional shortage of dollar funding on the balance sheet of banks in many developed economies, the result of previous large build ups of dollar denominated assets from structured products that in the summer of 2007 became virtually unmarketable (see, e.g., Coffey, Hrung, Nguyen, and Sarkar 2009). Bank funding problems eventually mounted in the following months, and with the Lehman Brothers bankruptcy event in September 2008, dollar funding sources for banks effectively froze across the board. Ex ante vulnerability to dollar funding was significantly heterogeneous across banks, and, when aggregated to the country level, also significantly heterogeneous across banking systems. Similar to Khwaja and Mian (2008), the original balance sheet shock was felt differently across banking systems. These differences created associated balance sheet shocks and the potential lending supply shocks to differ across countries that previously had been a common source of funding to emerging market economies.

Going back to Khwaja and Mian (2008), the derived lending supply schedule in terms of (log) changes from before to after the shock is[7]

$$(1) \qquad \Delta L_{ij} = \beta_0 + \beta_1 \cdot \Delta D_i + \eta_j + \varepsilon_{ij}$$

In their article, the dimension i represented individual banks, and j individual borrowing firms. β_0 is a constant term, ΔD_i the indicator of the liquidity shock sustained by bank i, and η_j an unobservable term capturing simultaneous shocks to firm j credit demand. The term ΔL_{ij} captures the change in lending from before to after the event, and banks that were hit more by the liquidity shock should be those that reduce more (or grow less) their lending. As shown by Khawja and Mian, specification (1) as estimated with basic OLS would likely generate biased estimates of $\hat{\beta}_1$ because of a correlation with simultaneous demand shocks embedded in the unobservable term η_j. In normal circumstances, for instance, one would expect a simultaneous reduction in credit demand when there is a liquidity shock, so that not taking this effect into

[7] We defer to the original Khwaja and Mian (2008) article for the details of the model.

account would lead to an over-estimate of the true supply shock.[8] However, introducing borrowers' fixed effects on model specification (1) would absorb any demand driven contamination thus resolving the bias problem affecting the OLS estimation. Consequently, the alternative model specification for estimation is

$$(2) \qquad \Delta L_{ij} = \gamma_1 \cdot \Delta D_i + \gamma_j + \varepsilon_{ij}$$

with γ_1 now unbiased and γ_j being a vector of fixed effect coefficients. In essence, this alternative model specification achieves identification comparing the impact on lending of separate banks *i* to the *same* firm *j*. Under the less stringent assumption that the same firm uses multiple banks to obtain similar type of loans, any common shock on demand factors would not affect the identification of the supply effect.

In our study, we use data on the aggregate international lending activity (cross border claims and local claims) of developed countries *i* to emerging market economies *j*. We rely on the fact that the banking systems of the lending countries had built up significantly different degrees of reliance on dollar-denominated liabilities, and, therefore, from an ex ante perspective exhibited substantially different degrees of vulnerability to what happened next, a sudden shortage in dollar funding. In terms of the identification strategy above, this translates in different ΔD_i . Through model specification (2), where destination country fixed effect indicators are included, we test if the lending to a certain emerging market economy by banking systems that were ex ante highly vulnerable to dollar funding shocks changed more from the crisis than the lending to the same emerging market by banking systems that were ex ante less dollar vulnerable. We perform these tests separately for cross-border lending and for local lending by foreign-owned banks. We also explore whether government interventions to affect the bank lending channel and maintain loan supply were effective. In particular, we focus on the so-called Vienna Initiative, discussed further below.

While our empirical exercise lends itself very nicely to the same identification strategy, we are obviously limited by the scope of our sample size: Khawja and Mian (2008) had extensive micro-level data where each observation was a bank-firm loan, with a total sample size

[8] Khawja and Mian (2008) actually argue for a possible negative correlation and in their case found evidence consistent with their prior.

above 20,000 observations.[9] In our case, as discussed in section III.2, we use data for 17 source countries lending to 94 emerging economies, with a total theoretical sample size of 1598 observations, but that is smaller in practice since not all source countries may be lending to all destinations.

Another part of our empirics considers whether domestically-owned banks in emerging markets had balance sheet vulnerabilities to supply shocks via their reliance on cross-border sources of funding, leading to a loan supply response. The testing of the existence of this third channel of transmission, however, can only be based on simple cross sectional regressions using lending data by domestic banks in the emerging markets. The inability to "correct" for contemporaneous changes in loan demand is a problem. However, we can assess the potential severity of the demand bias from the estimation results obtained analyzing the local lending of foreign banks, under the assumption that local foreign banks and local domestic banks face similar loan demand schedules. In the empirical exercise we analyze post-pre crisis domestic lending growth in relation to two variables related to cross-border funding. One variable is total cross-border bank lending to the emerging market (summed across all source markets) relative to total domestic bank lending in the same emerging market. The second variable embeds a more nuanced view of which source countries accounted for this cross-border bank lending. Specifically, we consider the extent of funding sourced from low ex ante dollar-vulnerable countries or from high ex ante dollar-vulnerable countries. This exercise allows us to address the issue of whether loan supply contracted the most in the crisis for the domestically-owned banks that relied the most on *any* cross-border financing (emerging market banking system most open to international funding markets), or whether instead the contraction was mainly the result of relative high exposure to a set of foreign countries that ex ante had become especially dollar vulnerable.

[9] The constraint imposed by the fixed effect specification is that, by relying on a *within* firm comparison of lending by two separate banks, it can only be implemented on the subset of firms borrowing ex ante from more than one bank. This limitations lead to a drastic reduction in sample size in the Khawja and Mian (2008) exercise (but still leaving them with more than 5,000 unique bank/firm observations). In our case, this is less of an issue, since at an aggregate level only a handful of destination countries in the dataset borrow from just one source country. In our regression analysis those destination countries are excluded.

III.2 Data

Bank lending data. The bilateral data on international bank lending are from the Bank for International Settlements' (BIS) Consolidated International Banking Statistics. This database contains information on positions of banks from BIS reporting countries with respect to counterparties around the world, with data aggregated across all reporting banks from the source countries. The two main lending variables are: 1) international claims, which capture the sum of cross border lending and local claims extended in foreign currency, and 2) local claims in local currency. These variables are our proxies for cross-border lending and local lending, respectively, by foreign-owned banks in destination markets.[10] Our analysis includes data for 17 source countries and 94 destination countries from three emerging market regions: Latin America (30 countries), Emerging Asia (21 countries), and Emerging Europe (43 countries). The source countries are: the United States, Japan, Australia, Belgium, Canada, Switzerland, Denmark, Germany, Spain, France, Great Britain, Ireland, Sweden, Portugal, the Netherlands, Luxembourg, and Italy. The list of destination countries is provided in Appendix Table 1.[11]

The pattern of partnering between developed countries and the emerging markets validates our application of the Khwaja and Mian (2008) approach. Table 1 presents the destination countries as rows, focusing only on the 8 largest emerging markets in each region, and shows how many of the seventeen source countries were partners in cross-border lending or local lending for each destination in the pre-crisis and crisis period. The cross-border flows come from a wider array of source countries compared with local claims, where financial sector foreign direct investment is a precondition. The similarity of pre- and post- columns for both international claims and local claims shows that the capital flow adjustments were on the intensive margin (quantity adjustments vis-a-vis existing partners) and not the extensive margin (countries added or dropped as partners), at least as measured at the level of bank-country observations. Table 1A presents information on the number of destination countries, out of the

[10] The treatment of local claims in foreign currency in the database makes these proxy variables instead of true representations.

[11] Some gaps appear in the data available in DBSonline, and are due to confidentiality concerns of the reporting central banks. For example, Both Denmark and Finland no longer have a numerous national banking system, as most of their domestic banks have over time been bought up by larger banks from other Scandinavian countries. When reported data is the aggregate from a small number of commercial banks, the reporting central banks may report the observations to the BIS marked with Observation Level Confidentiality C Confidential, and this data is suppressed from export to DBSonline. The bank type B Domestic Banks amounts vis-à-vis developing countries are not in DBSonline, but the bank type A All Banks amounts are available there.

full sample of 94, that are served by very few of the (17) source countries. All destination EMs receive cross-border funds. Only two EMs are served by a single source, and need to be dropped from the fixed effects estimation sample. Almost all destination EMs receive cross-country funds from more than three sources. The patterns, as expected, are much different for local claims. Twenty-six EMs do not have local claims extended by any of the 17 source countries, while another 19 EMs have only 1 source presented. The EM country sample for the fixed effects specifications is the remaining group of 49 countries.

Table 2 provides a complementary set of observations from the vantage point of the respective source countries. In cross border flows (international claims), a majority of the emerging markets were served by France and Great Britain, followed by another broader group of active European lenders and the United States. In local claims, source countries have more limited international footprints as measured in terms of numbers of EM destinations. Some source countries have had very little entry into EM banking systems (Australia, Ireland, Luxembourg) while banks from other source countries have a broader global presence (United States, France, Great Britain, Netherlands).

The upper panel of Table 3 provides detailed summary information covering bilateral and domestic lending growth pre-crisis versus in the post-crisis period. These summary data directly pertain to the dependent variables to be used in the formal econometric exercises. Cross-border lending will include 1032 observations, while the number of local claims observations is smaller, at 267. Positive mean pre-post values pick up a general upward trend in lending patterns. Nonetheless, there is a wide range of experiences across pairs of countries, as illustrated by the minimum, maximum, and standard deviation columns.

The final piece of lending information pertains to lending by domestically-owned banks. Since such information is not readily available for the broad group of 94 EMs we construct a proxy by combining the BIS local claims data and information from the International Monetary Fund's International Financial Statistics (IFS). From the IFS data we extract series on Bank Claims on Private Sector and Bank Claims on the Central Government.[12] Then, we construct domestic bank lending as the sum of Bank Claims on Private Sector plus Claims on Central

[12] IFS 22d for bank lending means something slightly different for different countries (most often claims on private sector from banking institutions, but sometimes claims on other sectors from deposit money banks or another combination). 22a through c are claims on central government, state and local governments, and nonfinancial public enterprises.

Government from (both IFS), net of the total of Local Claims in Local Currency from all BIS reporting countries. The last row of Table 3 shows that our analysis will work with a smaller sample of data, on 62 country observations on the change in domestic bank lending growth, with there being a wide range of positive and negative values across countries.

Banking Sector Dollar Vulnerability. A third type of data used in the econometrics is a constructed indicator of banking system vulnerability at the onset of the crisis. Recall that the strategy for identifying lending supply shocks relies on the observation that, from an ex ante perspective, banks from different developed countries had differing degrees of vulnerability to U.S. dollar funding shocks. This vulnerability was the result of the buildup of dollar-denominated assets on their balance sheets and degrees of maturity mismatching between dollar assets and corresponding funding sources. As shown by McGuire and von Peter (2009a, b), there were substantial differences across countries in the tendency of internationally active banks to accumulate mismatches.

Using confidential components of the BIS International and Consolidated Banking Statistics, McGuire and von Peter have constructed three alternative measures capturing the degree of dollar vulnerability for a number of developed-economy banking systems (see box). The basic idea is that the measures reflect gross short term U.S. dollar funding risks. All measures include the summed external liabilities of banking systems, with differences in whether some exposures are treated as gross or as net of corresponding asset positions. For example, measures V1 and V2 differ only with respect to treatment of liabilities to banks, taken either as net or gross positions. V3 also contains net positions of country banks vis-à-vis non-banks, but only if these positions are liabilities of the banks.

We use the values of these three alternative measures of country-specific dollar vulnerability calculated at the time right before the onset of the crisis. Basic summary statistics are provided in Table 3, Panel B, together with the computation of the pair wise correlations across the three ex-ante measures of banking system dollar vulnerability. The summary statistics show a substantial degree of cross-sectional variability for each measure. The pairwise correlations of measures are high, especially across V1 and V2. By construction, V3 is most different from the other two (reflected also in the lower correlations) and also based on the strongest assumptions.

Definitions of the three gross short term dollar funding need measures.

All three measures are normalized by each country's total international claims for the econometric work.

V1: Liabilities to official monetary authorities + International liabilities to non-banks + Local liabilities to US residents booked by US offices + Liabilities to banks + cross-currency FX swap (if negative);

V2: Liabilities to official monetary authorities + International liabilities to non-banks + Local liabilities to US residents booked by US offices + Net Liabilities to banks + cross-currency FX swap (if negative);

V3 either : Liabilities to official monetary authorities + Net Liabilities to banks + cross-currency FX swap (if negative) + Net positions vis-à-vis non-banks (if negative), or Liabilities to official monetary authorities + Net Liabilities to banks + cross-currency FX swap (if negative) (if Net positions vis-à-vis non-banks is positive).

Panel B also provides information of the magnitude of banking system imbalances in 2007, at the outset of the crisis, for a subset of the group of seventeen source countries.[13] Using V2 as the reference measure, the data show that German banks had $865 billion of dollar funding needs, while Spanish and U.K. banks had needs of $247 billion and $1.5 trillion, respectively. When these constructions are normalized by the total international claims of banks from these same countries, Germany had relatively low ex ante dollar vulnerability, at 25.4 percent of external loans, while the U.K. banks had relatively high funding needs, at 90 percents of international loans. Based on the distribution of observations across source banking countries, Germany had low (percentage) banking sector dollar vulnerability, while Spain was moderate, and U.K. banking system vulnerability was high.

<u>Policy Initiative</u>. Finally, our econometric exercise allows for the possibility of global bank transmission consequences of the so-called Vienna Initiative that was contracted between banks and internally active banks in Europe in February 2009 with the goal of preventing a destabilization of Emerging Europe. This joint international financial institution action plan

[13] Due to the confidential nature of the data, we are only authorized to display actual vulnerability figures for a limited subset of the source countries.

resulted in a total of $10.8 billion of support committed to a range of European banks to support their lending to ten European Union countries, the Western Balkans, and Turkey. Beyond the private banks participating in this program, the public policy partners included the European Bank for Reconstruction and Development, the European Investment Bank Group, and the World Bank. Appendix Table 2 provides details on reported disbursements through this program through September 2009, by bank and by destination country.

III.3 Bank transmission from industrialized to emerging markets

A non-parametric illustration. The identification strategy can be appreciated first with a simple, non-parametric exercise comparing average international lending to emerging markets before and after the crisis event, between banking systems that were ex ante highly vulnerable to dollar funding shocks and those that were instead less vulnerable. We defined the pre-crisis period from 2006q2 to 2007q2 and the post-crisis period from 2008q3 to 2009q2. As previously noted, we purposefully leave out the intermediate period between 2007q3 and 2008q2. Arguably the Lehman's events in September 2008 mark the cleanest and most important crisis event, but at the same time the last quarter of "normal" market functioning goes back to the time prior to August 2007. Alternative datings of the period before the dollar funding shock and following this shock certainly can be argued and were considered in robustness tests.[14]

For this first exercise, we divide source banking countries into two groups – those with high or low ex ante dollar vulnerability. We compute the (log of) lending growth by source country vis-à-vis each destination country and then take averages across pre- or post- periods, averages across destinations, and averages across groups of source countries. We defined high (low) dollar vulnerable countries as those with values of the vulnerability measure V2 above (below) the median. In the subsequent regression analysis, we make use of the whole information embedded in the continuous variables V's, and not just use of the coarse high-low vulnerability groupings.

Time averages across each of the intervals and broad vulnerability divisions are provided in Table 4. For cross-border lending, shown in the top panel, countries with high ex ante dollar vulnerability exhibited higher average lending growth than low vulnerability countries before the

[14] In order to address the robustness of the empirics under alternative timing assumptions, we have experimented with a number of alternative definitions for both the pre and post periods. The choice of alternative dates does not really have any material impact on the results. Results based on alternative time windows are available upon request.

crisis (first row comparison). While these level differences can be attributed to basic country-specific factors, such differences are not what drive the identification. In the period after the dollar crisis hit, the data indicates higher average numbers for both sub group of countries and the same rank order (second row comparison).[15] However, even the difference in post crisis lending levels is not driving the identification. What matters is the comparison of the lending growth pre to post period between the high and the low vulnerability countries. This comparison, obtained taking the difference-in-difference value from Table 4 (figure in bold) shows that ex ante high vulnerability countries displayed ex post about 15 percent lower cross-border lending growth to emerging markets than low vulnerability countries. Another way to interpret this result, based on comparing the level difference pre crisis with the level difference post crisis (figures in the row marginals), is that due to the crisis and the consequent balance sheet liquidity shocks hitting banks, the countries that ex ante were less exposed to the dollar funding shock were more able to partially close the cross-border lending gap to emerging markets compared to the more exposed source countries.

The same exercise performed for the local lending in local currencies by the foreign banks is shown in the right-most cells of the same rows of Table 4. As with cross border lending, local lending exhibits similar pre- and post- crisis patterns for both high and low vulnerability funding source countries. The only difference is in the scale. As the difference-in-difference comparison shows, low vulnerability countries exhibited a 49 percent higher local lending growth rate in the crisis aftermath, compared with the high vulnerability countries.

These results for cross-border lending growth and local lending growth are suggestive of a potentially important lending supply shock from developed country banks to emerging market economies, with the shock magnified for banks that ex ante exhibited greater balance sheet vulnerabilities. While suggestive, this non-parametric exercise, however, is limited as it cannot take into account differences in the lending *destinations*. It could be that high vulnerability countries were disproportionately focusing their lending in a particular group of emerging markets that perhaps experienced stronger credit demand shocks.

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[15] Higher numbers post crisis are likely driven by a steep increase in the pre-crisis quarters, so that time averaging yields relatively lower numbers pre than post. We could have chosen the observation right at the quarter before the crisis and the last quarter in the data set to do the comparison, but the time averages have the advantage of smoothing out quarter-specific idiosyncratic factors. In any case, as argued in the main text, the identification does not rely on the simple pre-post comparison on levels but on the comparison in the pre-post growth *between* the two sub-group of countries.

As another exploratory exercise prior to starting the formal empirical analysis, we performed a basic check on the reliance of the vulnerability measures. We ran basic regressions using the post-pre growth measures for both cross-border and local lending as dependent variables and the whole set of fixed effects for source and destination countries on the right hand side. If the presumption is correct, that source countries with ex-ante higher dollar imbalances should be the ones to suffer the largest balance sheet shock and therefore those that reduce lending the most, it should be the case that the vulnerability measures should be correlated with the series of estimated coefficients of the source country indicator variables. In other words, those countries exhibiting larger changes in lending growth around the crisis should also be the ones with the higher values of the vulnerability measures. This pattern is verified in the data.[16]

Formal econometric study of transmission. To separate loan demand from loan supply effects we next turn to the more formal approach involving the estimation of equations (1) with OLS and equation (2), where destination country differences are taken into account by the destination fixed effect (FE) indicator variables. Both OLS and FE specifications are informative. While the OLS estimates are by construction biased, their comparison with the FE estimates provides insights on the degree of bias associated with the simultaneous shocks to lending demand experienced by destination markets. Specifications are performed over cross-border lending growth, with baselines presented in Table 5, and local claims growth, presented in Table 6. Columns 1-3 of each table focus on the basic OLS specifications, columns 4-6 prove the results of fixed effects specifications, and columns 7-8 includes consideration of the Vienna Initiative implemented within Europe. Since we have three alternative measures of ex ante vulnerability, we run similar regressions using the three measures separately. Moreover, in order to fully exploit the information contained in the vulnerability measures, in the regression analysis we use

[16] The results from these regression checks are reassuring. The V measures exhibit high correlations with the fixed effect estimated coefficients from both cross-border and local lending regressions. The correlations vis-à-vis the coefficients from the cross-border lending regression are higher, around 0.6, and highly significant. The correlations vis-à-vis the coefficients from the local lending regression are smaller, ranging between 0.35 and 0.55 across the three V measures, and significant for one of the three measures. This pattern of relative strength in the results will be found in the formal regression analysis as well, in large part probably due to the fact that, as already mentioned above, the sample size for cross-border lending is much greater than that for local lending. We thank Romain Ranciere for suggesting running this test.

the actual indexes rather than the simpler dummy grouping countries that indicated ex ante vulnerability above or below the median of the source countries.

First, consider the pre-post shock consequences for cross-border lending growth (Table 5). The coefficients on the vulnerability proxies in the first three columns show the relationship between ex ante source country vulnerability and the extent of slowed lending growth ex post. Countries that ex ante had more severe potential exposure to a dollar funding crisis had significantly lower ex post rates of cross-border lending growth to emerging markets. The results are consistent across the three different vulnerability measures. A low vulnerability banking source would have continued lending growth post shock, while high vulnerability was associated with reversals.

In columns 4 to 6 we report the results from the corresponding fixed effect estimations.[17] The estimates of γ_1 still are largely negative and significant. As expected, the comparison of 4-6 with the OLS estimates of 1-3 indicates some role played by concomitant changes in demand. The fixed effect estimates are systematically lower (in absolute value) than the corresponding OLS ones. At least part of the reduction in cross-border lending activity is attributable to a simultaneous decline in demand for cross-border loans. The magnitude of this loan demand shock, however, seems to be relatively small.

Next, consider the impact of the crisis on growth of local claims, with results reported in Table 6. As before, the OLS estimates using the three distinct measures of vulnerability are reported in the first three columns. The estimated effects of the shock event are again quite strong and in the expected direction with loan supply contractions particularly strong when affiliate banks overseas were ex ante more vulnerable. The model with fixed effects, columns 4-6, indicates relatively smaller estimated coefficients (in absolute value). By and large, however, the results confirm that the lower growth in local claims on emerging markets is largely due to the supply shock from ex ante vulnerable banking systems.

Next, consider the magnitude of effects for local claims growth when controls are introduced for the Vienna Initiative (columns 7 and 8). These specifications lead to reduced

[17] Note that the FE specification is based on the comparison of lending growth by at least two different source countries with different degrees of dollar vulnerability to the same destination country. Hence, in what follows we need to restrict the regression analysis by excluding those destination countries that do not maintain flows from at least two source countries. Of course this set if different in the analysis for cross border lending from that for local lending, but the differences in sample size with the corresponding OLS regressions is explained by the imposition of this constraint.

significance of ex ante vulnerability in general. Instead, the Vienna countries appear to be associated with mitigated local lending declines. Such reduced effects of the crisis on local claims growth, in particular in emerging Europe, were a key goal of the Vienna Initiative.

Also notice that the magnitude of reported coefficients in Table 6 is significantly smaller (in absolute terms) than in Table 5. The implication is that the role of differences in banking system vulnerability plays out strongest in the arena of cross border flows. We calculated the economic significance of the identified supply shocks. Table 7 presents examples of such impacts, focusing on three source countries for funding that are in the low, median, and high end of the ex ante vulnerability spectrum across the countries of our sample. Using the specifications of column (5) of Tables 5 and 6, we observe cross border lending supply growth after the crisis that was 8.02 percent lower than in the pre-crisis period for Germany, and comparable changes of 28.44 percent lower for the United Kingdom. Local claims supply adjustments also were quite large and quantitatively important across the lower and higher ex ante vulnerability countries.

III.4. Robustness

There are various potential critiques of the methodology we have applied to isolate loan demand from international loan supply effects of the shock. Such critiques include questioning the assumption of exogeneity of the shock event, our treatment of ex ante dollar vulnerability as a defining feature of source country banking systems while instead potentially proxying for other source country bank characteristics, time trends in lending across destinations, and the inclusion of United States as a source country. Below, we consider the robustness of our results to each of these critiques.

Shock endogeneity. The significance of the econometric results is heavily based on the presumption that the shock event, materializing in a severe shortage of U.S. dollar funding, is exogenous to the lending dynamics to emerging market countries. We think there is a legitimate case for the assumed exogeneity of the shock event. First, this particular crisis did not originate in emerging markets. Second, the accumulation of dollar exposure by developed countries' banks was very much driven by investment strategies of the developed economy's banks and did not derive in any quantitatively significant way from economic dynamics in emerging markets countries, nor from specific lending policies toward these economies. As McGuire and von Peter (2009b) clearly state: "…banks' (particularly European banks') foreign positions have surged since 2000 … As banks' balance sheets grew, so did their appetite for foreign currency assets, notably US dollar-denominated claims on non-bank entities. These assets include retail and corporate lending, loans to hedge funds, and holdings of structured finance products based on US mortgages and other underlying assets. During the build-up, the low perceived risk (high ratings) of these instruments appeared to offer attractive return opportunities; during the crisis they became the main source of mark to market losses. …" (p. 1). Consequently, the dollar vulnerability of different developed countries banking systems in the months prior to the crisis can be reasonably assumed to be independently determined by the concomitant level of lending activity to emerging market countries.

Dollar vulnerability as a proxy for other bank balance sheet characteristics. A related concern is that, in fact, different levels of dollar vulnerability are just the reflection of specific ex-ante differences across source country banks in other balance sheet characteristics and do not reflect the relative severity of balance sheet shocks. We can test this alternative hypothesis by conducting a series of "horse races", by sequentially controlling for pre-crisis bank balance sheet characteristics by country in the main fixed effect specification of equation (2). The set of country-level bank balance sheet variables identified for this purpose are: the ratio of private credit by deposit money banks to GDP as a measure of the importance of banking activity in source markets (*pcrdbgdp*); the ratio of bank's overhead costs to total assets as a measure of banking efficiency (*overhead*); the return on equity (*roe*) and return on assets (*roa*) as measures of performance; the equity to asset ratio as a measure of banking capitalization (*cap*); the z-score as a measure of risk (*zscore*); [18] a measure of the share of deposits that are offshore (*offdep*); and the log of total international claims as a broad measure of global size (*linclaims*). Table 8, Panel A, reports the pairwise correlations among these variables and the measure V2 of dollar vulnerability. While there are strong correlations across some of these financial variables, for example between *cap* with *roa* or *overhead*, the correlations are weaker for the V2 variable (adjusted by international claims).

[18] The data is from the World Bank update to Beck, Demirgüç-Kunt and Levine (2000).

In Table 8, Panel B, we report the estimation results from a range of alternative specifications, which are the baseline specifications (columns 5 of Tables 5 and 6) where the V2 measure "competes" against each of these additional variables that are introduced within the regression. We report only the resulting coefficients and the significance of the variable V2 from these alternative FE regression specifications, with each cell of Panel B drawn from a distinct regression specification. The coefficients estimated for V2 remain fairly stable, both for cross border lending growth and for local claims growth. This finding indicates that the degree of dollar vulnerability is capturing a specific type of funding fragility exhibited by developed countries' banks prior to the crisis and had a direct impact on lending dynamics in emerging market countries.

Time trends. Another potential critique of our findings is that the accumulation of dollar liabilities and the subsequent crisis had no effect on changes in lending to EM economies, and that the difference detected between high- and low-vulnerability source countries is just the result of pre-existing differences in time trends. Analyses of the time series dynamics in both cross-border and local lending for high- and low-vulnerability countries do not support this claim. In Table 9 we report quarterly averages in (log) lending for the two separate groups of countries. For ease of comparison, both series are depicted as differences between value in each quarter and value at time zero (set at 2007q2), so that the vertical axis indicates the growth rate between each respective quarter and time zero. Panel A reports cross-border lending. While there was a detectable difference in time trends in the pre-crisis quarters, or at least through 2006, the chart shows that there was a visibly significant change in trend for both series in the quarters after 2007q2, and certainly an important difference in growth rate trends from 2008q3 and onward. A similar pattern can be detected for local lending in Panel B. Pre-crisis time series had a similar trend, but trends changed, even more dramatically in the post-crisis period.

Results driven by the inclusion of U.S. banks. We recognize that the dollar vulnerability measure may have a distinct interpretation for U.S. banks which can readily access dollar-based liquidity facilities such as the discount window and special facilities that emerged during the crisis.[19] In

[19] Goldberg, Kennedy, and Miu (2010) provide details on the availability of dollars to financial institutions outside the United States via central bank dollar swap facilities that were established.

addition, the conversion of investment banks into commercial banks, with data for the latter included in the post sample of BIS data, may influence the outcomes of the regression analysis.[20] We perform regression specifications excluding observations on U.S. lending to the respective emerging markets and generate qualitatively similar results.

III.5 Domestic lending

The final channel of international transmission through banks was posited to work through the funding of local, domestic banks. In this section we test whether such banks in emerging markets experienced a loan supply shock of their own as a result of the changes in cross-border lending of foreign banks. One component of cross-border lending is lending to local banks, in which case the original supply shock transmitted into cross-border financing could also determine a second round lending supply effect through the impact on the balance sheet of the local banks.[21] For this part of the empirical exercise, data at the level of aggregate lending by domestic banks leaves just the cross-sectional variability of destination countries for analysis. Moreover, while our full sample of emerging markets covers 94 countries, a significant share of these countries do not have adequate domestic lending data in the IFS or have totals for domestic lending that show some inconsistencies with the BIS local claims data. 58 countries are used in the final regression analysis. For this reason, we can produce qualitative results that can, at best, provide indications of the existence of this effect.

If local domestic banks experience a lending supply shock as a result of changes in cross-border funding by foreign banks, then one could expect that – all else equal – this shock would be larger exactly in those emerging markets where cross-border bank borrowing came predominantly from those banking systems that were ex ante more vulnerable to the original credit market disruptions. The BIS international banking statistics provide a breakdown of total cross border claims in cross border lending to banks and cross border lending to non banks (private and public sectors). Hence, from the cross border lending *to banks* data by source and destination country we compute total cross-border lending to banks for each destination country from all BIS reporting countries during the pre-crisis period. We then compute the fraction of this total that came from ex ante vulnerable countries, using the same high versus low ex ante

[20] We thank Patrick McGuire for pointing this out.
[21] At least for Latin American countries we know of significant tightening in domestic funding sources as a result of the crisis (Jara, Moreno and Tovar, 2009)

vulnerability classification used in the non-parametric exercise of Table 4. Subsequently, we compute for each destination country the fraction of total cross-border bank borrowing from high vulnerable countries. We also compute the ratio of cross-border bank-to-bank lending into a destination, relative to the total amount of lending done by domestic banks (*share x-border*). This second variable captures the degree of overall "openness" to international funding markets by banks in EM countries. The dependent variable in our regressions is the pre-post comparison of lending growth for domestic banks in each emerging market.

If lending of domestic banks in emerging markets was exposed to the financial crisis through cross-border linkages, is it the case that countries with banks having the highest reliance on cross-border borrowing overall were the one to suffer the largest declines in domestic lending? Or is the exposure only through reliance on banking systems with high ex ante vulnerability? Table 10, column (1), shows that lending contractions by domestic banks in emerging markets were stronger if they had been especially dependent on cross border borrowing from ex ante more vulnerable banking systems. Column (2) shows that differences across countries in the overall openness to cross-border borrowing were instead *not* significant in explaining ex post lending growth contractions. If anything, overall openness generated an opposite, positive effect. Columns (3) and (4) combine these terms in regression specifications, but continue to support the same suggestive relationships between ex ante exposures to international capital and ex post adjustments. Hence, openness of emerging market banking systems to international funding does not seem to have been a source of propagation of the original shock. Exposure to international funding from source countries that were ex ante more likely to suffer from the shock instead provided for multiple and independent channels of shock transmission.

The economic effect of such changes cannot be accurately gauged from these econometric specifications as we cannot correct for concomitant changes in demand. However, the results from the regressions on local claims of foreign banks offer information on this issue: assuming that both local domestic banks and local foreign banks face a similar demand schedule, we know that the FE regressions on local lending by foreign banks indicated the existence of a simultaneous demand change, which amounted to a reduction of about 25 percent in the size of the estimated coefficient of the vulnerability measure (comparing column (2) and (5) of Table 6).

Applying a similar correction to the estimated coefficient in column (1) of Table 10 suggest that the effective supply shock on domestic lending was still substantial.

IV. Concluding Remarks

The opening of capital markets to allow foreign bank participation, either through expanded cross-border lending activity or via direct entry into local banking markets, produces significant benefits to emerging markets in terms of enhanced efficiency, liquidity provision, risk-sharing, and overall superior growth opportunities. Global banks also have been demonstrably more resilient and better prepared to handle shocks originating in emerging markets. However, the transmission of a large shock from source countries to emerging markets has raised concerns about the mechanisms for such transmission and appropriate policy responses. Our analysis has demonstrated that both foreign-owned banks and local stand-alone banks are expected to be impacted by foreign liquidity conditions but to differing degrees. These magnitudes are based on their exposure to cross-border funding and to the internal capital markets of the broader banking organizations in which they participate.

Direct transmission of the shock is through the cross-border lending of source countries. Indirect transmission occurs through the internal capital markets of globalized banks,[22] where reduced support of emerging market affiliates or increased outflows from emerging markets trigger reduced lending at home by these affiliates. Domestically-owned banks in emerging markets are not immune to transmission and associated lending growth contraction. Reliance on cross-border funding does not necessarily lead to international transmission of shocks. The ex ante balance sheets of source countries appear to matter for the ex post consequences.

While cross-border lending and internal capital markets are both conduits for international shock transmission, both positive and negative, these features are not an argument for concluding that closed or reduced access to international capital markets is welfare-improving for emerging markets. Instead, the results suggest the importance of addressing the vulnerabilities in source funding markets so that these funding sources remain a net positive for the economies in which they operate. The results also highlight a potentially new reality across markets on the relative importance of respective channels of international transmission. As stated

[22] Cetorelli and Goldberg (2008) show that such internal capital markets are activated in U.S. banks in response to monetary policy conditions.

by Donald Kohn, the vice chairman of the Federal Reserve, "… when liquidity conditions tighten in one country, globally active banks may attempt to pull liquidity from overseas affiliates, reducing the liquidity consequences at home but simultaneously transmitting the shock abroad. What is particularly interesting is that in some cases, financial linkages might now be more important for transmission than the traditional trade linkages." [23]

[23] Kohn (2008).

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Table 1A Number of BIS Countries (of 17) Engaged in Lending to 24 Emerging Markets

		International Claims		Local Claims in Local Currency	
	EM Borrower	Pre Crisis 2006Q3-2007q2	Post Crisis 2008q3-2009q2	Pre Crisis 2006Q3-2007q2	Post Crisis 2008q3-2009q2
Latin America	Argentina	17	17	9	10
	Brazil	17	17	10	12
	Chile	17	16	8	9
	Colombia	16	16	6	6
	Costa Rica	15	16	4	4
	Mexico	17	17	7	8
	Peru	15	16	7	5
	Venezuela	17	16	4	4
Emerging Asia	China	17	17	10	12
	India	17	17	8	9
	Indonesia	17	17	8	8
	Malaysia	16	16	9	9
	Philippines	17	16	6	7
	Korea	17	17	10	8
	Taiwan	17	17	10	11
	Thailand	16	16	9	8
Emerging Europe	Turkey	17	17	10	8
	Slovakia	16	16	9	8
	Russia	17	17	8	9
	Romania	16	17	6	6
	Poland	16	17	13	13
	Hungary	17	16	11	10
	Czech Republic	17	17	10	10
	Croatia	16	16	2	3

Table 1B Number of Emerging Market Destinations with Counts of Source Countries

Lending Type	Time Frame	# of Destinations with Source Countries			
	# of Source Countries:	0	1	2	3+
International Claims	Pre Crisis (2006Q3- 2007 Q2)	0	2	3	89
	Post Crisis (2008Q3-2009Q2)	0	2	5	87
Local Claims in Local Currency	Pre Crisis (2006Q3- 2007 Q2)	26	19	12	37
	Post Crisis (2008Q3-2009Q2)	24	19	15	36

Table 2 Number of Emerging Market Countries (of 94) in BIS Reporting Country Lending

	International Claims (Cross-Border)		Local Claims in Local Currency	
Source Country	Pre Crisis 2006Q3-2007q2	Post Crisis 2008q3-2009q2	Pre Crisis 2006Q3-2007q2	Post Crisis 2008q3-2009q2
United States	72	76	41	42
Japan	50	47	15	15
Australia	33	32	1	3
Belgium	72	71	11	14
Canada	63	65	21	22
Switzerland	80	79	23	23
Germany	82	81	19	23
Denmark	59	58	13	1
Spain	70	67	16	17
France	86	82	34	43
Great Britain	86	86	37	35
Ireland	46	43	2	1
Sweden	64	63	6	7
Portugal	52	49	5	5
Netherlands	79	78	29	29
Luxembourg	37	38	0	0
Italy	66	72	20	19

Table 3A Summary statistics on Lending Growth

Variable	Obs	Mean	Std. Dev.	Min	Max
Pre-post cross-border lending growth	1032	0.263	0.968	-6.031	4.727
To EM Europe	303	0.459	0.919	-5.524	4.054
To EM Latin America	346	0.207	0.892	-3.105	4.727
To EM Asia	383	0.159	1.049	-6.031	4.094
Pre-post local lending growth	267	0.394	0.889	-6.788	5.215
To EM Europe	88	0.688	0.921	-0.766	5.215
To EM Latin America	85	0.243	0.760	-2.100	3.379
To EM Asia	94	0.254	0.907	-6.788	2.197
Pre-post domestic lending growth	62	0.409	0.306	-0.755	1.023

Table 3B Summary statistics on ex ante dollar vulnerability

	correlations		Obs	Mean	Std. Dev.	Min	Max
V1			17	0.780	0.506	0.064	1.674
V2	0.992		17	0.611	0.447	0.051	1.455
V3	0.702	0.710	17	0.208	0.207	0.009	0.831

Examples of ex ante dollar vulnerability values and scale

	Germany		Spain		United Kingdom	
	$billion	share	$billion	share	$billion	share
V1	1,165	0.342	294	0.693	1,797	1.060
V2	865	0.254	247	0.578	1,524	0.900
V3	311	0.091	72	0.169	265	0.156

Lending in the “pre” crisis period is defined as the time average between 2006q2 and 2007q2. Lending in the “post” crisis period is defined as the time average between 2008q3 and 2009q2. Cross-border lending is lending of foreign banks to an EM destination country originated in the source country. Local lending is the lending of local offices of foreign banks in local currency in each EM country. Domestic lending is the aggregate lending by domestic banks in each EM country. Pre-post lending growth is calculated as the log change between the post- and the pre-crisis periods. Twenty-six of the 94 countries had missing or incomplete domestic claims data (IFS), and six other emerging markets had domestic claims data (IFS) exceeded by total local claims data.

The measures of ex-ante dollar vulnerability are calculated using country-specific gross and net US Dollar aggregates. The definitions of the three measures are as follows. V1: Liabilities to official monetary authorities + International liabilities to non-banks + Local liabilities to US residents booked by US offices + Liabilities to banks + cross-currency FX swap (if negative); V2: Liabilities to official monetary authorities + International liabilities to non-banks + Local liabilities to US residents booked by US offices + Net Liabilities to banks + cross-currency FX swap (if negative); V3 either : Liabilities to official monetary authorities + Net Liabilities to banks + cross-currency FX swap (if negative) + Net positions vis-à-vis non-banks (if negative), or Liabilities to official monetary authorities + Net Liabilities to banks + cross-currency FX swap (if negative) (if Net positions vis-à-vis non-banks is positive). Shares are presented in the correlations and summary statistics cells. These shares are the raw values of the vulnerability measures divided by country international claims.

Table 4 Non-Parametric Comparisons of Lending Growth

	Cross-Border Lending			Local Lending		
	Low Vulnerability	High Vulnerability	Low-High	Low Vulnerability	High Vulnerability	Low-High
Pre-Crisis	4.16	4.41	-0.25	5.39	6.34	-0.95
Post-Crisis	4.53	4.63	-0.10	6.13	6.59	-0.46
Post-Pre	0.37	0.22	**0.15**	0.74	0.25	**0.49**

Low vulnerability countries are those source countries with a measure of vulnerability V2 below the median. High vulnerability countries have a measure V2 above the median. The "pre" crisis period is defined as the time average between 2006q2 and 2007q2. The "post" crisis period is defined as the time average between 2008q3 and 2009q2. The figures reported in the table are time averages of quarterly log lending data.

Table 5 Cross-border lending growth to emerging markets

VARIABLES		(1) OLS	(2) OLS	(3) OLS	(4) FE	(5) FE	(6) FE	(7) OLS	(8) FE
ΔD_i proxy	V1	-0.307***			-0.271***				
		(0.063)			(0.0606)				
	V2		-0.354***			-0.316***		-0.417***	-0.380***
			(0.0711)			(0.0689)		(0.081)	(0.078)
	V3			-0.778***			-0.605***		
				(0.176)			(0.172)		
Vienna								-0.113	-0.037
								(0.227)	(0.218)
V2·Vienna								-0.049	-0.309
								(0.650)	(0.625)
Constant		0.508***	0.486***	0.410***				0.561***	
		(0.058)	(0.054)	(0.045)				(0.070)	
Observations		1,032	1,032	1,032	1,029	1,029	1,029	1,032	1,029
R-squared		0.023	0.024	0.019	0.249	0.250	0.243	0.026	0.253

The measures of ex-ante dollar vulnerability are calculated using country-specific gross and net US Dollar aggregates. The definitions of the three measures are as follows. V1: Liabilities to official monetary authorities + International liabilities to non-banks + Local liabilities to US residents booked by US offices + Liabilities to banks + cross-currency FX swap (if negative); V2: Liabilities to official monetary authorities + International liabilities to non-banks + Local liabilities to US residents booked by US offices + Net Liabilities to banks + cross-currency FX swap (if negative); V3 either : Liabilities to official monetary authorities + Net Liabilities to banks + cross-currency FX swap (if negative) + Net positions vis-à-vis non-banks (if negative), or Liabilities to official monetary authorities + Net Liabilities to banks + cross-currency FX swap (if negative) (if Net positions vis-à-vis non-banks is positive). The first three columns report results from OLS regressions. The next three columns are from fixed effect regressions. Fixed effect coefficients not reported. The final two columns introduce a dummy variable, Vienna, indicating source countries involved in the Vienna initiative. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6. Local claims lending growth in emerging markets

VARIABLES		(1) OLS	(2) OLS	(3) OLS	(4) FE	(5) FE	(6) FE	(7) OLS	(8) FE
ΔD_i proxy	V1	-0.291***			-0.206				
		(0.111)			(0.126)				
	V2		-0.364***			-0.271*		-0.256	-0.269
			(0.126)			(0.147)		(0.166)	(0.189)
	V3			-1.184***			-1.050***		
				(0.347)			(0.384)		
Vienna								-0.865**	-0.927**
								(0.404)	(0.420)
V2.Vienna								3.304***	3.070***
								(1.090)	(1.131)
Constant		0.674***	0.675***	0.636***				0.529***	
		(0.120)	(0.111)	(0.0889)				(0.170)	
Observations		267	267	267	245	245	245	267	245
R-squared		0.025	0.030	0.042	0.395	0.397	0.409	0.073	0.421

The measures of ex-ante dollar vulnerability are calculated using country-specific gross and net US Dollar aggregates. The definitions of the three measures are as follows. V1: Liabilities to official monetary authorities + International liabilities to non-banks + Local liabilities to US residents booked by US offices + Liabilities to banks + cross-currency FX swap (if negative); V2: Liabilities to official monetary authorities + International liabilities to non-banks + Local liabilities to US residents booked by US offices + Net Liabilities to banks + cross-currency FX swap (if negative); V3 either : Liabilities to official monetary authorities + Net Liabilities to banks + cross-currency FX swap (if negative) + Net positions vis-à-vis non-banks (if negative), or Liabilities to official monetary authorities + Net Liabilities to banks + cross-currency FX swap (if negative) (if Net positions vis-à-vis non-banks is positive). The first three columns report results from OLS regressions. The next three columns are from fixed effect regressions. The final two columns introduce a dummy variable, Vienna, indicating source countries involved in the Vienna initiative. Fixed effect coefficients not reported. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7 Quantitative significance of ex ante vulnerability on lending

	Cross-Border Lending		**Local Lending**	
	Pre-Crisis Bilateral Quarterly Average ($ millions)	Post-Pre % Change	Pre-Crisis Bilateral Quarterly Average ($ millions)	Post-Pre % Change
Germany	9,233	-8.02%	5,136	-6.88%
Spain	1,454	-18.26 %	14,417	-15.66%
United Kingdom	3,644	-28.44%	8,547	-24.39%

The Post-Pre % change figures are obtained using the values of V2 for the three countries, as reported in the bottom panel of Table 3B, and the estimated coefficients of the V2 variable from column (5) regressions in table 5 (for Cross-Border Lending) and 6 (for Local Lending).

Table 8 Robustness Test Details

Panel A. Correlations among Country Control Variables

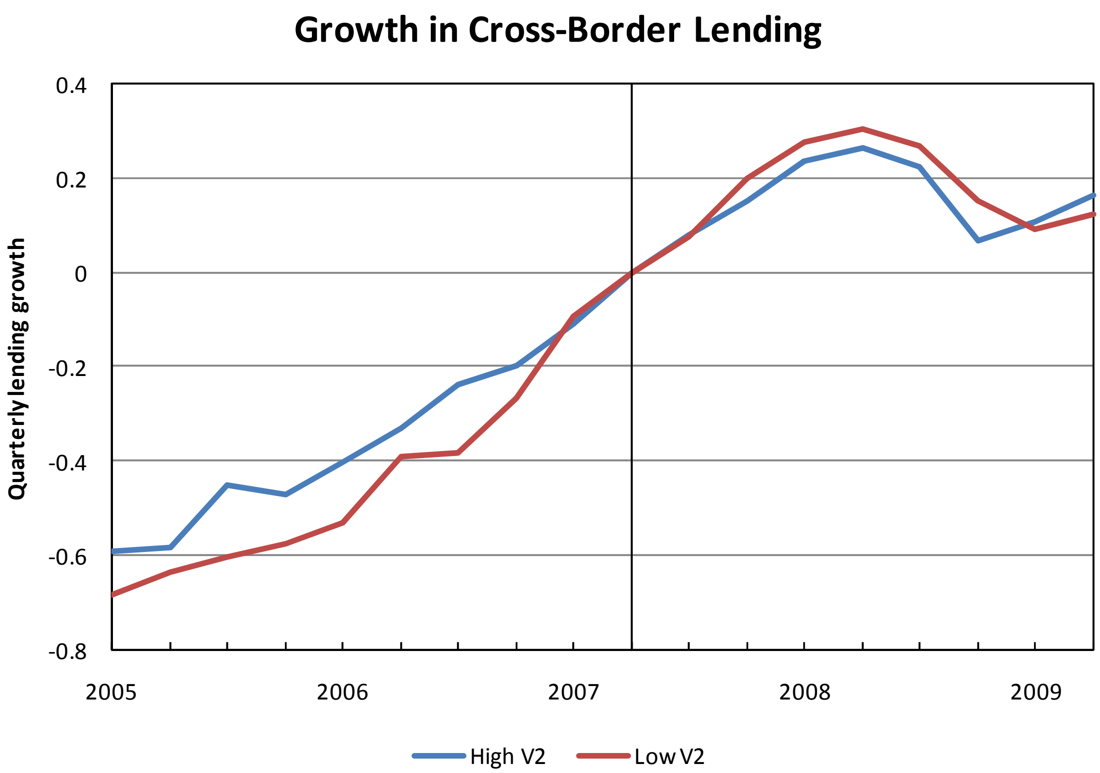
	pcrdbgdp	overhead	roa	roe	zscore	offdep	cap	lintclaims	v2_adj
pcrdbgdp	1.000								
overhead	0.040	1.000							
roa	0.304	0.417	1.000						
roe	0.107	-0.168	0.608	1.0000					
zscore	0.212	-0.555	-0.340	-0.202	1.000				
offdep	0.347	-0.174	-0.079	0.149	0.090	1.000			
cap	0.271	0.695	0.812	0.068	-0.231	-0.155	1.000		
lintclaims	-0.262	0.605	-0.112	-0.501	-0.318	-0.097	0.195	1.000	
V2	-0.138	0.183	0.185	0.189	-0.464	-0.324	0.078	0.027	1.000

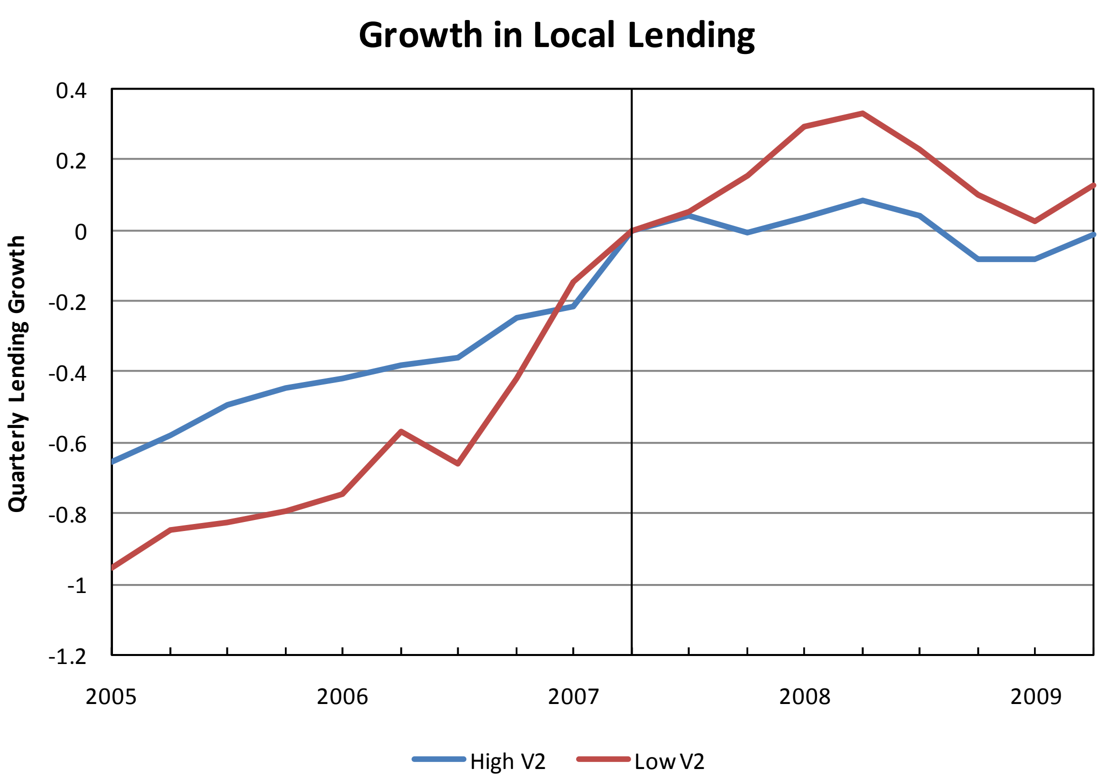
Panel B. Regression Coefficients on V2 in specifications that control for banking variables

	pcrdbgdp	overhead	roa	roe	zscore	offdep	cap	lintclaims	All bank variables
X-border	-0.315***	-0.303***	-0.313***	-0.320***	-0.362***	-0.290***	-0.312***	-0.314***	-0.336***
	(0.069)	(0.067)	(0.069)	(0.069)	(0.077)	(0.070)	(0.070)	(0.069)	(0.091)
Local	-0.269*	-0.271*	-0.267*	-0.272*	-0.208	-0.280*	-0.264*	-0.246	-0.367
	(0.148)	(0.147)	(0.147)	(0.147)	(0.161)	(0.154)	(0.146)	(0.149)	(0.259)

The source-country controls are defined as follows: pcrdbgdp is private credit by deposit money banks and other financial institutions to GDP; overhead is accounting value of a bank's overhead costs as a share of its total assets; roa is net bank income over total bank assets; roe is net bank income over total equity; zscore is (roa+equity/assets)/standard deviation(ROA; offdep is offshore bank deposits relative to domestic deposits; cap is equity to asset ratio; lintclaims is the log of total international claims. The estimated coefficients in Panel B are those of the V2 measure in fixed effects regressions including the country control(s) listed in each column. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 9 Time Trends by Ex-Ante Dollar Vulnerability





The charts depict quarterly averages of log cross-border and local lending for source countries with low or high V2. Figures on the vertical axis are rescaled so that they are both equal to zero at time zero. Time zero is 2007q2.

Table 10 Domestic Lending Supply Growth Shock

VARIABLES	(1)	(2)	(3)	(4)
High V2 share in cross border (H)	-0.370***		-0.348**	-0.453***
	(0.135)		(0.135)	(0.160)
Cross border share in funding (X)		0.431*	0.311	-0.174
		(0.243)	(0.238)	(0.467)
(H)·(X)				0.818
				(0.678)
Constant	0.654***	0.370***	0.610***	0.677***
	(0.093)	(0.044)	(0.098)	(0.112)
Observations	58	58	58	58
R-squared	0.118	0.050	0.145	0.167

The dependent variable is domestic bank lending growth pre-post crisis for each emerging market country. Lending in the "pre" crisis period is defined as the time average between 2006q2 and 2007q2. Lending in the "post" crisis period is defined as the time average between 2008q3 and 2009q2. High V2 share in cross border is the share of cross border interbank funding obtained from source countries with V2 values above the median value across source countries. Cross-border share in funding is the ratio of total cross-border interbank funding to total domestic lending. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1 .

Chart 1

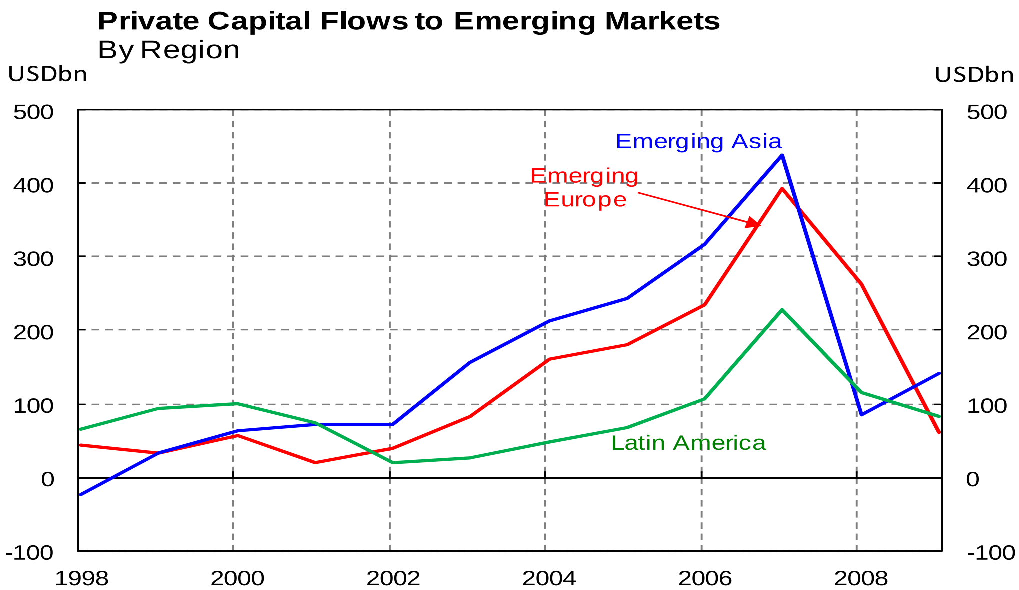
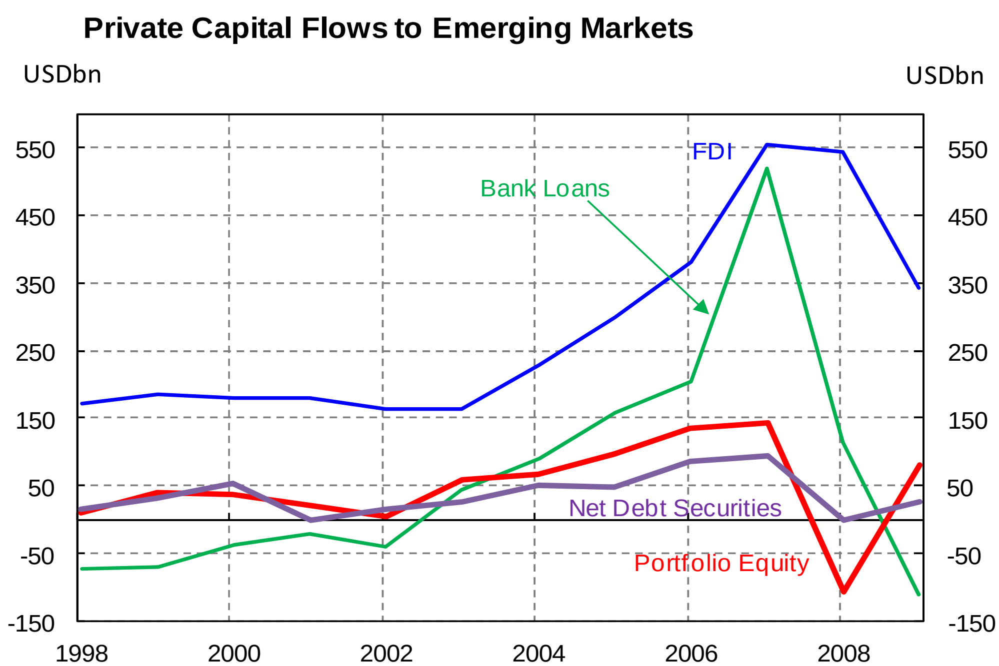


Chart 2



Source for Charts 1 and 2: BIS Locational Banking Statistics, Bank Loans (Table 7c), Net Bond Issues (Table 11); Foreign Direct Investment from the Global Development Fund; Portfolio equity data from CEIC; also Federal Reserve Bank of NY staff estimates. Annual data.

Appendix Table 1. Sample of Developing Countries

Latin America (30)	**Emerging Europe (21)**	**Emerging Asia (43)**	
Argentina	Albania	Afghanistan	Solomon Islands
Belize	Belarus	Armenia	South Korea
Bolivia	Bosnia and Herzegovina	Azerbaijan	Sri Lanka
Brazil	Bulgaria	Bangladesh	Taiwan
Chile	Crotia	Bhutan	Tajikistan
Colombia	Cyprus	Brunei	Thailand
Costa Rica	Czech Republic	Cambodia	Timor Leste
Cuba	Estonia	China	Tonga
Dominica	Hungary	Fiji	Turkmenistan
Dominican Republic	Latvia	French Polynesia	Uzbekistan
Ecuador	Lithuania	Georgia	Vietnam
El Salvador	Macedonia	India	Wallis and Futuna
Falkland Islands	Malta	Indonesia	Western Samoa
Grenada	Moldova	Kazakhstan	
Guatemala	Poland	Kiribati	
Guyana	Romania	Kyrgyz Republic	
Haiti	Russia	Laos	
Honduras	Slovakia	Malaysia	
Jamaica	Slovenia	Maldives	
Mexico	Turkey	Marshall Islands	
Nicaragua	Ukraine	Micronesia	
Paraguay		Mongolia	
Peru		Myanmar	
St. Lucia		Nauru	
St. Vincent		Nepal	
Suriname		New Caledonia	
Trinidad and Tobago		North Korea	
Turks and Caicos		Pakistan	
Uruguay		Papau New Guinea	
Venezuela		Philippines	

Appendix Table 2 Delivery on EIB's Commitments under the *Joint IFI Action Plan*

By Institution up to end-September 2009 (Euro millions)

Bank	Available	Disbursed	2009 pipeline	Total
UniCredit Group (Italy)	951	204	75	1,230
Erste Bank Group (Austria)	446	280	0	726
Société Générale (France)	393	59	40	492
Intesa Sanpaolo (Italy)	265	139	50	454
Dexia Group (Belgium)	226	117	100	443
Bayern LB (Germany	242	100	100	442
EFG Eurobank (Greece)	315	35	0	350
BNP Paribas / Fortis (France)	300	30	0	330
RZB (Austria)	230	8	40	278
KBC Group (Belgium)	110	63	100	273
Total	**3,478**	**1,035**	**505**	**5,018**
Other Banks	4,051	682	1,005	5,738
Grand Total	**7,529**	**1,717**	**1,510**	**10,756**

By Country up to end-September 2009 (Euro millions)

Country	Available	Disbursed	2009 pipeline	Total
Bulgaria	169	25	60	254
Czech Republic	591	269	0	860
Estonia	25	50	0	75
Hungary	679	409	0	1,088
Latvia	115	30	145	290
Lithuania	25	23	0	48
Poland	1,023	211	275	1,509
Romania	424	65	50	539
Slovakia	260	22	100	382
Slovenia	709	40	100	849
Total EU – 10	**4,019**	**1,144**	**730**	**5,893**
Albania	0	0	20	20
Bosnia Herzegovina	291	37	120	449
Croatia	540	34	40	613
FYROM	110	0	0	110
Montenegro	132	0	0	132
Serbia	583	44	100	727
Total Western Balkans	**1,655**	**115**	**280**	**2,050**
Total Turkey	**1,855**	**459**	**500**	**2,813**
Total	**7,529**	**1,717**	**1,510**	**10,756**

"Progress Report on the Joint IFI Action Plan," European Bank for Reconstruction and Development, European Investment Bank Group, and World Bank Group, October 2009, pp. 14-15.

Interbank Exposures: An Empirical Examination of Contagion Risk in the Belgian Banking System*

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Robust (cross-border) interbank markets are important for the proper functioning of modern financial systems. However, a network of interbank exposures may lead to domino effects following the event of an initial bank failure. We investigate the evolution and determinants of contagion risk for the Belgian banking system over the period 1993–2002 using detailed information on aggregate interbank exposures of individual banks, large bilateral interbank exposures, and cross-border interbank exposures. The "structure" of the interbank market affects contagion risk. We find that a change from a complete structure (where all banks have symmetric links) toward a "multiple-money-center" structure (where money centers are symmetrically linked to otherwise disconnected banks) has decreased the risk and impact of contagion. In addition, an increase in the relative importance of cross-border interbank exposures has lowered local contagion risk. However, this reduction may have been compensated by an increase in contagion risk stemming from foreign banks.

JEL Codes: G20, G15.

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1. Introduction

A well-functioning and robust interbank market is an essential element of the integration of a financial system. However, although interbank markets strengthen financial integration, they also increase linkages within the banking sector. Interbank markets therefore may represent an important channel of contagion through which problems affecting one bank or one country may spread to other banks or other countries.

In this paper, we empirically address the implications of domestic as well as cross-border interbank linkages for interbank contagion risk. Contagion results from the materialization of two risks: first, the risk that at least one component of the system is hit by a shock (likelihood of a shock) and, second, the risk that this shock propagates through the system (potential impact of the shock). As the former can result from a variety of unexpected situations, we focus on the latter. In particular, we evaluate the potential damages that a chain reaction in the interbank market—i.e., a situation where the failure of one bank would lead to the default of one or more of its interbank creditors—could create. We undertake a stylized exercise—resembling a stress test—in which we simulate the consequences of nonrepayment of interbank loans of an individual bank on the capital of its bank lenders, and any further domino-like effects. In order to isolate the potential impact of contagion, we assume that the initial default is caused by a sudden, unexpected, and idiosyncratic shock. Recent history has shown that this kind of shock is not totally unlikely (see, for instance, the failure of Barings in the United

Markets and Financial Integration in Europe, the FIRS conference on Banking, Insurance and Intermediation, the ECB workshop on Financial Stability, the Sveriges Riksbank conference on Banking, Financial Stability and the Business Cycle, and the Banco de Portugal conference on Financial Fragility and Banking Regulation for providing helpful discussions and comments. We especially thank Janet Mitchell for her detailed guidance and invaluable suggestions. The views expressed in this paper are those of the authors and do not necessarily reflect the views of the National Bank of Belgium. The first author acknowledges financial assistance from FWO–Flanders, NWO–The Netherlands, and the research council of the University of Leuven. Hans Degryse holds the TILEC-AFM Chair on Financial Market Regulation. Corresponding author: Degryse: CentER–Tilburg University, P.O. Box 90153, NL-5000 LE Tilburg, The Netherlands; e-mail: H.Degryse@uvt.nl.

Kingdom or Drexel Burnham Lambert in the United States) and may trigger a systemic crisis. Worries of a systemic crisis and domino effects induced, for instance, the bailout of Continental Illinois.[1]

Our empirical analysis considers contagion risk in the Belgian financial system. Why should the reader be interested in Belgium, which only covers a small part of the euro zone? The Belgian interbank market is an instructive case for several reasons.[2] First, it is very international, a feature that may become a key characteristic of many interbank markets in the future. In addition, the Belgian financial landscape contains a number of key players in the payment and securities settlement infrastructure (such as, e.g., Euroclear Bank or SWIFT). Second, the Belgian banking sector underwent a period of significant consolidation in the years 1997–2001. As a result, some large banks now have total assets that far exceed the GDP of the country, a situation that is typical for many other small countries (e.g., the Netherlands, Sweden, or Switzerland). Such countries then may face a potential too-big-to-save situation. However, only the analysis of the propagation channels of a crisis will ultimately determine its gravity. Third, the structure of the Belgian interbank market has changed over time: it has moved from a "complete" structure (where all banks have reciprocal links) toward a "multiple-money-center" structure (where a few "money-center banks" are linked together and linked to otherwise disconnected banks). These observations raise several interesting questions, which are also relevant for the analysis of contagion risk within and across financial systems of other countries. How has interbank contagion risk evolved over time? How important is the interbank market structure in explaining interbank contagion risk? To what extent could the failure of a foreign bank affect domestic banks through cross-border interbank exposures? How does contagion risk in Belgium compare with assessments for other countries? What measures can a regulator take to limit interbank contagion risk?

[1]The Federal Reserve decided immediately to step in. Later, Paul Volcker, then Chairman of the Board of Governors of the Federal Reserve System, argued that "if [they] had not stepped in, the ultimate domino effect that so many people have feared for so long, would have occurred and wiped out the Western financial system" (Feltham 2004).

[2]By "Belgian interbank market," we refer here to the set of interbank exposures where at least one of the counterparties is a bank incorporated in Belgium.

Our analysis goes beyond the existing literature in several respects. First, we point out that it is important to take into account time variation in interbank linkages. In contrast to most existing studies, we make use of time-series data on interbank exposures; other papers focus only on a single point in time. This enables us to examine the evolution over the past decade of contagion risk associated with the failure of Belgian banks. We find that contagion risk due to domestic interbank defaults has varied significantly over time, according to a well-identifiable pattern. In particular, contagion risk increased over the period 1993–97, decreased afterward, and flattened out at a very low level at the end of the sample period (end of 2002).

Second, we investigate the determinants of contagion in an attempt to explain the evolution of contagion risk over time. Although historical events—such as the long-term capital management (LTCM) crisis or the default on Russian debt—could potentially account for the peak in contagion risk observed in 1997, we argue that changes in the structure of the Belgian interbank market and in the capitalization of Belgian banks are the main drivers behind this evolution. Theory suggests that market structure may play an important role in determining contagion risk in interbank markets (see, e.g., Allen and Gale 2000 or Freixas, Parigi, and Rochet 2000). To our knowledge, this is the first paper to empirically investigate the impact of interbank market structure on contagion risk, employing regression analysis that allows us to control for other variables in the conditioning set. We find that a move from a complete structure toward a "multiple-money-center" structure and an increase in concentration in the banking market lead to a decrease in domestic contagion. In addition, an increase in the proportion of cross-border interbank assets further decreases the risk and impact of domestic contagion. Increases in bank capitalization also have a first-order effect in reducing interbank contagion when the loss given default (LGD) is relatively low.

Third, we investigate the contagion risk stemming from interbank linkages with foreign banks, in addition to the risk associated with linkages between domestic banks. The sharp increase in the proportion of cross-border interbank assets for Belgian banks, combined with the decrease in the indicators of domestic contagion, indeed suggests that the potential contagion risk stemming from foreign interbank exposures has gained in importance. According to our simulations, the failure of some foreign banks could have a sizable effect on Belgian banks' assets, albeit only for high values of loss given default. Since large banks are more involved in international interbank markets than small banks, contagion effects triggered by foreign banks generate higher levels of contagion.

Fourth, in addition to running simulations for a range of (exogenous) levels of LGD, we also attempt, in a supplementary exercise, to endogenize banks' LGD. This allows LGD to vary across banks. These simulations still reveal an evolution over time of contagion risk; however, at any given point in time, we no longer observe a strong correlation between the average implied LGD across banks and the level of contagion, as reflected in the worst-case scenario. This is because the average LGD interacts with the other dimensions of the market structure, which remain determinant in the propagation of contagion. In addition, we find that for a given average LGD across banks, contagion risk is higher when there is more cross-sectional variation in LGD. Heterogeneity in LGD appears to exacerbate contagion risk.

Finally, in robustness tests, we analyze several alternative scenarios. For example, we show that netting of interbank exposures—the setoff of bilateral positions—may substantially reduce contagion risk. In addition, we test the potential effect of a coordination mechanism whereby the supervisor requires some banks to merge in order to reduce contagion effects. Although mergers are often used in practice as a mechanism for dealing with ailing banks, in our simulations mergers seldom decrease contagion.

The rest of the paper is organized as follows. Section 2 reviews the literature on interbank contagion risk. Section 3 introduces the data set, describes the methodology and contagion indicators, and presents the most important features of the Belgian interbank market. Section 4 discusses the results of the various simulation exercises. Section 5 presents the regression results of the impact of the interbank market structure on contagion risk. Section 6 concludes.

2. Literature Review on Interbank Market Contagion

In some circumstances, the failure of an individual bank may lead to a domino effect. This happens when the nonrepayment of interbank obligations by the failing bank jeopardizes the ability of its creditor banks to meet their obligations to their interbank creditors. Contagion occurs then "mechanically" through the direct interlinkages between banks. *Theory* shows that the extent to which a crisis is propagated through the system depends on the structure of interbank linkages. The market structure of interbank claims can take different forms. Allen and Gale (2000) distinguish three structures: (i) the "complete structure" where banks are symmetrically linked to all other banks, (ii) the "incomplete market structure" where banks are only linked to neighboring banks, and (iii) the "disconnected incomplete market structure" where two disconnected markets coexist. They show that complete structures are less prone to contagion than incomplete market structures, since with complete structures, the impact of a financial crisis in one bank is absorbed by a large number of banks. Freixas, Parigi, and Rochet (2000) introduce a fourth structure: the "money center." The money center is symmetrically linked to all the other banks, which are themselves not linked together. They show that, in some cases, the failure of a bank linked to the money center will not trigger the failure of the money center, but the failure of the money center itself may trigger failures of the linked banks. Our paper empirically investigates how the market structure of the interbank market influences contagion risk.

Current *empirical work* mainly focuses on interbank contagion within a national banking system. Two empirical approaches are implemented, each having its strengths and weaknesses. A first approach tries to isolate contagion from other shocks affecting the economy. It simulates the consequences of an individual bank failure given observed or estimated interbank exposures and looks at the potential domino effects, i.e., first-round and potential further-round effects. This approach was applied to (part of) banking systems in several countries and—although contagion indicators were more important in some countries than in others—delivered generally reassuring results (see Sheldon and Maurer 1998, Furfine 2003, Cifuentes 2004, Upper and Worms 2004, Wells 2004, or van Lelyveld and Liedorp 2006 for Switzerland, the United States, Chile, Germany, the United Kingdom, and the Netherlands, respectively[3]).

[3]Upper (2006) provides a comparative overview of these contributions.

However, all these studies look at contagion at one moment in time and generally focus on domestic contagion only. Our paper adds to this literature by considering a time series covering Belgian banks during ten years, allowing us to investigate how and why contagion risk evolved over time.[4] Furthermore, we also try to adapt the mechanics of the exercise to better reflect real-life features. This allows us to endogenize the LGD and to subsequently analyze the extent to which the results depend upon a standard assumption used in this literature, i.e., a fixed LGD. Finally, we investigate how the failure of foreign banks affects interbank contagion within the Belgian banking market. The latter issue becomes more important as cross-border exposures grow. Following our empirical analysis on the role of interbank market structure and cross-border exposures, Mistrulli (2005) documents that the Italian interbank market also moved from a "complete" structure toward a "multiple-money-center" structure. In contrast to our findings for Belgium, he reports that the importance of cross-border exposures has decreased and that the transition toward the multiple-money-center structure has increased contagion risk. While the conclusions for Italy are drawn on the basis of simulations, our regression analysis allows us to disentangle the impact of the different determinants of contagion.

A second approach to estimate contagion risk takes into account a larger variety of shocks. Müller (2003) combines a network and a simulation approach to assess the risk of contagion in the Swiss interbank market and takes into account credit and liquidity effects in bank contagion. Elsinger, Lehar, and Summer (2006) simulate the joint impact of interest rate shocks, exchange rate shocks, and stock market movements on interbank payment flows of Austrian banks. These states of the world determine the net value of the bank and the feasibility of interbank payments. They distinguish between insolvency due to correlated exposures and due to domino effects. Their simulations indicate that although the probability of contagious default is low compared to the total default probability, there are situations in which up to 75 percent of the defaults

[4]Guerrero-Gómez and Lopez-Gallo (2004) study a short time series for interbank contagion in Mexico (December 2002–August 2003) and find considerable variation of contagion in this short time window.

are due to contagion.[5] Instead of simulating interbank contagion, another method to take into account a larger variety of shock is to investigate banks' stock price behavior. Lehar (2005) estimates correlations between bank portfolios to compute different measures of systemic risk. Gropp and Vesala (2003) use the tail properties of distance to default to study contagion risk. They find the presence of both domestic and cross-border contagion within Europe, although domestic contagion seems to dominate cross-border. The advantage of this second approach is that it takes a systemwide view. However, as we want to focus on contagion risk and perform a stress test, starting from an individual bank failure may yield more insights in the evolution of risk over time, in the propagation mechanism and ultimate consequences of contagion risk. In addition, some of these techniques require time series of stock prices. Since few Belgian banks are publicly listed, this second approach appears inadequate to study the Belgian financial system.

3. Data, Methodology, and Structure of the Interbank Market

3.1 Data

The data stem from a confidential database (Schéma A) containing banks' balance sheet statements and a set of key financial figures collected for supervisory purposes at a monthly frequency. This database provides valuable information with respect to interbank positions:

- At an aggregate level, each bank reports its total interbank loans and deposits and provides breakdowns of these "aggregate positions" according to the type of loan or deposit, the geographical origin of the lender or the borrower (Belgium,

[5]Elsinger, Lehar, and Summer (2006) also use their simulation to compare two generated matrices of bilateral exposures representing a complete and an incomplete structure. They find more contagion when they use a complete market structure. Note finally another study in that second approach: Iyer and Peydro-Alcalde (2006) study a postmortem case to see how an idiosyncratic shock that affected an Indian bank was transmitted to the other Indian banks. Their study includes indirect effects through depositors' runs and media destabilizing effects.

one of the other EU members, or the rest of the world [RoW]), and the residual maturity of interbank loans or deposits. The aggregate positions used in this paper cover a period ranging from December 1992 to December 2002.

- At an individual bank level, banks report their "large exposures" to both domestic and foreign single obligors, including their interbank exposures (i.e., exposures exceeding 10 percent of their own funds). Reliable data on large exposures are only available from 2002:Q3 onward. We use a cross-section of data on large exposures to banks for December 2002.

Figures are reported on a firm basis; i.e., they include banks incorporated in Belgium (i.e., Belgian banks and Belgian subsidiaries of foreign banks) as well as their foreign branches, and consequently exclude Belgian branches of foreign banks or foreign subsidiaries of Belgian banks. The Belgian banking system, at the end of 2002, comprises 65 banks with total assets of €792 billion. The banking system is characterized by a high degree of concentration, since the four largest banks account for 85 percent of total assets of Belgian banks. This concentration results from several mergers over the period 1997–2001 and from an overall decrease in the number of banks, from 112 in 1992 to 65 in 2002.

The interbank market evolution in Belgium was partly determined by the overall evolution of money markets in Europe over the last decade. First, the establishment of the Economic and Monetary Union (EMU) radically changed the European financial landscape and allowed greater market integration. Baele et al. (2004) find that the euro-area money markets have reached a very advanced level of integration. This "near-perfect" integration fostered a higher internationalization of interbank transactions, also observable in the Belgian data. Second, the launch of the EMU required efficient cross-border payment systems. To this end, the 1997 implementation of TARGET (Trans-European Automated Real-time Gross settlement Express Transfer system) facilitated the integration of European money markets and the setting up of international bank exposures. In Belgium, the entry point to TARGET is the real-time gross settlement system ELLIPS (ELectronic Large value Interbank Payment System). ELLIPS is structured in two tiers, with direct and indirect participants. Direct participants must have an account with the central bank. At the end of 2002, there were seventeen direct participants and seventy-six indirect participants. In our data set, accounts that direct participants must have with the central bank are not considered interbank exposures. On the other hand, accounts between participants and subparticipants are considered interbank exposures. One might expect that the two-tier structure of payment systems and the subsequent access to international payment systems influence the structure of the resulting interbank linkages.

As shown in table 1, the interbank loans of Belgian banks represent a gross exposure of €176 billion at the end of 2002, while interbank deposits amount to €228 billion.[6] On both sides of the balance sheet, term and secured loans/deposits represent the largest portions of interbank positions. The current level of secured loans is the consequence of a shift in the strategy of Belgian banks in the beginning of the 1990s, probably nurtured by the monetary policy reform in Belgium in 1991, which stimulated the use of repos between Belgian banks. Over the period 1992–2002, interbank loans always account for 20 to 27 percent of total assets of Belgian banks, and interbank deposits account for 29 to 35 percent of their total liabilities.[7]

Another noteworthy characteristic of interbank positions of Belgian banks is their high degree of internationalization. At the end of 2002, less than 15 percent of interbank exposures of Belgian banks were to other Belgian banks. Hence, Belgian banks might be more sensitive to international bank failures than to domestic ones. Manna (2004) reports that the share of interbank deposits traded within the euro area on a cross-border basis increased from 20.6 percent in 1998 to 25.2 percent in 2002. Countries with large domestic markets

[6]In 2002, banks reported large exposures amounting to 79.5 percent of the domestic interbank loans and to 70.1 percent of the foreign interbank loans. They reported 109 large exposures to domestic banks and 226 large exposures to 135 different foreign banks. These exposures account for a total value of €126 billion. The average value of a domestic large exposure (€190 million) is lower than the average value of a foreign large exposure (€467 million).

[7]These figures are in line with EMU averages, although one can observe huge differences between some countries.

Table 1. Structure of Interbank Loans and Deposits of Belgian Banks

Interbank Loans	**Belgium**	**EMU**	**RoW**	**Total**
Demand Loans	603 *0.3%*	1,047 *0.6%*	2,017 *1.1%*	3,667 *2.1%*
Term Loans	10,909 *6.2%*	48,020 *27.2%*	22,816 *12.9%*	81,744 *46.3%*
Secured Loans	10,680 *6.1%*	32,623 *18.5%*	43,844 *24.8%*	87,147 *49.4%*
Other	3,788 *2.1%*	110 *0.1%*	16 *0.0%*	3,914 *2.2%*
Total	25,980 *14.7%*	81,799 *46.4%*	68,692 *38.9%*	176,472 *100.0%*
Interbank Deposits				
Sight Deposits	739 *0.3%*	2,892 *1.3%*	2,868 *1.3%*	6,499 *2.8%*
Term Deposits	16,771 *7.3%*	26,670 *11.7%*	80,927 *35.4%*	124,368 *54.4%*
Secured Deposits	15,308 *6.7%*	46,425 *20.3%*	35,894 *15.7%*	97,627 *42.7%*
Total	32,818 *14.4%*	75,988 *33.3%*	119,688 *52.4%*	228,494 *100.0%*

Source: National Bank of Belgium.
Note: Data are for December 2002, in € million, with percentages shown in italics.

currently exhibit a smaller share of cross-border activity.[8] In that respect, Belgium's high degree of cross-border interbank exposures could provide a good assessment of the future ingredients of national money markets and interbank linkages in other European countries.

[8]Manna (2004) reports that in 2002 the share of cross-border interbank deposits amounted to approximately 15 percent in Finland, France, and Germany; amounted to 30 percent in Italy, the Netherlands, and Spain; and exceeded 50 percent in Belgium and Portugal.

3.2 Methodology

The methodology, based on Upper and Worms (2004), aims at assessing the impact on the Belgian financial system of the sudden and unexpected default of each banking counterpart of Belgian banks. The test of contagion uses a $(N \times (N+M))$ matrix of interbank bilateral exposures, X, to study the propagation mechanisms of crises. The matrix of bilateral exposures summarizes the interbank exposures of Belgian banks toward the other $(N-1)$ Belgian banks and the M foreign banks:

$$X = \left[\begin{array}{ccccc|ccc} x_{11} & \cdots & x_{1j} & \cdots & x_{1N} & w_{1N+1} & \cdots & w_{1M} \\ \vdots & \ddots & \vdots & \iddots & \vdots & \vdots & & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{iN} & \vdots & & \vdots \\ \vdots & \iddots & \vdots & \ddots & \vdots & \vdots & & \vdots \\ x_{N1} & \cdots & x_{Nj} & \cdots & x_{NN} & w_{NN+1} & \cdots & w_{NM} \end{array}\right]$$

with

$$\sum_{j=1}^{N} x_{ij} = a_i; \sum_{i=1}^{N} x_{ij} = l_j \quad \text{and} \quad \sum_{j=N+1}^{M} w_{ij} = fa_i,$$

where x_{ij} represents the gross exposure of the Belgian bank i to the Belgian bank j, w_{ij} represents the gross exposure of the Belgian bank i to the foreign bank j, a_i represents the domestic interbank assets of bank i, l_j represents the domestic interbank liabilities of bank j, and fa_i represents the foreign interbank assets of bank i.

The simulations successively study the impact of the failure of each of the N Belgian banks and each of the M foreign banks for a given LGD. The initial failure is assumed to cause an additional failure when the exposure of one bank to failed banks is large enough to offset its tier 1 capital. More specifically, bank i fails subsequently to other failures when

$$C_i - \sum_{j=1}^{N} \lambda_j \theta x_{ij} - \sum_{j=N+1}^{M} \lambda_j \theta w_{ij} < 0,$$

where C_i refers to the tier 1 capital of bank i, θ refers to the LGD, and λ_j is a dummy variable equal to 1 if bank j fails and 0 otherwise. The LGD is assumed to be constant and identical for all failed banks. We assume that in the event of bankruptcy there is no netting, so we use gross exposures x_{ij} and w_{ij} rather than net exposures $(x_{ij} - x_{ji})$. The initial default may cause several successive rounds of failures. The contagion stops when banks that failed during the last round do not cause any additional failures, i.e., when the system is again stable.

The matrix of bilateral exposures is (partly) unknown and, hence, must be inferred. The inference technique (hereafter called *aggregate exposures technique*) is based on the observed aggregates a_i and l_j, which only provide incomplete information on interbank exposures of Belgian banks to Belgian banks—namely, the column and row sums of the matrix X, i.e., the marginal distribution of the x_{ij}. Since this information is partial, we need to make an assumption on the distribution of the individual interbank exposures. Following other papers,[9] we assume that banks seek to maximize the dispersion of their interbank activities.[10] This kind of problem is easily solved with the RAS algorithm.[11] Details on the methodology can be found in Upper and Worms (2004). Since we unfortunately lack the necessary data to apply this methodology to foreign banks, we cannot infer a matrix of international bilateral exposures for Belgian banks. Large exposures are used in this case to estimate the w_{ij}.

Any inference technique, and the general contagion exercise, involves biases—some of which tend toward underestimation and others toward overestimation of contagion risk. The sources of underestimation of contagion risk include the measure of interbank exposures, which is based on interbank loans and deposits only and

[9] See Upper and Worms (2004), Wells (2004), and Elsinger, Lehar, and Summer (2006).

[10] In order to test the robustness of our results, we use two additional techniques. The first one (*large exposures technique*) consists of using the matrix of bilateral exposures based on large exposures only. The second one (*mixed technique*) mixes both approaches by incorporating large exposures in the matrix of bilateral exposures and by using the a_i and l_j, net of large exposures, to calculate the residual, unreported exposures. However, since time series of large exposures are not available, analyses over time are only based on the aggregate exposures technique.

[11] See, e.g., Blien and Graef (1997).

consequently does not include other interbank exposures, such as off-balance-sheet exposures. The distributional assumption of maximum dispersion of banks' interbank exposures also potentially leads to an underestimation of contagion risk, as there are fewer peaks in the distribution[12] (on the other hand, the distributional assumption also creates interbank linkages that do not exist and that are new ways for contagion propagation). Moreover, indirect effects of the failure of foreign banks are not taken into account, since we are unable to measure contagion between foreign banks. Our results may thus suffer from a potential censoring bias. Another source of underestimation is the fact that credit risk is the only source of interbank contagion; liquidity risks are ignored. Furthermore, we use a conservative definition of bank failure, as, in reality, banks may fail before their tier 1 capital is exhausted by interbank losses.[13] Finally, bank panics by depositors are assumed not to occur.[14] On the other hand, since banks are assumed not to be able to refinance or to raise additional capital, we overestimate contagion risk. We also assume that they are not able to anticipate crises and to subsequently reduce their interbank exposures. The absence of safety nets also tends to generate an overestimation bias. Another source of overestimation is the measure of interbank exposures that is on a firm basis and not on a consolidated basis.[15] The extent to which contagion risk will actually be underestimated or overestimated in our simulations will

[12]The distributional assumption also rules out the possibility of having interbank relationship lending. Cocco, Gomes, and Martins (2003) find evidence of lending relationships in the interbank market. Interbank lending relationships could help to mitigate the risk of contagion (as, for instance, monitoring could be more efficient) but could also give rise to very high peaks in the matrix of bilateral exposures.

[13]While the contagion algorithm assumes that a bank only fails once its interbank losses amount to at least its tier 1 capital, there are situations in which a bank may fail before it reaches this threshold. For instance, even small interbank losses could generate additional non-interbank losses (e.g., if the interbank losses trigger a bank run).

[14]Bank panics may occur following an individual bank's failure if depositors make inferences about systemic weakness based on observation of the individual failure (see Aghion, Bolton, and Dewatripont 2000).

[15]Although the use of data at a company level leads to the implicit assumption that cross-border intragroup exposures are between different banks, our actual simulations reveal few cases where such exposures cause "contagion." Assuming away intragroup contagion would be equivalent to making the assumption that the subsidiary will receive assistance from its parent company. However, facing a

obviously depend upon the importance of each of these sources. We deal with some of these potential biases in section 4.2.

Since we want to investigate extreme events, our main indicator of contagion over time is the worst-case scenario (WCS). It is defined as the scenario for which the percentage of total banking assets represented by banks losing their entire tier 1 capital due to contagion is largest. We also provide information on the next-to-worst-case scenario. For brevity, and as the results are in line with the WCS, we do not report the results for two other contagion indicators—i.e., the number of cases of contagion, which measures the likelihood of the occurrence of a contagion effect conditionally to a bank failure, and the number of rounds of contagion, which provides some information on the interbank market structure.[16]

3.3 Structure of the Belgian Interbank Market

Table 2 presents a matrix of bilateral exposures based on the aggregate technique. For presentation purposes, we grouped banks by size in five groups (designated G1–G5). Natural thresholds in the empirical bank-size distribution were used in order to determine groups' composition. G1 comprises the four banks whose assets exceed €99 billion, G2 comprises five banks with assets between €8 and €14 billion, G3 comprises seven banks with assets between €3 and €6 billion, G4 comprises fifteen banks with assets between €1 and €2.6 billion, and G5 comprises thirty-four banks with less than €700 million in assets. Recall that bilateral interbank positions are determined before the grouping procedure. Note also that EMU, RoW, and total interbank rows and columns are directly observed and are thus independent of distributional assumptions.

Most domestic interbank transactions seem to involve large banks. Indeed, positions between G1 banks and other banks exceed by far positions between G2–G5 banks. This structure has not always been prevalent in Belgium. Table 3 shows the evolution over time of the total amount G2–G5 cells can account for. The first row of

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large shock, the parent company may not be in a situation in which such a rescue is possible. Therefore, we prefer to treat intragroup exposures similarily to other exposures. Using consolidated data would implicitly rule out the possibility for banking groups to close down an ailing subsidiary.

[16] Results can be found in Degryse and Nguyen (2004).

Table 2. Bilateral Interbank Exposure by Size Categories—December 2002

	% of Assets of Banking System	G1	G2	G3	G4	G5	EMU	RoW	Total Interbank Loans	Foreign Interbank Loans as % of Total Loans
G1	85.10%	15.1	1.0	0.9	2.8	1.1	70.6	64.0	155.4	86.6%
G2	6.80%	2.6	0.1	0.1	0.4	0.1	4.2	2.8	10.4	67.9%
G3	3.50%	2.1	0.1	0.1	0.3	0.1	5.1	0.2	8.0	66.1%
G4	3.40%	2.7	0.1	0.1	0.4	0.2	0.9	1.4	5.7	39.4%
G5	1.30%	1.9	0.1	0.1	0.3	0.1	1.0	0.3	3.8	35.8%
EMU		71.4	3.0	0.6	0.8	0.2				
RoW		111.7	3.3	1.5	2.6	0.6				
Total Interbank Deposits		207.4	7.7	3.4	7.5	2.5				
% of Foreign Interbank Deposits		88.3%	81.5%	61.3%	45.6%	32.4%				

Notes: Data are for December 2002, in € billion, except when expressed as percentages.
Domestic Exposures: Estimates of the matrix of bilateral exposures are based on the aggregate technique, which maximizes the distribution of total interbank loans and deposits.
Banks were grouped by size for expositional purposes. Natural thresholds in the empirical bank-size distribution were used in order to determine groups' composition. G1 comprises the four banks whose assets exceed €99 billion, G2 comprises five banks with assets between €8 and €14 billion, G3 comprises seven banks with assets between €3 and €6 billion, G4 comprises fifteen banks with assets between €1 and €2.6 billion, and G5 comprises thirty-four banks with less than €700 million in assets.
Foreign exposures are based on reported figures.

Table 3. Interbank Share of Nonlarge Banks

	1993:Q2	1994:Q2	1995:Q2	1996:Q2	1997:Q2	1998:Q2	1999:Q2	2000:Q2	2001:Q2	2002:Q2	2002:Q4
Maximum	68.1%	42.4%	48.2%	46.5%	53.6%	40.4%	33.5%	40.0%	40.4%	23.2%	25.8%
Aggregate Exposures Technique	36.4%	30.0%	32.0%	30.7%	35.4%	17.1%	14.6%	20.5%	18.5%	6.1%	8.1%

Note: Figures are for Q2 of each year. "Maximum" and "Aggregate Exposures Technique" represent the percentage of total aggregate exposures of Belgian banks' domestic interbank exposures accounted for by small and medium-sized banks. "Maximum" is based on the minimum of the total interbank loans and total interbank deposits of small and medium-sized banks. "Aggregate Exposures Technique" is computed on the basis of the aggregate exposures technique.

the table shows the maximum amount these cells can represent. This maximum is calculated independently from any distributional assumption. It is defined as the minimum between the sum of domestic interbank deposits of G2–G5 banks (i.e., the sum of the l_j of G2–G5 banks) and the sum of their domestic interbank loans (i.e., the sum of their a_i).[17] The second row of the table presents the calculated G2–G5 total in the aggregate exposures technique. Both series show a downward time trend. In 1993, the structure of the interbank market was similar to a complete structure where estimated exposures between G2–G5 banks represent 36 percent of the domestic market (and could not exceed 68 percent with any alternative distributional assumptions). However, the interbank positions between G2–G5 banks decrease drastically between 1993 and 2002 (it is estimated to 8.1 percent with the aggregate exposures technique and to 10 percent with the mixed technique). So, although we still assume a complete structure,[18] small and medium-sized banks do not seem to have significant exposures to each other in 2002. We observe the same time trend in the maximum. In fact, it mainly reflects the very high concentration of interbank positions involving large banks on both sides of the balance sheet.[19] The evolution over time of the matrix of bilateral exposures thus demonstrates that the aggregate exposures technique is able to capture changes in the market structure, despite the initial assumption of maximum entropy.

Although interbank activities with foreign banks are mainly concentrated in large banks (table 2), access to international interbank markets does not seem to be strictly limited to large banks only. Nevertheless, we observe that the proportion of foreign interbank loans or deposits tends to decrease with bank-size category. Possible explanations are that smaller banks may not reach the critical

[17]By definition, the sum of G2–G5 cells will never exceed the minimum of domestic interbank loans and domestic interbank deposits of these banks. In fact, taking the minimum even constitutes an overestimation of the total G2–G5, as it does not take into account constraints such as a null diagonal.

[18]Assuming a maximum dispersion of interbank activities is similar to assuming a complete structure of claims as described in Allen and Gale (2000).

[19]The concentration on the interbank market increased over the last decade. As far as interbank activities are concerned, the Herfindahl index currently exceeds 0.25, while the market share of the five main players reaches about 90 percent.

size and be internationally less known to tap into the international interbank markets. This would be in line with one of the scenarios presented in Freixas and Holthausen (2005), where large banks with a good international reputation act as correspondent banks for their domestic peers in order to overcome asymmetric information problems.

The few interbank positions between G2–G5 banks, combined with their decreasing share of international financing, suggest that large banks (G1) tend to operate as money centers à la Freixas, Parigi, and Rochet (2000). One important difference in relation to their structure is that several money centers would be linked together, as reflected by the substantial position between the G1 banks.[20] Thus, each large bank tends to function as a money center connected to the other money centers. The Belgian interbank market would thus be characterized by a multiple-money-center structure versus the single money center of Freixas, Parigi, and Rochet (2000).

4. Simulation Results

This section presents the results of the simulations. Section 4.1 discusses the impact of both domestic and foreign contagion in the simulation for 2002:Q4. In section 4.2, the evolution of contagion risk over time is investigated using the algorithm with standard assumptions, such as described in section 3 (4.2.1), but also with additional assumptions aiming at endogenizing the LGD (4.2.2) and aiming at modifying players' behavior as robustness tests (4.2.3).

4.1 Simulations for 2002:Q4: Domestic and Foreign Contagion

Table 4 presents the results of the contagion exercises. Results are reported for five different LGD rates (first column). The second column gives the number of scenarios that generate contagion. The third column presents the median scenario. The median scenario

[20] In unreported data, we find that large banks hold cross-deposits in other large banks.

gives the median value of the percentage of total banking assets represented by banks losing their tier 1 capital, across all of the scenarios where contagion occurs. The two following columns provide information about the state of the banking system in the next-to-worst-case scenario and in the WCS, respectively. For the latter, we display the percentage of assets represented by, and the number of, failing banks and banks losing, respectively, between 100 percent and 70 percent, between 70 percent and 40 percent, between 40 percent and 10 percent, or less than 10 percent of their tier 1 capital. Finally, the last column presents an indicator of risk associated with the "domino" generating the WCS—namely, the rating of the first domino. Since few Belgian banks are publicly listed, neither a rating nor any other market-based indicator is available for a large number of Belgian banks.[21]

Panel A of table 4 reports the result of the simulations for *domestic contagion*, i.e., where contagion is triggered by exposures toward a Belgian bank. In December 2002, there were sixty-five banks incorporated in Belgium, i.e., sixty-five potential sources of domestic contagion. The frequency of domestic contagion occurring is limited. Under the assumption of 100 percent LGD, only four out of these sixty-five banks' defaults cause the failure of at least another Belgian bank. The knock-on effects are also limited. In the median scenarios, the percentages of assets represented by banks losing their tier 1 capital are extremely low. In the WCS, which is always caused by the default of a large bank, simulations show that banks that would lose their tier 1 capital as a result of the interbank defaults never represent more than 3.8 percent of the total assets of Belgian banks. Thus, the default of a Belgian bank in the interbank market does not cause a large Belgian bank to lose its entire tier 1 capital.

[21] Accounting risk measures for Belgian banks, such as the level of tier 1 capital of the domino generating the WCS (as a percentage of its total assets) or the level of its losses for bad loans (as a percentage of its commercial loans), are imperfect measures of risk, as there could be specific reasons, not necessarily linked to risks, justifying special levels for these ratios for a given bank (e.g., a large diversified bank may have a lower capital ratio). Similarly, an apparently sound bank may fail because of fraud, risk concentration, etc. Since presenting such indicators of risk could be misleading, we prefer to present no risk indicator for Belgian banks.

Table 4. Contagion Exercise 2002:Q4

LGD (%)	Number of Scenarios Where Contagion Occurs	Median Scenario Assuming Contagion. Percentages of Balance Sheet Assets Represented by Failing Banks (Excluding Assets of "First Domino")	Next-to-Worst-Case Scenario		Worst-Case Scenario (Excluding First Domino)										
			Banks Failing		Banks Failing		Banks Losing 100%–70% of Tier 1 Capital		Banks Losing 70%–40% of Tier 1 Capital		Banks Losing 40%–10% of Tier 1 Capital		Banks Losing Less Than 10% of Tier 1 Capital		Rating of the First Domino
			% Balance Sheet Assets	# of Banks	% Balance Sheet Assets	# of Banks	% Balance Sheet Assets	# of Banks	% Balance Sheet Assets	# of Banks	% Balance Sheet Assets	# of Banks	% Balance Sheet Assets	# of Banks	
A. Domestic Exposures															
100	4	3.33%	3.75%	15	3.79%	17	0.09%	3	53.67%	17	2.29%	12	40.17%	16	n.a.
80	4	2.13%	3.75%	14	3.75%	15	0.03%	≤2	0.94%	9	55.01%	21	40.27%	18	n.a.
60	4	1.73%	3.04%	9	3.33%	11	0.42%	4	0.12%	5	55.67%	25	40.46%	20	n.a.
40	2	2.98%	2.91%	5	3.04%	9	0.29%	≤2	0.45%	6	55.23%	25	40.98%	23	n.a.
20	2	0.50%	0.50%	3	0.50%	3	0.00%	≤2	2.54%	6	1.31%	12	95.66%	44	n.a.

(continued)

Table 4 (continued). Contagion Exercise 2002:Q4

LGD (%)	Number of Scenarios Where Contagion Occurs	Median Scenario Assuming Contagion. Percentages of Balance Sheet Assets Represented by Failing Banks (Excluding Assets of "First Domino")	Next-to-Worst-Case Scenario		Worst-Case Scenario (Excluding First Domino)										
			Banks Failing		Banks Failing		Banks Losing 100%–70% of Tier 1 Capital		Banks Losing 70%–40% of Tier 1 Capital		Banks Losing 40%–10% of Tier 1 Capital		Banks Losing Less Than 10% of Tier 1 Capital		Rating of the First Domino
			% Balance Sheet Assets	# of Banks	% Balance Sheet Assets	# of Banks	% Balance Sheet Assets	# of Banks	% Balance Sheet Assets	# of Banks	% Balance Sheet Assets	# of Banks	% Balance Sheet Assets	# of Banks	
B. Foreign Exposures															
100	13	0.07%	20.01%	0.07	20.01%	7	0.00%	≤2	1.02%	5	67.36%	8	11.61%	45	AA−
80	9	0.04%	0.29%	≤2	19.97%	6	0.04%	≤2	0.44%	3	32.34%	6	47.21%	49	AA+
60	8	0.04%	0.08%	≤2	18.15%	4	1.82%	≤2	0.04%	≤2	32.78%	9	47.21%	49	AA+
40	3	0.08%	0.08%	≤2	18.08%	≤2	0.04%	≤2	1.89%	4	20.22%	7	59.77%	51	AA+
20	1	0.08%	0.00%	≤2	0.08%	≤2	0.00%	≤2	0.00%	≤2	0.00%	≤2	99.92%	64	A

Note: The table presents the results of the contagion exercises for December 2002. Results are reported for five different LGDs. The second column gives the number of scenarios that generate contagion. The third column presents the median scenario. The median scenario gives the median value, across all of the scenarios where contagion occurs, of the percentage of total banking assets represented by banks losing their tier 1 capital. The remaining columns provide some statistics on the state of the banking system in the next-to-worst-case and worst-case scenarios. The table presents the percentage of assets represented by, and the number of failing banks and banks losing, respectively, between 100% and 70%, between 70% and 40%, between 40% and 10%, or less than 10% of their tier 1 capital. Cells with two or fewer banks are marked "≤ 2" in order to make single bank identification impossible. The last column presents the rating of the first domino in the WCS. Panel A presents the results of the contagion exercises assuming that the first defaulter is a Belgian bank. It is based on a matrix of bilateral exposures estimated with the aggregate exposures technique. Each line is based on 65 different scenarios (i.e., the individual failure of each of the sixty-five Belgian banks). Panel B, simulating the default of a foreign bank, is based on a matrix of bilateral exposure estimated with the large exposures technique. It is based on 135 different scenarios.

In addition, losses decrease in parallel with the LGD.[22] Although the losses in the next-to-worst-case scenario are lower, they remain very close to the WCS outcome.

As results are very similar to the results of the aggregate exposures technique, and for the sake of brevity, we do not report the results based on the large exposures and on the mixed techniques.[23] This comparability across techniques validates our use of the aggregate exposures technique for the estimation of contagion risk over time.[24]

Panel B of table 4 displays the results for *foreign contagion*. We identify 135 foreign banking counterparts for Belgian banks. For a 100 percent LGD, the default of 1 large foreign bank can lead to

[22]The statistical estimation of an LGD for Belgian banks is very difficult, since fortunately very few Belgian banks have failed in the last decades. Moreover, actual losses on a defaulting bank can prove very complicated to calculate, since they depend on the time horizon chosen. Altman and Kishore (1996) estimate average recovery rates on defaulting bonds of financial institutions (for the period 1978–95) to be about 36 percent. However, recovery rates vary by type of institution, from 68 percent for mortgage banks to 9 percent for savings institutions. Moreover, the LGD for bonds is probably very different from the LGD for comparable loans (which in our case comprise secured and unsecured assets). James (1991) estimates that losses average 30 percent of the failed bank's assets and that the direct expenses associated with bank closures average 10 percent of assets, making a total of about 40 percent. Seeing that more than 50 percent of interbank loans granted by Belgian banks are secured, it may therefore be realistic to assume a recovery rate of somewhere between 60 and 80 percent (i.e., an LGD between 40 and 20 percent). On the other hand, as domino effects may be considered instantaneous, one could also argue that the time pattern of recovery does not matter and that an LGD of 100 percent should be used to simulate liquidity shocks. Yet the time pattern of recovery may matter, depending on the maturity of the liabilities.

[23]They are, however, available on request.

[24]In a recent paper, Mistrulli (2005) compares the estimated and observed large exposures techniques for Italy and finds that they may differ depending on the level of LGD. In particular, he finds that the observed bilateral exposures generate higher contagion (as a share of total assets) for low LGDs, whereas the opposite holds for large LGDs. In general, it is unclear whether using estimated bilateral exposures leads to overestimation or underestimation. This should, however, not influence our results under the assumption that the potential biases remain constant over time. Note in addition that van Lelyveld and Liedorp (2006) conclude that "the entropy estimation using large exposure data as applied in many previous papers gives an adequate approximation of the actual linkages between banks. Hence this methodology does not seem to introduce a bias." However, they also find that entropy maximization leads to an overestimation of contagion risk.

the failure of 7 Belgian banks whose assets account for 20 percent of total Belgian bank assets. These numbers are considerably higher than those of our simulations with Belgian banks as first domino. The results for the WCS also indicate that, even for an LGD of 40 percent, the default of a foreign bank can have a significant impact on Belgian banks. Note, however, that large differences exist between the median and the worst-case scenarios. For an LGD of 100 percent, only three of the thirteen simulations that involved contagion entailed the failure of banks representing at least 10 percent of the total assets of the Belgian banking system. The next-to-worst-case scenario shows that, for reasonable LGD, contagion is not likely.[25] In addition, all of the foreign banks representing the first domino in the WCS are European banks, and all rank as investment grade, which suggests that actual interbank defaults by these banks, although possible, are not frequent.

Our contagion analysis cannot incorporate indirect effects of the failure of foreign banks, which may be important (i.e., failure of other foreign banks caused by the failure of a given foreign bank). One way to proxy for indirect effects is to simulate the impact of the combined default of several foreign banks coming from the same country. Belgian banks provide a breakdown of their aggregate interbank exposures (the fa_i) by EU countries. The data are available for the last five years. We make the assumption that x percent of the interbank exposures of Belgian banks to banks in a particular EU country are unrecoverable. We use the propagation mechanism explained earlier to measure the impact on the Belgian system. Unreported results show that with the exception of France, the Netherlands, and the United Kingdom, simulations involving defaults on other countries' interbank loans (including Germany and Luxembourg) do not result in significant contagion in the Belgian banking sector at the end of 2002.[26] For example, for an LGD of

[25]This finding was confirmed afterward by van Lelyveld and Liedorp (2006), who found that below an LGD of 75 percent, domestic and foreign contagion was unlikely.

[26]Although the results are quite stable over 1999–2002 (the period over which data are available), with France and the United Kingdom often representing major risks, other neighboring countries sometimes show a higher potential for contagion. These jumps in simulated country impact probably reflect larger interbank positions with those countries. We do not observe any significant increase

100 percent, a simulation of the failure of all German banks shows that Belgian banks losing their entire tier 1 capital represent less than 1 percent of total Belgian bank assets. When we use a lower LGD, only bank defaults in the United Kingdom would yield significant levels of contagion in Belgium. This in fact reflects the United Kingdom's role as a money center and the importance of UK banks as counterparts of Belgian and other European banks. Manna (2004) finds that London is indeed an important nexus for all EMU banks, as UK banks account for more than one-third of their cross-border interbank deposits.

4.2 Evolution over Time: Simulations of Domestic Contagion Based on Aggregate Exposures

4.2.1 Baseline Case

The simulations used to study the evolution of the domestic contagion risk over time cover the period 1992:Q4–2002:Q4. Figure 1 shows the behavior of the WCS over the period 1993–2002 for twenty different LGDs ranging from 5 percent to 100 percent, in steps of 5 percent. Thus, for each quarter, the number of scenarios tested amounts to twenty times the number of banks (between 65 and 112).[27]

Figure 1 shows that, over the last decade, the WCS has been subject to three major evolutions. Between 1993 and 1997, the WCS consistently worsens. Between 1997 and 1999, the WCS affects less of Belgian banking assets; i.e., there is a steep decrease between 1997 and 1999. Finally, between 1999 and 2002, the surface flattens and contagion remains limited, even with high LGDs. Thus, the degree of contagion generated in simulations with data for the last quarter of 2002 appears to be at a record low. These trends are particularly striking for an LGD of 60 percent. In this case, the percentage of total banking assets affected by contagion, excluding the first

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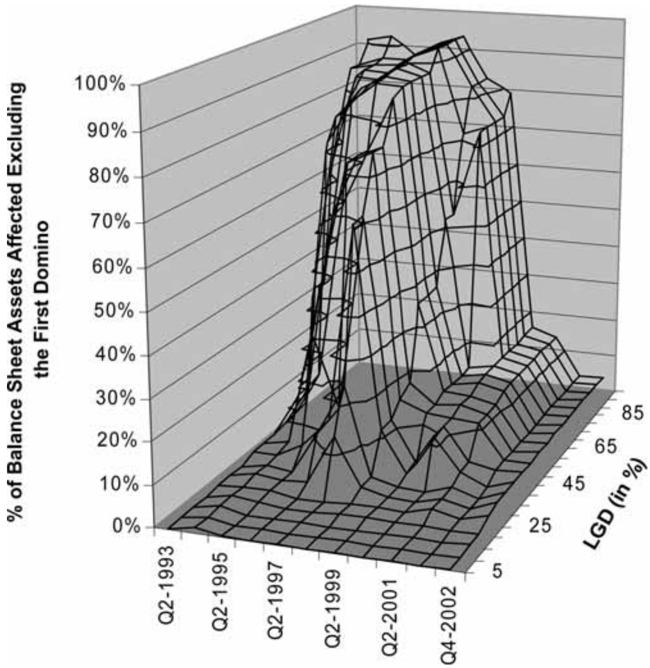
in the cross-border contagion risk over 1999–2002. However, such an increase may have taken place earlier, in years in which internationalization of interbank exposures of Belgian banks substantially increased.

[27]For presentation purposes, figure 1 presents the results for Q2 only. Tests reported in subsection 5 show that the trends in the WCS presented in figure 1 are not sensitive to the quarter chosen.

Figure 1. Contagion Effect—Worst-Case Scenario: 1993–2002



Note: The graph presents the evolution of the worst-case scenario for twenty different LGDs over time, from 1993:Q2 to 2002:Q4. LGDs are shown as percentages. The results are based on contagion exercises using matrices of bilateral exposures estimated with the aggregate exposures technique.

domino, varies over the period from 86 percent to 3 percent. We also find that (i) the next-to-worst-case scenario is affected by the same structural changes as the WCS and (ii) the level of the next-to-worst-case scenario is similar to the level of the WCS (unreported).[28]

The WCS is frequently—but not always—generated by the default of a large bank. Actually, an analysis of banks initiating

[28] A potential concern is that the WCS is initiated by sound banks in a particular period and not-very-sound ones in other periods. We find that the bank triggering the WCS persistently belongs to the lowest quartile in terms of capitalization (unreported). This suggests that if the capital ratio is a good proxy for the likelihood of failure, the likelihood of failure of the bank initiating the WCS remained quite constant over time.

the WCS shows that different banks cause the WCS in different years, although some banks tend to do so more often than others. For instance, large banks generate the WCS more often than small banks. In addition, banks initiating the WCS are not only different from year to year but also, to a certain extent, within a given year, depending on the applied LGD. We also find that the default of a large bank is always directly preceded either by the default of another large bank or by the default of a medium-sized bank. Indeed, the tier 1 capital of large banks is never totally absorbed by the combined default of several small banks. However, the default of a small bank may trigger the failure of several small and medium-sized banks and, in turn, of a large bank. Note also that in some cases, no large bank fails, even in the WCS.[29]

The results on domestic contagion suggest that contagion risk in Belgium has evolved over time. Any attempt to compare our results with the results of simulations for other countries must therefore take the time dimension into consideration. A comparison with studies using the same methodology indicates that the simulated failure of a Belgian bank in December 1998 produced smaller contagion effects than the simulated failure of a German bank in the same period, at least for a high LGD (Upper and Worms 2004). Results for the United Kingdom (Wells 2004), which uses data for end 2000, show that the Belgian simulations produced a greater impact of contagion at the same time period. However, contagion occurred in a higher proportion of cases in the United Kingdom. Finally, the simulated impact of contagion for 2002:Q4 is similar in Belgium and in the Netherlands (van Lelyveld and Liedorp 2006). As results for Belgium are broadly similar to results for Germany, the Netherlands, and the United Kingdom at similar time periods, it is impossible to know whether dissimilarities between Germany, the Netherlands, and the United Kingdom are due to structural differences or to general time trends affecting several European countries. We investigate the determinants of domestic contagion in Belgium in section 5.

[29]Since the WCS is a very extreme outcome, we investigate, in unreported exercises, other measures of contagion, i.e., the variations in the percentage of banks intitiating contagion and the propagation mechanisms of contagion (number of rounds). The evolution over time of these indicators is similar to the evolution of the WCS.

4.2.2 Endogenous LGD

Our baseline simulations assume a fixed LGD for all banks. It is not obvious a priori that endogenizing the LGD would deliver additional results, especially as we already test very extreme LGD, ranging from 100 percent to 5 percent. Surprisingly, however, there are some indications that it may do so.

We take two complementary steps to endogenize the LGD. In both steps, the core of the endogenization process is that the LGD of a given bank depends upon the LGD of all the other banks to which it is linked. In a first step, we endogenize the LGD on interbank claims only and apply an exogenous LGD on other "remaining assets."[30] In a second step, we add some admittedly ad hoc assumptions to endogenize the recovery rate on the other remaining assets as well. The LGD is calculated for failing banks only, at each round of the algorithm, in order to assess the value of their remaining assets. The calculation of the LGD for a given bank does not determine whether a bank is bankrupted. It only assesses the value of its assets once it has been declared bankrupted, i.e., the value of the bankrupted bank for its creditors.

We start with the endogenization of the LGD on interbank claims. The LGD on interbank claims of bank i is defined as

$$\theta_i = \left[\frac{\sum_j(\theta_j x_{ij}) + \textit{remaining assets} * \textit{LGDs remaining assets}}{\textit{Total Assets} - \textit{shareholders' equity}}\right],$$

where θ_i is the LGD of bank i, x_{ij} is the gross interbank exposure of bank i to bank j, *remaining assets* represents all the other remaining assets of bank i, and *LGDs remaining assets* stands for the loss rate that bank i has to bear on its assets because of its default. Solving the system of equations for all failed banks simultaneously gives a different endogenous LGD for each failed bank.

We first distinguish between liquid and illiquid assets (partial endogenization). We assume a 0 percent LGD on liquid assets. We simulate different LGDs on the remaining illiquid assets. All simulations assume a 60 percent LGD on the first domino. Results are

[30] Note that by LGD on remaining assets, we mean the loss given the default of the bank to which these assets belong. The assets themselves, however, have not defaulted.

reported in panel A.1. of table 5. We present the results for two polar cases in which the LGD on illiquid assets is, respectively, equal to 100 percent and 0 percent, as well as for an intermediate LGD of 60 percent. The latter can be compared to the baseline simulation, which is based on a fixed 60 percent LGD. For each assumed LGD on illiquid assets, the first line presents the WCS, while the second line gives the average implied LGD in the WCS.

We conclude two things from the simulations. Firstly, although the level of and changes in the WCS are broadly similar to the results of simulations that assume a fixed LGD for all assets, the average implied LGD varies substantially within a given year. For instance, in 2002, the minimum LGD—assuming a 100 percent LGD on illiquid assets—was 8.8 percent, while its maximum was 76.5 percent. Thus, endogenizing only the LGD on interbank exposures already suffices to introduce a large heterogeneity between banks, even though it does not affect the general trends. Secondly, although the average implied LGD varies over time, we do not observe a strict correlation between the LGD and the WCS. Because the LGD interacts with other dimensions of the market structure, a higher average LGD does not necessarily generate a higher WCS.

Next, we try to endogenize the LGD on the "remaining assets" as well (labeled "Complete Endogenization"). Besides interbank loans, we distinguish five categories of assets:

(i) Liquid Assets: We assume a 100 percent recovery rate.

(ii) Customer Loans: We assume that the loss rate on a bank's loan portfolio is equal to the average residual maturity of its loan portfolio times its annual loan-loss provisions (as a percentage of its total loans). This amounts to 4 percent on average in 2002. The minimum is equal to 0 percent and the maximum to 35 percent.[31]

[31] As this is a broad measure of the expected losses of the loan portfolio in a going concern, it does not take into account losses resulting from the loss of information that could arise when the loan portfolio is sold. In an unreported test, we assume that the loss on the portfolio is an average between 30 percent and our estimates. The average LGD of commercial loans is indeed approximately 30 percent (see, e.g., Bank for International Settlements 2005). Remember, however, that in our simulations, loans are not in default. This does not qualitatively affect the results.

Table 5. Alternative Scenarios

	1993	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**
Baseline	3.3%	14.1%	58.5%	73.0%	86.4%	35.7%	13.6%	13.2%	11.5%	2.9%
A. Endogenous LGD										
A.1. Partial Endogenization										
LGD Illiquid 100%	3.8%	76.8%	85.9%	90.9%	91.9%	52.0%	13.6%	14.9%	13.3%	2.9%
Average LGD	*64.8%*	*82.5%*	*85.9%*	*85.0%*	*90.3%*	*86.6%*	*71.0%*	*78.5%*	*76.5%*	*59.3%*
LGD Illiquid 60%	2.5%	13.1%	54.3%	72.9%	75.6%	17.1%	12.4%	13.2%	11.5%	2.8%
Average LGD	*33.5%*	*26.5%*	*27.3%*	*37.9%*	*49.7%*	*43.9%*	*38.1%*	*43.9%*	*38.6%*	*41.0%*
LGD Illiquid 0%	1.9%	1.8%	8.5%	4.5%	10.7%	9.0%	11.6%	9.5%	10.8%	2.8%
Average LGD	*16.2%*	*20.2%*	*9.8%*	*10.0%*	*13.5%*	*14.4%*	*9.0%*	*10.1%*	*9.1%*	*8.7%*
A.2. Complete Endogenization										
LGD First Domino 100%	12.2%	12.5%	32.1%	29.4%	18.7%	15.3%	12.0%	29.1%	12.5%	0.8%
Average LGD	*19.2%*	*19.8%*	*22.1%*	*18.7%*	*20.1%*	*20.2%*	*19.6%*	*21.5%*	*20.4%*	*16.9%*
LGD First Domino 60%	6.2%	6.9%	13.5%	11.6%	17.0%	14.2%	10.4%	9.6%	10.8%	0.6%
Average LGD	*18.4%*	*16.3%*	*18.6%*	*16.7%*	*17.9%*	*18.2%*	*18.2%*	*18.6%*	*18.7%*	*17.9%*
LGD First Domino 5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Average LGD	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*	*NA*

(continued)

Table 5 (continued). Alternative Scenarios

	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
Baseline	3.3%	14.1%	58.5%	73.0%	86.4%	35.7%	13.6%	13.2%	11.5%	2.9%
B. Players' Behavior										
Anticipation	NA	1.9%	29.6%	11.3%	55.9%	8.9%	3.1%	9.7%	8.6%	0.4%
TBTF	3.3%	4.2%	41.2%	10.2%	55.0%	2.4%	3.9%	2.4%	4.1%	0.0%
Coordination	3.3%	14.1%	58.5%	0.0%	0.0%	0.0%	13.6%	13.2%	11.5%	2.9%
Netting	0.7%	2.0%	1.1%	0.6%	0.6%	0.6%	3.3%	1.0%	4.1%	2.8%
C. Correlated Shocks										
Macro Shock	3.7%	75.9%	84.9%	88.6%	87.8%	35.9%	13.6%	14.9%	13.3%	2.9%
Two Failures	31.6%	72.5%	83.1%	84.8%	88.3%	36.1%	30.9%	14.9%	13.6%	3.4%
Three Failures	45.0%	74.0%	83.4%	85.3%	88.5%	55.7%	49.2%	14.9%	13.6%	3.7%
Four Failures	45.4%	75.6%	85.1%	85.3%	88.9%	70.3%	49.2%	14.9%	13.6%	3.7%

Note: Figures are for Q2 of each year. The table presents the evolution of the WCS under alternative assumptions. In the baseline case, a fixed LGD of 60 percent is assumed. Panel A presents results of simulation when the LGD is endogenous. For each assumption, we present both the WCS in the first line and the average implied LGD in the second line. In panel B, assumptions relating to banks' anticipation, too-big-to-fail mechanisms, coordination mechanisms, and netting are modified. In panel C, macro shocks are simulated.

(iii) Government Bonds: Similarly to Cifuentes, Ferrucci, and Shin (2005), we assume that failed banks liquidate their government bonds portfolio and that their value is inversely proportional to the supply of government bonds in the market. We apply a haircut of 1 percent on the portfolio each time the cumulated sales of government bonds by failed banks amount to 10 percent of the market, defined as the sum of government bonds held by Belgian banks. To ensure comparability, we assume that banks do not mark to market their bonds portfolio so that sound banks are not affected by this decrease. Hence, in our model, government bonds do not constitute an additional direct contagion channel.

(iv) Intangible Assets: We assume an LGD of 100 percent on intangible assets.

(v) Other Assets: We apply an arbitrary LGD of 30 percent on all the remaining assets. The latter is based on James (1991), who finds that loss on assets of failed banks amounts to 30 percent on average. These assets represent, on average, 17 percent of total assets in 2002.

In addition, we apply a fixed cost of bankruptcy amounting to 10 percent of total assets (see James 1991). We also take into account two kinds of privileged creditors—namely, the state and the employees of the bank. By subtracting claims of the latter from both the numerator and the denominator of the LGD ratio, we make the assumption that they are first served in the liquidation process. This increases the LGD applied on interbank claims. As we do not have any other information regarding the seniority of the remaining claims, we assume that the proceeds of the liquidation are shared proportionally.

In panel A.2. of table 5, we present the results using three different levels for the exogenous LGD applied to the first domino. Endogenizing the LGD decreases substantially the level of contagion. Yet, we still observe the same trend over time, with very low contagion indicators in 2002. The average implied LGD amounts to 19 percent. As indicated in section 4.1, this seems to be reasonable, although maybe conservative. A striking result is that the simulations implying an average endogenous LGD of around 20 percent result in more contagion than those with a fixed LGD of 20 percent, in which contagion was inexistent. This is partly due to two effects. Firstly, in two out of the three cases, the LGD of the first domino is assumed to be higher than 20 percent. Secondly, precisely because the LGD is endogenous, we observe heterogeneous LGD with sometimes high levels of losses, helping to propagate contagion. Thus, it is likely that the propagation of contagion is not only determined by the pattern of links defining the market structure but also by the relative strength of each counterpart to which banks are linked.

4.2.3 Robustness

In this subsection, we present some additional robustness checks related to the *behavior of market participants and market rules* and possible *correlated shocks*. The first one relates to *banks' expectations*. Banks may be able to (partly) *anticipate* a bank failure. In the simulation, we assume that banks are able to withdraw the short-term loans granted to all failed banks before the failure occurs. The residual maturity of more than 35 percent of interbank loans granted by Belgian banks at the end of 2002 does not exceed eight days. As we have information on each bank's aggregate short-term bilateral positions only, we assume that the maturity structure of interbank loans granted to each counterpart of a given bank is the same. The results are displayed in the first row of panel B of table 5. Although the WCS is lower than in the baseline case, its evolution over time remains very similar to the evolution of the WCS in the baseline case.

A second assumption relates to the potential presence of a *safety net*. Although interbank loans are not covered by explicit deposit insurance, issues like being "too big to fail" (TBTF) may introduce implicit deposit insurance. To proxy for this possibility, we assume that large Belgian banks would not be allowed to fail.[32] These banks would thus not create initial and additional contagion and could

[32]We define large banks as banks representing more than 10 percent of the total assets of Belgian banks. The TBTF policy is a working assumption made by the authors in order to test the sensitivity of the results. There is absolutely no certainty regarding the effective application of such a threshold or such a policy in case of a large bank failure.

even stop it. The results are displayed in the second row of panel B. Unsurprisingly, a TBTF policy reduces the WCS. Remarkably, however, our simulations indicate that contagion still propagates in 1995 and 1997, despite the safety net. In these two years, contagion effects are caused, in the first instance, by the successive failure of many small and medium-sized banks.

In the baseline simulations, banks do not have the opportunity to *coordinate* in order to avoid liquidation. Leitner (2004) develops a model in which liquid banks bail out illiquid banks because of the threat of contagion. To capture coordination, we will assume that banks may "merge" to avoid failure.[33] An important objection to this procedure is that, in reality, mergers are not observed at such short notice. However, one can view these "mergers" as alternatives to the bailout in Leitner (2004). We address coordination by starting from the WCS in the baseline case. We assume that neither banks nor the regulator know the full matrix of bilateral exposures. Banks only know their direct counterparts. After the initial shock on the first domino, banks observe their losses. At that moment, we assume that banks have time to start "merger discussions" with other banks in order to avoid liquidation.[34] Other banks will accept such a merger if, thanks to this operation, they avoid their own failure. As the matrix of bilateral exposures is unknown to participants, we assume that mergers are only possible between banks failing in the "second round" (subsequently to the first domino) and their direct counterparts, i.e., banks failing in the "third round."

[33]Suppose there are three banks: bank A, bank B (with a tier 1 capital of 2.4 and an exposure of 5 to bank A), and bank C (with a tier 1 capital of 1.9 and an exposure of 4 to bank B). The first domino is bank A. Merging bank B and bank C would give a bank with an exposure of 5 to bank A and a capital of 4.3. Assuming a 100 percent LGD, the failure of bank A triggers the failure of bank B, and the failure of bank B triggers the failure of bank C. Merging both banks would not have an impact on contagion, as the new bank would not be resilient to a loss of 5. With a 50 percent LGD, the failure of bank A triggers the failure of bank B and indirectly of bank C if banks do not coordinate. The merged entity, however, would be able to resist to a shock of 2.5, as it would present a tier 1 capital of 4.3. In this case, merging both banks is optimal, as it allows avoiding domino effects.

[34]Such a period could be due, for instance, to a lag between the failure of the first domino and the realization of losses, due to an arbitrary decision of the regulator, or due to bankruptcy procedures such as chapter 11.

We simulate the consequences of each possible merger involving one or more banks that would have failed in the second round and one or more banks that would have failed in the third round.[35] We identify the merger that minimizes the assets of the failing banks. The third row of panel B of table 5 presents the results assuming coordination. We observe that in some cases coordination would prevent contagion from taking place. Successful mergers involve relatively small banks, as the implied increase in the Herfindahl index never exceeds 58 points. This happens exactly in periods when the WCS affected a large proportion of total banking assets and when contagion was slow to propagate, affecting firstly small banks (i.e., 1996–98).

The baseline simulations started from a matrix of gross bilateral exposures. To the extent that legislation allows for bilateral setoff—*netting*—of interbank positions,[36] we performed contagion simulations based on "netted" matrices of domestic bilateral exposures (i.e., $x_{ij} - x_{ji}$). These simulations assume that all the interbank claims are covered by bilateral netting agreements. The results are displayed in the fourth row of panel B of table 5. Netting substantially reduces contagion toward very low levels and this for all years.[37] Furthermore, the WCS assuming netting becomes flat over the entire period 1992–2002, in contrast to the baseline case. However, our distributional assumption may partly drive the results, as

[35]The total number of mergers involving at least one bank that failed in the second round and one bank that failed in the third round is equal to the number of possible combinations of banks that failed in the second round times the number of possible combinations of banks that failed in the third round. For instance, in 1997, in the WCS, two banks fail in the second round and one in the third round. In total, there are thus three different possible mergers. The total number of potential mergers ranges from 3 in 1997 to 65,025 in 1999.

[36]The European Directive 2002/47/EC on financial collateral arrangements obliges all EU member states to recognize closeout netting arrangements. In the Belgian law, netting arrangements are accepted provided they have been concluded before the opening of the insolvency procedure. In case of bankruptcy, a claim that is not protected by a netting agreement is generally treated as a normal claim and is reimbursed, proportionally to the value of recovered assets, after privileged creditors have been served.

[37]Note, however, that netting may also present some drawbacks. For instance, Emmons (1995) shows that netting of interbank claims shifts the bank default risk away from interbank claimants toward nonbank creditors; i.e., the risk is transferred to the banks' creditors who are not included in the netting agreement.

we assume a complete matrix of bilateral exposures. In other words, we assume that each bank is both debtor and creditor of all the other Belgian banks. Bilateral netting with a given bank becomes effective once this bank is both debtor and creditor, which in practice may represent a limited number of cases.

While our baseline simulations assumed idiosyncratic initial shocks, the initial shock could also be common to several banks or the whole banking system. We address the impact of correlated shocks in two complementary ways. First, we simulate a macro shock in combination with an idiosyncratic shock. In order to simulate a macro shock, we assume that each bank loses 10 percent of its tier 1 capital. The results are displayed in the first row of panel C, table 5. The WCS remains relatively similar over the entire 1993–2002 period. Second, we simulate the consequences of multiple simultaneous failures (two, three, or four banks). The WCS results of each possible joint default of two, three, or four banks are shown in rows 2–4 of panel B. Although allowing for multiple failures increases the level of the WCS, its level remains very low in 2002.

5. Interbank Market Structure and Domestic Contagion

Because nearly all our contagion indicators tend to follow a regular time pattern, they are more likely to be caused by trends in the organization of the interbank market than by exceptional events. For instance, although the Russian crisis as well as the LTCM failure could have influenced the pattern of contagion in 1997, it is difficult to ascribe the whole evolution of contagion indicators over time to these two events. Rather, the combination of two main trends in the banking landscape could explain the changes in our simulation results over the period 1993–2002. First, the estimated matrix of bilateral exposures went through some structural changes. As described earlier, large banks now seem to show an increased tendency to operate as multiple money centers. Freixas, Parigi, and Rochet (2000) show that, for certain parameter values, a single-money-center structure could reduce the contagion risk, as banks at the periphery no longer trigger contagion. A multiple-money-center structure will also reduce contagion provided the exposures between banks at the center are such that they do not propagate contagion.[38] Second, following consolidation and international financial integration, (large) Belgian banks have further increased their cross-border interbank exposures.[39] Consequently, the bilateral interbank exposures between the large Belgian banks could be such that they would no longer propagate contagion.

In order to test for the respective impact of interbank market structure and internationalization on contagion risk, we estimate OLS regression models of the form

$$WCS_t = \beta_0 + \beta_1 LB_t + \beta_2 DOM_t + \beta_3 CAPDUMMY_t * LB_t + \beta_4 CAP_t + \sum_{i=5}^{9} \beta_i \, Control\ variable_{it} + u_t$$

for WCS, calculated employing several LGDs and using quarterly data from 1992:Q4 to 2002:Q4.[40]

Table 6 provides definitions and descriptive statistics for the variables employed in the regression.[41] *LB* captures the interbank market structure. It measures the domestic interbank exposures of large banks as a fraction of the total domestic exposures. In a money center, *LB* should be equal to 1 since small banks are not linked together and all interbank transactions transit through the money center. In a complete structure, we expect *LB* to be smaller, as small banks have

[38] Of course, the reverse causation, although unlikely, cannot be entirely ruled out. Banks may adopt a given market structure in reaction to a perceived increase in the risk of contagion. However, we believe that the interbank market structure is determined by business rationales rather than by systemic concerns.

[39] Although the share of international interbank loans has always been high for large banks, it has increased over the last decade. In December 1992, the interbank loans granted by large Belgian banks to foreign banks accounted for 79 percent of total interbank loans. This proportion reached 89 percent at the end of 2002.

[40] In order to isolate contagion from other simulated effects, we use the baseline WCS.

[41] For each variable, we performed Phillips-Perron tests to test for unit roots. The series appear stationary. We can reject the hypothesis of a unit root at a 10 percent level for all the dependent and explanatory variables, with exception of the WCS for an LGD of 80 percent and 60 percent, and *DOM* and *CAP*. Although we cannot formally reject the null hypothesis of unit roots for these series, there is a strong economic rationale to reject it, as they are, by construction, constrained between 0 and 1.

direct links. *DOM* is a proxy for the degree of internationalization and is defined as the total domestic interbank exposure of Belgian banks as a fraction of their total interbank exposures. A ratio equal to 1 would represent a "closed" system, relying only on the domestic interbank market. A ratio equal to 0 would represent a fully internationalized system. Our regression analysis also contains some control variables. Two variables are included to control for bank-capital cyclical patterns. *CAPdummy* aims at identifying periods in which large banks are well capitalized. It is a dummy variable equal to 1

Table 6. Definition of Explanatory Variables

Variable	Definition	Rationale	Min	Max	Median
Dependent Variables					
WCS100	Worst-case scenario assuming a fixed LGD of 100%		0.033	0.964	0.874
WCS80	Worst-case scenario assuming a fixed LGD of 80%		0.032	0.931	0.747
WCS60	Worst-case scenario assuming a fixed LGD of 60%		0.009	0.918	0.158
Variables Capturing the Hypotheses					
LB	Domestic interbank exposures of/to large banks as a percentage of the total domestic exposures	Proxies for the type of interbank market structure. In a money center, this ratio should be equal to 1 since small banks are not linked together. To the extent that the structure moves to a complete structure, this ratio decreases.	0.636	0.941	0.700
DOM	Domestic interbank exposures as a percentage of the total interbank exposures	This ratio indicates the level of internationalization of interbank positions. A ratio equal to 1 would represent a "closed" system relying only on the domestic interbank market. A ratio equal to 0 would represent a fully internationalized system.	0.147	0.373	0.297

(continued)

Table 6 (continued). Definition of Explanatory Variables

Variable	Definition	Rationale	Min	Max	Median
Variables Capturing Other Structural Changes					
CAP	Nonweighted average of the ratio tier 1 capital of Belgian banks on assets of Belgian banks	A higher capitalization of banks should increase their resiliency to shocks and decrease indicators of contagion.	0.075	0.109	0.089
CAPdummy	Dummy variable equal to 1 when the tier 1 capital ratio of large banks exceeds its long-term average and 0 otherwise	Used in combination with *LB* as an interaction variable measuring to what extent the money centers need to be well capitalized to reduce contagion.	0	1	
Variables Capturing Macroeconomic Evolution					
GDP	Quarterly GDP growth	Banks' profits should increase when the GDP growth is high, as the quality of their assets improves.	−0.041	0.058	0.017
INT	Term spread of the interbank interest rate (Bibor before 1999 and Euribor from 1999 onward)	The term spread of the interbank interest rate represents the difference between the one-year and the one-month interbank interest rate. A high spread will constitute a positive environment for banks whose interbank liabilities are short term and whose interbank assets are long term (which is, to a certain extent, the position of Belgian banks). A low spread, on the other hand, will constitute a negative environment for these banks.	−0.016	0.019	−0.002
Other Control Variables					
Q2, Q3, Q4	Dummy variables identifying quarters	Control for seasonal effects			

Note: The table presents the variables used in the regression analysis. The first column gives the name of the variable, the second column gives its definition, and the third column gives the rationale for including each of the variables in the analysis. The remaining three columns give, respectively, the minimum, maximum, and median value over the observation period.

when the average tier 1 capital ratio of large banks exceeds the long-term average of the ratio and 0 otherwise. *CAPdummy* is used in interaction with *LB*. This interaction variable captures the extent to which a change in the structure, combined with a higher capitalization of money centers, effectively reduces contagion. We also control for the leverage of banks (*CAP*). In addition, we control for the macroeconomic environment with the GDP growth rate (*GDP*) and the term spread of the interbank interest rate (*INT*), defined as the spread between the one-year and the one-month interbank interest rate.[42] Finally, we also introduce quarterly dummies (*Q2, Q3, Q4*) to control for potential seasonal effects.

Table 7 displays the results of our regression analysis. The three panels report the results for the levels of LGD at 100 percent, 80 percent, and 60 percent, respectively.[43] For each LGD, *LB* and *DOM* are significantly different from 0, and both have the expected sign. That is, a move toward a money-center structure (an increase in *LB*) and a higher internationalization (decrease in *DOM*) reduces the WCS. For example, a 10 percent increase in *LB* would lead to a decrease of 23 percent, 29 percent, and 14 percent of the WCS for the 100 percent, 80 percent, and 60 percent LGD, respectively. Similarly, a 10 percent decrease in *DOM* would lead to a decrease in the WCS of 38 percent, 41 percent, and 23 percent for the 100 percent, 80 percent, and 60 percent LGD, respectively. However, in some regressions, coefficients of *LB* and *DOM* are not significant when entered jointly, pointing to potential multicollinearity problems.[44] Mistrulli (2005) uses simulations keeping the tier 1 capital-to-asset

[42]We control for macroeconomic conditions, as they might affect the ability/willingness to take or grant interbank loans and might influence the behavior of interbank players.

[43]The results using the 40 percent LGD and the 20 percent LGD are less significant. This is not too surprising, as changes over time in the WCS are much more important for an LGD of 100 percent than for an LGD of 20 percent, where little or no contagion at all is observed.

[44]The correlation between the variables *LB* and *DOM* is -0.76. This high negative correlation is not too surprising. Indeed, an increase in *LB* goes together with an increase in concentration as large banks become more important. In small countries, a higher concentration may lead to a higher degree of internationalization. Technically, the relatively high correlation might prevent us from obtaining statistically significant results when including these variables jointly in a regression framework.

Table 7. Regression Results for the Worst-Case Scenario

Intercept	*LB*	*DOM*	*LB* CAPdummy*	*CAP*	*GDP*	*INT*	R^2	*DW*
LGD 100%								
2.69 (6.66)***	−2.28 (−4.69)***			−3.41 (−0.58)	2.03 (0.87)	0.88 (0.10)	0.61	1.26
1.65 (5.91)***	−0.97 (−2.85)**		−0.58 (−7.61)***	−0.83 (−0.23)	−3.25 (−0.63)	−0.22 (−0.15)	0.86	2.82
−0.01 (−0.01)		3.80 (6.82)***		−4.26 (−0.96)	6.06 (0.92)	1.74 (0.89)	0.73	1.35
0.56 (0.96)	−0.89 (−1.76)*	3.02 (4.33)***		−0.69 (−0.15)	1.59 (0.84)	1.79 (0.26)	0.76	1.62
1.23 (2.69)**	−0.78 (−2.05)**	0.78 (1.14)	−0.51 (−5.13)***	−0.45 (−0.13)	−0.05 (−0.04)	−2.50 (−0.48)	0.87	2.72
LGD 80%								
3.23 (8.47)***	−2.87 (−6.27)***			−4.92 (−0.89)	−1.04 (−0.47)	−9.98 (−1.24)	0.73	1.04
2.41 (7.36)***	−1.84 (−4.62)***		−0.46 (−5.17)***	−2.87 (−0.69)	−13.26 (−2.19)**	−2.83 (−1.67)	0.85	2.17
0.30 (0.54)		4.10 (6.79)***		−9.15 (−1.90)*	−1.26 (−0.18)	−1.15 (−0.54)	0.75	1.24
1.36 (2.35)**	−1.65 (−3.33)***	2.66 (3.89)***		−2.52 (−0.54)	−1.42 (−0.77)	−9.18 (−1.37)	0.81	1.49
1.83 (3.44)***	−1.57 (−3.57)***	1.07 (1.35)	−0.36 (−3.14)***	−2.35 (−0.57)	−2.59 (−1.54)	−12.23 (−2.03)*	0.86	2.11

(continued)

Table 7 (continued). Regression Results for the Worst-Case Scenario

Intercept	*LB*	*DOM*	*LB* CAPdummy*	*CAP*	*GDP*	*INT*	R^2	*DW*
LGD 60%								
2.58 (6.09)***	−1.36 (−2.66)**			−13.33 (−2.17)**	0.74 (0.30)	−10.28 (−1.15)	0.59	1.09
2.50 (5.10)***	−1.27 (−2.12)**		−0.04 (−0.30)	−13.15 (−2.11)**	−10.57 (−1.16)	0.58 (0.23)	0.59	1.11
0.91 (1.52)		2.35 (3.58)***		−13.43 (−2.57)**	−7.48 (−0.96)	0.53 (0.23)	0.64	1.41
1.21 (1.67)	−0.46 (−0.74)	1.95 (2.28)**		−11.57 (−1.99)*	0.46 (0.20)	−9.70 (−1.15)	0.65	1.31
−0.32 (−0.72)	0.53 (1.44)	2.42 (3.64)***	0.26 (2.73)**	−8.69 (−2.51)**	3.39 (2.40)**	11.22 (2.22)**	0.54	1.53

Note: Dependent variable is the worst-case scenario, measured as the percentage of total assets accounted for by failed banks (*WCS*). Explanatory variables are *GDP*, *INT*, *CAP*, *LB*, *DOM*, *LB*CAPdummy*, and three dummy variables for the quarters (not reported). Definitions are provided in table 6. Each cell displays the t-statistic for the OLS coefficient. For each OLS estimation, the R and the Durbin-Watson (*DW*) are given. The sample comprises forty-one observations (one per quarter between 1992:Q4 and 2002:Q2). The first panel of the table assumes an LGD of 100 percent, the second panel an LGD of 80 percent, and the third panel an LGD of 60 percent. Significance level of the t-tests: (***) at the 1 percent level, (**) at the 5 percent level, and (*) at the 10 percent level.

ratio at the sample mean. He reports that contagion has increased by moving from a complete structure toward a multiple-money-center structure. His analysis, however, does not control for the documented decrease in the degree of internationalization. As the Italian interbank market has become more domestic over time—in contrast to many other European countries—this reduction in internationalization may actually have caused the greater domestic contagion. In addition, because he keeps the tier 1 capital-to-asset ratio at the sample mean, he may fail to capture changes in bank capitalization that would constitute responses to higher contagion risk.

In regressions where both *LB* and *LB*CAPdummy* are used, both are negative and statistically significant (except for the 60 percent LGD where *LB*CAPdummy* is negative but not significantly different from 0). The mitigation effect of money centers is thus reinforced when money centers are well capitalized. *CAP*, the proxy for the capitalization of the whole banking system, also has a negative coefficient and is economically relevant. However, its coefficient is only statistically significant when the LGD is not too high. Thus, during the periods in which banks were holding more capital, contagion was less likely for lower LGDs. The impact of capitalization is also economically relevant: based on the first regression for an LGD of 60 percent, an increase in *CAP* from its lowest level to its highest level (i.e., from 0,075 to 0,109) reduces the WCS by 45 percent. In most cases, the unreported coefficients of the quarterly dummy variables are insignificant. The macroeconomic variables are also generally not significantly different from 0.

We investigate the *robustness* of our regression results by performing some additional tests. First, we employ instrumental variables for *LB* and *DOM*. We use instrumental variables to control for the fact that the same data set is used to generate simulations and to partially construct *LB* and *DOM*. As instrument for *LB*, we employ the Herfindahl index based on total assets (concentration in a money-center structure will tend to be higher than in a complete structure, as the money-center bank tends to be larger than banks at its periphery), and to instrument *DOM*, we compute an index of bank internationalization based on total assets. A second set of instruments uses lagged *LB* and *DOM*. Finally, we also test alternative specifications for the money-market structure such as the average of the ratio (exposure of bank i to small and medium-sized banks/exposure of bank i to large banks) over all small and medium-sized banks. The (unreported) results confirm our analysis.

The results hold when we run regressions for other characteristics of the distribution. For instance, the signs of the coefficients of the regression with the median value remain unchanged although, in some specifications, they are not statistically different from 0. In regressions where *LB* and *DOM* are taken separately, both coefficients remain significant for the 100 percent and 80 percent LGDs. A further issue is that our results may suffer from a potential censoring bias, as knock-on effects of foreign banks to Belgian banks are disregarded. We investigate this issue by using the WCS after one round (*WCS1r*).[45] Although the *WCS1r* suffers less from this censoring bias, it only measures the direct exposures of the banking sector to a given bank and, by construction, does not capture the whole contagion process. Therefore, if the market structure is an important driving factor of the second and further rounds of contagion, we may not observe any significant link between market structure and *WCS1r*. In unreported regressions, we find that *LB* and *DOM* are not significant, as *WCS1r* does not present sufficient heterogeneity. This paradoxically shows that the market structure strongly affects contagion propagation in second and further rounds.[46]

6. Concluding Remarks and Policy Implications

This paper exploits a unique time-series data set on interbank exposures in Belgium to study the determinants of interbank contagion. In our simulations, we track the consequences of nonrepayment of (a fraction of) interbank loans on the equity capital of other banks,

[45] *WCS1r* is defined as the maximum percentage of total banking assets accounted for by failing banks after one round of contagion.

[46] In unreported robustness exercises, we find that the results for the two other indicators of contagion, the percentage of banks initiating contagion and the "propagation mechanisms of contagion (rounds)," are similar to those of WCS. Namely, a change to a money-center structure leads to a decrease in the number of cases of contagion in the simulations. Although the proportion of banks capable of triggering contagion decreases when a multiple-money-market structure is adopted, the structure may become more risky if the probability of default of these banks, precisely because of the structural changes, increases.

including any further domino effects. The exercise provides insights on the potential impact of "stress" situations on the Belgian financial system, which may be representative for many other small countries due to the high degree of internationalization of its interbank market, the economic significance of its large banks, and the similarities in the structure of its interbank market.

We find that the risk of contagion due to domestic interbank defaults varies substantially over time: it increased over the period 1993–97, decreased afterward, and flattened out at a very low level at the end of the sample period (end of 2002). This is important, as existing studies focus on a single point in time. Our results reveal that the interbank market structure, the overall bank capitalization, and the degree of internationalization are important in explaining the time-series behavior of contagion. In Belgium, the structure of the interbank market has moved over time from a complete structure à la Allen and Gale (2000) toward a multiple-money-center structure. If large money centers are robust and can set off obligations against each of their counterparties, or if they are too big to fail, this move results in a de facto multilateral netting agreement for small banks. Simulations indicate that bilateral netting agreements dramatically reduce contagion indicators.

Interbank exposures between Belgian banks currently represent only 15 percent of total Belgian interbank exposures, suggesting that the potential contagion risk stemming from foreign interbank exposures is more important. We find that the failure of some foreign banks could have a sizable effect on Belgian banks' assets. Cross-country analyses could deliver additional results on the relationship between the interbank market structure and the risk of contagion, but to the best of our knowledge, there exists no database that covers interbank exposures in a region such as the European Union. In addition, since in some regions in the European Union, clear geographical segmentation remains, making the assumption of maximal dispersion of interbank loans and deposits would not be correct, while it is acceptable in a domestic context.

Existing methodologies assume a fixed LGD. When we endogenize the LGD, we find not only that the LGD interacts with other determinants of contagion such as the market structure but also that contagion effects are more important when cross-sectional variations in LGD are introduced than they are with the corresponding average

LGD. Assuming a fixed LGD may thus lead to an underestimation of contagion risk.

The findings of the paper highlight some specific regulatory issues. First, though the risk of contagion is currently low—the analysis shows that contagion is a low-frequency event—interbank exposures at some time periods may constitute a devastating contagion channel. This kind of event is particularly relevant for banking supervisors. As contagion risk evolves over time, supervisory practices should include not only a frequent monitoring of interbank large exposures but also a regular assessment of the interbank market structure. Yet, interbank contagion risk should not be monitored in isolation of other risks.

Second, to the extent that large money centers are resilient, we should not observe significant domestic contagion processes. Supervisory efforts to control propagation processes will thus be more successful if they are focused on large banks. In addition, although small banks may trigger some limited contagion effects, they do not cause a systemic crisis if large banks are resilient. Analyzing the different propagation channels will allow supervisors to distinguish nonsystemic contagion effects from real systemic crises.

Third, the default of some large foreign banks has the potential to trigger significant domino effects in Belgium. This suggests that it is important for regulators to monitor cross-border sources of interbank systemic risk. However, domestic regulators do not have any control over these banks. Fostering international regulatory cooperation is thus essential. To this extent, European initiatives such as the Committee of European Banking Supervisors or bilateral or multilateral memoranda of understanding agreed upon by regulators in different countries constitute significant progresses.

Finally, the current structure and characteristics of the Belgian interbank market reflect several changes that have taken place over the past decade. Integration of money markets at the European level, increased recourse by banks to secured interbank exposures, and several major mergers between Belgian banks have resulted in a trend toward market tiering and appear to have reshaped the risk of contagion. In the coming years, changes in the microstructure of interbank markets may further alter the structure of interbank markets, thus keeping alive the debate about interbank contagion risk.

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Cross-Border Exposures and Financial Contagion

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ABSTRACT

Integrated financial markets provide opportunities for expansion and improved risk sharing, but also pose threats of contagion risk through cross-border exposures. This paper examines cross-border contagion risk over the period 1999–2006. To that purpose we use aggregate cross-border exposures of 17 countries as reported in the Bank for International Settlements Consolidated Banking Statistics. We find that a shock that affects the liabilities of one country may undermine the stability of the entire financial system. Particularly, a shock wiping out 25% (35%) of US (UK) cross-border liabilities against non-US (non-UK) banks could lead to bank contagion eroding at least 94% (45%) of the recipient countries' banking assets. We also find that since 2006 a shock to Eastern Europe, Turkey and Russia affects most countries. Our simulations also reveal that the 'speed of propagation of contagion' has increased in recent years resulting in a higher number of directly exposed banking systems. Finally, we find that contagion is more widespread in geographical proximities.

I. INTRODUCTION

The recent financial crisis, while having its roots in the United States, spread globally in a very short span of time. The higher delinquencies in the mortgage market quickly ripple through, not only other financial markets in the United States, but also abroad. As a result, the US subprime crisis turned into a global macroeconomic shock leading the United States, along with the Euro zone and Japan, into recession. Although the governments and international financial institutions have announced bailout packages of trillions of dollars, the crisis is still unfolding. The deteriorating conditions, despite all coordinated interventions worldwide, expose fundamental weaknesses in the international financial system. The ongoing banking problems illustrate that monitoring financial stability is important locally as well as globally. Therefore, it is worth studying the transmission channels to be able to identify the vulnerabilities in the international banking system.

Banks are important because the instability of the banking sector in a country may have severe effects on other sectors of the economy. Moreover, the banking sector has a large penetration in the international market.[1] Therefore, a shock can be easily transmitted across borders due to an unsustainable loss on bank lending to foreign counterparties. In this paper, we study cross-border financial contagion, defined as the situation when an idiosyncratic shock that hits the foreign counterparty of a banking system results in non-payment of its foreign claims. If the banking system's aggregate equity is not enough to absorb this shock, the affected banking system will not fulfill its foreign obligations in the next round. This starts a domino effects that impact other banking systems worldwide. Our focus is then on contagion due to non-repayment of cross-border credit exposures.

Foreign claims have increased both in absolute terms as well as relative to aggregate measures of real economic activity. The Bank for International Settlements (BIS) reported an increase in international claims on banks (in absolute terms), from US$584 billion at the end of 1977 to US$21 trillion in the second quarter of 2007.[2] Similarly, in relative terms, cross-border exposures increased from 10% of world GDP in 1980 to 48% of world GDP in the second quarter of 2006.

Despite increasing foreign claims, only a few papers deal with this topic even though the ongoing credit crisis shows that cross-border contagion has become more important. The papers that deal with cross-border contagion can be subdivided into two groups, depending on their approach. The first group employs equity prices to measure cross-border contagion (Gropp and Moerman 2004; Hartmann et al. 2005; Gropp et al. 2006; Bautista et al. 2007).[3] These papers mostly study within country contagion or contagion within continents. The second group of papers uses data on bank exposures. In particular, they employ cross-border exposures, but focus on the effects on a single country (Van Lelyveld and Liedorp (2006) study interbank contagion for the Netherlands, while Degryse and Nguyen (2007) focus on Belgium), or they study contagion originating from the failure of emerging countries (McGuire and

1 The reasons for international presence of banking system include: financial sector liberalization during the late 1990s has provided opportunities for international and cross-state (cross-border) banking. Second, the wave of mergers and acquisitions in the banking sector, both within and outside the United States, led to banking conglomerates at the international level that have greater financial needs and therefore establish banking relationships across the world. Third, the integration of European countries into one monetary union also increased significantly the cross-border relationships. Fourth, banks have developed risk management systems allowing them to price and manage more adequately international assets.

2 The increase may partially be attributed to a widening of the reporting area as data for the Cayman Islands, Hong Kong SAR, Singapore and other off-shore financial centers are only available from end-1983. Whereas Australia, Bermuda, Greece, Guernsey, the Isle of Man and Portugal start reporting in or after 1998. However, banks located in these countries accounted for less than 5% of total claims of BIS reporting banks in 2006.

3 De Bandt and Hartmann (2001) provide a survey of various studies using asset price (equity) co-movements for measuring the impact of contagion.

Tarashev 2007).[4] These papers highlight the increasing importance of cross-border exposures. We contribute to this literature by focusing on foreign claims of a sample of developed and developing countries to investigate empirically the potential for contagion risk through cross-border bank exposures across a more diverse set of countries and continents. We use the BIS Consolidated Banking Statistics for this purpose. We discuss several scenarios where we assume that an exogenous, sudden and idiosyncratic shock hits the foreign liabilities (entirely or partly) of a country. Following the initial failure, the shock propagates through cross-border exposures to banks in other countries and results into domino-type effects potentially causing systemic crisis. The contagion risk is gauged through the number of banking systems in other countries that potentially default following the non-payment of foreign claims against the failing country(ies).

Our paper therefore aims to contribute in several respects. First, it studies cross-border contagion for the first time using foreign claims from the BIS database. Second, while most papers focus on domestic interbank contagion at one point in time, our study provides an extension by looking at the evolution of cross-border contagion over the period 1999–2006. Third, we attempt to identify the size of a systemically important shock for cross-border contagion. Fourth, our analysis shows the economic impact of cross-border contagion besides indentifying highly vulnerable banking systems.

In this paper, we find that contagion risk and the speed of contagion through cross-border exposures have increased during 1999–2006. We find that a shock that affects partially the liabilities of one country may undermine the stability of the entire financial system. Particularly, a shock wiping out 25% (35%) of US (UK) cross-border liabilities against non-US (non-UK) banks could lead to bank contagion eroding at least 94% (45%) of the recipient countries' banking assets, assuming 100% loss given default (LGD). We also find that since 2006 a shock to Eastern Europe, Turkey and Russia affects most countries. Our simulations also reveal that contagion is often more confined to geographical proximities (i.e., regional, if not global), and that the United States is the only country immune to cross-border shocks and contagion stemming from other countries.

The remaining of this paper is organized as follows. Section II introduces the dataset while Section III elaborates on methodological details. The results are analyzed in Section IV. Section V concludes this paper.

II. DATA

We use *bank credit* to foreign countries as the source of cross-border exposures. These foreign claims include the exposure of a country's banking system to all

4 Recently, a series of papers have studied banking contagion stemming from within country interbank exposures [see, e.g., Angelini et al. (1996) and Mistrulli (2007) for Italy; Blavarg and Nimander (2002) for Sweden; Furfine (2003) for the United States; Wells (2004) for the United Kingdom; Upper and Worms (2004) for Germany; Lublóy (2005) for Hungary; Elsinger et al. (2006) for Austria; and Müller (2006) for Switzerland].

sectors (i.e., bank, non-bank and public sector) of other countries. BIS provides information on such foreign claims of reporting countries to the rest of the world in the *Consolidated Banking Statistics*.[5] It covers data on (national) contractual lending by the headquartered banks and all of their branches and subsidiaries worldwide to borrowers residing outside the country of origin (where the bank's headquarter is stationed) on a consolidated basis (i.e., net of interoffice account). It is one of the two broad categories in which BIS compiles data through the central banks of the reporting countries.[6] Further, we use foreign claims on immediate borrower basis, that is, the allocation of foreign claims of reporting banks to the country of operations of the contractual counterparty. It means that, for example, we employ the foreign claims of *British* banks on *all* financial institutions operating in the United States (irrespective of their nationality).

The reporting institutions in each country include all institutions that are allowed to *receive deposits and/or close substitutes for deposits and grant credits or invest in securities on their account*. Therefore, the reporting institutions include commercial banks, savings banks, savings and loan associations, credit unions or cooperatives, building societies and post office savings banks or other government-controlled savings banks, but not central banks.

Our sample includes foreign claims outstanding at the end of each year for the banking systems of 14 European countries, Canada, Japan and the United States.[7] The foreign claims of these countries' banking systems are available for a long time period (1999–2006) allowing us to study contagion risk over time. These foreign claims differ across countries, not only in absolute terms, but also in relation to the size of the banking system's aggregate equity. Figure 1 shows the ratio of foreign claims to a banking system's aggregate equity averaged over time for each country, both for the total foreign claims (sum over all countries) and the largest foreign claim (the country with the largest liability). The solid horizontal line at ratio=1 represents a situation where the foreign claims would be equal to a banking system's aggregate equity. If the ratio of a country is below the solid line, then the country has complete immunity against cross-border contagion. The reason is that the domestic banking system's aggregate equity is large enough to absorb a foreign shock due to non-payment of even all foreign claims. We find that the ratio of total foreign claims to bank aggregate equity is 0.4 in the United States, which makes the United States immune against to any cross-border contagion. While Italy and Japan have a low total foreign claims to

5 'Reporting countries' include all participating countries in the BIS consolidated banking statistics. These countries report foreign claims vis-à-vis each other as well as against all non-participating countries. These non-participating countries are hereby called the non-reporting countries.

6 BIS also reports *locational banking statistics*, that is, international financial claims of all banks located in reporting countries to borrowers outside the geographical boundary on a gross (unconsolidated) basis.

7 Included European countries are Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden, Switzerland and the United Kingdom.

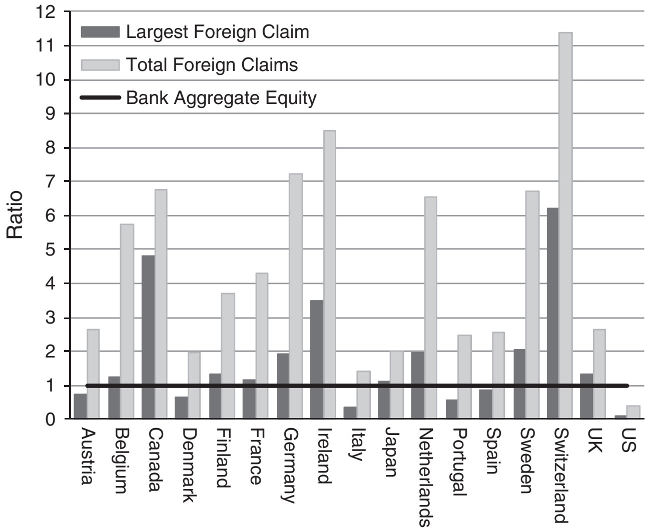


Figure 1 The Ratio of Foreign Claims to Bank Aggregate Equity.
The figure shows the ratio of foreign claims to bank aggregate equity averaged over time for each country. A solid horizontal line at ratio=1 represents a situation when foreign claims is equal to bank aggregate equity.

bank capital ratio, it is still greater than 1, implying that these banking systems may default in later rounds of contagion. Other banking systems have a very high ratio so that even the largest foreign claim exceeds aggregate equity (i.e., a ratio larger than 1). In some cases, these banking systems default already in the first round of contagion.

Table 1 provides another set of summary statistics on foreign claims. We find that foreign claims are clustered in geographical regions. For example, Austria has 28% of its foreign claims on Germany; Belgium has 32% on France and the Netherlands; Denmark has 41% on Germany and Sweden; Finland has 62% on Denmark and Sweden; Italy has 28% on France and Germany; Portugal has 36% on France and Spain; Sweden has 64% on Denmark, Finland and Germany; and Canada has 72% of foreign claims on the United States only. The exceptions to the geographical proximities rule are the United States and the United Kingdom. Many countries (especially Japan and Switzerland) have a high proportion of foreign claims on the United States and the United Kingdom irrespective of their location.

The dataset we use has several advantages. The consolidated banking statistics assigns foreign offices to their country of origin. This may be a better representation if foreign offices are affected more by an adverse shock in the country of origin as compared with a similar shock in the country of operations (in the latter case they could be rescued by the headquarters). Moreover, the consolidated banking statistics, though, are not the interbank data; it connects

Table 1 Foreign claims of reporting banks to all 17 countries

	AT (%)	BE (%)	CA (%)	DK (%)	FI (%)	FR (%)	DE (%)	IE (%)	IT (%)	JP (%)	NL (%)	PT (%)	ES (%)	SE (%)	CH (%)	GB (%)	US (%)
Austria (AT)	–	1.1	0.5	0.4	0.6	0.8	4.7	2.2	1.0	0.4	0.8	1.5	0.5	0.4	0.6	0.7	1.1
Belgium (BE)	1.7	–	0.7	1.9	0.8	4.2	2.4	1.1	7.6	1.3	7.4	2.0	2.5	0.8	1.2	2.4	2.9
Canada (CA)	0.9	0.5	–	0.2	0.7	1.4	1.1	1.4	0.5	2.3	1.8	0.8	0.3	0.3	0.9	2.1	7.7
Denmark (DK)	1.0	0.8	0.3	–	27.8	0.3	1.4	0.7	0.5	0.5	0.9	1.6	0.4	23.2	0.4	0.7	2.0
Finland (FI)	0.7	0.4	0.2	2.8	–	0.4	0.7	0.6	0.3	0.3	0.3	0.3	0.4	17.0	0.1	0.3	0.5
France (FR)	5.3	11.2	1.8	1.8	2.1	–	7.5	5.4	14.3	6.2	6.0	16.0	8.1	2.1	3.2	8.7	7.1
Germany (DE)	28.2	8.4	2.8	11.9	5.7	10.1	–	24.0	14.2	9.5	13.7	7.0	9.7	24.4	4.5	6.7	15.7
Ireland (IE)	4.6	5.8	2.1	4.2	0.9	2.1	3.6	–	4.7	1.7	2.2	4.4	2.7	0.8	0.9	5.7	1.8
Italy (IT)	10.3	8.8	1.0	0.9	1.6	11.4	7.4	8.1	–	3.0	6.7	6.3	7.1	0.8	2.2	4.4	5.4
Japan (JP)	0.8	0.9	2.2	0.2	0.3	9.6	4.8	2.9	2.3	–	3.4	0.5	0.2	0.4	6.8	5.0	11.7
The Netherlands (NL)	6.6	21.3	1.4	2.4	1.8	5.1	5.5	1.6	3.4	3.3	–	4.9	4.0	1.9	1.8	4.1	6.8
Portugal (PT)	1.0	1.1	0.2	0.1	0.2	1.0	1.3	0.0	3.2	0.2	0.8	–	11.2	0.1	0.1	0.9	0.4
Spain (ES)	2.5	3.4	0.5	1.2	0.6	5.5	5.1	4.8	4.7	1.6	5.2	20.4	–	0.8	0.8	4.2	3.5
Sweden (SE)	0.8	0.4	0.5	28.9	33.9	0.6	1.3	1.1	0.6	0.8	1.2	0.5	0.4	–	0.5	1.0	1.4
Switzerland (CH)	4.7	1.2	0.4	2.1	0.2	2.7	2.5	0.6	2.3	0.9	1.1	2.0	0.7	0.6	–	1.2	2.6
United Kingdom (GB)	16.1	20.3	13.6	31.6	8.7	16.6	26.0	35.4	24.6	11.9	18.0	18.5	37.7	13.4	20.4	–	29.6
United States (US)	14.7	14.4	72.1	9.4	13.9	28.3	24.8	9.9	15.9	56.0	30.5	13.6	13.8	13.0	55.5	51.9	–

The table provides the distribution of foreign claims of reporting countries. Each column gives the percentage of foreign claims of a reporting country vis-à-vis other reporting countries averaged over time.

domestic banking system to foreign economies, thus providing a channel to gauge the impact of external shock. On the other side, the non-availability of interbank data is due to the fact that the BIS does not report the sectoral classification (i.e., bank, non-bank and public sector) of foreign claims of reporting countries vis-à-vis each counterparty.[8] Further, the consolidated banking statistics on immediate borrower basis does not take into account the nationality of contractual counterparties (i.e., for example, it reports foreign claims of British banks on all financial institutions in the United States, but not on all American financial institutions). The BIS has managed this issue by reporting foreign claims on the ultimate risk basis, that is, the allocation of claims of banks of reporting countries to the country of origin of the ultimate obligor. However, the data on ultimate risk basis are only available since March 2005, preventing us from evaluating contagion risk over time.

Data on bank equity for the financial institutions of each reporting country are taken from *Bankscope*. We sum up ordinary equity of all financial institutions except the Central banks to obtain the aggregate bank equity at country level for each year. We preferably use consolidated accounting statements of all reporting financial institutions in Bankscope in these calculations. If the consolidated statement is not available, then we use the unconsolidated/aggregate accounting statement, whatever is available. Similarly, if accounting statements are available on both IFRS and Local GAAP reporting conventions, then we use the former convention.

III. METHODOLOGY

We use the methodology of Upper and Worms (2004) for our contagion exercises. This methodology simulates a mechanical chain of domino effects caused by an exogenous initial shock. Our exogenous shock is the default of a triggering country (i.e., its bank, non-bank and public sector) on its foreign liabilities. As a result, the banking system of the recipient country suffers from non-payment of its foreign claims on the triggering country. The banking system of the recipient country defaults in the first round when its foreign claims against the bank, non-bank and public sector of the triggering country exceed its aggregate bank equity. The failing recipient countries in each round may affect other countries in successive rounds due to their combined effects. The contagion process stops when there is no new country that defaults in that round (i.e., combined foreign liabilities of both the trigger and failed recipients of previous rounds are less than the bank equity of each non-failed recipient country). We employ this methodology over our entire sample period 1999–2006 to evaluate the impact of contagion over time.

8 BIS reports sectoral classification at aggregate level only. For example, it reports foreign claims of British banks on banks of the rest of the world, but not foreign claims of British banks on banks in the United States.

We can represent the countries' foreign claims and liabilities as follows:

$$X = \begin{bmatrix} \overbrace{x_{1,1} \quad \cdots \quad x_{1,j} \quad \cdots \quad x_{1,N}}^{\text{Reporting Countries}} & \overbrace{x_{1,N+1} \quad \cdots \quad x_{1,N+M}}^{\text{Non-Reporting Countries}} \\ \vdots \quad \ddots \quad \vdots \quad \iddots \quad \vdots & \vdots \quad \ddots \quad \vdots \\ x_{i,1} \quad \cdots \quad x_{i,j} \quad \cdots \quad x_{i,N} & x_{i,N+1} \quad \cdots \quad x_{i,N+M} \\ \vdots \quad \ddots \quad \vdots \quad \iddots \quad \vdots & \vdots \quad \ddots \quad \vdots \\ x_{N,1} \quad \cdots \quad x_{N,j} \quad \cdots \quad x_{N,N} & x_{N,N+1} \quad \cdots \quad x_{N,N+M} \end{bmatrix}$$

$$\text{with} \sum_{j=1}^{N+M} x_{ij} = a_i \quad \text{and} \sum_{i=1}^{N} x_{ij} = l_j$$

where x_{ij} is the consolidated foreign claims of the banking system of country i on the bank, non-bank and public sector of country j, N is the number of reporting countries (N=17 in our case) and M is the number of non-reporting countries. The summation $\sum_{j=1}^{N+M} x_{ij} = a_i$represents the total foreign claims of country i on the rest of the world. Similarly, $\sum_{i=1}^{N} x_{ij} = l_j$ represents the total foreign liabilities of country j toward the rest of the reporting countries. This matrix also shows the foreign claims on the M non-reporting countries.

The aggregate bank equity has an initial value C_i equal to the ordinary equity directly observed from the balance sheets of financial institutions in country i. It is reduced by the amount of the foreign claims of country i against the triggering country in the first round, and then by the cumulative amount of the foreign claims of country i against all failing recipient countries in each round of contagion. Therefore, the country i defaults when

$$C_i - \sum_{j=1}^{N+M} \lambda_j \theta x_{ij} < 0$$

where C_i represents aggregate bank equity of country i, λ_j is a dummy variable whose value is 1 if the country j defaults, and 0 otherwise, θ shows the percentage of LGD, whereas x_{ij} is obtained from the previous matrix representing the consolidated foreign claims of country i on country j.

Figure 2 depicts the same procedure in a graphical manner. The domino effect starts when the triggering country defaults on its foreign liabilities. Depending on our assumptions on LGD, the loss on foreign claims to the triggering country is fully or partially ascertained by recipient countries. If aggregate bank equity of a recipient country is larger than the shock, the banking system survives with partial damage to the aggregate equity. On the other hand, if the aggregate bank equity of the recipient country is not sufficiently high to absorb the shock, the banking system defaults. Here, we assume that the banking system's default would lead to the default of all sectors of the country through domestic spillovers; therefore, the foreign claims on this

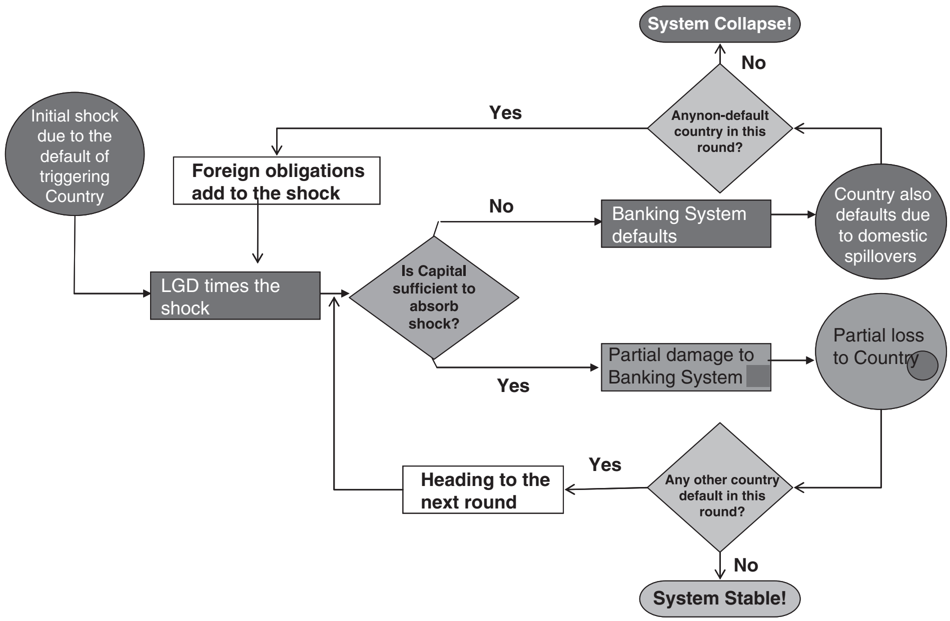


Figure 2 The Contagion Process.
The figure shows the contagion process. The red circle on the left represents an initial shock triggered by the default of a reporting country. The shock is then multiplied by the Loss Given Default (LGD) to determine the effective burden on recipient countries; if that burden is less than the aggregate bank capital, then the country survives to the next round though it looses bank capital partially. Such country is represented by a green circle, and the partially lost capital is represented by the red circle inside. On the other hand, if the burden is greater than aggregate bank capital, then the recipient country would also default as represented by the red circle on the right. Contagion would continue to the next round if there is at least one additional country defaulting in the current round.

country add to the shock for the next round of contagion.[9] In each successive round, all non-defaulting countries have lower chances of survival due to combined losses on foreign claims to defaulting countries in the preceding round. The system becomes stable when no country defaults in the current round or all countries default.

There are some caveats to this simulation process. Although aggregate foreign claims at the country level are directly observable, the distribution of

9 Unfortunately we do not have data on a country's *banking system* exposure to another country's *banking system*. We only have data on the claims of a country's *banking system* against *all other sectors* (i.e., bank, non-bank and public sector) of each of the other countries. So, unless we assume that the banking system's default would lead to the default of bank, non-bank and public sectors, we cannot see the contagion in later rounds. To the best of our knowledge, there is still no available cross-country dataset that would allow to do the simulations with actual interbank cross-border exposures.

foreign claims among financial institutions within each country is not known. This implies that we need to make some assumptions on the distribution of foreign claims. As a first step, we assume that *all* banks share foreign claims on other countries proportional to their assets. Furthermore, we assume that *all* banks' equity is employed as a cushion to absorb the shock. Therefore, the failure of a triggering country on its foreign liabilities affects all banks together. In later exercises, however, we assume that foreign claims are distributed among *large* banks only.

Further, we assume an exogenously determined LGD that is kept constant over time, and during all rounds of contagion and across all countries. While this may seem a very strong assumption, we find, however, that all included countries have a similar and stable sovereign credit rating throughout the sample period. Therefore, we deduce that all countries may have similar standing to deal with a crisis and hence a similar LGD for their respective debtors. In relation to the percentage of the LGD, we analyze several scenarios, given that there is no consensus in existing estimations about the recovery rates.[10] Lastly, it is also assumed that no netting of exposures occurs in the event of default.[11]

IV. RESULTS

We analyze the impact of a country's default on its foreign liabilities. The non-payment of the foreign claims of the banking systems of recipient countries vis-à-vis this triggering country erodes the bank capital of the recipient countries. The magnitude of the final shock is the LGD times the initial shock. In our examination, we use various levels of LGD (i.e., 20%, 40%, 60%, 80% and 100%); however, we find a significant decline in contagion when LGD is below 60%. Therefore, we report simulation results for 100% LGD (worst case) and 60% LGD (intermediate case) only. We present simulation results for two different cases: (1) *all* banks are internationally exposed and (2) only *large* banks are internationally exposed. In each case, we evaluate the possible contagion stemming from exposures to reporting and non-reporting countries, identify the most vulnerable banking systems, examine contagion risk over time and report the economic significance of potential contagion.

10 For example, James (1991) estimates losses for US bank failures for the period 1985–1988, and finds that the loss is on average 30% of the failed bank's assets. For the United Kingdom, a bank study of recoveries by the UK Deposit Protection Fund in the early 1990s reports a median loss-given-default of 35% for failed UK banks (see Jackson 1996). However, the sample contains only 14 banks, which are small and the LGD has a large variance, from 0% to 100%. One important issue to keep in mind is that these are ex-post loss rates. It is possible that expected losses at the moment of the shock are higher and therefore banks may not be able to continue to operate if all its capital is *perceived* to be at risk.

11 It is important to assess contagion risk under different netting assumptions, given that it is possible that some netting would occur. However, we are prevented from doing this exercise, given that our data do not allow us to calculate a country's banking system net exposures to another country' banking system.

A. Case 1: All banks are internationally exposed

In case 1, we investigate cross-border contagion of a default of the triggering country on all its foreign liabilities, under the assumption that foreign claims toward a recipient country are distributed among all banks in that country. Cross-border contagion occurs when the banking system in at least one of the recipient countries is not able to absorb the shock triggered by the non-payment of its foreign claims at the given LGD (i.e., the banking system's aggregate equity is less than the foreign claims on the triggering country). In this exercise, the national banking system acts as one unit, that is, all banks hypothetically pool their equity to compensate the losses incurred on foreign claims to defaulting countries. We have 17 reporting countries that may be a trigger. We label these as *reporting triggers*. We also have the claims of the banking systems of the different reporting countries on 20 non-reporting countries, which we label as *non-reporting triggers*. These non-reporting countries include countries from Eastern Europe (plus Russia and Turkey), Latin America and Asia.

Figure 3 displays the results of our simulation exercise. It shows that contagion risk has increased over time particularly in terms of an increasing number of triggering countries that may lead to contagion, as well as more failing recipient countries to each trigger. The upper panels show the results for reporting triggers, while lower panels elucidate contagion from non-reporting triggers. Each scenario is evaluated at 100% LGD and 60% LGD. Panel (a) shows that the number of reporting triggers increased to eight in 2006 (i.e., the United States, the United Kingdom, Germany, Italy, the Netherlands, Denmark, Sweden and Finland), as compared with only four countries in 1999 (i.e., the United States, the United Kingdom, Germany and the Netherlands). The United States, the United Kingdom and Germany would have triggered cross-border contagion over the entire sample period. The contagion triggered by the United States is the most severe, and spreads to almost all reporting countries in many years. The default of the United Kingdom also affects a majority of other reporting countries (12–15 countries). The United States and the United Kingdom have triggering potential even at low percentages of LGD. The impact of cross-border contagion from Germany has particularly increased over time, affecting 13 countries in 2006. The Netherlands almost always affects Belgium, while default of any Scandinavian country affects the whole neighboring region. Japan triggers cross-border contagion in 2002 only affecting Ireland. Similarly Italy triggers cross-border contagion in 2006 only, however, it would affect 14 out of 16 recipient countries. Panel (b) depicts a similar pattern for 60% LGD: cross-border contagion is triggered by the United States, the United Kingdom, Germany and Scandinavian countries.

Similarly, panel (a) of Figure 4 reports contagion triggered by non-reporting countries/regions at 100% LGD. Norway causes cross-border contagion to neighboring countries in the Scandinavian region. Moreover, the default of Latin American countries has cross-border implications for Spain throughout. Distinctively, the default of Eastern Europe (plus Russia and Turkey) affects 15

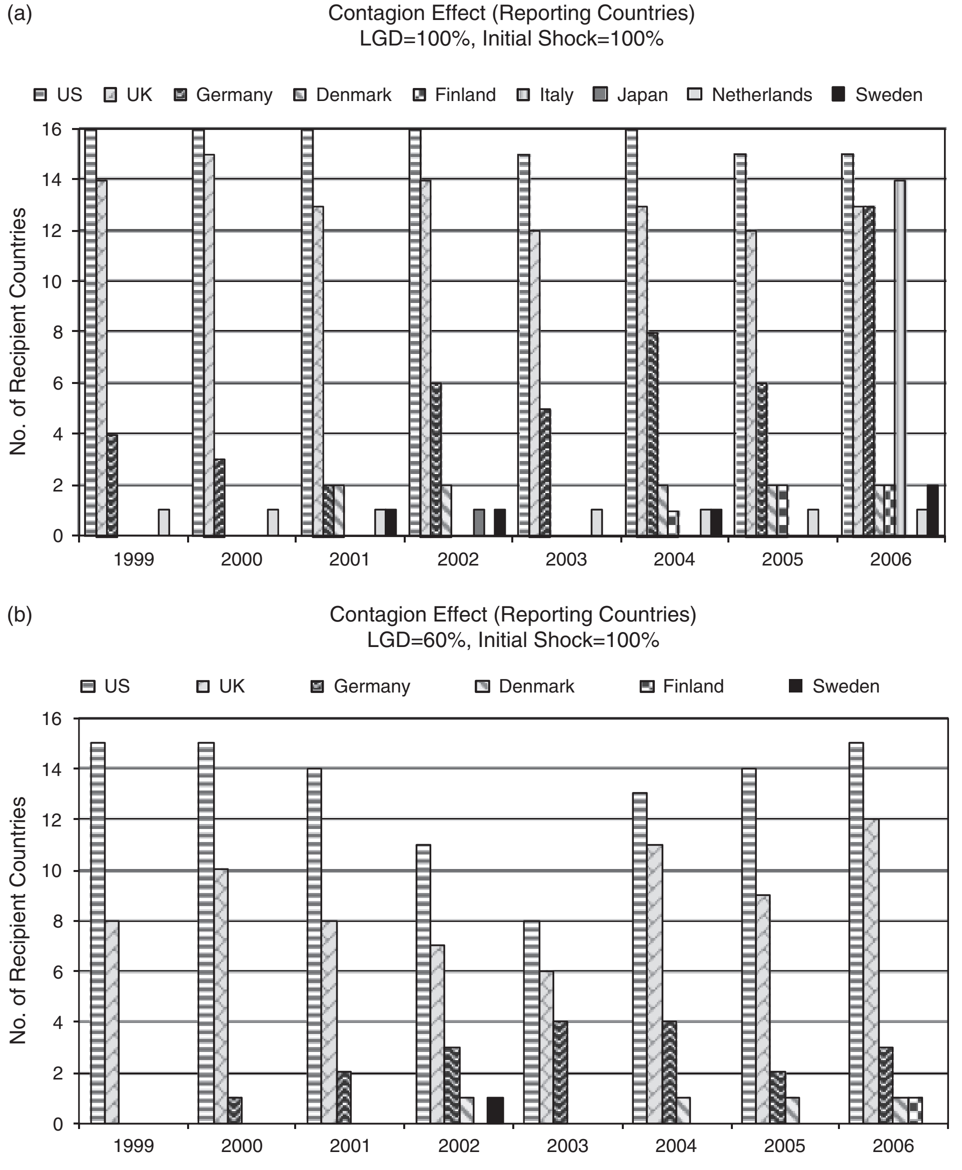


Figure 3 Contagion Triggered by Reporting Countries – All Banks are Internationally Exposed.

The figure illustrates the number of countries (on y-axis) that default due to cross-border contagion from reporting countries. Each column represents a triggering country during 1999–2006. Panel (a) is based on 100% Loss Given Default (LGD) whereas panel (b) is based on 60% LGD.

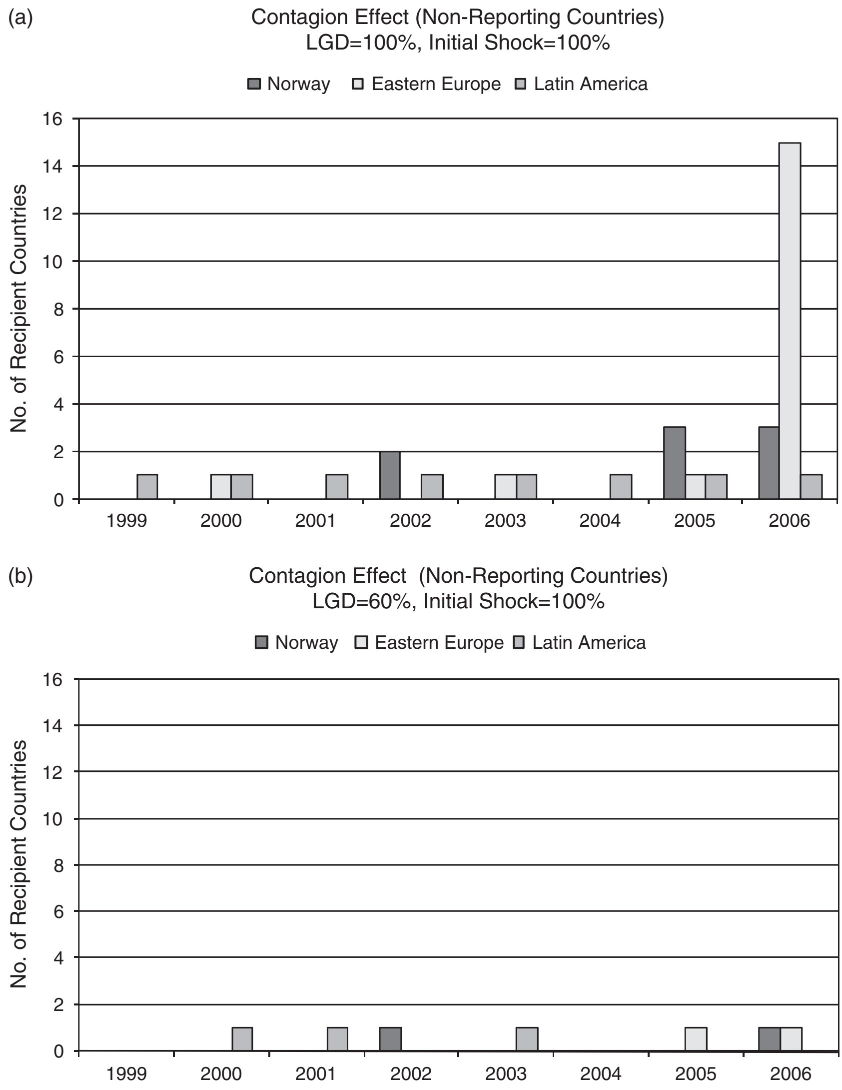


Figure 4 Contagion Triggered by Non-Reporting Countries – All Banks are Internationally Exposed.

The figure illustrates the number of countries (on *y*-axis) that default due to cross-border contagion from non-reporting countries. Each column represents a trigger during 1999–2006. Panel (a) is based on 100% Loss Given Default (LGD) whereas panel (b) is based on 60% LGD.

recipient countries. Although Austria is the only country that is directly exposed to the shock, the combined effect in later rounds causes Scandinavian countries to default and then the contagion spread to Ireland and other major

European countries in later rounds. Panel (b) of Figure 4, that reports results for 60% LGD, shows a low contagion potential from non-reporting countries.

Another interesting question is which banking systems are more vulnerable to contagion, and thus often appear as failing recipient countries. We find that the number of directly exposed banking systems (that default in first round) reaches its highest level in 2006, when 12 banking systems default immediately after the triggering countries experience the shock. Tables 2 and 3 provide the direct and total cross-border contagion risk in 2006, respectively. The rows indicate the triggering countries that initiate contagion whereas the columns represent the recipient countries. Sweden and Ireland are the most directly exposed banking systems that default five and four times, respectively (see Table 2). On the other hand, Italy and the United States are completely immune to cross-border shocks taking into account 'all-round' contagion effects as shown in Table 3.

Our results show that the US banking system is always resilient to cross-border contagion risk. Also, in recent years, the Italian banking system has become resilient to contagion risk from any of the triggering countries. This may stem from the large number of small banks in Italy that are not exposed heavily. Therefore, the result here may be driven by our strong assumption that all banks, including small banks, are internationally exposed. We relax this assumption in the next exercise. Other recipient countries including Austria, Denmark and Finland are not completely resilient to contagion risk but default occasionally only in the last rounds. Therefore, we classify them as less vulnerable recipient countries. Lastly, Japan, France and Portugal have moderate level of contagion risk as they default in intermediate rounds.

We also find that the number of banking systems that default in the first two rounds has increased for each triggering country in recent years. The increase is more profound when the triggers are the United States and the United Kingdom, as shown in Figure 5. Specially, the United States affects 13 or more countries in just two rounds [see Figure 5, panel (a)]. Similarly, the default of the United Kingdom leads to a cross-border contagion affecting nine or more countries in first two rounds throughout the sample period as shown in panel (b) of Figure 5.

The economic impact of possible contagion is shown in Figure 6. We measure the economic impact of contagion as the percentage of total assets of the defaulting banking system(s) compared with total assets of all banking systems that could potentially be affected (excluding the triggering country). We find that the failure of the United States has the largest economic impact throughout the time period. Its failure would potentially affect more than 90% of the global banking assets. Next to the United States, the impact of the failure of the United Kingdom is the most severe as it would affect around 50% of the banking assets in many years. The impact of Germany's failure is increasing over time and would potentially affect around 50% of banking assets in 2006 (similar to the United Kingdom). Other countries' cross-border exposures generate a much lower impact.

Table 2 Directly exposed banking systems when all banks are internationally exposed

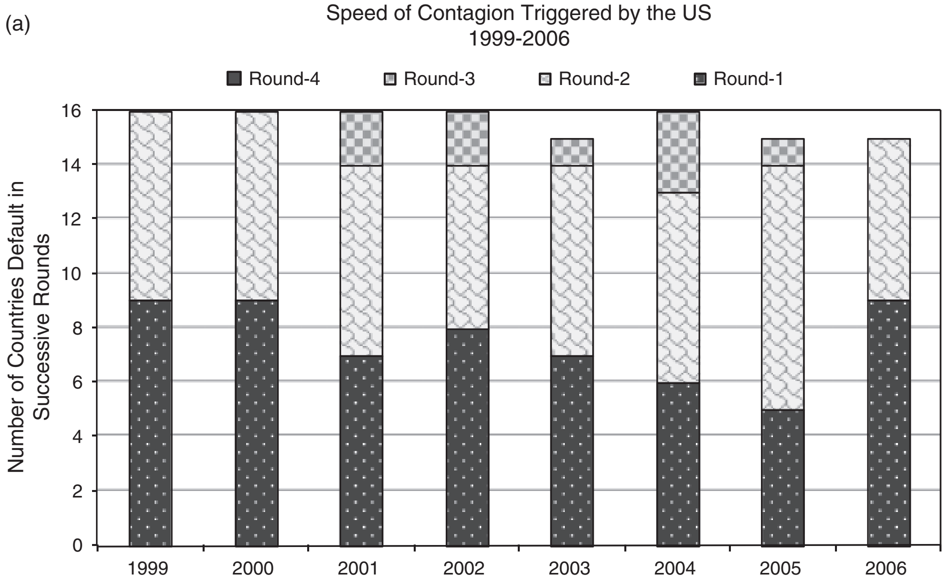
Year 2006 (first round) LGD=100%	Recipient countries																	Total
	DK	FI	SE	AT	BE	FR	DE	IE	IT	NL	PT	ES	CH	GB	JP	CA	US	
Triggering countries																		
Denmark (DK)			■															1
Finland (FI)			■															1
Sweden (SE)	■																	1
Italy (IT)								■										1
The Netherlands (NL)					■													1
Germany (DE)			■					■										2
United Kingdom (GB)	■		■		■		■	■		■		■	■					**8**
United States (US)			■			■	■	■		■			■	■	■	■		**9**
Total	2	0	**5**	0	2	1	2	**4**	0	2	0	1	2	1	1	1	0	24

The table shows the details of directly exposed banking systems in 2006. For each triggering county (left column), the (defaulting) recipient countries are marked with a gray box. The total on the right column gives total number of recipient countries for each triggering country. Whereas the total number of times a country defaults in the first round is mentioned at the bottom.

Table 3 Contagion effect when all banks are internationally exposed

Year 2006 (all rounds) LGD=100%	Recipient countries																	Total
	DK	FI	SE	AT	BE	FR	DE	IE	IT	NL	PT	ES	CH	GB	JP	CA	US	
Triggering countries																		
Denmark (DK)																		2
Finland (FI)																		2
Sweden (SE)																		2
Italy (IT)																		**14**
The Netherlands (NL)																		1
Germany (DE)																		**13**
United Kingdom (GB)																		**13**
United States (US)																		**15**
Total	6	6	6	4	5	4	3	4	**0**	4	4	4	4	3	1	4	**0**	62

The table shows the extent of contagion in 2006 taking into account all round effects when all banks are internationally exposed. For each triggering country (left column), the (defaulting) recipient countries are marked with a gray box. The total on the right column gives total number of recipient countries for each triggering country. Whereas the total number of times a country defaults is mentioned at the bottom.



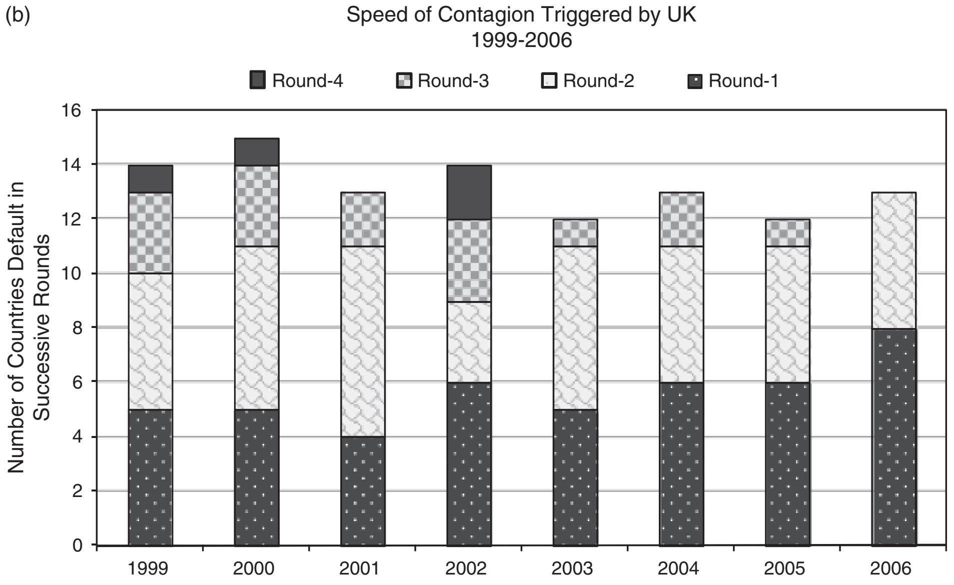


Figure 5 Speed of Contagion – All Banks are Internationally Exposed.
The figure shows the number of recipient countries in each round. Segments in columns represent the number of countries that default in each round. Panel (a) depicts the contagion effect due to the United States whereas panel (b) reflects contagion that is triggered from the United Kingdom. The analysis is based on 100% LGD during 1999–2006.

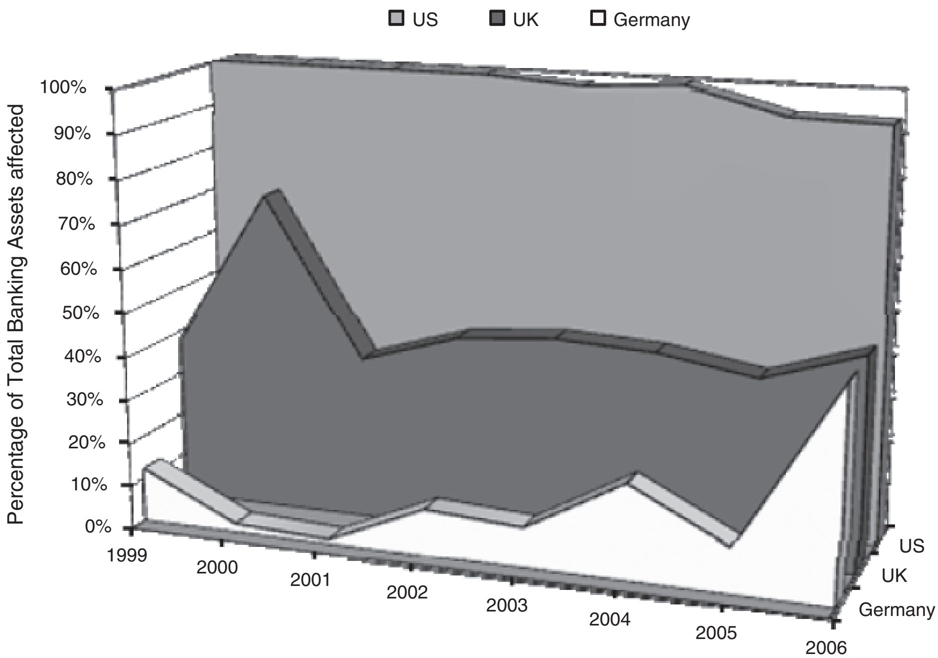


Figure 6 Economic Impact of Contagion – All Banks are Internationally Exposed. The figure shows the economic impact of contagion that is triggered by the United States, the United Kingdom and Germany during 1999–2006. It is measured as the percentage of total assets of banking systems recipient countries relative to total assets of all banking systems (excluding triggering country). The analysis is based on 100% LGD.

B. Case 2: Only large banks are internationally exposed

In case 2, we assume the same initial shock as in case 1; however, foreign claims are assumed to be distributed among large banks only. We are therefore considering that the international banking market presents a two-tier structure, where only large banks operate across borders in the interbank market and act as money centers for smaller domestic banks. Evidence consistent with this structure is found, for example, by Gropp et al. (2006), who show that small banks neither cause nor suffer from cross-border contagion, even though all banks are equally likely to experience domestic contagion. We define large banks as banks with at least US$127 billion in assets, this is the maximum possible bank asset size such that we include at least one bank from each country [this cutoff is close to the US$170 billion cutoff used in Gropp et al. (2006)]. There are 193 banks of the total 6392 banks that report to Bankscope, that have US$127 billion or more total assets. Moreover, we assume that the selected large banks in each country act as one unit and hypothetically pool their equity to safeguard against contagion risk. Here, we investigate whether the aggregate bank equity of the large banks is sufficient to absorb the shock. In this case, our assumption about domestic spillovers is more stringent (i.e., the failure of large banks leads to the default of all sectors of the recipient country). In general, we expect more contagion to take place compared with case 1, as we only include banks' equity of large banks as a cushion for default on foreign claims.

For brevity, we only discuss the main findings and differences compared with case 1. We find more intense contagion as expected. At 100% LGD, all countries except Switzerland and Canada trigger in at least 1-year contagion that affects at least 15 countries. More specifically, France, Germany, Italy, Japan, the Netherlands, the United Kingdom and the United States trigger contagion throughout the sample period, while other countries trigger contagion only occasionally. The United States again turns out to be a trigger that affects all other countries, while other countries affect all but the United States.

We find that the Italian banking system that is immune to any cross-border shock in case 1, not only triggers contagion but is also affected by other triggers. The default of the Italian banking system has severe implications for neighboring European countries including Portugal, Austria and Germany. Once any of these European countries defaults, then a chain of bank failures starts that ultimately leads to the default of all banking systems except the United States. However, the speed of contagion is low, as it takes several rounds to complete the contagion process.

With 60% LGD, we find that the United States affects all countries during each year in the sample period. The United Kingdom, Italy, Japan, the Netherlands, France, Germany and Spain also trigger significant contagion even at 60% LGD. Other countries are gaining contagion momentum in recent years, especially after 2002. Scandinavian countries trigger contagion, but only on a limited scale at the regional level.

Regarding the effects of the non-reporting countries with 100% LGD, Eastern Europe (plus Russia and Turkey) and Latin America affect almost all countries throughout our sample period, whereas Norway's contagion impact is limited to the Scandinavian region except for 2003–2005. Asia and off-shore centers cause contagion mainly during 1999–2002. With an LGD of 60%, Eastern Europe, Latin America and off-shore centers cause global contagion whereas Norway causes regional contagion.

In terms of direct exposure (recipient countries which fail in the first round), we find a similar pattern as the one we observe in case 1. Table 4 reports direct cross-border contagion in 2006 and reveals that the banking systems that are often directly exposed are Portugal (13 times), Ireland (6 times), the Netherlands (5 times), Sweden (5 times) and Switzerland (5 times). The recurrence of Portugal is expected because of the low representation of large banks. We find that Italy and the United States are not directly exposed to any triggering countries. On the other side, the United Kingdom and the United States affect most countries in the first round. Finally, Table 5 shows the total contagion effect. The United States affects all other countries, and France, Germany, Italy, the Netherlands, Spain and the United Kingdom affect all countries but the United States. Again, we observe Scandinavian countries affect other countries in their region.

Table 4 Directly exposed banking systems when only large banks (more than US$127 billion assets) are internationally exposed

Year 2006 (first round) LGD=100%	Recipient countries																	Total
	DK	FI	SE	AT	BE	FR	DE	IE	IT	NL	PT	ES	CH	GB	JP	CA	US	
Triggering countries																		
Denmark (DK)																		3
Finland (FI)																		1
Sweden (SE)																		2
Austria (AT)																		1
Belgium (BE)																		1
France (FR)																		5
Germany (DE)																		6
Ireland (IE)																		1
Italy (IT)																		3
The Netherlands (NL)																		2
Spain (ES)																		2
Switzerland (CH)																		1
United Kingdom (GB)																		10
Japan (JP)																		2
United States (US)																		13
Total	3	2	**5**	2	4	1	2	**6**	0	**5**	**13**	1	**5**	1	1	2	0	53

The table shows the details of directly exposed banking systems in 2006 when only large banks are internationally exposed. For each triggering country (left column), the (defaulting) recipient countries are marked with a gray box. The black boxes represent additional contagion effect compared with previous case. The total on the right column gives total number of recipient countries for each triggering country. Whereas the total number of times a country defaults in the first round is mentioned at the bottom.

Table 5 Total contagion effect when only large banks (more than US$10 billion assets) are internationally exposed

Year 2006 (all rounds) LGD=100%	Recipient countries																	Total
	DK	FI	SE	AT	BE	FR	DE	IE	IT	NL	PT	ES	CH	GB	JP	CA	US	
Triggering countries																		
Denmark (DK)																		3
Finland (FI)																		3
Sweden (SE)																		3
Austria (AT)																		1
Belgium (BE)																		1
France (FR)																		15
Germany (DE)																		15
Ireland (IE)																		1
Italy (IT)																		15
The Netherlands (NL)																		15
Spain (ES)																		15
Switzerland (CH)																		1
United Kingdom (GB)																		15
Japan (JP)																		2
United States (US)																		16
Total	9	9	9	7	7	6	6	7	6	6	15	6	8	6	7	7	**0**	121

The table shows the extent of contagion in 2006 taking into account all round effects when only large banks are internationally exposed. For each triggering country (left column), the (defaulting) recipient countries are marked with a gray box. The black boxes represent additional contagion effect compared with previous case. The total on the right column gives total number of recipient countries for each triggering country. Whereas the total number of times a country defaults is mentioned at the bottom.

It is important to note that the United States remains completely resilient to contagion risk in case 2 as well. Moreover, Italy as well as Austria, Finland and Portugal may be classified as less vulnerable countries.

C. Systemically Important Country Shock/Bank

The recent subprime crisis also raises questions whether a single large bank or a group of banks can trigger a chain of dominos that potentially leads to cross-border contagion. We investigate this possibility by considering a shock to a fraction of a country's cross-border exposure only. We simulate initial shocks ranging from 5% to 100%, in steps of 5% each. This allows us to check the critical magnitude of the initial shock that would potentially cause a significant loss of banking assets of recipient countries through cross-border contagion, and compare it with the concentration of the triggering countries banking system. There is no clear definition of a systemically important bank/shock. For our analysis, we consider a systemically important bank/shock to be one affecting 20% of other banking systems assets.

Figure 7 panels, (a), (b) and (c), display the results for our three most important triggers, the United States, the United Kingdom and Germany, respectively. Figure 7, panel (a), shows that, in 2006, an initial shock of as low as 25% of the US's foreign exposure would have triggered cross-border contagion, eroding 95% of the banking assets at 100% LGD, of which 80% of banking assets are lost in the first round. Whereas the same initial shock would erode only 3% of banking assets at 60% LGD. However, an increased initial shock of 60% shock could lead to a massive erosion of 72% of the banking assets.

A similar analysis for the United Kingdom is reported in panel (b) of Figure 7, again assuming a LGD of 100%. It reveals that an initial shock of 35% of its cross-border exposures lead to an erosion of 45% of the banking assets of all recipient countries. Compared with this 35% shock, a 100% default of the United Kingdom would lead to the erosion of 49% of the banking assets, of which 33% would happen in the first round. On the other hand, assuming 60% LGD, a 75% initial shock would have resulted in cross-border contagion eroding 45% of the banking system. Lastly, panel (c) reports the results for Germany: an initial shock wiping out 60% of Germany's cross-border liabilities affects 50% of the banking assets assuming 100% LGD. However, Germany would not trigger any significant contagion assuming 60% LGD during our sample period.[12]

In sum, based on an LGD of 100% and for 2006, we find that a 25%, 35% and 60% shock to, respectively, the United States, the United Kingdom and Germany can be classified as a systemically important shock. This compares to three-bank concentration ratios of 20%, 44% and 25% for the United States, the United Kingdom and Germany, respectively. This shows that a shock that

12 We have also checked the systemically important shock for the United States, the United Kingdom and Germany during initial years of the sample period. Our findings are similar to what we have found in 2006 as reported above.

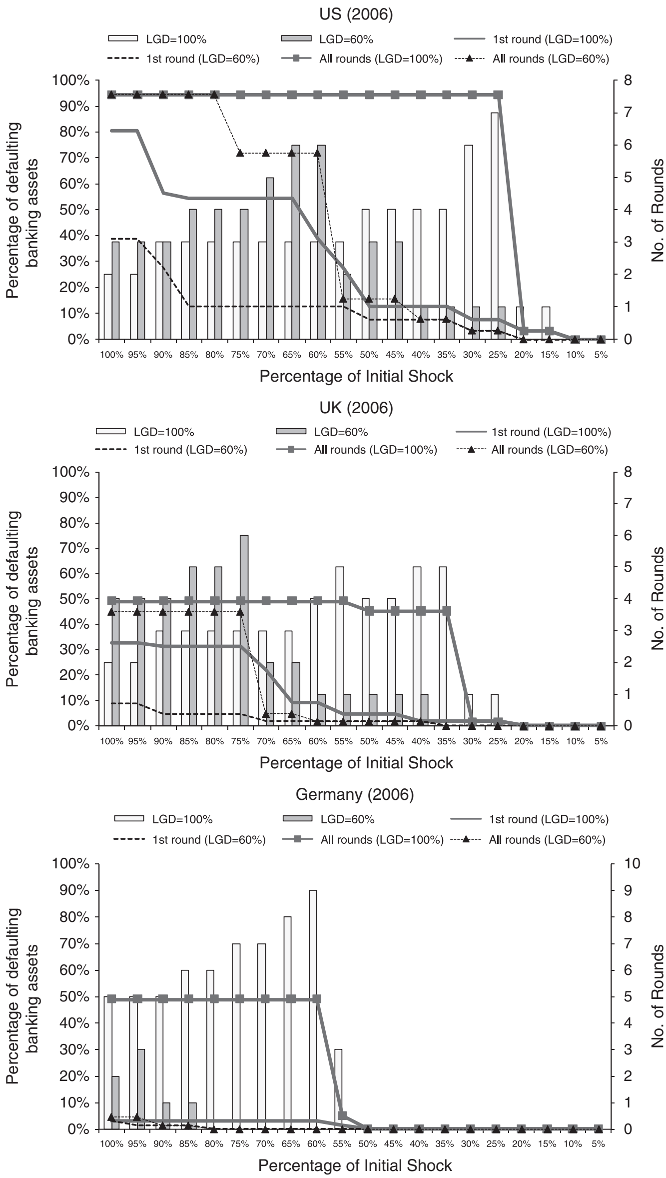


Figure 7 Systemically Important Shock.
The figure shows results for the exercise on a systemically important shock for the United States, the United Kingdom and Germany at 100% and 60% LGD. The columns show the number of rounds, measured on the *y*-axis (right side). The lines show the percentage of total assets of defaulting banking systems relative to total assets of all banking systems (excluding triggering country), measured on the *y*-axis (left side).

would affect the liabilities of the three largest banks (and an equal fraction of the non-bank and public sector) in the United States and the United Kingdom has the potential to lead to a systemically important shock. In unreported exercises, we also find that over time a smaller shock might become a systemically important one. For example, the size of a systemically important bank/shock dropped for the United States from 45% in 1999 to 25% in 2006, and for the United Kingdom from 50% to 35%.

D. Is contagion a result of high exposures or limited capital?

Our results show that contagion risk exhibits considerable heterogeneity among countries as well as important time variation. We now investigate how sensitive contagion risk is to high cross-border exposures and to insufficient bank capital during our sample period. We do this by employing a probit model where the dependent variable is a binary number that equals one whenever a country is a failing recipient after a triggering country fails, and zero otherwise. The independent variables employed in the regression include the ratio of capital to total assets of the recipient, the ratio of foreign claims to total assets of the recipient and the ratio of foreign claims against the triggering country. We also control for year-fixed effects in a separate model.

We report the summary statistics of the capital to asset ratio and the foreign claims to asset ratio in Table 6. We find that financial institutions in Finland,

Table 6 Summary statistics

	Capital to asset ratio			Foreign claims to asset ratio		
	Mean	Median	Standard deviation	Mean	Median	Standard deviation
Austria	0.06	0.05	0.02	0.35	0.36	0.06
Belgium	0.11	0.11	0.01	0.38	0.38	0.04
Canada	0.04	0.04	0.01	0.21	0.20	0.03
Denmark	0.08	0.07	0.03	0.34	0.33	0.07
Finland	0.17	0.19	0.06	0.76	0.82	0.19
France	0.08	0.07	0.02	0.25	0.24	0.03
Germany	0.05	0.05	0.01	0.22	0.22	0.03
Ireland	0.06	0.05	0.01	0.53	0.53	0.17
Italy	0.09	0.09	0.02	0.39	0.38	0.04
Japan	0.05	0.04	0.02	0.06	0.06	0.01
The Netherlands	0.09	0.09	0.02	0.41	0.40	0.04
Portugal	0.06	0.06	0.01	0.44	0.45	0.06
Spain	0.08	0.08	0.02	0.25	0.24	0.04
Sweden	0.07	0.07	0.02	0.38	0.36	0.07
Switzerland	0.10	0.09	0.02	0.38	0.38	0.05
United Kingdom	0.09	0.09	0.02	0.44	0.41	0.07
United States	0.12	0.12	0.01	0.33	0.32	0.06
Total Sample	0.08	0.07	0.04	0.36	0.36	0.16

The table reports descriptive statistics of capital to asset ratio and foreign claims to asset ratio averaged over time.

the United States, Belgium and Switzerland, on average, have 10% or more equity capital relative to their total assets. Whereas Canada, Japan and Germany are on the lower side of the equity capital ratio, financial institutions around the globe have a capital ratio of 8% on average. With respect to the foreign claims to assets ratio, we find that Japanese institutions are not highly exposed (only 6% foreign claims relative to total assets), while European institutions have around 40% foreign claims relative to total assets. The standard deviation of the entire sample is 4% for the capital to asset ratio and 16% for the foreign claims to asset ratio. Table 7 reports that the variables in the probit model (1) explain 38% of the variation in the probability of being a recipient country. With the addition of year-fixed effects, the fit improves to 39%. The likelihood ratio test rejects the null hypothesis that the joint effect of all independent variables is equal to zero. We find that both the foreign claims to total assets ratio and ratio of foreign claims to trigger are statistically significant at 1%, whereas the capital to asset ratio is significant at 5%. The marginal effects show that a one standard deviation increase in capital to asset ratio decreases the probability of the default of recipient country by 2.2 percentage points. Similarly, one standard deviation increase in foreign claims to total assets ratio increases the probability of the default of a recipient country by 4.5 percentage points. Moreover, all signs are robust to year-fixed effects whereas marginal effects slightly decline.

Table 7 Regression results

	Model 1		Model 2	
Number of observations	2312		2312	
LR $\chi^2(3)$	759.94		785.59	
Pseudo-R^2	0.3768		0.3896	
Log likelihood	−628.35		−615.53	
Probit regression	**Coefficient**	**Standard error**	**Coefficient**	**Standard error**
Constant	−2.120***	0.111	−2.179***	0.158
Capital to asset ratio	−2.961**	1.253	−2.752**	1.287
Foreign claims to asset ratio	1.498***	0.288	1.267***	0.297
Exposure to trigger	10.127***	0.462	10.354***	0.470
Year-fixed effect			Yes	
Marginal effects	**d*F*/d*x***	**Standard error**	**d*F*/d*x***	**Standard error**
Capital to asset ratio	−0.557**	0.236	−0.504**	0.236
Foreign claims to asset ratio	0.282***	0.054	0.232***	0.054
Exposure to trigger	1.906***	0.113	1.898***	0.113
Year-fixed effect			Yes	

The table reports probit regression results. The dependent variable is a binary number being 1 if country defaults and 0 otherwise.
**Significant at 5%.
***Significant at 1%.

E. Robustness

We investigate the robustness of our results to a set of extensions. The contagion potential is evaluated with different LGD on short- and long-term liabilities. We also use an alternative classification of foreign claims, ultimate risk basis, for robustness check. Finally, we consider the European Union (EU) and the Euro area to be one banking system. This allows us to study contagion interaction with the other countries we consider (i.e., Canada, Japan, Switzerland and the United States).

In cases 1 and 2, we assumed that the idiosyncratic shock affects all exposures equally whether short term or long term. We understand that this may be a strong assumption, given that it is likely that recovery rates will be higher for long-term exposures. Therefore, we next assume that countries default only on their short-term liabilities (i.e., we assume 100% LGD for the short-term foreign claims and 0% LGD for the long-term). This exercise can be seen as a scenario in which a country faces a shortage of liquidity and therefore the shock is mainly due to a refinancing problem.

We refer to short-term liabilities as foreign claims of less than 1-year maturity. This presents an extreme scenario when short-term claims have no collateral whereas long-term loans are completely secured. The results are shown in Figure 8. Panel (a) reveals that the United Kingdom is the most important triggering country while the United States now has very low triggering potential. For example, Figure 8, panel (a), shows that the United Kingdom can affect nine recipient countries while the United States affects only one country in 2006. The main reason could be the dominance of European countries in our sample. As London is the financial hub for international banking, the United Kingdom owes relative more short-term claims than long-term claims. Further, Switzerland and Ireland emerge as the most directly exposed countries in our sample period. Particularly, in 2006, the United Kingdom directly affects Ireland and Switzerland while the United States affects Switzerland only as shown in Table 8. However, in later rounds, the United Kingdom affects seven more countries as shown in Table 9.

Second, our analysis up to now employed foreign claims on immediate borrower basis (i.e., allocation of foreign claims to the country of operations of the contractual counterparty). The BIS has started compiling data of foreign claims on ultimate risk basis (i.e., allocation of foreign claims to the nationality of the contractual counterparty) in March 2005, but only for 11 countries in our sample. These countries are Belgium, Canada, France, Germany, Italy, Japan, the Netherlands, Portugal, Switzerland, the United Kingdom and the United States. We replicate case 1, where we assumed that all banks are internationally exposed, but now with foreign claims on ultimate risk basis for December 2006 for these 11 countries only.

Assuming 100% LGD, we find contagion results similar to case 1. The United States again is the most devastating triggering country and may lead to contagion that affects all other reporting countries except Italy. Similarly, the default of the United Kingdom poses contagion threat to seven other countries, Germany is important for three other countries and the Netherlands only

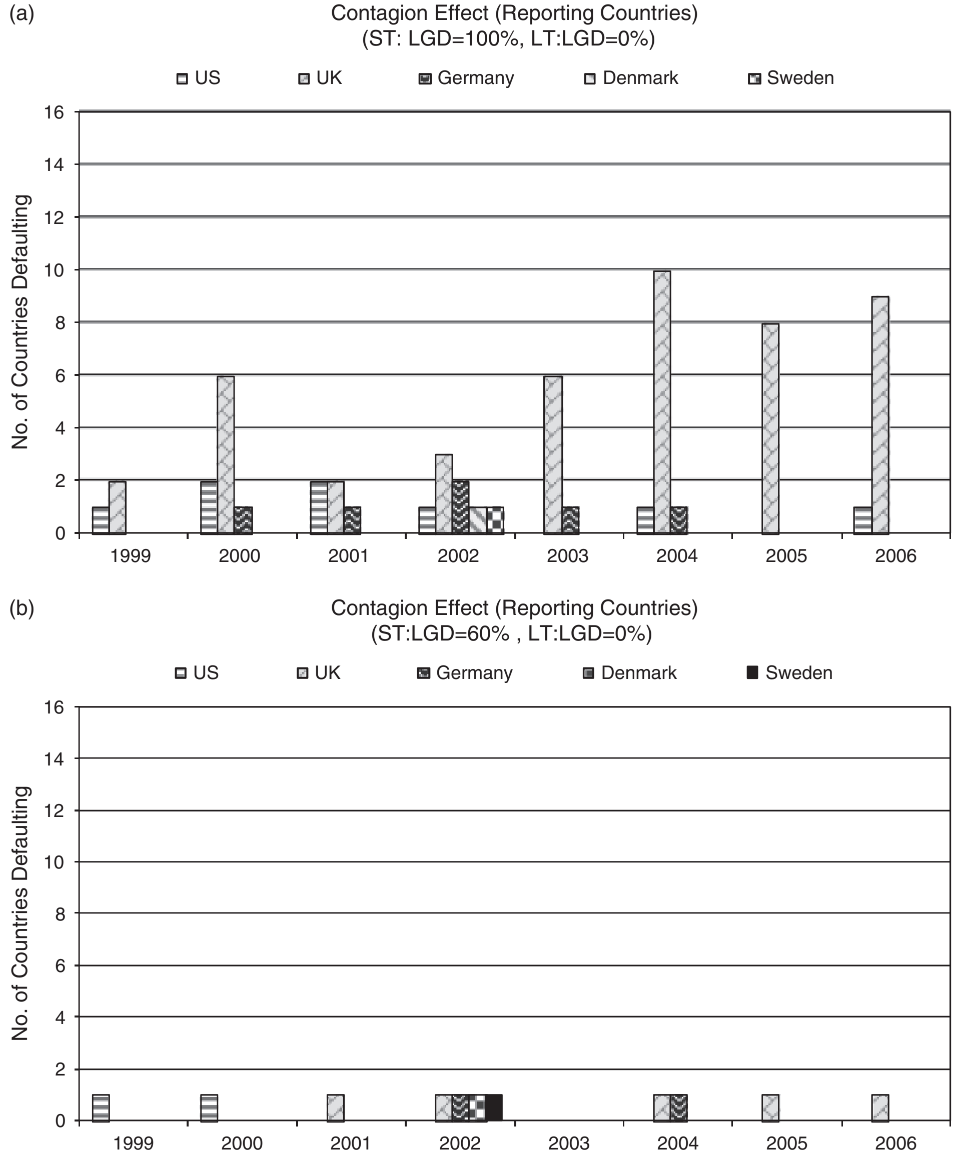


Figure 8 Contagion Results Considering Only Short-Term Claims.
The figure shows the contagion results due to the default of triggering country assuming different LGD on short- and long-term liabilities. Each column depicts the number of recipient countries for the triggering country during 1999–2006. Panel (a) evaluates the effect with 100% LGD on short-term liabilities and 0% LGD on long-term liabilities. Whereas panel (b) evaluates the similar effect due to 60% LGD on short-term liabilities and 0% LGD on long-term liabilities.

Table 8 Directly exposed banking systems when a country defaults only on short-term liabilities

Year 2006 (first round) LGD=100%	Recipient countries																	Total
	DK	FI	SE	AT	BE	FR	DE	IE	IT	NL	PT	ES	CH	GB	JP	CA	US	
Triggering countries																		
Denmark (DK)																		0
Finland (FI)																		0
Sweden (SE)																		0
Italy (IT)																		0
Japan (JP)																		0
The Netherlands (NL)																		0
Germany (DE)																		0
United Kingdom (GB)																		**2**
United States (US)																		1
Total	0	0	0	0	0	0	0	1	0	0	0	0	**2**	0	0	0	0	3

The table shows the details of directly exposed banking systems in 2006 when a country defaults only on short-term liabilities. We use the same set of triggering countries (left column) though only the United Kingdom and the United States trigger contagion in this case. The (defaulting) recipient countries are marked with a gray box. The total on the right column gives total number of recipient countries for each triggering country. Whereas the total number of times a country defaults is mentioned at the bottom.

Table 9 Contagion effect when a country defaults only on short-term liabilities

Year 2006 (all rounds) LGD=100%	Recipient countries																	Total
	DK	FI	SE	AT	BE	FR	DE	IE	IT	NL	PT	ES	CH	GB	JP	CA	US	
Triggering countries																		
Denmark (DK)																		0
Finland (FI)																		0
Sweden (SE)																		0
Italy (IT)																		0
Japan (JP)																		0
The Netherlands (NL)																		0
Germany (DE)																		0
United Kingdom (GB)																		**9**
United States (US)																		1
Total	1	0	1	0	1	1	1	1	0	1	0	1	2	0	0	0	0	10

The table shows the extent of contagion in 2006 taking into account all round effects when a country defaults only on short-term liabilities. We use the same set of triggering counties (left column), though only the United Kingdom and the United States trigger contagion in this case. The (defaulting) recipient countries are marked with a gray box. The total on the right column gives total number of recipient countries for each triggering country. Whereas the total number of times a country defaults is mentioned at the bottom.

affects Belgium. The speed of contagion increases in this exercise as all triggering contagion takes at most two rounds.

The economic impact is also similar to our findings as discussed for case 1: an exogenous default to the United States may affect 94% of total assets of other banking systems. Similarly, the contagion triggered by the United Kingdom, Germany and the Netherlands affect 40.9%, 12.8% and 3.6% of total assets of other banking systems, respectively. Finally, we observe that the pattern of direct exposure is also exactly the same in both cases (i.e., comparing directly exposed contagion from ultimate risk basis with immediate borrower basis of the corresponding reporting countries).

The results on direct exposure are also robust: the United States causes five recipient countries to fail immediately due to cross-border contagion. Similarly, the United Kingdom affects three recipient countries, while the Netherlands and Germany affect one recipient country each. Further, using cross-border claims on ultimate risk basis, we find the Netherlands to be the most vulnerable recipient country for cross-border contagion. This is in line with earlier findings using cross-border claims on immediate borrower basis.

Next, we consider the EU or the Euro area as one banking system, and include also Canada, Japan, Switzerland and the United States. We assume 100% LGD and all banks to be internationally exposed. We find that the United States is still immune to contagion. Moreover, the United States has an impact on Europe, and on all other countries. This contagion pattern is consistent throughout all the sample period. These results reflect the fact that the United States is less exposed to Europe than Europe is to the United States. The ratio of the United States claims against the EU over its domestic banking assets is 3.7%, less than half the ratio of the EU claims against the United States over EU's banking assets (which average 8.5% over our sample period). Therefore, transatlantic contagion is still important for Europe as a whole. Moreover, the financial integration process that Europe has experienced in the last decades should lead to larger cross-border exposures among all member countries, leading to higher within Europe contagion potential. This process actually increases the probability that a US shock that may initially affect only a few countries will end up affecting most of the member countries.

Finally, we also wanted to check the possibility for contagion with risk-weighted capital instead to total ordinary equity capital as reported in balance sheets on financial institutions. However, we find that financial institutions in many countries do not report risk-weighted capital in a consistent manner. Therefore, the results would be highly biased toward the countries reporting the risk-weighted capital only.

V. CONCLUDING REMARKS

The risk of contagion through the banking system is not limited to domestic boundaries. In recent years, foreign claims held by the banking system have increased substantially suggesting that cross-border contagion needs further consideration as it may pose serious threats to financial stability. We find for 2006 that a shock wiping out 25% (35%) of US (UK) cross-border liabilities against non-US (non-UK) banks could lead to bank contagion eroding at least 94% (45%) of the recipient countries' banking assets. We also find that since 2006 a shock to Eastern Europe, Turkey and Russia affects most countries. Moreover, our simulations reveal that contagion risk and the 'speed of propagation of contagion' have increased over time during the period 1999–2006. Finally, we find that contagion is more widespread in geographical proximities.

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The real effect of banking crises ☆

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Abstract

Banking crises are usually followed by low credit and GDP growth. Is this because crises tend to take place during economic downturns, or do banking sector problems have independent negative real effects? If banking crises exogenously hinder real activity, then sectors more dependent on external finance should perform relatively worse during banking crises. The evidence in this paper supports this view. The differential effects across sectors are stronger in developing countries, in countries with less access to foreign finance, and where banking crises were more severe. Robustness checks include controlling for recessions, currency crises, and alternative proxies for bank dependence.

JEL classification: E44; G21

Keywords: Banking crises; Credit crunch; Bank lending channel

1. Introduction

Banks are thought to be central to business activity. Therefore, when they experience financial distress, governments usually come to the rescue, offering emergency liquidity and various forms of bailout programs. The case for generous bank support, however, is murky for a number of reasons. First, we have the standard identification problem: if bank distress and economic distress occur at the same time, how can we tell the direction of causality? Second, if bank distress does in fact impair economic activity, under what circumstances is this likely to be most harmful? Third, while interventions may save banks, they may not necessarily prevent the distressed banks from

☆ The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the IMF, its Executive Directors, or the countries they represent.

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affecting economic activity. So do any interventions prevent banks from impairing economic activity, and if so, which ones are they? Fourth, how do the costs of intervention weigh up against the benefits? This paper focuses on the first two questions, shedding limited light on the last two issues.

Empirical studies show that credit to the private sector and aggregate output do in fact decelerate during banking crises (see, for example, Kaminsky and Reinhart, 1999; Eichengreen and Rose, 1998; Demirgüç-Kunt et al., 2006). However, this is not necessarily evidence that banking problems contribute to the decline in output: first, the same exogenous adverse shocks that trigger banking problems may also cause a decline in aggregate demand, leading firms to cut investment and working capital and, ultimately, demand for bank credit. These same shocks may also cause a temporary increase in uncertainty, leading firms to delay investment and borrowing decisions. In addition, adverse shocks might hurt borrower balance sheets and exacerbate the effects of asymmetric information and limited contractibility, prompting banks—even healthy ones—to curtail lending to riskier borrowers ("flight to quality") or raise lending spreads. To summarize, output and bank credit are likely to decelerate around banking crises even in the absence of a feedback effect from bank illiquidity and insolvency to credit availability.[1] To identify the real effects of banking crises it is necessary to sort out this joint endogeneity problem.

Problems of joint endogeneity are familiar in studies of whether finance matters to the real economy. They are central to the literature on financial development and growth (Levine, 2005) and to the work on whether financial market imperfections worsen economic downturns (the so called "credit channel" literature). To test whether banking crises have real effects, we adopt the "difference-in-difference" approach used by Rajan and Zingales (1998) to study the effects of finance on growth.[2] Our premise is that, if industries more dependent on external finance are hurt more severely after a banking crisis, then it is likely that banking crises have an independent negative effect on real economic activity. Using panel data from 41 countries from 1980 to 2000, we test whether more financially dependent industries experienced slower growth in banking crisis periods, after controlling for industry-year, country-year, and industry-country fixed effects. This profusion of dummy variables controls for all possible time specific, country specific, and industry specific shocks that may affect firm performance, thereby avoiding the usual difficulties of choosing an appropriate set of control variables.

In Rajan and Zingales (1998) industry dependence on external finance is measured by the fraction of investment not financed through retained earnings. We use the same index in our main specification.[3] As an alternative measure of bank dependence, we use average establishment size in a sector, under the assumption that sectors dominated by small firms are more dependent on domestic bank financing.[4] In the credit channel literature, identification based on firm size has been used, for instance, by Gilchrist and Himmelberg (1995).

[1] There are also measurement issues. Specifically, changes in the aggregate stock of real credit to the private sector are not a good measure of the flow of credit available to the economy, especially around banking crises. The stock may fall because a jump in inflation erodes the value of nominal contracts, or because restructuring operations transfer non-performing loans to agencies outside the banking system. On the other hand, a devaluation increases the domestic currency value of foreign-currency denominated debt (Demirgüç-Kunt et al., 2006).

[2] The "difference-in-difference" methodology has also been used in a variety of related problems (see, for example, Cetorelli and Gambera, 2001; Beck, 2003; and Bonaccorsi di Patti and Dell'Ariccia, 2004).

[3] For several countries in our sample banks are overwhelmingly the main (and often the sole) source of external capital for firms. On average, in our sample the stock of bank credit is about 7 times larger than equity market capitalization.

[4] An establishment is better thought of as a plant rather than a firm. In general, the majority of firms in any sector consist of single plant firms, so there will be a strong correlation between establishment size and firm size.

The results are supportive of the joint hypothesis that banking crises have real effects, and at least part of this effect is through the lending channel. More financially dependent sectors perform significantly worse during banking crises, and the magnitude of the effect is non-trivial: more financially dependent sectors (in the 4th quartile of the dependence distribution) lose about 1 percentage point of growth in each crisis year compared to less financially dependent sectors (in the 1st quartile of the dependence distribution). Of course, not all doubts about causality are laid to rest by this methodology, and we conduct a number of additional tests.

In particular, one criticism of our testing strategy is that because of balance sheet effects or other financial market imperfections, externally dependent sectors may grow more slowly during *any* economic downturn, whether a banking crisis or not (Braun and Larraín, 2005). A related concern is that the differential effect might be driven by balance sheet effects following currency crises (which often accompany banking crises). This may happen if more externally dependent sectors tend to have more foreign currency debt. When we allow for separate differential effects during recessions or currency crises, however, the differential effect during banking crises remains significant, suggesting that we are not simply picking up balance sheet effects.

We also address the issue of the residual endogeneity of the banking crisis variable. If bank dependent sectors are relatively more represented in bank portfolios, asymmetric sectoral shocks affecting these sectors might cause both the banking crisis and the relative underperformance of these sectors. However, we find that more external dependent industrial sectors perform poorly during banking crises even in countries/crises where they are likely to represent a smaller share of bank portfolios. This suggests that our correlations are not driven only by asymmetric sectoral shocks.

Another criticism may be our reliance on the Rajan–Zingales measure of external dependence. When instead we differentiate across industries based on average establishment size, our tests show that small-scale sectors suffer more during crises, consistent with the hypothesis that the lending channel is operative.

Tornell and Westermann (2002, 2003) have argued that asymmetries in the response to financial crises in emerging markets are not just between large and small firms, but also between firms in traded and non-traded sectors, because the firms in traded sectors have better access to alternative sources of financing (especially foreign finance) when domestic credit is depressed. We also examine if such asymmetric effects are present in our data. We do not, however, find significant differences across manufacturing sectors during banking crises based on their propensity to export, though we do find such differences during currency crises.

The second question we posed at the outset is to examine where the differential effect is stronger. On the one hand, this gives us a sense of where intervention may be more critical, on the other, if the differential effect is stronger where the theory plausibly suggests the costs of banking crises are likely to be larger, the differential effect itself gains credibility as a measure of the impact of the crisis. We find the differential effects to be stronger in developing countries, in countries where the private sector has less access to foreign finance, and where the crises are more severe (in a way we will make more precise). These results make intuitive sense: externally dependent sector should suffer less from a banking crisis if they can tap domestic bond or stock markets (as in developed countries) or foreign capital markets. Also, the more severe the disruption in the banking sector, the stronger should be the differential effect.

We turn next to the question of how different government intervention policies might affect the bank lending channel. Using data on intervention policies for 22 crisis episodes from Honohan and Klingebiel (2003), we find some evidence that regulatory forbearance is associated with a lower cost of crisis. Because the sample is small, however, the evidence is only suggestive.

Nonetheless, the finding is consistent with our hypothesis: if banks are special, keeping them alive is essential for credit to flow to financially dependent industries. Moreover, banks that are kept alive might focus on squeezing borrowers in order to regain liquidity. That they do not seem to do so when given maneuvering room is interesting.

Of course, policy makers are particularly interested in whether the benefits of an intervention outweigh the cost. Since our methodology allows us only to identify the differential effect of an intervention and not the aggregate effect (for instance, if spillovers from the increased growth of financially dependent industries prevents the whole economy from falling into recession) we have little to say here other than interventions that do not affect the differential are unlikely to affect activity through the lending channel, and therefore have to be justified for other reasons.

The paper is structured as follows: In Section 2, we review the related literature; in Section 3 we explain the empirical methodology and the data; in Section 4 we present the results; Section 5 concludes.

2. Related literature

There is a long literature focusing on the effects of banking crises. For example, Lindgren et al. (1999) summarizes many early experiences, and concludes that "*episodes of fragility in the banking sector have been detrimental to economic growth in the countries concerned*" (p. 58). Cross-country studies of banking crises have also shown that output growth and private credit growth drop significantly below normal levels in the years around banking crises, but do not attempt to sort out the direction of causality (Kaminsky and Reinhart, 1999; Eichengreen and Rose, 1998; Demirgüç-Kunt et al., 2006).

In their study of the so-called capital crunch in the United States in 1990, Bernanke and Lown (1992) in fact express skepticism that the credit crunch played a major role in the recession of 1990. Instead, they stress demand effects, pointing to the fact that there was little relation between bank capital ratios and employment growth across states, and all types of credit, not just bank credit, fell.

The question of whether banking crises cause a credit crunch was resurrected once more following the Asian crises of 1997–1998. Some studies attempted to provide answers, reaching different conclusions. For instance, Domaç and Ferri (1999) interpreted evidence that small and medium-sized enterprises were hurt disproportionately in Malaysia and Korea as indicative of a credit crunch, while most Thai firms surveyed after the crisis attributed low production levels not to lack of credit, but to poor demand (Dollar and Hallward-Driemeier, 2000).

A number of papers have tried to tackle the identification problem in clever ways. Some have examined the issue from the side of banks. Peek and Rosengren (2000) use geographical separation as their means of identifying supply shocks: Japanese banks lost capital as a result of bad loans made in Japan. The authors then show that the withdrawal of these banks from lending to real estate in the United States had a strong dampening effect on US commercial real estate markets. Clearly, it is hard to attribute the fall in real activity to demand side effects. Kashyap and Stein (2000) suggest a lending channel for monetary policy by pointing out that small, less liquid banks seem to curtail credit more in response to tight monetary conditions than large, liquid banks.

Our paper differs from these in that it attempts to identify supply effects by looking to see if borrowing sectors that are more likely to be sensitive to a supply shock are indeed disproportionately affected by it. In this, our paper is closely related to two recent papers:

Braun and Larraín (2005) tests whether industries more dependent on external finance experience a sharper output contraction than other industries during economic downturns, and finds a large positive differential effect. They also find this effect to be larger in countries with poor accounting standards and for industries whose assets are less tangible, supporting the interpretation that financial frictions are at work, and thus may amplify economic fluctuations especially for industries more dependent on external finance. In contrast, in the present paper, we focus more narrowly on the effects of banking sector distress on the real economy. This allows us to identify the presence of a bank lending channel to the extent that the effects of the disruption in loan supply associated with the crises are greater that those stemming from the deterioration of firm balance-sheet quality (possibly also associated with the crisis).

In a contemporaneous and closely related paper, Krozner et al. (2007) study whether banking crises impact sectors dependent on external finance more severely in countries with a less developed financial system. While both papers investigate how banking crises affect the real economy, they examine two different aspects of this relationship. Here, we, first, present evidence in support of the assumption that banking crises have real effects by showing that it is the sectors more dependent on external finance that suffer the most during these crises. Then, we consider how several country characteristics affect these effects.

In other words, we are interested in the differences within a country over time of the relative growth of financial dependent industries. We find they do particularly badly during a banking crisis, suggesting that those are periods of low availability of finance. By contrast, Krozner et al. (2007) examine the effects of the financial development of a country on the relative growth of financially dependent industries in non-crisis and crisis periods. They find that the relative growth in value added of financially dependent industries is faster in financially developed countries in pre-crisis periods but slower in crisis periods. This has implications for the effects of financial development in different states of the economy, but has little light to shed on the effects of the different states of the economy themselves. Econometrically speaking, we look for a within country across industry effect over time (including country-industry indicators along with the usual panoply of country and industry indicators), while they examine the differential effect between industries across countries for two different states of these countries (not including country-industry indicators). Their finding is that the differential effect found by Rajan and Zingales is present in pre-crisis periods, but becomes insignificant (and even changes sign) during crises. The interpretation is that operating in an environment where financial markets are well developed is an advantage for more financially dependent industries in good times, but a disadvantage in times of banking crises.

The problem of separating out the effect of bank distress from other contemporaneous shocks hinders efforts to measure the economic cost of banking crisis and to understand the determinants of these costs. Most existing studies have looked at the decline in output as a yardstick to differentiate across crises. For instance, Bordo et al. (2001) argue that financial crises (currency crises, banking crises, or both) have entailed similar-sized output losses in recent years as compared to previous historical periods, although they are more frequent now than during the gold standard and Bretton Woods periods and as frequent as in the interwar years. Hoggarth et al. (2002) claim that, contrary to popular belief, output losses associated with banking crises are not more severe in developing countries than in developed countries.

More recently, Claessens et al. (2003) study how output losses following banking crises are affected by institutions and policy interventions. As in our paper, the latter are identified through the Honohan–Klingebiel data set. The main finding is that generous support to the banking system does not reduce the output cost of banking crises. This conclusion, however, does not take into account that omitted exogenous shocks may cause both a stronger output decline and more generous intervention measures. Using a measure of the cost of crises less marred by this problem, we find that forbearance may indeed be effective in reducing the real cost of crises.

3. The basic test

3.1. Methodology

To study whether banking crises have real effects, we ask whether industries more dependent on external finance experience a more severe output loss following a banking crisis. In the benchmark specification, value added growth in industry j at time t in country i is regressed on three sets of fixed effects (industry-year, country-year, and industry-country) and the variable of interest, an interaction term equal to the product of the financial dependence measure for industry j and the banking crisis dummy for year t and country i. Following Rajan and Zingales (1998), we also include the lagged share of industry j in country i to account for "convergence" effects, i.e. the tendency of larger industries to experience slower growth. The benchmark regression is:

$$y_{i,j,t} = \sum_{ij} \alpha_{i,j} d_{i,j} + \sum_{i,t} \beta_{i,t} d_{i,t} + \sum_{j,t} \gamma_{j,t} d_{j,t} + \delta FINDEP_j * BANK\_CRISIS_{i,t} + \varphi SHARE_{i,j,t-1} + \varepsilon_{i,j,t}$$

where the d's denote dummy variables. A negative and significant δ indicates that banking crises have a relatively worse impact on industries that depend more heavily on external finance. The three sets of fixed effects should control for most shocks affecting firm performance, including—for instance—the severity of the banking crisis, the level of financial development, global shocks to the industry, aggregate country-specific shocks. This gets around the usual difficulties with omitted variable bias. Indeed, the only shocks not controlled for are those varying simultaneously across countries, industrial sectors, and time. Standard errors are clustered by industry and country. As robustness tests, we also use gross capital formation, employment, and number of establishments as the dependent variable instead of value added.

3.2. Data

Data on manufacturing value added, investment, and number of establishments are disaggregated at the 3-digit ISIC level and come from the *UNIDO, Industrial Statistics, 2003* (summary statistics for these variables are in Table 1). There are 28 industries at this level of disaggregation. Value added is deflated using consumer price indexes from the *International Financial Statistics*.[5]

External dependence is defined as the share of capital expenditure not financed with cash-flow from operations. The data come from Rajan and Zingales (1998), who take them from Compustat. Following Krozner et al. (2007), and in contrast with Rajan and Zingales, to preserve sample size we include only 3-digit ISIC level sector rather than a mixture of 3 and 4-digit level

[5] The producer price index would be a more appropriate measure of prices in manufacturing, but it was not available for a number of countries in our sample. In any case, the price index does not affect differences in growth rates across sectors, which is what matters to our tests.

Table 1
Summary statistics

	Mean		Median		Standard Dev.		Max		Min		No. of obs.	
	Normal	Crisis	Normal	Crisis	Normal	Crisis	Normal	Crisis	Normal	Crisis	Normal	Crisis
Value added growth (in percent)	4.20	1.70	2.22	−0.42	22.26	24.63	107.44	107.40	−54.12	−54.09	13168	3059
Growth in capital formation (in percent)	12.75	10.60	2.76	−1.09	55.91	57.49	240.70	239.99	−80.51	−79.70	7858	1894
Employment growth (in percent)	1.23	−0.83	0.49	−1.22	8.58	9.19	29.00	28.88	−20.43	−20.36	13053	2887
Growth in number of establishments (in percent)	2.13	0.68	0.00	0.00	9.96	10.38	45.77	45.95	−22.12	−22.14	7598	2086

Notes. Crisis refers to observations that correspond to the year of inception of a banking crisis or the two subsequent years. Normal refers to all other observations.

sectors.[6] The figures are for US manufacturing firms and reflect industry medians during the 1980s (Table A2). An important assumption underlying our approach is that external dependence reflects technological characteristics of the industry that are relatively stable across space and time (see Rajan and Zingales, 1998 for a discussion of this assumption). In Section 5 below we explore alternative proxies for a sector's reliance on bank finance: average establishment or plant size and export orientation (Table A3 reports the correlations between these measures).[7]

To identify banking crisis inception dates, we rely on information from case studies, including Lindgren et al. (1999) and Caprio and Klingebiel (2003). Following Demirgüç-Kunt and Detragiache (1998), we consider episodes of bank distress to be systemic crises when at least one of the following conditions holds: there were extensive depositor runs; the government took emergency measures to protect the banking system, such as bank holidays or nationalization; the fiscal cost of the bank rescue was at least 2 percent of GDP; or non-performing loans reached at least 10 percent of bank assets. A list of banking crises is in Table A4.

The crisis dummy variable takes the value 1 for the crisis inception year and the two following years, under the hypothesis that the real effect of the crisis dissipate after three years or so. Table A5 shows that if crises are set to last four years there is not much difference in aggregate value added growth rates between crisis and non-crisis periods, while for shorter durations crisis years have lower growth. Also, in a sample of 36 crises, Demirgüç-Kunt et al. (2006) find that GDP growth returns to its pre-crisis level in the fourth year of a crisis. For robustness, we also consider narrower and wider crisis windows.

To maximize sample size we use an unbalanced panel in which some country/year/sector observations are missing. We exclude, however, country/years for which less than 10 industrial sectors are available to ensure that there is enough information to estimate the differential effect. Constraints on the availability of banking crisis and sectoral value added information leave us with data from 41 countries from 1980 to 2000 for a total of over 16,000 observations, after excluding 2 percent of outliers on either tail of the distribution.[8] Summary statistics for the alternative dependent variables (manufacturing value added, investment, employment, and number of establishments) for crisis and non-crisis observations are in Table 1.

4. Results

4.1. The benchmark test

Estimates from the benchmark regression support the hypothesis that banking crises have an exogenous effect on the real economy. The coefficient of the interaction term is negative and significant at the 5 percent level, indicating that the growth rate of sectors that rely more heavily on external finance is relatively more affected in crisis years compared to sectors that rely less on external finance (Table 2, column 1). The economic magnitude of this effect is substantial. On average, in a country experiencing a banking crisis, the difference in value added growth between a sector at the 25 percentile and one at the 75 percentile of the external dependence distribution

[6] Table A1 reports the Rajan and Zingales index.

[7] It should be emphasized that, if the Rajan–Zingales does not capture meaningful differences across sectors in our sample, then our coefficient estimates should be insignificant and not biased toward overrejection.

[8] Countries that did not experience banking crises during the 1980s or 1990s are excluded from the sample. Including these observations would only serve to estimate more accurately the time-industry dummies, but would sharply increase the already large number of parameters to be estimated.

Table 2
Differential effect of banking crises on value added growth

	Benchmark	Sectoral correlations	Recessions	Currency crises
Crisis3 ∗ Dep	−2.74		−2.55	−2.87
	[2.27]**		[1.98]**	[2.32]**
High-Corr ∗ Crisis3 ∗ Dep		−2.07		
		[1.36]		
Low-Corr ∗ Crisis3 ∗ Dep		−3.39		
		[1.93]*		
Recession ∗ Dependence			−0.77	
			[0.64]	
Currency crisis ∗ Dep				1.38
				[0.98]
Lagged share	−2.44	−2.44	−2.44	−2.44
	[7.51]***	[7.51]***	[7.50]***	[7.52]***
Constant	8.46	8.49	8.53	−29.61
	[1.45]	[1.45]	[1.46]	[3.23]***
Observations	16227	16227	16227	16227
R-squared	0.35	0.35	0.35	0.35

Notes. t-statistics in parenthesis. Crisis3 is a dummy variable for the year of banking crisis inception and two following years. Dep is a parameter measuring an industry's dependence on external finance (Rajan and Zingales, 1998). High corr are crisis episodes in which sectoral dependence for the country is highly (correlated with sectoral share). Lagged share is the share of the sector's value added in total value added lagged by one period. Regressions are estimated with OLS, standard errors are clustered by industry-country, and also include time-country, time-industry, and industry-country dummy variables.

* Significance at the 10% level.
** Idem, 5%.
*** Idem, 1%.

is 1.1 percentage point per year of crisis. This compares with an average rate of growth of 3.7 percent in the sample as a whole and 1.7 percent during crisis years.

As sensitivity analysis, we drop from sample the 5-percent tails of the dependent variable distribution. When this is done, the coefficient of the interaction term remains negative and significant.[9]

4.2. *Are the result driven by asymmetric sector-specific shocks?*

The methodology employed in this paper greatly reduces the concern for simultaneity biases in the relationship between growth and banking crises. However, the endogeneity of the banking crisis variable is still an issue since bank dependent sectors are likely to be more heavily represented in bank portfolios than less bank dependent sectors. Asymmetric sectoral shocks concentrated in bank dependent sectors could cause both the banking crisis and relatively poor growth in those sectors.

[9] We also change the sample by considering only observations for which data for all the 28 sectors are available. The sample size drops by almost one half. For the baseline specification the coefficient of the interacted term remains negative but is no longer significant. However, when we allow the effect of a crisis to vary between advanced economies and developing countries, the coefficient for the latter is significant. Similar results arise if the crisis window is changed from three to four years. These results are not reported.

To address these concern, we proceed as follows. We do not have data about the sectoral composition of bank portfolios, but we conjecture that, in each country, sectors are relatively more represented in bank portfolios if they are relatively large *and* they are relatively more dependent on external finance. For each country and year, we compute the correlation between the sectoral share and the external dependence variable. In countries where this correlation is high, bank dependent sectors are likely to account for a significant share of bank balance sheets, while in countries with low correlation, they are not. Then, under the null hypothesis of asymmetric sectoral shocks, crisis episodes in which this correlation is high should exhibit larger differential costs of crises than crisis episodes in which this correlation is low. In other words, since countries with a high correlation are ones where external finance dependent industries account for a large share of the economy, it is more plausible that the banking crises in these countries were caused by problems originating in externally dependent industries. A finding that our interaction coefficient is significant in these countries but not in countries with a low correlation would lend support to the reverse causality explanation, i.e. it is the slow growth of dependent industries that caused the banking crisis rather than vice versa.

To test this, we split the sample around the cross-country median of the distribution of the correlation between external dependence and relative size, and rerun the baseline specification allowing the coefficient of the interaction term to differ between the two groups (Table 2, column 2). We find that the coefficient for the crises where bank dependent sectors represent a relatively smaller portion of bank portfolios is *larger* than that in our baseline regression and remains significant at the 10 percent level. The coefficient for the other crises, on the other hand, is not significant. This evidence suggests that the hypothesis of asymmetric sectoral shocks should be rejected.

4.3. Bank distress or balance sheet effects?

A concern with our interpretation of the basic regression is that the differential effects we document may reflect balance sheet problems among borrowers rather than their banks. In other words, banking crises often coincide with economic downturns which worsen firm balance sheets. This, in turn, aggravates agency problems and other financial frictions, causing all banks (even healthy ones) to cut back on lending, presumably hurting bank-dependent sector disproportionately more.[10] As discussed in Section 2 above, Braun and Larraín (2005) find that during recessions output declines disproportionately more in sectors more reliant on external finance.

To separate out the effect of financial frictions during recessions from the specific effect of banking crises, we construct a recession dummy variable using GDP data from the World Bank World Development Indicators. Following the peak-to-trough criterion (Braun and Larraín, 2005), we date recessions as follows: first, a trough is identified when GDP falls more than one country-specific standard deviation below its trend level (where trend is computed with a standard Hodrick–Prescott filter). Then, a peak is identified as the last year with positive GDP growth before the trough. The recession dummy variable takes the value of one from the year after the peak to the year of the trough. Using this dummy variable, we estimate the following

[10] On a related point, we find a very low correlation between sectoral cyclicality (measured as the correlation between the cyclical components of real GDP and sector specific value added) and external dependence (about 0.1 on average). This addresses the potential concern that our interacted term picks up the effects of sectoral cyclicality rather than the effect of banking crises.

equation:

$$y_{i,j,t} = \sum_{ij} \alpha_{i,j} d_{i,j} + \sum_{i,t} \beta_{i,t} d_{i,t} + \sum_{j,t} \gamma_{j,t} d_{j,t} + \delta FINDEP_j * BANK\_CRISIS_{i,t} + \varphi SHARE_{i,j,t-1} + \xi FINDEP_j * RECESSION_{i,t} + \varepsilon_{i,j,t}.$$

If the coefficient δ captures the differential effect of recessions rather than the banking crises, it would lose significance in this specification, while ξ would be negative and significant.

As it turns out, there is an overlap between recessions and banking crises, but the overlap is far from perfect: not all recessions coincide with banking crises and not all banking crises occur during economic downturns. When we estimate the regression with both interaction terms, the coefficient of the crisis/dependence interaction term becomes a bit smaller, as one might expect, but remains significant at 5 percent in both specifications (Table 2, column 3). On the other hand, the coefficient of the recession/dependence interaction term has the expected sign (negative), but it is not significant. This finding supports the interpretation that we are picking up not only balance sheet effects, but also disruptions in credit supply due to the banking crisis.[11]

This result may be in part driven by the fact that we consider only countries that experienced at least one crisis, while Braun and Larrain consider a broader sample. This may also reflect different mechanisms in advanced economies and developing countries since these represent the majority in our sample (more on this in the next section).

Similar arguments apply to currency crises. These events, especially in countries where the corporate sector has large unhedged foreign currency exposures, may cause large balance sheet effects. If more leveraged firms are also more dependent on external finance, and if large currency depreciations occur in association with banking crises (the "twin crises"), then the differential effect found in the baseline regression may reflect the balance sheet channel rather than distress in the banking sector. To sort out this issue, we rerun the benchmark regressions by adding an interaction term between external dependence and a currency crisis dummy. Following Milesi-Ferretti and Razin (1998), a currency crisis is defined as a year in which the exchange rate satisfies the following three conditions: it depreciates (vis-à-vis the US dollar) at least 25 percent; it depreciates at least twice as fast as in the previous year; and the previous year it depreciated by less than 40 percent.[12]

When currency crises are controlled for, the coefficient of the bank-crisis/dependence interaction term remains negative and significant and of similar magnitude as in the baseline regression (Table 2, column 4). The coefficient of the currency-crisis/dependence interaction term has a positive sign, perhaps because more externally dependent sectors tend to be exporting sectors which benefit from a devaluation, but is not significant. It could also be that twin crises are banking crises in which the government provides banks with more extensive liquidity support. While the exchange rate depreciates as a result of the liquidity injections, the real effects of the crisis may be mitigated.

[11] This results is also consistent with what reported by Krozner et al. (2007) in their Table 10.

[12] The latter condition serves to eliminate cases of chronically high inflation countries, in which large rates of depreciation are recorded on a regular basis. This definition corresponds to the second of the four definitions of crisis considered by Milesi-Ferretti and Razin (1998).

4.4. Where do crises matter most?

In our baseline specification all banking crises are treated as having the same differential effect on industries. In practice, this is unlikely to be the case, as different characteristics of the economy may affect the impact of the banking crises, and the crisis itself may be of different nature and magnitude. So the question we now turn to is if bank distress does in fact impair economic activity, under what circumstances is this likely to be most harmful?

Banking crises are likely to have relatively larger real effects in developing countries where bond and equity markets are less developed and where governments may find it more difficult to provide support for troubled banks. For this reason we consider an alternative specification where the coefficient of the interaction term is allowed to differ across advanced and developing countries (as defined by the IMF's World Economic Outlook). The results confirm this conjecture (Table 3, column 1). While the coefficient for advanced countries is not significant, that for developing countries is larger than in the benchmark specification and significant at the 5 percent

Table 3
Differential effects of banking crises on value added growth: Differences between developed and developing countries

	3-year window	4-year window	Excluding 5-percent outliers	Recessions	Currency crises
Crisis3 ∗ Dep ∗ DC	−0.07		−1.43	0.72	−0.02
	[0.04]		[1.00]	[0.37]	[0.01]
Crisis3 ∗ Dep ∗ LDC	−3.73		−2.24	−3.66	−4.01
	[2.46]**		[1.74]*	[2.30]**	[2.56]**
Crisis4 ∗ Dep ∗ DC		0.52			
		[0.36]			
Crisis4 ∗ Dep ∗ LDC		−2.58			
		[1.91]*			
Recession ∗ Dep ∗ DC				−2.07	
				[1.38]	
Recession ∗ Dep ∗ LDC				−0.34	
				[0.23]	
Currency crisis ∗ Dep ∗ DC					−1.66
					[0.98]
Currency crisis ∗ Dep ∗ LDC					2.41
					[1.35]
Share $(t-1)$	−2.44	−2.44	−1.69	−2.44	−2.45
	[7.52]***	[7.51]***	[7.18]***	[7.52]***	[7.53]***
Constant	8.41	8.37	10.82	3.90	8.04
	[1.44]	[1.43]	[1.43]	[0.76]	[1.25]
Observations	16227	16227	15213	16227	16227
R-squared	0.35	0.35	0.36	0.35	0.35

Notes. t-statistics are in parenthesis. Crisis3 is a dummy variable for the year of banking crisis inception and two following years. Crisis 4 is a dummy variable for the year of a banking crisis and the following three years. Dep is a parameter measuring an industry's dependence on external finance (Rajan and Zingales, 1998). DC is a dummy for developed countries. LDC is a dummy for developing countries. Recession is a dummy for recession years. Currency crisis is a dummy for currency crisis years. Lagged share is the share of the sector's value added in total value added lagged by one period. Regressions are estimated with OLS, Standard errors are clustered by industry-country, and regressions also include time-country, time-industry, and industry-country dummy variables.

* Significance at the 10% level.
** Idem, 5%.
*** Idem, 1%.

level. The difference in value added growth between a sector at the 25th percentile and one at the 75th percentile of the external dependence distribution becomes 1.5 percentage points per year of crisis. For robustness, we ran alternative specifications with different crisis windows and with and without outliers (Table 3, columns 2 and 3).

Interestingly, the Braun and Larrain coefficient of the recession/dependence interaction term is larger (and almost significant) for advanced economies where banking crises tend to be less common and for which the crisis/dependence interaction term is not significant (Table 3, column 4). This suggests that in advanced economies, possibly because of the existence of sources of external finance other than the banking system, overall macroeconomic conditions are more important than the health of the banking system in determining how funds are allocated to the real sector. In emerging markets and developing countries, the absence of alternative sources of finance may make growth differentials among sectors with different reliance of external finance more sensitive to banking crises than to the business cycle.

In a related vein, the effects of banking crises should differ across countries with different access to foreign finance, under the hypothesis that industries dependent on external finance should be more severely affected by banking crises in countries with more limited access to foreign sources of capital.

To proxy for access to alternative sources of finance we use data on disbursement of foreign loans and bonds to the private sector (scaled by the sum of imports and exports). The data come from the Global Development Finance database of the World Bank. Since developed countries are not covered by this database, we arbitrarily set the value for these countries at the largest sample observation, under the assumption that developed country firms have broad access to alternative finance. We then allow for separate interaction coefficients between crisis and external dependence for countries with access above the sample median and countries with access below the sample median. The estimation results suggest that the real effects of banking crises are more pronounced when access to foreign finance is more limited (Table 4, column 1). This suggests that access to foreign finance can help mitigate the real effects of banking crises.[13]

If our hypothesis is correct, banking crises should have more significant real effects in those cases where they are more pervasive and involve the disruption of the orderly functioning of the banking system. We consider three indicators of crisis severity: the fiscal cost of the crisis, the share of non-performing loans on total loans, and the fraction of insolvent bank assets in total bank assets. The sample is then split according to whether the severity ranking (an average of these three measures) is above or below its median, and the usual regression is estimated with two separate interaction terms, one for more severe and one for milder crises. As expected, we find that externally dependent sectors suffer more in more severe crises (Table 4, column 2). Similar results are obtained if we split the sample according to the aggregate output loss experienced during the crisis, where the loss is computed as the difference in average GDP growth between the three years preceding a crisis and the three years of the crisis (Table 4, column 3).

Another interesting question is whether the differential effects of crises are more pronounced when bank distress is accompanied by a currency crisis, as is has been the case in a number of well known episodes. When we split the sample between "twin crises" and stand-alone crises,

[13] An intriguing question is whether the presence of foreign banks can mitigate crisis costs. Unfortunately, measures of foreign bank presence for a cross-section of countries are available only beginning in the mid-1990s. In a study of the Malaysian crisis of 1997–1998, Detragiache and Gupta (2006) find that foreign banks from outside the region performed better than domestic banks or foreign banks with a regional focus.

Table 4
Differential effect of banking crises on value added: Difference among countries and crises

	Foreign access	Crisis severity	Large crises	Twin crises
Crisis3 ∗ Dep ∗ High access	−1.83			
	[1.27]			
Crisis3 ∗ Dep ∗ Low access	−4.28			
	[2.18]**			
More severe Crisis3 ∗ Dep		−4.18		
		[2.14]**		
Less severe Crisis3 ∗ Dep		−2.51		
		[1.26]		
Dep ∗ Crisis3 ∗ Large output loss			−4.48	
			[3.04]***	
Dep ∗ Crisis3 ∗ Small output loss			−0.58	
			[0.30]	
Twin crisis ∗ Dep				−1.25
				[0.75]
Non-twin banking crisis ∗ Dep				−3.74
				[2.24]**
Share $(t-1)$	−2.43	−2.39	−2.47	−2.44
	[7.49]***	[6.70]***	[7.20]***	[7.51]***
Constant	9.37	1.11	−10.14	8.45
	[0.81]	[0.14]	[1.42]	[1.45]
Observations	15640	13464	15909	16227
R-squared	0.35	0.36	0.35	0.35

Notes. t-statistics are in parenthesis. Crisis3 is a dummy variable for the year of banking crisis inception and two following years. Dep is a parameter measuring an industry's dependence on external finance (Rajan and Zingales, 1998). High (low) access is a dummy for countries with access to foreign capital markets above (below) the sample median. More (less) severe denotes crises where the banking sector was more (less) severely disrupted than the median. Large (small) output loss denotes crises where the decline in output relative to trend was above (below) the sample median. Twin crises are banking crises accompanied by currency crises. Lagged share is the share of the sector's value added in total value added lagged by one period. Regressions are estimated with OLS. Standard errors are clustered by industry-country, and regressions also include time-country, time-industry, and industry-country dummy variables.

** Significance at the 5% level.

*** Idem, 1%.

differential effects are significant only for the latter episodes. This might be explained by the fact that during twin crises, the adverse effects on the bank lending channel might be offset by the (favorable) effects of exchange rate devaluation on exports and profitability (Table 4, column 4).

Finally, thus far we have looked at overall value added growth. One might expect the effects of lending to be more direct and pronounced on capital formation. Using investment growth as the dependent variable (dropping 5 percent of outliers, since this variable is noisier) in the baseline regression, the coefficient of the interaction term remains negative and statistically significant at the 5 percent level (Table 5). The differential effect is economically more significant than in the case of value added: an industry at the 25th percentile of the external dependence distribution has investment growth 4 percentage points higher than one at the 75th percentile during crisis years.

Another measure that is likely to be sensitive to bank lending is employment. This variable has the advantage of not being affected by changes in relative prices across sectors, which we cannot control for because of lack of data. Consistent with the importance of the bank lending channel, we find that employment growth is slower in more financially dependent sectors during

Table 5
Differential effects of banking crises on growth in capital formation and the number of establishments

	Capital formation		Employment		Number of establishments	
	Benchmark	DC-LDC split	Benchmark	DC-LDC split	Benchmark	DC-LDC split
Crisis3 * Dependence	−9.85		−1.47		−1.11	
	[2.31]**		[2.01]**		[2.27]**	
Crisis3 * Dependence * Developed		−9.32		−0.93		−1.25
		[1.83]*		[0.89]		[1.57]
Crisis3 * Dependence * Developing		−10.12		−1.71		−1.06
		[1.77]*		[1.79]*		[1.72]*
Share $(t-1)$	−2.21	−2.21	−0.47	−0.47	−0.83	−0.83
	[3.53]***	[3.53]***	[2.54]**	[2.54]**	[7.46]***	[7.46]***
Constant	28.52	28.51	−7.80	17.57	−0.66	18.73
	[1.20]	[1.20]	[1.14]	[1.92]*	[0.24]	[5.09]***
Observations	9752	9752	9684	9684	15940	15940
R-squared	0.32	0.32	0.44	0.44	0.38	0.38

Notes. Robust t-statistics are in parenthesis. Crisis3 is a dummy variable for the year of banking crisis inception and two following years. Dep is a parameter measuring an industry's dependence on external finance (Rajan and Zingales, 1998). DC is a dummy for developed countries. LDC is a dummy for developing countries. Lagged share is the share of the sector's value added in total value added lagged by one period. Regressions are estimated with OLS. Standard errors are clustered by industry-country, and regressions also include time-country, time-industry, and industry-country dummy variables.

* Significance at the 10% level.
** Idem, 5%.
*** Idem, 1%.

banking crises. When we differentiate between developed and developing countries, the effect on employment seems to be more pronounced in the latter, consistent with the result for value added.

A third alternative dependent variable is growth in number of establishments. To the extent that this variable reflects the birth of new firms, it has the advantage of being less sensitive to balance sheet effects than value added (see earlier): a new firm is unencumbered by past liabilities, and therefore growth in the number of firms will not be influenced by how the roots of the crisis affect firm balance sheets. In addition, like employment growth this variable is not muddled by relative price changes The differential effect is again negative and significant in developing countries, while it is not significant in advanced economies. An industry at the 25th percentile of the external dependence distribution has growth in establishments 0.6 percentage points higher than one at the 75th percentile during crisis years. This result is consistent with the hypothesis in Aguiar and Gopinath (2005) that firm liquidity may play a role in determining the cross-industry pattern of mergers and acquisitions. To the extent that illiquid firms make easier targets, and conditionally on sufficient variability of liquidity within sectors, one banking crises may lead to industry consolidation in more bank dependent sectors.

In sum, our methodology suggests that banking crises have the most effect where we would expect from the theory the lending channel to be most operative. Next we turn to alternative ways of identifying differences in reliance on domestic banking across industries.

4.5. *Differences among sectors based on firm size*

In corporate finance it is well known that small firms tend to rely more on domestic bank finance than large firms, as the latter can raise capital through domestic securities markets or international capital markets. Thus, other things being equal, sectors dominated by small firms should be more severely affected by disruptions in the domestic banking sector. The distinction between small and large firms, therefore, can provide an identification strategy alternative to the Rajan–Zingales index.

While we do not have cross-country panel data on value added by firm size, we construct a proxy for this variable using industry level data on employment and number of establishments. We conjecture that industries with a larger average number of employees per establishment are dominated by large, less bank dependent firms. As such, they should experience a less pronounced contraction during banking crises than industries with a smaller average plant size. To avoid endogeneity issues, we measure plant size as the logarithm of the average over the sample period.[14] In contrast to the Rajan–Zingales index, which is common to all countries, this measure of bank dependence is country specific, and can thus capture differences in technology and product mix across countries.

Table 6 presents the results of regressing value added growth on country-time, industry-time, and country-industry dummies and an interaction term between average industry plant size and the banking crisis dummy. The positive and significant coefficient for the interaction term indicates that industries with larger plant size tend to grow faster during banking crises, which we interpret as evidence of the bank lending channel. This result is robust to controlling for differential effects during currency crises, but loses significance when controlling for recessions (more on this below), during which large scale sectors do relatively better, consistent with the credit channel literature (Gertler and Gilchrist, 1994).

When we introduce separate interaction terms for developed and developing countries, once again we find the differential effects to be larger and more statistically significant in developing countries. This may indicate that asymmetries in access to finance between large and small firms are stronger in developing countries, or that shocks leading to crises, on average, are more severe in developing countries, which magnifies the effect of asymmetries.

Notably, these estimates also confirm the prevalence of the effect of recessions (as identified by Braun and Larraín, 2005) in advanced economies and of the effect of banking crises in developing countries and emerging markets. When we control for recessions, the differential effect during banking crises is borderline significant in developing countries, but essentially zero for developed economies. The recession coefficient is strongly significant in developing countries, but, as before, is not significant in developing countries. Again, a possible explanation is that in developed countries banks are not special because firms have alternative sources of finance. As a result, asymmetries between large and small firms are only driven by differential access to finance, which gets accentuated by weakened small borrower balance sheets and consequent borrower agency problems in recessions. In developing countries, by contrast, small firms may be restricted to borrowing only from banks so bank financial distress accentuates large-firm/small-firm growth differentials.

4.6. *Differences among sectors based on export orientation*

As argued in Tornell and Westermann (2002, 2003), firms in the traded sector may have better access to alternatives to domestic bank finance, especially foreign finance, and thus suf-

[14] The results are robust to using plant size at the beginning of the sample to identify bank dependence.

Table 6
Differential effects of banking crises on value added growth: Industries differentiated based on establishment size

	Baseline		Currency crises		Recessions	
	Benchmark	DC-LDC split	Benchmark	DC-LDC split	Benchmark	DC-LDC split
Size * Crisis3	1.52		1.36		1.18	
	[2.09]**		[1.83]*		[1.54]	
Size * Crisis3 * DC		1.04		1.03		−0.07
		[0.88]		[0.86]		[0.06]
Size * Crisis3 * LDC		1.67		1.45		1.53
		[1.86]*		[1.56]		[1.65]
Currency crisis * Size			0.99			
			[1.13]			
Currency crisis * Size * DC				0.67		
				[0.72]		
Currency crisis * Size * LDC				1.06		
				[0.95]		
Recession * Size					1.29	
					[1.87]*	
Recession * Size * DC						2.84
						[2.99]***
Recession * Size * LDC						0.65
						[0.76]
Lagged share	−2.46	−2.46	−2.46	−2.46	−2.45	−2.46
	[7.41]***	[7.42]***	[7.39]***	[7.40]***	[7.35]***	[7.42]***
Constant	7.72	45.45	6.67	72.61	45.01	−13.81
	[1.30]	[5.54]***	[1.11]	[7.66]***	[5.54]***	[1.57]
Observations	15985	15985	15985	15985	15985	15985
R-squared	0.35	0.35	0.35	0.35	0.35	0.35

Notes. t-statistics are in parenthesis. Crisis3 is a dummy variable for the year of banking crisis inception and two following years. Size is average employees per establishment in sector j in country i averaged over the sample period. DC is a dummy for developed countries. LDC is a dummy for developing countries. Recession is a dummy for recession years. Currency crisis is a dummy for currency crisis years. Lagged share is the share of the sector's value added in total value added lagged by one period. Regressions are estimated with OLS. Standard errors are clustered by industry-country, and regressions also include time-country, time-industry, and industry-country dummy variables.

* Significance at the 10% level.
** Idem, 5%.
*** Idem, 1%.

fer less than firms in non-traded sectors during financial crises. If this conjecture is true, trade orientation can provide an identification strategy to test for the presence of a bank lending channel.

In the next set of regressions (Table 7), we interact the banking crisis dummy with the ratio of exports to value added for each industry and country (averaged over the sample period).[15] The coefficient of the interaction term has the correct sign, but is far from being statistically significant. This remains the case when we control for currency crises, when export sectors can be expected to perform better on account of the real exchange rate depreciation. Interestingly, the interaction term of export orientation with currency crises is positive and significant, so our regressions do pick up this effect. During banking crises, however, we find no evidence that more export oriented sectors perform better, casting doubt on a credit channel interpretation of

[15] Export data by sector are from the World Bank's World Integrated Trade Solution (WITS) database.

Table 7
Differential effects of banking crises on value added growth: Industries differentiated based on export orientation

	Baseline		Currency crises	
	Benchmark	DC-LDC split	Benchmark	DC-LDC split
Crisis3 ∗ Export/VA	0.78		0.71	
	[0.97]		[0.87]	
Crisis3 ∗ Export/VA ∗ DC		0.98		0.92
		[0.94]		[0.89]
Crisis3 ∗ Export/VA ∗ LDC		0.71		0.65
		[0.69]		[0.63]
Currency crisis ∗ Export/VA			2.11	
			[2.34]**	
Currency crisis ∗ Export/VA ∗ DC				3.08
				[2.90]***
Currency crisis ∗ Export/VA ∗ LDC				1.78
				[1.57]
Share $(t-1)$	−2.44	−2.44	−2.44	−2.44
	[6.56]***	[6.56]***	[6.60]***	[6.60]***
Constant	30.11	13.16	−21.39	12.99
	[2.39]**	[1.23]	[2.98]***	[1.21]
Observations	14499	14499	14499	14499
R-squared	0.35	0.35	0.35	0.35

Notes. t-statistics are in parenthesis. Crisis3 is a dummy variable for the year of banking crisis inception and two following years. Export/VA is the ratio of export to value added in industry j and country i averaged over the sample period. DC is a dummy for developed countries. LDC is a dummy for developing countries. Currency crisis is a dummy for currency crisis years. Lagged share is the share of the sector's value added in total value added lagged by one period. Regressions are estimated with OLS. Standard errors are clustered by industry-country, and regressions also include time-country, time-industry, and industry-country dummy variables.

** Significance at the 5% level.

*** Idem, 1%.

asymmetries across industry based on export orientation. We should note that one reason we may not find strong support for the hypothesis is that our data are confined to the manufacturing sector, leaving out important segments of non-traded productive activities, such as construction and services.

4.7. Interventions and the lending channel

We now turn to estimating the effect of different forms of intervention on the lending channel. We obtain a list of policy interventions undertaken in each of the 22 crises in our sample from Honohan and Klingebiel (2003) (Table 8). These authors classify interventions into six categories: blanket depositor protection (including both explicit blanket guarantees to depositors and cases in which depositors are implicitly protected because most of the banking sector is publicly-owned); prolonged and extensive liquidity provision to banks; forbearance of type A (when insolvent/illiquid banks are allowed to continue operating without restriction for at least 12 months); forbearance of type B (either there is forbearance of type A or some regulations, such as loan classification and provisioning, are not enforced); repeated recapitalizations; and, finally, government-sponsored initiatives for corporate or private borrowers. All these variables are captured by simple zero-one dummies.

To test whether the differential effect of banking crisis depends on policy intervention, we interact the intervention dummies of Honohan and Klingebiel with the interaction term between

Table 8
Policy interventions during crises as classified by Honohan and Klingebiel (2003)

Episode	Blanket guarantee	Liquidity support	Forbearance A	Forbearance B	Repeated recaps	Relief to debtors	Total
Ghana 1982	1	1	1	1	0	1	5
Turkey 1994	1	0	0	1	0	0	2
Malaysia 1997	1	0	0	1	1	0	3
Brazil 1994	0	0	1	1	0	1	3
Finland 1991	1	1	0	1	0	0	3
Korea 1997	1	1	1	1	1	0	5
Colombia 1982	1	1	0	0	0	0	2
USA 1980	0	0	1	1	0	0	2
Turkey 1982	0	0	0	0	0	0	0
Philippines 1981	0	1	1	1	0	1	4
Ecuador 1995	0	0	1	1	0	1	3
Mexico 1994	1	1	0	1	1	1	5
Argentina 1995	0	0	0	0	0	0	0
Malaysia 1985	0	1	0	1	0	0	2
Sweden 1990	1	0	0	0	0	0	1
Japan 1992	1	1	0	1	1	0	4
Norway 1987	1	1	0	1	0	0	3
Uruguay 1981	1	1	0	1	1	1	5
Sri Lanka 1989	1	0	0	1	1	0	3
Indonesia 1992	0	0	0	1	0	0	1
Chile 1981	0	1	0	1	0	1	3
Venezuela 1993	0	1	0	1	0	0	2
Total episodes	12	12	6	18	6	7	

Notes. Blanket guarantee is a dummy for extensive depositor protection. Forbearance A is a dummy for letting insolvent banks operate unrestricted. Liquidity support is a dummy for providing extensive liquidity to troubled banks. Forbearance B is a dummy for letting insolvent banks operate unrestricted or not enforce some regulations. Repeated recaps is a dummy for repeated government recapitalizations of banks. Debtor relief is a dummy for government programs to subsidize bank debtors.

crisis and external dependence (Table 9). First, we establish that financially dependent sector grow less during crises also in this drastically restricted sample of 22 crises (column (1)). Next, we test whether differential effects were smaller in countries with a larger number of interventions (column (2)). This does not appear to be the case. When we examine the effects of each type of intervention in isolation, the policy with the largest positive coefficient is forbearance A. Other policies, have much smaller or even negative coefficients. While none of the coefficient is statistically significant at the usual confidence levels, we still think that this evidence is suggestive that allowing insolvent banks to continue operating during the initial phase of a crisis may help alleviate the real cost of the crisis. Obviously, more research is necessary to understand what are successful crisis mitigation strategies.

5. Conclusions

We have studied the effects of banking crises on growth in industrial sectors and find that in sectors that are more dependent on external finance value added, capital formation, and the number of establishments grew relatively less than in sectors less dependent on external finance. We interpret this finding as evidence that there is a real cost to banking crises. Specifically, while

Table 9
Differential effects of banking crises and intervention policies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Crisis3 ∗ Dep	−3.45	−4.30	−5.02	−1.23	−5.19	−1.67	−3.42	−3.33
	[1.89]*	[1.34]	[1.66]*	[0.42]	[2.56]**	[0.68]	[1.67]*	[1.73]*
Crisis ∗ Dep ∗ Relief to debtors								−0.43
								[0.09]
Crisis ∗ Dep ∗ Repeated recap							−0.10	
							[0.03]	
Crisis ∗ Dep ∗ Forbearance B						−2.14		
						[0.67]		
Crisis ∗ Dep ∗ Forbearance A					6.95			
					[1.45]			
Crisis ∗ Dep ∗ Liquidity provision				−3.61				
				[1.02]				
Crisis ∗ Dep ∗ Blanket guarantee			2.73					
			[0.79]					
Crisis3 ∗ Dep ∗ Number of interventions		0.30						
		[0.29]						
Lagged share	−2.55	−2.55	−2.55	−2.54	−2.55	−2.55	−2.55	−2.55
	[4.39]***	[4.39]***	[4.40]***	[4.38]***	[4.36]***	[4.39]***	[4.39]***	[4.39]***
Constant	−2.36	11.47	5.71	11.64	−2.25	−2.56	−0.48	−2.37
	[0.41]	[1.83]*	[0.60]	[1.86]*	[0.39]	[0.49]	[0.08]	[0.41]
Observations	9040	9040	9040	9040	9040	9040	9040	9040
R-squared	0.39	0.39	0.39	0.39	0.39	0.39	0.39	0.39

Notes. t-statistics are in parenthesis. Crisis3 is a dummy variable for the year of banking crisis inception and two following years. Dep is a parameter measuring an industry's dependence on external finance (Rajan and Zingales, 1998). Blanket guarantee is a dummy for extensive depositor protection. Forbearance A is a dummy for letting insolvent banks operate unrestricted. Liquidity support is a dummy for providing extensive liquidity to troubled banks. Forbearance B is a dummy for letting insolvent banks operate unrestricted or not enforce some regulations. Repeated crecap is a dummy for repeated government recapitalizations of banks. Debtor relief is a dummy for government programs to subsidize bank debtors. Regressions are estimated with OLS. Standard errors are clustered by industry-country, and regressions also include time-country, time-industry, and industry-country dummy variables.

* Significance at the 10% level.
** Idem, 5%.
*** Idem, 1%.

adverse shocks cause both poor economic performance and bank distress, bank distress has an additional, adverse effect on growth, as banks must cut back their lending. As might be expected, the differential effect is stronger in developing countries (where alternatives to bank financing are more limited), in countries with less access to foreign finance, and where bank distress is more severe. In addition, we find that the effect we have measured is not just the reflection of balance sheet effects during recessions or currency crises, but appears to be special to periods in which banks experienced liquidity and solvency problems.

These results lend support to the view, often expressed by policy makers, that banks need more support than other commercial enterprises in time of financial distress. If bank credit cannot be easily replaced by other sources of finance, at least for some businesses, then profitable production activities may have to be cut back and viable investment projects abandoned, leading to a misallocation of resources. In addition, the bank lending channel can ratchet up the macroeconomic effects of an adverse shock, leading to a downward spiral in which a contraction in economic activity and bank distress reinforce each other.

How to design and implement appropriate policies to support banks during crises, however, remains difficult in practice. With our results it is possible to study how the differential effect of crises changes with different intervention policies. Unfortunately, data on interventions are hard to come by and quantify and, perhaps more importantly, unobservable shocks affect both the lending channel impact and the propensity and modalities of intervention. Future research to tackle these difficulties would undoubtedly be very valuable.

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Appendix A. Data appendix

Table A1
External dependence index

Industrial sector	External dependence
Tobacco	−0.45
Pottery	−0.15
Leather	−0.14
Footwear	−0.08
Non-ferrous metal	0.01
Apparel	0.03
Petroleum refineries	0.04
Non-metal products	0.06
Beverages	0.08
Iron and steel	0.09
Food products	0.14
Paper and products	0.17
Textile	0.19
Printing and publishing	0.2
Rubber products	0.23
Furniture	0.24
Metal products	0.24
Industrial chemicals	0.25
Wood products	0.28
Petroleum and coal products	0.33
Transportation equipment	0.36
Other industries	0.47
Glass	0.53
Machinery	0.6
Other chemicals	0.75
Electric machinery	0.95
Professional goods	0.96
Plastic products	1.14

Source: Rajan and Zingales (1998) and Krozner et al. (2007).

Table A2
Summary statistics

	Mean	Median	Std. Dev.	Max	Min	No. obs.
VA growth (in percent)	3.7	1.8	22.7	107.4	−54.1	16227
Growth in capital formation (in percent)	12.3	2.0	56.2	240.7	−80.5	9752
Employment growth (in percent)	0.9	0.1	8.7	29.0	−20.4	15940
Growth in number of establishments (in percent)	1.8	0.0	10.1	45.9	−22.1	9684
Access to foreign financing (in percent of trade volume)	1.8	0.6	3.0	25.5	0.0	482
Output loss during crisis (in percent; by episode)	1.8	2.0	3.9	12.0	−7.4	46
Rajan–Zingles index (by industry)	0.3	0.2	0.4	1.1	−0.5	28
Average plant size (by country/industry)	125.3	65.6	232.3	4197.7	1.5	1012
Export/Value added (by country/industry) (in percent)	71.2	41.3	73.1	297.8	0.0	872

Table A3
Correlations between measures of external dependence

	Rajan–Zingales	Average plant size	Exports/VA
Rajan–Zingales	1		
Average plant size	−0.16	1.00	
Exports/VA	0.02	−0.03	1

Table A4
Banking crises inception dates

Countries	Banking crisis inception	Countries	Banking crisis inception
Argentina	1989	Malaysia	1997
Argentina	1995	Mexico	1994
Bolivia	1986	Nepal	1988
Bolivia	1994	Nigeria	1991
Brazil	1994	Norway	1987
Cameroon	1995	Panama	1988
Central African Republic	1988	Papua New Guinea	1989
Chile	1981	Peru	1983
Colombia	1982	Philippines	1981
Colombia	1999	Portugal	1986
Costa Rica	1994	Senegal	1983
Ecuador	1995	South Africa	1985
Finland	1991	Sri Lanka	1989
Ghana	1982	Swaziland	1995
India	1991	Sweden	1990
Indonesia	1992	Tanzania	1988
Israel	1983	Tunisia	1991
Italy	1990	Turkey	1982
Japan	1992	Turkey	1991
Jordan	1989	Turkey	1994
Kenya	1993	Turkey	2000
Korea	1997	United States	1980
Madagascar	1988	Uruguay	1981
Malaysia	1985	Venezuela	1993

Note: Total number of crises = 48.

Table A5
Average growth of real value added in crisis and non-crisis years

Crisis duration	Crisis	No. obs.	Non-crisis	No. obs.
1-year dummy	0.10	1130	4.00	15097
2-year dummy	−0.92	2167	4.45	14060
3-year dummy	1.70	3059	4.20	13168
4-year dummy	3.33	4012	3.86	12215
5-year dummy	3.84	4851	3.69	11376

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Discussion

Moral hazard and adverse selection in the originate-to-distribute model of bank credit

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1. Introduction

Antje Berndt and Anurag Gupta have written an empirical paper that tells a story. Consider firms that have borrowed money in the form of syndicated loans. The empirical evidence is that stocks of these firms have negative alphas if the loans are actively traded in the secondary market. If the loans are not actively traded in the secondary market, the stocks do not have negative alphas. The alphas might well be positive.

According to the story, there is an asymmetric information problem associated with banks selling their stakes in the original syndicated loan. Outside investors (those who set stock prices) either do not realize it or, if they realize it, underestimate its importance. Perhaps banks are selling off loans of firms that the banks' private information tells them are poor risks. Alternatively, once a bank sells off its share of the loan, it reduces its monitoring, allowing the firm to destroy value.

The authors work hard to convince the reader that the empirical evidence is robust. We can quibble about details of the implementation (and I have), but the evidence for negative alphas seems statistically strong. Yet before we accept the authors' interpretation of these alphas, a closer appraisal of the underlying theory is warranted.

2. Markets with asymmetric information

It is hard to argue with the view that banks have access to private information about many of their borrowers. A long literature pursues implications of this asymmetric information. Theory tells us that the magnitude of the asymmetry may prevent a loan-sale market from developing. Theory also tells us that if conditions allow for such a market, equilibrium requires that banks cannot exploit purchasers of the loans, at least in expectation.

For concreteness, consider an adverse selection model. Then the expectation in the above paragraph refers to the quality of loans that the banks happened to originate at time *t*. Banks are not in complete control of the characteristics of these loans. If, say, the period-*t* pool borrowers are unusually (and unobservably) poor, purchasers of these loans are likely to realize negative returns subsequent to purchase. Similarly, the stocks of the borrowers are also likely to underperform. It is

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important to understand that in equilibrium, any unexpected poor performance of the borrowers is a consequence of an exogenous shock to the borrower pool; the banks cannot produce this outcome on their own. Outside investors do not overestimate the truthfulness of the banks. They can only be hurt by the random draw of originated loans.

Put differently, everyone in financial markets understands that if it is profitable for banks to lie, they will lie. There is a good reason why academics typically do not build models in which investors have some prior probability distribution of "moral" and "amoral" counterparties. Sophisticated investors have too much market experience to be so naïve—or perhaps they simply extrapolate from their own profit-seeking behavior.

3. Is the paper's evidence consistent with theory?

At first glance, it is hard to reconcile the authors' empirical evidence with our standard theory. In equilibrium, banks with private information cannot systematically take advantage of outside investors. However, the paper argues that the market for sales of syndicated loans may not have been in equilibrium during the early years of the market. As outsiders observe the underperformance, they will draw more accurate inferences about borrower quality. Perhaps this view is correct. But it is not an easy argument to make. The syndicated loan-sale market may be new to investors, but the idea that banks have private information and want to exploit it is not.

Pooling equilibria, separating equilibria, and signaling are features of a wide variety of markets. No sensible investor could fail to consider the adverse selection and moral hazard implications of the loan-sale market. Indeed, as shown by Gande and Saunders (2008), stock prices react upon the announcement of a sale in the syndicated loan market—a reaction that is consistent with the view that outside investors understand that a loan sale tells them something about a bank's private information.

One possible view is that outside investors did not overestimate the truth-telling desires of banks, but, owing to the newness of the market, they underestimated the amount of private information that banks gleaned from their borrowers. I would be more comfortable with that view if it was formally modeled in a setting where outsiders have some prior distribution over the extent of asymmetric information. The tricky part of such a model is explaining why outsiders cannot infer the amount of private information by observing the aggressiveness of banks in the loan-sale market.

Even if such a setting is theoretically sound, it leads to policy implications that differ from those suggested in this paper. It must still be true that on average—across all possible new markets—insiders cannot exploit outsiders. If outsiders did not benefit ex-ante from each new market, they would not participate. Ex post, the sold assets (and assets linked to them, such as stocks in the case of loans) may persistently outperform or underperform other assets while outsiders learn about the specific characteristics of the asymmetric information.

As outsiders learn about a new market, the requirement that they benefit ex-ante from participation may shut the market down, or at least change market-clearing prices. Unless government regulators have private information about the magnitude of asymmetric information in a new market, there is no role for government intervention.

4. Are we sure the borrowers with actively-traded loans underperform?

The ideal empirical experiment is to compare stock returns of two sets of firms. To outsiders, the firms should be identical at *t*, aside from the fact that one set consists of firms that have actively-traded syndicated loans and the other set does not. We could then look at the difference in the period-*t* stock returns of these two sets of firms.

Unfortunately, as the paper notes, this experiment cannot be performed because borrowers with actively-traded loans have substantially different characteristics than do borrowers without actively-traded loans. Evidence of these observable differences is in Gupta et al. (2008). Therefore we cannot draw definitive conclusions from the difference between mean stock returns to borrowers without actively-traded loans and mean stock returns to borrowers with actively-traded loans.

Nonetheless, a quick glance at these means is illuminating. I report them in Table 1. The observation that leaps out of the table is *not* the poor performance of borrowers whose loans trade actively. Instead, borrowers whose loans do not trade actively perform spectacularly, with mean excess returns of about 1.4% per month. The evidence for underperformance

Table 1
Mean monthly excess returns to stock portfolios.

Portfolio	Mean excess return (percent)
Borrowers with active secondary loan market	0.25
Aggregate stock market	0.27
SMB factor	0.58
HML factor	0.65
Momentum factor	0.23
Borrowers without active secondary loan market	1.39

Firms included in the sets of borrowers with and without actively-traded loans in the secondary market are defined using the 36-month window of Berndt and Gupta. The portfolios of the borrowers are equal-weighted. Excess returns to the aggregate stock market, the Fama–French SMB and HML factors, and the momentum factor are from the website of Ken French. The sample period is April 2000 through December 2007.

relies on the four-factor risk adjustment. Thus the critical question is whether statistical tests of alphas are equivalent to statistical tests of the hypothesis that outside investors are insufficiently aware of the asymmetric information problem. Alternatively, the alphas may simply represent an insufficient adjustment for risk.

Nonzero alphas appear in all sorts of empirical work. For example, papers that follow Fama and French (1993) use various models to calculate alphas for the Fama–French 5×5 sorted portfolios. The profession does not interpret nonzero alphas for these portfolios as evidence of investor ignorance. Instead, we interpret them as our profession's ignorance, in that we do not have the right risk-adjustment model. By contrast, alphas associated with, say, earnings announcements are more frequently viewed as evidence of investor ignorance (or overreaction, or some other odd behavior).

What drives this difference in interpretation? Within each portfolio formed by the 5×5 sort, the firms have similar capital structures, common components in stock returns, and correlated investment. These common features are not as closely shared with firms in other portfolios. Moreover, the features are all plausibly related to risk. By contrast, all firms announce earnings. There is no common component to capital structure, stock returns, or investment across the firms that make these announcements. A risk-based explanation for post-announcement drift is thus hard to conjecture (although many have tried).

I believe the results of this paper are more closely related to the example of the 5×5 sort than to the example of earnings drift. Firms that have borrowed money in the syndicated loan market and subsequently have those loans actively traded are firms with many ex-ante similarities. More importantly, the firms are ex-ante different from firms with syndicated loans that do not actively trade. An explicit comparison with portfolios formed by the 5×5 sort is helpful.

Table 2 reports correlations between monthly stock returns to portfolios of firms with syndicated loans and returns to the Fama–French portfolios. All portfolios are constructed using equal weights. The correlations in Panel A are for firms with loans that actively trade, while the correlations in Panel B are for firms with loans that do not actively trade. Because all of these portfolios are well-diversified, correlations are high. The portfolio of stocks with actively-traded loans are most closely correlated with somewhat small (quintiles 2 and 3 of ME), growth-oriented (quintiles 2 and 3 of BE/ME) stocks. By

Table 2
Correlations of monthly excess returns.

	Small	2	3	4	Big
Panel A. Borrowers with active secondary market					
Growth	0.82	0.89	0.85	0.86	0.82
2	0.88	0.91	0.92	0.88	0.86
3	0.88	0.90	0.88	0.87	0.82
4	0.84	0.88	0.85	0.83	0.81
Value	0.84	0.88	0.86	0.83	0.76
Panel B. Borrowers without active secondary market					
Growth	0.89	0.91	0.87	0.87	0.81
2	0.95	0.92	0.91	0.86	0.83
3	0.95	0.91	0.86	0.88	0.77
4	0.94	0.89	0.81	0.80	0.71
Value	0.93	0.88	0.88	0.79	0.64

Stock returns to portfolios of borrowers with and without actively-traded loans in the secondary market are constructed as in Table 1. Panels A and B report correlations between these returns and returns to equal-weighted portfolios of stocks sorted by market capitalization and book/market. The latter returns are from the website of Ken French. The sample period is April 2000 through December 2007.

Table 3
Correlations of monthly residuals from a three-factor model.

	Small	2	3	4	Big
Panel A. Borrowers with active secondary market					
Growth	0.18	0.28	0.30	0.13	0.03
2	0.15	0.13	0.17	0.04	−0.04
3	0.05	−0.05	0.03	0.00	0.01
4	0.03	0.01	−0.01	0.03	0.27
Value	0.08	0.15	−0.02	0.13	0.35
Panel B. Borrowers without active secondary market					
Growth	0.56	0.42	0.47	0.28	0.27
2	0.53	0.02	0.11	−0.04	0.11
3	0.53	−0.17	−0.10	0.24	−0.13
4	0.62	−0.15	−0.26	0.01	−0.15
Value	0.60	−0.07	0.16	0.00	−0.21

The portfolios are described in Table 2. Residuals are constructed by regressing returns on excess returns to the market, HML, and SMB. The sample period is April 2000 through December 2007 contrast, the portfolio of stocks without actively-traded loans are much more closely correlated with very small (quintile 1 of ME) stocks that tend to the value side of the spectrum (quintiles 2–5 of BE/ME). Table 3 reports correlations for the same portfolio returns after extracting loadings on the three Fama–French factors. Residuals of the portfolio with actively-traded loans are not closely related to residuals of any Fama–French portfolio. Residuals of the portfolio without actively-traded loans closely track residuals to portfolios in the smallest quintile.

An important conclusion to draw from these correlations is that stock returns to the two sets of borrowers are driven by differing economic shocks. Another conclusion is that the high alphas for borrowers without actively-traded loans may be driven by the same determinants of the high alphas for the small-cap Fama–French portfolios. For example, over the sample examined in this paper, the alpha for the 5×5 portfolio with smallest ME and largest BE/ME is 0.67%/month. Until we are confident that we understand determinants of mean returns to such stocks, we cannot be confident in the accuracy of risk adjustments to returns of firms that borrow in the syndicated loan market.

The careful reader of these comments will note that I have no useful suggestions to the authors. Given the limitations of their data and our models, they've done everything possible to convince us that asymmetric information problems account for the poor relative performance of firms with actively-traded loans. The main message of my comments is that a skeptic will not be convinced because there are too many open questions in both the theory and empirical analysis.

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The Flight Home Effect:

Evidence from the Syndicated Loan Market During Financial Crises

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Abstract: In the context of the global market for syndicated bank loans, we provide evidence that the collapse of international markets during financial crises can in part be explained by a *flight home* effect. We show that the home bias of lenders' loan origination increases by approximately 20 percent if the bank's country of origin experiences a banking crisis. This flight home effect is distinct from a *flight to quality* effect because borrowers of different quality (or from countries with different degree of investor protection) are similarly affected by lenders rebalancing their loan portfolios in favor of domestic borrowers. Banks with less stable funding sources and larger losses, being more vulnerable to liquidity shocks, exhibit a stronger flight home effect. Overall, the results indicate that the home bias of international capital allocation tends to increase in the presence of adverse economic shocks affecting the net wealth of international investors. We provide evidence suggesting that the degree of proximity to the domestic market affects the perceived risk and expected returns of banks experiencing negative shocks.

Keywords: Financial crisis; Home Bias; Flight to quality; Syndicated loans

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1. Introduction

During financial crises, international markets often collapse. For instance, during the Japanese banking crisis of the nineties, Japanese banks and firms retracted from international financial and good markets, including the United States (Peek and Rosengren, 1997 and 2000; Klein, Peek, and Rosengren, 2002; Amiti and Weinstein, 2009). The recent global financial crisis that started in the summer of 2007 in the United States was no different. It was accompanied by a collapse of global trade (Levchenko, Lewis and Tesar, 2010), a reduction in gross capital flows (Broner et al., 2010), a reversal of capital flows from advanced economies to emerging markets (Tong and Wei, 2010; Milesi-Ferretti and Tille, 2010), and a decline in international bank lending (Cetorelli and Goldberg, 2010).

Existing research has shown that banks transmit negative shocks to their capital both domestically (Kashyap and Stein, 2000) and internationally (Peek and Rosengren, 2000; Cetorelli and Goldberg, 2009 and 2011; Popov and Udell, 2009; Schnabl, 2011) and some contraction in international bank lending following the global financial crisis was therefore to be expected. In this context, the reduction in international credit during financial crises can be viewed as a reflection of the reduction in the overall supply of credit owing to capital constraints. Importantly, the international transmission of shocks may happen simply because banks choose not to alter the mix of domestic and foreign loans in their portfolios and borrow from (lend less to) foreign subsidiaries to counterbalance the effect of capital shortages in their domestic market. The transmission of shocks and resulting decrease in international lending would then be a consequence of integration in international credit markets.

The dramatic collapse of international lending markets during 2008, however, raises the question whether lenders retract disproportionally from international markets to the advantage of domestic markets at times of crises, when uncertainty and risks increase and capital constraints become binding for many lenders. In other words, following negative shocks, banks may alter their loan mix in a way that decreases the level of credit market integration.

In this paper, we study whether lenders, when hit by shocks that negatively affect bank wealth in their home market, have a tendency to rebalance their portfolio away from international markets to their domestic market. We explore this *flight home* effect in the context of the syndicated loan market, a highly internationalized market, in which it is common for large banks to offer loans to a variety of borrowers in a broad set of countries. After carefully controlling for the effect of contemporaneous demand shocks in host countries, we explore whether foreign lenders not only transmit shocks to host markets, as highlighted in previous literature, but also whether they further amplify these effects by substituting foreign loans for domestic loans. To establish whether this is the case, we not only compare to what extent a bank's foreign loans are affected by negative shocks in the bank's country of origin relative to loans extended by domestic banks in the host country, as in most of the existing literature on the international transmission of shocks to bank lending, but also analyze how the relative importance of domestic and foreign loans of a given bank varies following negative shocks.

Our results are consistent with the existence of a *flight home* effect. The proportion of loans granted to domestic borrowers increases by approximately 20 percent if the country of origin of the bank experiences a banking crisis, or more generally, if the stock prices of banks in the home country show a large decline. Lenders with less stable funding sources, being more vulnerable to negative liquidity shocks (Demirgüç-Kunt and Huizinga, 2010; Ivashina and Scharfstein, 2010a), exhibit a stronger flight home effect. Overall, the results indicate that the home bias in the international allocation of syndicated loans increases in the presence of adverse economic shocks affecting the net wealth of international lenders. Put differently, the extent of integration of the syndicated loan market is positively related to the financial conditions of the participating banks.

The flight home effect coexists with, but is distinct from the *flight to quality* effect highlighted in previous literature. Bernanke, Gertler and Gilchrist (1996) and Lang and Nakamura (1995) argue that during recessions the share of credit flowing to borrowers with more severe asymmetric information and agency problems, such as small firms, decreases. The flight home effect does not appear to be driven by international banks' desire to rebalance their portfolios towards higher quality borrowers when faced with negative shocks. Banks rebalance their portfolio away from foreign borrowers, irrespective of whether these borrowers are affected by a banking crisis in their home country or not. Furthermore, when their country of origin experiences a banking crisis, lenders grant fewer loans to foreign borrowers in advanced economies and emerging markets alike. Similarly, the flight home of international lenders does not appear to be limited to borrowers with lower credit ratings or to countries with weak creditor protection. Also, the institutional environment in the origin countries of the lenders appears not to influence our findings: Banks rebalance their portfolios towards domestic borrowers independently from whether their country of origin has weak or strong institutions.

We provide empirical evidence suggesting that the degree of proximity to the domestic market affects the perceived risk and expected returns of banks experiencing negative shocks for the following reasons. First, the cost of negotiating and monitoring syndicated loans may be higher for foreign loans. Therefore, when reducing exposure in response to negative shocks, banks may revert to more profitable domestic markets. Second, banks that extend more domestic loans, especially to government and government-owned firms, may be more likely bailed out. Thus, banks may increase the proportion of domestic loans they extend in an attempt to increase the bailout probability. Finally, in response to negative shocks, banks face increased uncertainty regarding their ability to meet their capital requirements and, as a result, their effective risk aversion increases. If banks are also less able to evaluate foreign borrowers and view them as riskier, they may as a consequence of negative shocks choose to extend fewer foreign loans, as models of home bias based on ambiguity aversion would imply (Epstein 2001).

Our work complements and expands over a number of dimensions studies of the syndicated loan market during the 2007–08 crisis. Ivashina and Scharfstein (2010a and b) and Santos (2011) explore the effect of the 2008 crisis on the syndicated loan market in the U.S. to show that this market experienced a sharp decline in loan supply and an increase in loan spreads.[1] In contrast to these other papers, we study not only the U.S. syndicated loan market, but also foreign syndicated loan markets. Moreover, unlike these other papers, we incorporate both global and domestic shocks to bank capital into our multi-country analysis.

The distinction between shocks affecting the banks' country of origin (and ultimately banks' net wealth) and shocks affecting the banks' host countries (and therefore borrowers' net wealth) is similar to Morgan, Rime and Strahan (2004) who explore how banking system integration affects the evolution of business cycles, without considering the effects on bank loans. Their conclusion that banking system integration mitigates the effect of home-grown shocks on business cycles fluctuations but contributes to the transmission of foreign shocks on domestic business cycles is consistent with our findings.

Our work is also related to a vast literature on the home bias in the global allocation of capital (Lewis, 1999). The presence of home bias has been documented across countries with diverse institutional environments (Chan, Covrig and Ng, 2005), within countries because investors exhibit a preference for geographically proximate (domestic) assets (Coval

[1] Other studies of the syndicated loan market include Giannetti and Yafeh (2011) who indicate that familiarity biases are relevant in the international syndicated loan market, and De Haas, Van Horen and Zettelmeyer (2011) who find that lending to relationship borrowers was less affected during the 2008 financial crisis.

and Moskowitz, 1999, 2001; Grinblatt and Keloharju, 2001), and for different assets including bonds (Butler, 2008). While the presence of home bias in international capital allocation has been well documented in the literature, we are the first to show that home biases vary over time depending on the net wealth of investors.

Theory offers alternative explanations for the existence of a home bias, including informational advantages for domestic investors (Brennan and Cao, 1997; Ahearne et al., 2004; Portes and Rey (2005); Van Nieuwerburgh and Veldkamp, 2009; and Andrade and Chhaochharia, 2010) and biases arising from familiarity considerations (Grinblatt and Keloharju, 2000; Huberman, 2001; Seashole and Zhu, 2010).[2]

The observed increase in the home bias may come from a change in any of these underlying factors. Informational advantages could change at during financial crises, but it is unclear why during such times it should become costlier to screen foreign borrowers than domestic borrowers, especially if foreign borrowers are less affected by negative shocks resulting from a domestic financial crisis. Furthermore, the empirical evidence we present indicates that international banks extend fewer loans to foreign borrowers independently of their level of opacity, credit risk, and institutional environment, suggesting that informational asymmetries alone cannot explain our findings. We further surmise and test that closer bank relationships with domestic borrowers (for which informational asymmetries tend to be lower) may be driving our results, but find little evidence to support this.

Familiarity considerations, such as those based on borders, physical proximity or cultural affinity, also do not change much over time. However, their relevance may increase when investors experience negative shocks both for rational (e.g., binding capital

[2] There are other possible explanations for the home bias that appear less relevant in our context. For instance, while transaction costs could in theory explain a home bias in investments, actual transaction costs are insufficiently high to warrant such an explanation (French and Poterba, 1991).

requirements) and behavioral reasons. We argue that this and other non-mutually exclusive mechanisms can help explain our findings.

Several other papers have explored how the behavior of international investors changes over time and depending on economic conditions. For instance, Bohn and Tesar (1996) and Kim and Wei (2002) show that U.S. investors chase returns when they allocate their international equity portfolio, while Curcuru, Thomas, Warnock and Wongswan (2011) question these findings. Gelos and Wei (2005) find that global emerging market funds have a greater propensity to exit nontransparent countries during crises affecting those countries. Instead of highlighting economic conditions in host countries or differences across host countries, our paper stresses economic conditions in the home country of the investors.

The rest of the paper is organized as follows. Section 2 introduces the empirical strategy. Section 3 describes the data and some stylized facts. Section 4 describes the main results and several robustness tests. Section 5 considers possible mechanisms leading to the flight to home effect, and Section 6 concludes.

2. Empirical Methodology

During banking crises, banks experience negative shocks due to actual or anticipated losses and liquidity problems. Our goal is to explore how the negative shocks to bank net wealth affect bank lending and in particular whether the lending behavior of foreign banks during banking crises differs from that of domestic banks. Thus, we investigate whether the allocation of banks' loans during those periods favors domestic borrowers. In particular, we model the portfolio share of syndicated loans issued by bank *i* to borrowers in country *j* during month *t* as follows:

$$Loanshare_{ijt} = \alpha_1 Foreign\ Loan_{ij} + \alpha_2 Foreign\ Loan_{ij} * Shock\ Bank\ Country_{it} + \\ + \alpha_3 Foreign\ Loan_{ij} * Shock\ Borrower\ Country_{jt} + \Gamma \mathrm{X}_{\mathrm{ijt}} + \varepsilon_{\mathrm{ijt}} \qquad (1)$$

where $Foreign\ Loan_{ij}$ is a dummy variable that takes a value of 1 if the nationality of bank *i* is different from the nationality of the borrower, and zero otherwise; $Shock\ Bank\ Country_{it}$ measures shocks affecting the country of origin of the bank; $Shock\ Borrower\ Country_{jt}$ measures shocks affecting the country of origin of the borrower; X_{ijt} is a vector of control variables; and ε_{ijt} is an error term.

It is important to note that our dependent variable captures the geographical distribution of new loans (with respect to the total amount of loans issued by a given bank) rather than the total amount of loans in the bank's portfolio. Since by definition the portfolio share is standardized by the bank's supply of loans during month *t*, our dependent variable is unaffected by shocks changing the bank's overall supply of loans and instead captures how the bank's supply of loans is allocated, given the economic conditions. Precisely for this reason, we do not analyze the effect of the shocks per se, but only differences in the effect of the shocks across banks using interaction terms.[3]

A negative coefficient α_1 implies that banks systematically issue fewer loans to foreign countries, indicating that there is a home bias in banks' loan portfolios. Our main coefficient of interest is α_2: A negative sign here implies that banks reallocate the supply of loans towards domestic borrowers when their home country experiences a negative shock. In the empirical analysis, we measure $Shock\ Bank\ Country_{it}$ using different proxies capturing not only cross-sectional differences in the shocks to bank net wealth in different countries of origin, but also differences in the intensity of shocks across banks arising from their exposure to the shock within a given country (in that case, $Shock\ Bank_{it}$ would be a more accurate notation).

[3] In other words, since not all loan shares of bank *i* can drop at time *t*, our results cannot be driven by an overall shrinkage of the bank's supply of loans and the direct effect of the shock is zero by construction.

The interaction term $Foreign\ Loan_{ij} * Shock\ Borrower\ Country_{jt}$ allows us to capture any differential behavior of foreign banks when negative shocks hit host countries, increasing the risk of the borrowers located in these countries; α_3 is expected to be positive if, as argued in previous literature (Goldberg, 2009), foreign banks provide insurance against home-grown shocks. Importantly, this term also captures the possibility that uncertainty regarding these borrowers' creditworthiness may increase during banking crises, leading foreign banks to withdraw from the country, akin to a flight to quality effect. In contrast, a negative coefficient for our variable of interest, α_2, would indicate that banks issue more loans to domestic borrowers when their risk is higher, namely during a banking crisis.

The vector of control variables, X_{ijt}, includes year-month fixed effects capturing time-specific changes in the syndicated loan market. Also, in most specifications, we include deal nationality fixed effects to control for time-invariant differences in the demand for syndicated loans. Importantly, we control for demand shocks in the borrower's country by including the proportion of loans issued by the domestic banks to that country with respect to the total loans issued in the syndicated loan market in that period. To further address any concerns that our results may be driven by differences in demand for loans from borrowers in different countries, we make sure that our estimates are invariant when we use a within-country estimator, and control for time-varying differences in the demand for loans across countries, by including interactions of month and destination country fixed effects. Since banks' portfolio allocation exhibits geographical specialization and is therefore correlated over time, we cluster standard errors at the bank level.

While a negative coefficient on our variable of interest, α_2 is consistent with a flight home effect, it could also be driven by other forces. An obvious alternative explanation is that a negative α_2 signifies a *flight to quality* effect. For example, it could be that most lenders are from advanced economies and retract from emerging markets that are perceived to be riskier in the event of adverse economic shocks. The difference between the flight home effect and the flight to quality effect is that a flight home effect arises from banks' rebalancing of their loan portfolios towards domestic borrowers, while the flight to quality effect arises from banks' rebalancing of their portfolios towards higher quality borrowers. The latter would imply a larger bias towards advanced countries from countries with weaker institutional environments or riskier economies, rather than an increase in the home country bias. In other words, a flight to quality would imply an accentuation of the "high-quality" country bias that Forbes (2010) and Giannetti and Koskinen (2010) find to exist for some portfolio investors in the equity and bond markets in normal times.

We adapt our empirical strategy to disentangle the flight home effect from a potential flight to quality effect. Besides analyzing the response of syndicated bank lending to adverse shocks while distinguishing between shocks that affect the bank's country of origin and shocks that affect the borrowers' country, as we explain in more detail in Section 4, we also explore how the foreign banks' response to negative shocks varies across countries and borrowers using a variety of measures of perceived risk (including proxies for their creditworthiness, opacity and institutional environment). If we find that lenders that experience a banking crisis in their countries of origin retract to their home markets independently from the perceived risk of their own countries and the perceived risk of the countries of the borrowers they retract from, then the results are unlikely driven by a flight to quality effect alone and support the existence of a flight home effect.

3. Data and Descriptive Statistics

3.1. Data

To explore how negative shocks to banks' net wealth affect their supply of domestic and foreign loans, we resort to data from the international syndicated loan market. A syndicated loan is jointly extended by a group of banks, including one or sometimes a couple of lead banks and many participant banks. Prior to signing the loan contract, lead banks assess the quality of the borrowers and negotiate terms and conditions. Once the main terms are in place, lead banks invite participant banks to acquire a stake of the loan, but they remain responsible for the monitoring of the borrower.

Syndicated loans represent a significant part of international bank claims (Gadanecz and Von Kleist, 2002). We choose to explore the flight home effect in the context of the international syndicated loan market not only given its importance and high level of internationalization, but mainly because this is a context in which one can observe how individual banks extend credit to borrowers in a variety of countries, allowing us to differentiate the flight home effect from the well-established flight to quality effect. The BIS Consolidated International Banking Statistics are an alternative data source that is often used in related studies (e.g., Cetorelli and Goldberg, 2010). These data provide only aggregate amounts of the loans that borrowers in country *j* obtain from *all* banks from country *i* during quarter *t*. For our purposes, it is important to have data that are disaggregated at the bank level. Otherwise, we would not be able to rule out that banks that are more internationalized could simply have taken more risks and therefore be more exposed and respond stronger to negative shocks. Using aggregate data, an increase in the proportion of domestic loans extended in the aggregate by the banks in the country experiencing the shock could just indicate that the worse hit international banks are extending fewer domestic and foreign loans. If the less internationalized banks decrease their supply of loans to a lower extent, we would observe a decrease in the proportion of foreign loans extended by banks in country *i*, although no individual bank is altering its loan mix. This would clearly inhibit a clear interpretation of our findings.

There are several other reasons why the international syndicated loan data are preferable to the BIS banking statistics for our purposes. First, outstanding bank claims may be highly heterogeneous across banks and depend on banks' ability to adjust the amounts of different claims over time. Changes in the mix of outstanding loans could then be due to exogenous constraints, such as the difficulty of withdrawing long-term loans from domestic borrowers or the inability of domestic borrowers to repay loans during a banking crisis. The syndicated loan data allow us to focus on new lending. The extension of new loans is more likely to capture lending decisions of the bank at a given time and gives us better insights into how the mix of domestic and foreign loans varies under different economic conditions. Most importantly, as we explain in detail below, the disaggregated nature of the syndicated loan data allow us to shed light on the mechanisms leading to the flight home effect by exploring how different types of borrowers are affected and whether the flight home effect affects also the foreign subsidiaries of a bank, something that cannot be assessed with aggregate data on bank claims.

We obtain data on syndicated loans from Dealogic's Loan Analytics Database (previously named Loanware), which provides information on borrowers, lenders, and loan price and non-pricing terms at origination. This database is widely used for studying the international syndicated loan market (see, e.g., Esty and Megginson, 2003; and Carey and Nini, 2007). We extract information on loan contracts from the period 1997 to 2009, which covers the recent global financial crisis as well as a number of banking crises in a variety of countries around the world.

While the dataset provides loan level information, similarly to Ivashina and Scharfstein (2010a), we aggregate loans extended by a given bank during a month at the country level. The main reason for aggregating the loan level information is that, as we show, declines in the loan supply are mainly driven by a reduction in the number of loans that are issued. Thus, changes in the total amount of loans that are extended give us a better picture of changes in the supply of credit than changes in the amount of each loan that has been granted.

Also following Ivashina and Scharfstein (2010a), we measure bank lending as the dollar amount of loans in which a bank is lead originator. If a given loan is extended by more than one lead bank, then we assume that each lead bank extends the loan pro rata.[4] We construct banks' portfolio shares as follows: We first compute the total amount of loans that a bank issues during a month. Next, we compute the share of loans that bank i issues to country j as the proportion of all loans issued by bank i during month t. We similarly compute the proportion of loans issued to different categories of borrowers (such as investment grade, unrated, corporate, *et cetera*).

We attribute to each bank (including subsidiaries) the nationality of its parent bank, as is standard in the literature (e.g., Mian, 2006). A loan is considered foreign if the nationality of the borrower is different from the nationality of the (parent) bank. Our sample includes 256 (parent) banks from 55 countries, extending loans to borrowers in 192 countries. Together, these banks extended nearly 250,000 loans over the period 1997–2009, with a median loan value of US$ 200 million. Clearly, banks exhibit geographical specialization and not all banks are active in all markets. We exclude observations that refer to countries in which a bank has never lent during the sample period. Also, our sample of 256 banks includes only banks that have extended at least one foreign loan during the sample period.

Our main control variable for demand conditions in the host country is the total amount of loans issued by domestic banks during a month, standardized by the total amount of loans issued in the syndicated loan market during the same period.

[4] To make sure that our results are unaffected by changes in syndicate composition, in what follows, we show that our results are invariant if we measure new lending as the number of loan syndications of which a bank is lead originator. In addition, we show that there is no evidence that syndicate composition is differently affected for domestic and foreign lead banks when negative shocks occur.

Since our objective is to study bank behavior during banking crises, we obtain start and ending dates of systemically important banking crises from Laeven and Valencia (2010). They consider a banking crisis to be systemic if there are strong signs of financial distress in the banking system (as indicated by major bank runs, bank losses, and bank liquidations) and there are significant government interventions in response to such financial distress.[5] They use the first year that both conditions are met as the starting year of the banking crisis. The end of the crisis is defined as the year before both real GDP growth and real credit growth are positive for at least two consecutive years, truncating the maximum end year of a crisis at 5 years from the start of the crisis. In case the first two years record growth in real GDP and real credit, the crisis is dated to end the same year it starts.

For the purpose of the empirical analysis, we distinguish between crises that affect the bank's home country and crises that affect the borrower's country of origin. When hit by a banking crisis in their home country, banks are likely to experience or anticipate negative shocks to their net wealth, while banking crises in host countries impair the ability of host country borrowers to access credit from domestic banks. Furthermore, negative shocks in a borrower's home country may have stronger negative consequences for such a borrower's investment opportunities and demand for credit. Starting from 1997, our sample includes 43 episodes of banking crises that occur in banks' home countries and 44 crisis episodes in bank's host countries. Besides the countries affected by the 2007–08 financial crisis, these episodes include mostly banking crises associated with the Asian financial crisis in 1997, the Russian default crisis in 1998, and the Japanese financial crisis of the 1990's. While there is overlap between banking crises affecting the countries of origin of the banks and the host

[5] Policy interventions in the banking sector are considered to be significant if at least three out of the following six measures have been used 1) extensive liquidity support (5 percent of deposits and liabilities to nonresidents); 2) bank restructuring costs (at least 3 percent of GDP); 3) significant bank nationalizations; 4) significant guarantees put in place; 5) significant asset purchases (at least 5 percent of GDP); and 6) deposit freezes and bank holidays.

countries, for each of the episodes, we have banks' countries of origin and host countries that are unaffected in our control sample.

As an alternative measure of the economic conditions in which the bank operates, we use stock market returns that we obtain from Datastream. In particular, to capture shocks to the banking system in the country of origin of the bank on a monthly frequency, we use monthly stock returns of the banking industry (specifically, stock returns on an index of banking stocks) in that country during the previous month. This variable captures changes in lending policies following negative and positive shocks to bank net wealth. Similarly, we capture shocks to general economic conditions in the host country using the monthly return on the country's stock market index, which we also obtain from Datastream.

We merge the Loan Analytics database with Bankscope to obtain information on bank characteristics, including the total assets, which proxies for bank size, and the proportion of liabilities not funded by deposits.[6] Deposits, being implicitly or explicitly protected by deposit insurance, are a source of funding that is generally considered more stable than other sources of debt (Demirgüç-Kunt and Huizinga, 2010). Moreover, as Ivashina and Scharfstein (2010a) argue, during periods of financial turmoil, banks may experience difficulty rolling over their non-deposit debt because of concerns about their solvency and liquidity. Using information on these and other bank characteristics, we can explore how the flight home effect depends on bank specific conditions.

Finally, we obtain data on a host of country characteristics from a variety of sources. These include annual data on GDP per capita, trade openness, and financial and institutional development from the World Bank's World Development Indicators; information on country level creditor rights from Djankov et al. (2007); data on law and order tradition in the country

[6] Since there is no common identifier between Loan Analytics and Bankscope, the matching of banks was done using the first 15 letters of the bank name and the name of the home country (where the headquarters are located) of the bank. All matches were verified and some names had to be matched manually. Moreover, when the matching generated more than one Bankscope bank for a given Loan Analytics bank, the latter was matched to the largest Bankscope bank in terms of assets.

from the ICRG database, maintained by Political Risk Services; and data on a country's sovereign credit ratings from Standard and Poor's. The latter refer to the sovereign's long-term credit rating for external debt. We obtain data on the distance between the capital cities in each pair of countries in our dataset from Rose (2004) and data on export and import volumes (in US dollars) between countries from the IMF's Direction of Trade Statistics database. Finally, we collect information on each country's capital account restrictions from the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions database. Table 1 describes the main variables we employ in the empirical analysis.

3.2. Stylized Facts

While the size of the global syndicated loan market was more or less constant during the period 1997 to 2001, it grew rapidly over the period 2002 to 2006, increasing from a total amount of loan issuances of slightly less than US$ 2 trillion in 2002 to US$ 5 trillion in 2006 (Figure 1).[7] During 2007, this growth came at a halt as the ensuing financial crisis in the U.S. deteriorated global lending conditions. Starting in 2008, the global syndicated loan market collapsed and reached a volume of US$ 2.3 trillion in 2009, a decline of more than 50% from its peak. These patterns over time at a global level are similar to those found by Ivashina and Scharfstein (2010a) for the United States. The aggregate effect on the syndicated loan market of the 2008 global financial crisis is therefore evident in the data.[8]

During this decline, foreign lenders rebalanced their portfolio away from international markets, and as a result, the yearly fraction of syndicated loan volume issued by foreign lenders decreased by almost 5 percentage points from 48.3% of the total volume in

[7] According to Dealogic, the sample covers over 90% of the volume of syndicated loans worldwide and over 95% of the volume of cross-border syndicated loans.

[8] The BIS consolidated banking statistics show a comparable pattern over time with total international banking claims increasing from US$ 8 trillion in 1999 to a peak of US$ 28 trillion in 2007, and then steadily declining to US$ 25 trillion in 2009.

2007 to 43.5% in 2009 (Figure 2). In other words, while lending collapsed in both foreign and domestic markets, the collapse was more pronounced in foreign markets.[9]

While these findings are consistent with a *flight home* effect, one cannot rule out from this descriptive evidence that this effect is not driven by a flight to quality. For example, it could be that most lenders are from advanced economies and retract from emerging markets that are perceived to be riskier in the event of adverse economic shocks. In the empirical analysis, we distinguish the flight home effect from such a flight to quality effect by differentiating between destination countries (borrowers) that owing to their institutional environment are expected to be more or less affected by flight to quality, and further by incorporating local shocks that affected banks and borrowers in a subset of countries.

4. Empirical Evidence

4.1 Main Results

The estimates in Table 2 demonstrate that there exists a home bias in bank loan portfolios because foreign banks are found to extend systematically fewer loans to foreign borrowers. The effect is economically significant. Based on the estimates in column 1, being a foreign bank decreases the share of the bank's loans extended to the country by 0.51, which is economically sizeable compared to a standard deviation of the loan share variable of 0.38. More interestingly, it emerges from the analysis that when the bank's country of origin experiences a banking crisis, the home bias increases by nearly 20 percent. This is unlikely to be explained by demand effects, not only because we control for this possibility using the amount of loans extended by domestic banks as control variable, but also because negative demand shocks should be more likely in the bank's country of origin, which is experiencing a

[9] The BIS consolidated banking statistics show a similar pattern over time, with the average fraction of international banking claims in total banking claims (as computed by adding the difference between private credit and local claims to international claims—see section 4.3.1 for details) dropping from a peak of 42 percent in 2007 to 38 percent in 2009.

banking crisis, than in foreign unaffected countries. Similarly, one would expect that the credit risk of borrowers in countries directly affected by the banking crisis increases to a larger extent than for borrowers in countries that are not directly affected.

The effect is robust when we use alternative estimation methods, when we use alternative control variables, or when we estimate the regression model over different subsamples. For instance, although the portfolio shares vary between 0 and 1, we estimate the regression model using ordinary least squares because the high number of dummy variables we progressively include as control variables may create problems with maximum likelihood estimation. Nevertheless, in column 2, we include a minimum set of controls (as in column 1) and take into account that the dependent variable is truncated using a tobit model. The estimates are similar to the ones we obtain using ordinary least squares.

The estimates are also qualitatively similar when we include deal nationality fixed effects (column 3) and control for differences in foreign banks' lending policies when shocks affect the host countries (column 4). The coefficient of the new interaction term indicates that foreign banks indeed provide insurance against home-grown negative shocks, consistent with findings in the existing literature (see Goldberg, 2009). The increase in the proportion of loans extended by foreign banks when the host country experiences a banking crisis also indicates that foreign banks are scarcely concerned of being treated unfavorably in comparison to domestic claimants in case of defaults. Thus, these concerns are unlikely to explain the flight home effect.

In column 5, we consider that our results may be driven by the fact that foreign banks retract from countries that are marginal for their activities when they are hit by a crisis in their home countries. While this would be consistent with a flight home effect, the result would be less striking. We thus include only observations from countries in which banks have been the lead bank for a total of at least 10 syndicated loans. Our results remain qualitatively similar, suggesting that our finding is more general and foreign banks do not retract only from marginal foreign markets.

In column 6, we focus on the last crisis by restricting the sample to bank loan portfolio shares starting from 2006 and continue to find strong evidence in favor of the flight home effect. Our results are similarly unaltered when we exclude loans issued in 2008 and 2009, in other words, the time-period surrounding the Lehman Brothers' bankruptcy, indicating that our results are not driven by unusually large negative shocks. We then ask whether our finding depends on the behavior of the US and the UK banks that may have retracted to the domestic credit market during the last financial crisis. The estimates in column 7, where we exclude US and UK banks, indicate that the flight home effect is a far more general feature of bank lending policies and provide an initial indication that our results are unlikely to be driven by a flight to quality effect.[10]

A possible concern regarding our estimates so far is that we have captured changes in the demand for loans using changes in the volume of domestic loans. To eliminate any concern that the flight home effect is due to unobserved changes in the demand for loans across countries, we use a within-country estimator. Specifically, we include interactions of host country and month of the year fixed effects into the regression. This allows us to test whether foreign banks experiencing a banking crisis decrease the proportion of loans to a given country more than other banks. The estimates are reported in column 8 of Table 2 and fully support our previous results.

Another concern may be that our results depend on the monthly frequency of the observations. For this reason, we reconstruct the dataset by aggregating loans issued during a quarter rather than during a month. The estimates in column 9 of Table 2 show that our

[10] The results are similarly unchanged if we also drop banks from other financial center countries, such as Switzerland and Luxembourg.

results are both quantitatively and qualitatively invariant when using quarterly observations on syndicated loans.

4.2. Other Measures of Shocks and Home Bias

So far, we have identified banking shocks using binary variables for whether a given country has experienced a banking crisis. However, the intensity of banking crises and their negative impact on bank net wealth may vary. Moreover, negative shocks to the banking system may affect bank behavior even when a country does not experience a systemic banking crisis. For this reason, in column 1 of Table 3, we measure shocks to a bank's health using the stock return of the banking industry in the country of origin of the bank and economic conditions in the host country using the return on the stock market index in that country. The estimates fully support our previous findings: The home bias in bank portfolios appears to decrease when the return of the banking industry in the country of origin of the bank is higher, suggesting that bank health is associated with more international investment. Also, foreign banks seem to lend more when the stock market of the host countries experiences lower returns.

Not only may the intensity of banking crises vary across countries, but the exposure of banks within a country to a crisis may differ. If negative shocks to bank net wealth are indeed at the origin of the flight home effect, we would expect that the increase in home bias is larger for banks that are more exposed to the banking crisis. For this reason, we interact our dummies for banking crises in the bank's and the borrowers' home countries, respectively, with the proportion of non-deposit liabilities in total liabilities. Since non-deposit liabilities (especially wholesale funding) are a less stable source of funding for banks than traditional deposits, this proxy captures the possibility that a bank may experience liquidity pressures during a banking crisis. In column 2, our estimates indicate that the flight home effect is more pronounced for banks with a larger proportion of non-deposit liabilities. Interestingly, in normal times and when banking crises affect the host country, banks with a higher proportion of non-deposit liabilities extend more foreign loans, suggesting that they may be more flexible in expanding their assets. The bank-specific exposure to the banking crisis is positively related to the flight home also in column 3 of Table 3, where we use the proportion of bank losses in terms of loan charge-off rates as a proxy.

In column 4 of Table 3, we reformulate the dependent variable in a way that is common in the literature on the home equity bias. A bank without home bias would be expected to extend loans to borrowers in a country in proportion to the importance of this country in the international syndicated loan market. Following Ahearne, Griever and Warnock (2004), we define the home bias of bank *i* with respect to country *j* as, where $Bias_{ijt} = 1 - \left(\frac{Loanshare_{ijt}}{Sharecountry_{jt}}\right)$, where $Loanshare_{ijt}$ is as defined in equation (1) and $Sharecountry_{jt}$ is the proportion of the loans issued in country *j* at time *t* with respect to the total amount of loans issued in the syndicated loan market at time *t*. In these specifications, the flight home effect would imply a positive and significant coefficient for the interaction term $Foreign\ Loan_{ij} * Shock\ Bank\ Country_{jt}$. The estimates indicate that the home bias increases by over 75 percent when the bank experiences a banking crisis. We find no changes in home bias when host countries experience banking crises.

To provide further evidence of the flight home effect, we consider that home bias is associated with proximity and familiarity, as in Coval and Moskowitz (1999). Thus, an increase in home bias should imply not only more lending to domestic borrowers, but also to borrowers in proximate countries. Consistently, we find that banks decrease their loans to distant borrowers to a larger extent when they experience banking crises in their domestic country (column 5). We also find that banks tend to extend fewer loans to remote borrowers.

Next, we test whether there exists evidence of flight home using the BIS banking statistics. While as explained earlier concentrating on syndicated bank loans allows us to gain deeper insights in the factors driving the flight home effect, this is an important robustness test because it allows to evaluate whether a flight to home emerges when we consider the mix of outstanding loans (a stock variable) rather than new loans (a flow variable), a broader class of international bank claims, and a measure of outstanding loans that takes into account loan repayments and does not depend on the syndicate loan composition.

We construct the dependent variable as the fraction of international banking claims from banks in country *i* on host country *j* in total banking claims from banks in country *i*. We compute international banking claims using the bilateral foreign and international banking claims from Table 9b of the BIS Consolidated International Banking Statistics. Total banking claims are computed as the sum of international banking claims and domestic banking claims. The latter are not directly available from the BIS dataset and following Cetorelli and Goldberg (2010) are proxied using the difference between domestic credit from banks to the private sector—computed by aggregating figures from lines 22A through 22D from the IMF's IFS database—and local banking claims—computed as total local currency claims on local residents by foreign banks from Table 9al of the BIS Consolidated International Banking Statistics. In those few cases where the amount of local banking claims exceeds domestic credit to the private sector, we set observations to missing. We also limit the sample to the same set of countries and time period as that used in our main regressions using syndicated loan data. In this specification, we control for demand shocks in the host country by including interactions of deal nationality and time fixed effects. Estimates in Column 6 of Table 3 fully support the existence of a flight home effect.

4.3. Bank Parents, Subsidiaries and Borrower Types

An advantage of syndicated loan data is that we observe detailed bank and borrower characteristics on the loans, including whether loans are extended by the parent bank or by a subsidiary and whether the borrowers are private industrial corporations, sovereign or state-owned companies, or financial companies. Exploring bank lending in these different segments of the syndicated loan market can help to shed light on the sources of the flight home effect.

Some of the loans that we classify as foreign are issued by the subsidiaries of the banks in the country of the borrower. In the BIS international banking statistics, these loans would not be classified as international capital flows, but would be considered domestic loans. Furthermore, Cetorelli and Goldberg (2011) show that international banks obtain liquidity from their subsidiaries during times of strict monetary policies. Thus, one may wonder whether the increase in home bias of new loans we find depends on the fact that banks' foreign subsidiaries having to transfer resources to their parents are able to grant fewer loans. In column 1 of Table 3, we test whether we still find a flight home effect once we only include loans directly issued by parent banks. We continue to find evidence of a flight home effect when we focus on the loans directly granted by the bank parents.

Interestingly, in column 2 of Table 4, when we focus on the loans granted by the subsidiaries, we find that they too increase the proportion of loans they grant to borrowers from their parents' country of origin. This may depend on the fact that they increase the loan they grant to foreign subsidiaries of the firms from the origin countries of their parents. Also, it appears plausible that in normal times, the (foreign) subsidiaries of global banks extend mostly foreign loans and exhibit a foreign bias rather than a home bias.

Having established that our results do not depend on whether loans are granted by the parent or the foreign subsidiaries of global banks, we turn to analyze different types of borrowers: non-financial firms, other financial institutions, and sovereign states (including state-owned enterprises). In these specifications, we control for demand effects using the loans granted by the domestic banks in the host country to each of these types of borrowers.

For all borrower types, we find evidence of flight home, whether we distinguish between domestic and foreign loans or use measures of familiarity based on the physical distance between the country of origin of the bank and the host country. The great majority of loans in the syndicated loan market are granted to corporate borrowers. Thus, it is unsurprising that when we focus on loans granted to corporate borrowers (columns 3 and 4 of Table 4) the estimates are very similar to the ones shown before. Interestingly, the flight home effect appears somewhat more pronounced when we focus on loans granted to sovereign states and state-owned enterprises (columns 7 and 8 of Table 4). This may be related to the banks' attempt to increase the probability of a bail out. We revisit this argument in Subsection 5.4.

Finally, it is interesting to note that during banking crises affecting the host countries foreign banks extend larger loans to private companies as well as to government-owned enterprises, but not to other financial institutions, which during a banking crisis represent worse credit risks.

4.4. Robustness Tests

4.4.1. Borrower and Loan Heterogeneity

Syndicated loans are extended not only for real investment, but also for highly cyclical restructuring activities, such as leverage buyouts, merger and acquisitions and stock repurchases. The demand for the latter type of loans may be lower during periods of financial turmoil, even if the borrower's country does not experience a banking crisis. If more foreign loans were extended for restructuring activities compared to domestic loans, a drop in the demand of the more cyclical loans could explain the flight home effect, which would then be unrelated to negative shocks to the bank's net wealth.

Loan Analytics provides information on the purpose of the syndicated loan. We can thus perform our analysis focusing on loans that are intended for real investment (i.e., loans whose use is general corporate purposes or working capital). Results in column 1 of Table 5 show clear evidence of a flight home effect even if we restrict our attention to less cyclical loans. The estimates are not only statistically, but also economically invariant.

Another possibility is that the clients of domestic and foreign banks within a country differ. Any ex ante differences in the clients of domestic and foreign banks within a country should be reflected in the loan contracts they were offered. For instance, riskier borrowers with more cyclical demand presumably paid a higher interest rate on their loans. In column 2 and 3, we include controls for the average contract terms offered by each bank to borrowers in each country during the prior 12 months. Although our sample is reduced because of missing observations on contracts terms for loans in some countries, we continue to find clear evidence of a flight home effect. Like our previous results which distinguish among loans with different credit ratings, these findings indicate that the flight home effect is not due to ex ante differences between the clients of domestic and foreign banks.

Next, we consider that domestic and foreign loans may not be substitutes. In particular, they may be complementary especially if some foreign loans are used to fund domestic financial institutions. In this respect, it is reassuring that our results are robust when we exclude loans to other financial institutions and when we concentrate on loans that are used for real investment. To further mitigate these concerns, we exploit the fact that our control sample for banks experiencing a banking crisis includes the foreign loans of banks in countries that do not experience negative shocks at the same time. Thus, we exclude domestic loans from the sample and absorb demand shocks in the host country by including interactions of deal nationality and time fixed effects. The estimates in column 4 of Table 5 are still strongly supportive of the flight home effect and suggest that if, anything, the complementarity between domestic and foreign loans may lead us to slightly underestimated its magnitude.

4.4.2. Trade Openness and Financial Integration

The flight home effect could simply be an artifact of a country's openness to trade. For instance, international trade is known to drop during financial crises. Although syndicated loans are rarely used to fund exports, it could be that international loans closely follow the pattern of real transactions. The flight home of international banks could then depend on a decline in the real integration. However, the estimates in column 5 of Table 5 indicate that there is strong evidence of a flight home effect even after controlling for the evolution of trade flows between the country of the bank and the country of the borrower. Since we can relate trade flows only to observations that include loans to foreign countries, we omit the share of loans to domestic borrowers from this specification. Thus, a negative effect of the dummy Shock Bank Country indicates that the share of loans extended to each of the foreign countries in the bank's portfolio decreases. The effect is quantitatively similar to the regression specifications in which we do not control for trade flows. This suggests that the flight home effect is not driven by changes in the degree of real economic integration.

In columns 6 and 7 of Table 5, we consider whether fears that host countries may place restrictions on capital outflows during periods of financial turmoil abroad determines the behavior of our sample of internationally active banks. We conjecture that these concerns may be more relevant for countries that are less integrated with the rest of the world and use measures of *de jure* and *de facto* financial integration (notably an index of capital account restrictions and the ratio of foreign bank claims per capita) to capture the degree of financial integration of host countries. Unsurprisingly, the home bias in banks' portfolios is more pronounced towards countries with less open capital accounts and less pronounced in countries with more foreign bank claims per capita. The flight home effect, however, does not appear to depend on the extent of financial integration of the host country with the rest of the world.

4.4.3. Syndicate Composition

So far, consistent with previous literature, we have assumed that the lead bank is the lending bank. This measures the extent to which a bank is involved in originating new loans. However, after negotiating the loan with the borrower, the lead bank retains a fraction of the loan (generally 1/3) and sells the remaining part to participant banks and other investors. Lead banks are expected to retain a larger share of the loan when their access to privileged information increases with respect to participant banks (Gorton and Pennachi, 1995).

If during a downturn the share of the loan retained by the lead bank increases, as the findings of Ivashina and Scharfstein (2010b) for the US suggest, then we could observe that the lead bank originates less credit in terms of overall lending volume, while the amount of loans that the lead bank offers to each borrower need not decrease. This could affect our results only if the syndicate composition varies differently for domestic and foreign loans. If this were the case, one would expect that during a downturn the information asymmetry between lead banks and other participants in the syndicate is higher for domestic borrowers, because domestic banks tend to have privileged access to information on domestic borrowers. In this case, if the bank preferred not to change the geographical distribution of its loan exposure, we should observe that the lead bank originates a smaller amount of loans to the domestic country, *ceteris paribus*. In fact, we find the contrary.

Nevertheless, to mitigate concerns that our results are affected by the syndicate composition, we evaluate whether our estimates are robust if we focus on the fraction of the number (as opposed to the amount) of new loans that the bank originates in different countries. Column 1 of Table 6 shows that our results remain unaltered when we consider the number of loans: the proportion of new loans granted in foreign countries decreases when banks experience banking crises in their country of origin.

The regressions in Columns 2 and 3 of Table 6 consider the syndicate composition that we observe for slightly less than half of the loans in our sample. We explore whether the average number of participants and the average share of the loan retained by the bank for loans issued by bank *i* in country *j* at time *t* vary differently for foreign and domestic loans during banking crises. We find no evidence that the composition of syndicates led by foreign banks is affected differently when the banks experience banking crises in their country of origin: foreign banks retain a larger share of the loan in host countries that are experiencing banking crises, supporting our earlier finding that in these situations unaffected foreign banks are inclined to provide insurance and consistent with the notion that information asymmetries and agency problems become more severe when borrowers incur negative shocks.

Overall, the fact that the structure of the syndicate is unaffected when banking crises affect the country of origin of the banks fully supports our interpretation of the empirical evidence that banks hit by negative shocks have a tendency to concentrate on the domestic market, resulting in a flight home effect.

5. What Explains the Flight Home Effect?

This section considers potential explanations for the increase in home bias in loan origination when banks experience negative shocks using detailed bank and borrower characteristics. We suggest that higher expected returns of domestic loans and an increase in risk aversion can explain the flight home.

5.1. Flight to Quality

Previous literature highlights that during financial crises investors, and banks in particular, tend to rebalance their portfolios in favor of safer and less opaque assets, a phenomenon that is generally referred to as flight to quality. We thus explore to what extent our findings may be a consequence of a flight to quality.

A possibility could be that in periods of market turmoil banks from advanced economies retract from emerging markets, which are considered riskier or less transparent. We could then erroneously interpret the desire to hold safer and more transparent assets as a desire to hold domestic assets. This is unlikely to be the case because in column 7 of Table 2 we have already shown that the flight home effect arises even if we exclude banks from the U.S. and the U.K., whose home countries are arguably the two countries in our sample with the strongest and most transparent institutional environments to which investors revert during periods of financial turmoil. We also test whether our results hold if we include only observations from borrowers in countries that are not directly affected by a banking crisis in their home country and that are consequently unlikely to have become less creditworthy than borrowers in the bank's country of origin. The estimates which we omit for brevity are fully consistent with our previous results.

To further mitigate concerns that our results are due to a flight to quality effect, in column 1 of Table 7, we include a dummy that takes a value of one for emerging markets[11] and interact it with our main variables of interest capturing the reaction of banks to banking crises in the country of origin and in the host country. Our premise is that if a flight to quality effect dominates, then the withdrawal from foreign lending markets following a banking crisis should be more pronounced for emerging markets where on average borrowers tend to have lower credit quality than borrowers in advanced economies. Instead, we find that, while foreign banks tend to decrease the amount of loans they allocate to foreign borrowers when

[11] Since the World Bank classification of emerging markets varies over time depending on economic development of the country, this dummy variable varies over time for some emerging markets.

they experience a crisis in their country of origin, this effect is not more pronounced for foreign loans to emerging markets. This suggests that the flight home effect is not a consequence of flight to quality.

We do find evidence of flight to quality when host countries experience banking crises. When the banking crisis occurs in a host country that is an advanced economy, foreign banks appear to provide insurance by increasing the share of loans that they allocate. This is no longer the case if an emerging market experiences a banking crisis as the coefficient of *Shock Borrower Country×Emerging Market Loans×Foreign Loan* is negative, significant and (statistically) equal in absolute value to the positive coefficient of the *Shock Borrower Country×Foreign Loan variable*.

The distinction between emerging markets and advanced economies is a crude proxy for the risk of extending credit to borrowers in a country. For this reason, we consider different country level proxies for institutional development and risk and explore whether the flight home effect is driven by the fact that banks retract from countries with weak institutions and higher risk. Consistent with our previous results, we find that having strong institutions helps mitigate the effects of home-grown shocks, as foreign banks are more inclined to provide insurance, while having strong institutions appears to be irrelevant or even counterproductive for shocks affecting foreign banks. In columns 2 and 3 of Table 7, we interact our proxies for shocks in the bank's and the borrower's countries with an index of protection of creditor rights from Djankov, McLiesh and Shleifer (2007) and an indicator of law and order. While the latter seems to leave the flight home effect unaffected, it appears that the flight home effect is more pronounced from countries with stronger creditor protection, possibly because credit expansion is larger in these countries during good times.

In column 4 of Table 7, we interact our banking crises dummies with the difference between the S&P sovereign credit ratings of the bank's and the borrower's home country, respectively. Once again it appears that when their country of origin experiences financial turmoil, foreign banks distinguish only between domestic and foreign borrowers; foreign borrowers are granted less credit independently from their country's credit rating. Foreign banks appear to increase the proportion of loans they extend to countries that experience banking crises to a larger extent if these countries have higher sovereign credit ratings than their own country. This confirms that foreign banks tend to insure host countries against negative shocks to their banking systems, but only if these countries have stronger institutions and relatively lower risk. Interestingly, banks extend a larger proportion of loans to borrowers in countries with lower credit ratings, possibly suggesting that a higher level of debt decreases these countries' credit ratings.

Finally, we test whether the flight home effect is more pronounced for banks from strong institutional environments, which would suggest that the flight home and flight to quality effects are closely intertwined. Estimates in column 5 of Table 7 show that the flight home does not depend on the quality of institutions in the country of origin of the bank thus confirming that the effect we uncover is distinct from a flight to quality effect.

A possible limitation of the results presented thus far in Table 7 is that country risk and institutional development may not fully capture the quality of bank loans. For instance, the quality of the clients with access to foreign banks may be lower in riskier and less developed economies. This is unlikely because existing literature suggests that if foreign banks extend credit to more creditworthy and transparent borrowers. Nevertheless, to address these concerns, we note that information asymmetries and agency problems between banks and their borrowers vary across different segments of the syndicated loan markets. Therefore, in the remainder of Table 7, we split the sample depending on whether the borrower is rated or not. As rated borrowers tend to be investment grade, and borrowers without rating are more subject to asymmetric information, the existence of a credit rating is a proxy for loan quality. The estimates in column 6 of Table 7 reveal that the home equity bias is economically smaller for rated loans (i.e., higher quality loans). While on average foreign banks' loan portfolio shares are 50 percentage points smaller than those of domestic banks, we find that for rated borrowers, the portfolio shares are only 7 percentage points smaller. However, when the bank's country of origin experiences a banking crisis, the home bias in banks' portfolios increases by 15 percent, an increase that is only slightly smaller than the one obtained for the whole sample. For unrated loans (column 7 of Table 7), which are the most frequent in the syndicated loan market, the magnitude of the effects is similar to what we obtain for the whole sample.

Since borrowers with no credit ratings are more subject to information asymmetries, these results indicate that the home bias in the syndicated loan market is in part driven by asymmetric information. However, the comparable magnitude of the increase in the home bias when banks experience a banking crisis in their country of origin across rated and unrated loans suggests that information asymmetries are unlikely to be the main factor driving the flight home effect.

5.2. Bank Relationships

If banks had close relationships with domestic borrowers but not with foreign borrowers, their favorable treatment of relationship borrowers could explain why the home bias in their loan portfolios increases in periods of financial turmoil. For example, Bae, Kang and Lim (2002) show that firms with closer relationships to their banks benefited from easier access to credit during the Korean financial crisis of 1998. Thus, we explore to what extent foreign banks refrain from extending loans to borrowers with which they have no established relationship following a financial crisis, but continue to extend loans to relationship borrowers independently from whether they are domestic or foreign.

We consider loans to borrowers that did not receive a loan from a particular bank before as loans to first time borrowers and loans to borrowers that have received previous loans from this bank as relationship loans (to define previous loans we consider loans extended since 1990).[12] In columns 1 and 2 of Table 8, we present estimates for first time borrowers and relationship borrowers, respectively. The magnitude of the coefficient is similar in the two samples, indicating that a different treatment of relationship borrowers cannot explain the flight home effect. In unreported specifications, we also find that results are invariant if we increase the number of loans that a borrower must have received from a given bank for the borrower to be considered a relationship borrower.

To the extent that banks should have better information on repeated borrowers, these results also suggest that information asymmetries are unlikely to be at the origin of the flight home effect.

5.3. Government Interventions

Banks that benefit from government interventions during banking crises may be subject to conditions or moral suasion by politicians or the government to lend to domestic borrowers, possibly at the expense of foreign borrowers. Such pressures may be particularly pronounced when government interventions take place in the form of capital injections or outright bank nationalizations. These political influences associated with government bailouts of banks could drive the portfolio rebalancing of banks towards domestic loans.

To test this hypothesis, we obtain data from Laeven and Valencia (2010) on the list of intervened banks benefiting from government bailouts during the 2007–08 financial crisis. We define a dummy variable that takes value equal to 1 for banks that were nationalized or received government support in the form of capital injections or asset guarantees, and

[12] We only consider lead banks to define relationships. It would be incorrect to consider also other participants in the syndicate, as these have no direct relation with the borrower.

consider the period surrounding the latest banking crisis (2006–09), for which we observe all the interventions, to test whether government intervened banks drive our results. Column 3 in Table 8 presents the results. We find no evidence that these banks rebalance their portfolio towards domestic borrowers to a larger extent than other banks. Interestingly, banks that are intervened by the government have a higher proportion of foreign loans prior to the banking crisis, suggesting that they may have taken more risks. Overall, it appears that political factors related to government interventions cannot explain the flight home effect, as is consistent with the findings of Rose and Wieladek (2011), who show that the response of bank lending policies to government interventions varies not only across different types of government interventions, but also across different countries.

5.4. Core Business, Diversification, and Expected Returns

French and Poterba (1991) argue that investors' preferences for domestic assets are such that investors in each country expect significantly higher returns in their domestic asset markets compared to foreign asset markets. In a similar vein, our results suggest that banks' preferences for domestic loans become stronger when they experience negative shocks.

Expected returns on domestic loans can be higher because of several factors, including diseconomies of scale, higher costs of producing foreign loans, and non-pecuniary benefits related to the probability of a bailout. First, banks' desire to revert to their core business in the domestic market is consistent with the earlier work showing that due to the lack of economies of scale, diversification of the loan portfolio does not lead to higher profitability for banks (DeLong, 2001; Acharya, Hasan and Saunders, 2006; Laeven and Levine, 2007).[13] Moreover, Giannetti and Yafeh (2011) suggest that contracting costs are higher for loans to distant borrowers. Having experienced negative shocks to their net wealth,

[13] Asset diversification can also proxy for agency problems like empire building, resulting in lower profit margin investments (Laeven and Levine, 2007).

banks have to shrink their loan portfolio and are likely to cut their least profitable loans first, which this literature suggests are foreign loans and loans to the least proximate borrowers.

Such an interpretation implies that banks that have to scale down their activities to a larger extent exhibit a stronger flight home. This is consistent with the previously shown empirical evidence that banks with more non-deposit liabilities, which are more likely to be redeemed during a banking crisis, and larger bank losses exhibit a stronger flight home effect (column 2 and 3, Table 4). This line of argument would also imply that, *ceteris paribus*, banks that are more diversified and that presumably have extended relatively less profitable loans to foreign borrowers should exhibit a stronger flight home. Following Laeven and Levine (2007), we measure a bank's product diversification using $1 - \left|\frac{L_t - OEA_t}{EA_t}\right|$, where L denotes the bank's total net loans, OEA denotes earning assets other than loans (such as securities and other investments), EA denotes total earnings assets (the sum of loans and other earning assets), and $|.|$ denotes the absolute value indicator. This variable measures how much a bank is diversified in activities other than lending, and is increasing in diversification. On the basis of this proxy, we define a dummy variable that takes value 1 for banks with diversification above the median. Column 5 of Table 8 provides evidence that the flight home is indeed stronger for the most diversified banks.[14]

Extending loans to domestic borrowers could also entail higher non-pecuniary benefits during banking crises. By maintaining exposure to domestic loans especially to the government and to government-owned enterprises while cutting back on foreign loans, banks may increase their importance for the domestic real economy and increase the probability of being bailed out if needed (as in Farhi and Tirole, 2009). To the extent that loans to

[14] Results (not reported) are qualitatively similar if we use the number of markets in which the bank extended syndicated loans during the previous year as an alternative measure of diversification.[15] See Vayanos (2004) for a model in which an investor's effective risk aversion increases following weak performance due to the higher probability of withdrawals and termination.

government and government-owned firms are more effective in attracting the favors of politicians, the finding that the flight home effect is more pronounced for these loans supports the conjecture that domestic loans may involve non-pecuniary benefits. Moreover, focusing on domestic loans, we find that banks increase the percentage of loans they grant to the government and government-owned firms when their country experiences a banking crisis.

This interpretation is also consistent with the finding that the flight home effect is stronger for banks with more non-deposit liabilities or larger loan charge offs (column 3 and 4, Table 4). These banks are more likely to need a bailout during banking crises when non-deposit funding markets turn shallow and loan losses are realized, and may value more the implicit insurance associated with domestic loans. Furthermore, the finding that larger banks, often deemed too big to fail, exhibit a less pronounced flight home effect (column 4 of Table 8) can be interpreted along the same lines: Since ceteris paribus, smaller banks are less likely to be bailed out, they attempt to increase this probability by extending more domestic loans.

5.5. Risk Aversion

When banks experience negative shocks their effective risk aversion increases, because their license is subject to termination if they fail to meet minimum capital requirements.[15] Although loans to domestic borrowers may hardly be considered less risky during a banking crisis, banks may be able to better evaluate their risk. As in Epstein (2001), they may thus consider loans to domestic borrowers less ambiguous and increase their proportion after experiencing negative shocks. An increase in the risk aversion of global banks could also have behavioral origins. For example, Barberis (2010) suggests that after

[15] See Vayanos (2004) for a model in which an investor's effective risk aversion increases following weak performance due to the higher probability of withdrawals and termination.

suffering losses, even the professional decision makers employed by institutional investors or global banks may prefer to operate in more familiar environments.[16]

Interpretations of the empirical evidence based on an increase in risk aversion are also consistent with the previously reported evidence that banks more exposed to the shock exhibit a stronger flight home. Moreover, the flight home should be more pronounced for banks with lower tier 1 capital, for which fears of termination due to further negative shocks should be stronger and that theoretically are expected to have larger effective risk aversion. While the tier 1 capital does not appear to affect the magnitude of the flight home in the whole sample, our conjecture is confirmed if we restrict the sample up to 2007. Since the severity of the 2007–08 crisis was unprecedented, one may argue that any buffer was perceived to be too small for insuring banks from failure.

To provide additional empirical evidence that the flight home effect may depend on the fact that domestic and foreign banks have different views about the risk of the same borrower, we concentrate on exchange rate risk and specifically the currency of denomination of the loans. After experiencing negative shocks to their net wealth, foreign banks may want to decrease their exposure to exchange rate risk, especially if loans are extended in currencies other than the domestic currency.

While the currency of denomination of the loan is often a variable of choice when the contract terms are established, in some markets, banks may have less flexibility in issuing loans in their domestic currency. For instance, it is unlikely that US borrowers would accept loans in a currency other than the US dollar. To capture the bank's flexibility (or lack thereof) to issue loans in domestic currency in different markets, we measure the fraction of loans extended in the bank's home country currency during the prior 12 months to borrowers in

[16] Behavioral studies support this mechanism. Heath and Tversky (1991) present a theory in which the extent of familiarity biases varies depending on how competent an individual feels about the decision that needs to be taken. After good performance, agents who feel competent at analyzing the situation at hand may venture in unfamiliar environments, but they revert to the most familiar domestic market when negative shocks to their portfolio undermine their confidence.

each host market. We surmise that banks may be less able to issue loans in domestic currency to borrowers in countries where generally a lower proportion of loans was issued in this currency and test whether the flight home effect is more pronounced from these host markets.

Estimates in column 6 of Table 8 show that banks that have experienced a banking crisis in their country of origin decrease their loan exposure to a lesser extent to countries where they tend to extend loans in their domestic currency. In particular, the flight home effect decreases by 30 percent if the proportion of loans extended by a bank in its home currency increases by a one standard deviation. This supports the conjecture that banks view differently the risk of domestic and foreign loans and that this may affect their lending decisions when they experience negative shocks and their effective risk aversion increases.

6. Conclusions

In the context of the international syndicated loan market, we provide evidence that the collapse of international markets during financial crises can be explained by a flight home effect. We show that the home bias of lenders' loan portfolios increases by approximately 20% if the country of origin of the bank experiences a banking crisis. The flight home effect is distinct from a flight to quality effect because borrowers in countries with varying economic development are equally affected by banks' portfolio rebalancing in favor of domestic lenders. Similarly, the flight home of international lenders does not appear to be limited to countries with weak investor protection or to borrowers with lower credit ratings. Instead, it appears that after experiencing negative shocks to their net wealth, banks prefer the risk and return profile associated to domestic loans, compared to foreign loans, due to low expected returns from diversification in banking and higher probability of a bailout associated with domestic lending. We also argue that increased risk aversion by lenders following banking crises helps explain the decreased appetite for foreign loans, whose returns are more difficult to evaluate and are generally perceived as riskier.

We view our contribution as twofold. First, studying bank lending in the international syndicated loan market, we contribute to the literature on the transmission mechanism of shocks to bank lending and establish that banks decrease foreign loans to a larger extent than domestic loans when they are affected by negative shocks. Second, our paper suggests that the home bias increases when investors are subject to negative shocks. We believe that investigating the time series variation in the home bias for different types of investors and asset classes is an exciting area for future research, that could further improve our understanding of the home bias in international capital allocation, one of the most studied puzzles in international finance.

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Figure 1. Total amount of syndicated loans issued (US$ billions), 1997–2009

This figure displays total gross amount of syndicated loans issued worldwide in US$ billions in a given year over the period 1997–2009. Authors' calculations based on data from Dealogic's Loan Analytics Database.

Figure 2. Syndicated loan volume issued by foreign lenders, fraction of total, 1997–2009

This figure displays the yearly amount of syndicated loans issued by foreign lenders as a fraction of the yearly total amount of syndicated loans issued over the period 1997–2009. Authors' calculations based on data from Dealogic's Loan Analytics Database.

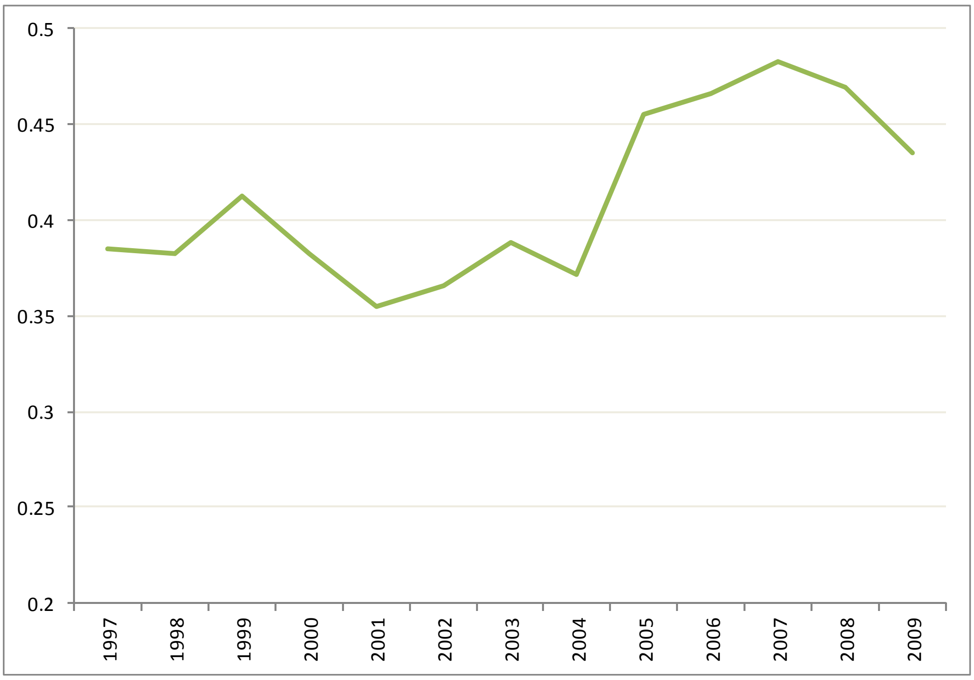

Table 1. Descriptive Statistics

This table displays summary statistics of the main regression variables. Syndicated loan variables are computed by the authors using data from Dealogic's Loan Analytics Database. Bank specific variables are computed using Bankscope, unless indicated otherwise. Country variables are from the World Bank's World Development Indicators database, unless indicated otherwise.

Variable	Definition	Mean	St. Dev.	Median	N
Bank-country-time specific variables					
Loan Share	Loans extended by bank i to borrowers in country j at time t/Total loans issued by bank i at time t	0.30	0.38	0.08	50710
Loan Share-Quarterly Data	Defined as above, but time t signifies a quarter instead of a month.	0.22	0.34	0.03	35235
Bias	$Bias_{ijt} = 1 - \left(\frac{Loanshare_{ijt}}{Sharecountry_{jt}}\right)$, where the $Sharecountry_{jt}$ is the proportion of the loans issued in country j at time t with respect to the total amount of loans issued in the syndicated loan market at time t.	203.79	3,903.91	-5.44	50704
Loan Share-BIS data	The fraction of international banking claims from banks in country *j* on host country *i* in total banking claims from banks in country *i* from the BIS Consolidated International Banking Statistics and IMF IFS database	0.03	0.13	0	17937
Loan Share-Bank Parents Only	Loans extended by the headquarters of bank i to borrowers in country j at time t/Total loans issued by the headquarters of bank i at time t	0.3	0.38	0.08	50430
Loan Share- Subsidiaries Only	Loans extended by the subsidiaries of bank i to borrowers in country j at time t/Total loans issued by the subsidiaries of bank i at time t	0.14	0.34	0	14939
Corporate Borrowers Loan Share	Loans extended by bank i to corporate borrowers in country j at time t/Total loans to corporate borrowers issued by bank i at time t	0.28	0.38	0.04	47817
Financial Institutions Loan Share	Loans extended by bank i to financial institutions in country j at time t/Total loans to financial institutions issued by bank i at time t	0.18	0.34	0	36819
Government Loan Share	Loans extended by bank i to the government and government-owned firms in country j at time t/Total loans to governments and government-owned firms issued by bank i at time t	0.15	0.33	0	30549
Loan A&B Share	Loans extended by bank i to A & B borrowers in country j at time t/Total loans issued by bank i at time t	0.06	0.17	0.00	50710
Loan Unrated Share	Loans extended by bank i to unrated borrowers in country j at time t/Total loans issued by bank i at time t	0.25	0.36	0.04	50710
Loan First-Time Share	Loans extended by bank i to first time borrowers in country j at time t/Total loans issued by bank i at time t	0.15	0.27	0.02	50710
Loan Relation Share	Loans extended by bank i to previous clients in country j at time t/Total loans issued by bank i at time t	0.15	0.26	0.01	50710

Variable	Definition	Mean	St. Dev.	Median	N
Loan Share Real Investment	Loans whose purpose is working capital or general corporate purposes issued by bank i to borrowers in country j at time t/Total loans whose purpose is working capital or general corporate purposes issued by bank i at time t	0.23	0.38	0	41,172
Loan Share-Number of Loans	Number of loans extended by bank i to clients in country j at time t/Total number of loans extended by bank i at time t	0.3	0.35	0.12	50720
Average Lead Bank Share	Average share of the loan retained by bank i for loans to borrowers of country j at time t	0.23	0.2	0.17	18068
Average Number of Participants	Average number of participants for syndicates led by bank i in country j at time t	9.17	8.4	7	43656
Average Loan Amount	Average amount of the loans extended by bank i to borrowers in country j at t-12	226.1	634.48	87.06	34,581
Average Interest Rate	Average interest rate of the loans extended by bank i to borrowers in country j at t-12	134.21	112.53	102.28	26,037
Average Maturity	Average maturity of the loans extended by bank i to borrowers in country j at t-12	1,248.90	1,435.03	793	9,772
Foreign Loan	Dummy variable that takes value 1 if bank i nationality is different from the nationality of the borrower; the variable equals zero otherwise	0.79	0.41	1.00	50725
Subsidiary	Dummy variable that takes value 1 if the bank has a subsidiary in the borrower's country; the variable takes value zero otherwise	0.05	0.22	0	50725
Proportion Loans in the Bank's Currency	Proportion of loans that bank i extends in country j at t-12 denominated in the domestic currency of the bank	0.1	0.29	0	50732
Bank specific variables					
Large Bank	Dummy variable that takes value equal 1 if the bank's total assets are above the mean and 0 otherwise	0.27	0.44	0	50732
Proportion of non-deposit liabilities	Ratio of non-deposit liabilities to total liabilities in a given year	0.92	1.92	0.35	26373
Bank's charge off	Proportion of nonperforming loans in the bank's assets in a given year	0.01	0.01	0.01	45412
Tier 1 Capital	The ratio of Tier-1 capital to risk weighted assets	0.088	0.052	0.082	18511
Asset Diversification	1 minus the absolute value of the ratio of loans minus other earning assets to total earning assets	0.68	0.26	0.74	24908
Government Intervention	Dummy variable that takes value equal to 1 if the bank was nationalized or received government support in the form of capital or asset guarantees between 2006 and 2009, and zero otherwise. Source: Laeven and Valencia (2010).	0.30	0.46	0	21694
Country-time specific variables					

Variable	Definition	Mean	St. Dev.	Median	N
Domestic Loans	Domestic loans in country j at time t/Total loans at time t	0.05	0.14	0.00	50732
Domestic Loans-Quarterly Data	Defined as above, but time t signifies a quarter instead of a month.	0.04	0.11	0	35252
Domestic Loans to Corporate Borrower	Domestic loans to corporate borrowers in country j at time t/Total loans to corporate borrowers at time t	0.14	0.24	0.03	45339
Domestic Loans to Financial Institutions	Domestic loans to financial institutions in country j at time t/Total loans to financial institutions at time t	0.12	0.25	0	33614
Domestic Loans to the Government	Domestic loans to the government and government-owned firms in country j at time t/Total loans at time t	0.13	0.27	0	25327
Domestic A&B Loans	Domestic loans to A& B borrowers in country j at time t/Total loans at time t	0.02	0.07	0.00	48488
Domestic Unrated Loans	Domestic loans to unrated borrowers in country j at time t/Total loans at time t	0.03	0.08	0.00	50732
Domestic First-Time Loans	Domestic loans to first time borrowers in country j at time t/Total loans at time t	0.02	0.03	0.00	34729
Domestic Relationship Loans	Domestic loans to previous clients in country j at time t/Total loans at time t	0.06	0.13	0.00	34729
Domestic Loans Real Investment	Domestic loans whose purpose is working capital or general corporate purposes issued by bank i to borrowers in country j at time t/Total loans whose purpose is working capital or general corporate purposes issued at time t				
Domestic Loans-Number of Loans	Number of loans in country j at time t/Total loans at time t	0	0	0	50732
Average Lead Bank Share	Average share of the loan retained by domestic lead banks in country j at time t	0.34	0.24	0.28	27044
Average Number of Participants	Average number of participants for syndicates led by domestic lead banks in country j at time t	7.45	5.17	6.08	29973
Shock Bank Country	Dummy variable that equals 1 if the country of origin of the bank experiences a banking crisis and equals zero otherwise	0.19	0.39	0.00	50732
Shock Borrower Country	Dummy variable that equals 1 if the country of origin of the borrower experiences a banking crisis and equals zero otherwise	0.14	0.34	0.00	50732
Banking Return in Bank's Country	Monthly return of the banking sector in the bank's country of origin from Datastream	-0.01	0.08	0.00	32768
Host Country's Mkt Return	Monthly market return in the country of the borrower from Datastream	0.00	0.06	0.01	28577
Emerging Market	Dummy variable that takes value 1 if the borrower's country has GDP per capita below USD 10000 and takes value zero otherwise	0.15	0.36	0.00	50732
Creditor rights	Index of creditor rights in the host country from Djankov et al. (2007)	2.05	1.12	2	29435
Law & Order	Index of law and order in the host country from ICRG	4.77	0.98	5	30018

Variable	Definition	Mean	St. Dev.	Median	N
Law & Order Home Country	Index of law and order in the country of origin of the bank from ICRG	5.16	0.60	5	33202
S&P Rating Borrower	S&P rating of the borrower country's government debt; lowest number denotes highest rating; data from Standard and Poor's	7.75	3.99	7	48148
S&P Rating Bank – S&P Rating Borrower	S&P rating of the bank country's government debt minus S&P rating of the borrower country's government debt; data from Standard and Poor's	1.06	4.05	0.00	47991
Capital Account restrictions	Index of capital account restrictions in the host country from IMF's AEREAR database	0.23	0.31	0.08	28235
Foreign Claims Per Capita	Foreign claims per capita in the host country	23020.33	69467.11	12716.54	30018
Distance	Log of physical distance in miles between the capital city of the bank's country and the borrower's country; the distance is zero for domestic loans	5.93	3.44	7.33	45349
Trade/Bank Country GDP	Exports to host country plus imports to home country of bank divided by GDP of home country of bank; data on bilateral exports and imports from IMF's Direction of Trade Statistics	1.77	5.50	0.25	38609

Table 2. Cross-Border Lending and the Flight Home Effect: Main Results

The dependent variable is Loan Share. Column 2 is estimated using a Tobit regression. Column 3 includes deal nationality fixed effects. Column 4 controls for differences in foreign banks' lending policies, when shocks affect the host countries. Column 5 only includes observations from countries in which banks have been the lead bank for a total of at least 10 syndicated loans. Column 6 limits the sample to bank loan portfolio shares starting from the year 2006. Column 7 excludes observations of US and UK banks from the sample. Column 8 includes interactions of deal country and month of the year fixed effects. Column 9 uses data aggregated at the quarterly level. All regressions include a constant and deal nationality and time fixed effects (not reported). Standard errors in parenthesis are corrected for heteroskedasticity and are clustered at the bank parent level. *, **, and *** indicate significant at 10 percent, 5 percent and 1 percent level.

	(1)	(2) Tobit	(3)	(4)	(5) Important markets only	(6) Latest crisis Only	(7) No US and UK banks	(8) Deal country x time fixed effects	(9) Quarterly Data
Foreign Loan	-0.507***	-0.600***	-0.506***	-0.511***	-0.497***	-0.523***	-0.523***	-0.509***	-0.580***
	(0.0218)	(0.0292)	(0.0224)	(0.0224)	(0.0342)	(0.0252)	(0.0271)	(0.0233)	(0.0188)
Shock Bank Country* Foreign Loan	-0.0896***	-0.0952***	-0.0764***	-0.0816***	-0.0549**	-0.0942***	-0.0629**	-0.0909***	-0.0591***
	(0.0210)	(0.0234)	(0.0207)	(0.0214)	(0.0212)	(0.0270)	(0.0307)	(0.0259)	(0.0155)
Shock Borrower Country* Foreign Loan				0.0355***	0.0303*	0.0758***	0.0339***	0.0699***	0.0373***
				(0.0106)	(0.0171)	(0.0162)	(0.0127)	(0.0230)	(0.00841)
Domestic Loans	0.501***	0.580***	0.499***	0.533***	0.549***	0.629***	0.693***		0.580***
	(0.0609)	(0.0715)	(0.0674)	(0.0688)	(0.0890)	(0.0848)	(0.0815)		(0.0883)
Deal Country FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal Country FE* Time FE	No	No	No	No	No	No	No	Yes	No
Observations	50710	50710	50710	50710	18717	21684	34316	50710	35235
R-squared	0.404	--	0.429	0.429	0.566	0.482	0.370	0.508	0.501

Table 3. Other Measures of Shocks and Home Bias

The dependent variable is Loan Share with the exceptions of columns 4 and 6. In column 4, the dependent variable, Bias, is a measure of home bias in the portfolio of bank i respect to country j, defined as in Ahearne, Griever and Warnock (2004), and in column 6, the dependent variable is a measure of home bias using the BIS Consolidated International Banking Statistics. Column 1 uses the contemporaneous stock return of the banking industry in the country of origin of the bank as a proxy for the home country shock and the return on the stock market index in the host country as proxy for the host country shock. Column 2 includes interactions with the bank's proportion of non-deposit liabilities. Column 3 controls for the proportion of bank losses in terms of loan charge-off rates to proxy for bank-specific exposure to the crisis. Column 4 uses Bias as dependent variable, computed as 1 minus the ratio of the loan share and the Share Country variables, with the latter computed as the proportion of loans issues in country j at time t with respect to the total amount of loans issued in the syndicated loan market at time t. Column 5 controls for the distance between the bank and its borrowers. Column 6 uses the fraction of international bank claims on country j in total bank claims from banks in country i computed using BIS data, as dependent variable, and includes interactions of deal country times month of the year fixed effects to control for unobserved changes in the demand for loans across countries. All regressions include a constant and deal nationality and time fixed effects (not reported). Standard errors in parenthesis are corrected for heteroskedasticity and are clustered at the bank parent level. *, **, and *** indicate significant at 10 percent, 5 percent and 1 percent level.

	(1) Stock returns	(2) Non-deposit liabilities	(3) Charge-offs	(4) Bias	(5) Distance	(6) BIS data
Foreign Loan	-0.545***	-0.533***	-0.534***	248.3***	0.128	-0.618***
	(0.0226)	(0.0306)	(0.0279)	(84.30)	(0.0797)	(0.00744)
Banking Return in Bank's Country * Foreign Loan	0.0988***					
	(0.0377)					
Host Country's Mkt Return	0.210**					
	(0.0819)					
Host Country's Mkt Return * Foreign Loan	-0.239***					
	(0.0756)					
Domestic Loans	0.483***	0.00272	0.00574		0.464***	
	(0.0688)	(0.00342)	(0.00358)		(0.0664)	
Shock Bank Country * Foreign Loan				192.2**		
				(95.99)		
Shock Borrower Country * Foreign Loan				-43.46	0.0111	-0.00359**
				(36.50)	(0.0102)	(0.00139)
Shock Bank Country * Foreign Loan * Distance					-0.00726***	0.0624***
					(0.00220)	(0.00679)
Foreign Loan * Distance					-0.0805***	
					(0.0102)	
Shock Bank Country * Foreign Loan * Proportion of non-deposit debt		-0.0201***				

	(1) Stock returns	(2) Non-deposit liabilities	(3) Charge-offs	(4) Bias	(5) Distance	(6) BIS data
		(0.00670)				
Shock Borrower Country* Foreign Loan* Proportion of non-deposit debt		0.0155**				
		(0.00655)				
Bank's proportion of non-deposit liabilities* Foreign Loan		0.0279**				
		(0.0117)				
Bank's proportion of non-deposit liabilities		-0.00453				
		(0.00787)				
Shock Bank Country * Foreign Loan * Bank's charge off			-4.413**			
			(1.858)			
Shock Borrower Country * Foreign Loan * Bank's charge off			0.680			
			(1.132)			
Bank's charge off * Foreign Loan			3.386***			
			(1.009)			
Bank's charge off			0.382			
			(1.114)			
Deal Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Deal Country FE* Time FE	No	No	No	No	No	Yes
Observations	28485	26370	45398	50704	45338	11139
R-squared	0.440	0.498	0.425	0.033	0.475	0.918

Table 4. Sources of the Flight Home Effect: Different Segments of the Syndicated Loan Market

The dependent variable is Loan Share. In column 1 Loan Share is constructed considering loans from parent banks only. In column 2 Loan Share is constructed considering loans from subsidiaries only. In columns 3 and 4 Loan Share is constructed considering loans to non-financial corporate borrowers only. In columns 5 and 6 Loan Share is constructed considering loans to other financial institutions only. In columns 7 and 8 Loan Share is constructed considering loans to governments and state-owned enterprises only. All regressions include a constant and deal nationality and time fixed effects (not reported). Standard errors in parenthesis are corrected for heteroskedasticity and are clustered at the bank parent level. *, **, and *** indicate significant at 10 percent, 5 percent and 1 percent level.

	(1) Loans from parent banks only	(2) Loans from subsidiaries only	(3) Loans to corporate borrowers	(4) Loans to corporate borrowers	(5) Loans to financial institutions	(6) Loans to financial institutions	(7) Loans to the government or state-owned enterprises	(8) Loans to the government or state-owned enterprises
Foreign	-0.526***	0.191***	-0.510***	0.0890	-0.352***	0.278***	-0.372***	0.125
	(0.0218)	(0.0557)	(0.0243)	(0.0773)	(0.0271)	(0.0876)	(0.0366)	(0.0821)
Shock Bank Country * Foreign Loan	-0.0785***	-0.0659**	-0.0600***		-0.0765***		-0.102***	
	(0.0211)	(0.0311)	(0.0191)		(0.0195)		(0.0258)	
Shock Borrower Country * Foreign Loan	0.0372***	-0.0228	0.0374***	0.0170	-0.0421***	-0.0588***	0.0407***	0.0266**
	(0.0102)	(0.0196)	(0.0114)	(0.0105)	(0.0118)	(0.0109)	(0.0127)	(0.0128)
Domestic Loans	0.517***	0.475**	0.174***	0.198***	0.454***	0.478***	0.499***	0.554***
	(0.0750)	(0.193)	(0.0354)	(0.0341)	(0.0349)	(0.0370)	(0.0353)	(0.0397)
Shock Bank Country * Foreign Loan * Distance				-0.00498**		-0.00652***		-0.00979***
				(0.00195)		(0.00209)		(0.00251)
Foreign Loan * Distance				-0.0749***		-0.0785***		-0.0612***
				(0.00991)		(0.0111)		(0.0108)
Deal Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	50430	12191	43324	40256	25531	23350	16491	14642
R-squared	0.434	0.241	0.446	0.484	0.318	0.354	0.335	0.367

Table 5. Loan and Borrower Heterogeneity and the Flight Home Effect

The dependent variable is Loan Share. In column 1, we only consider loans whose purpose is general corporate purposes or working capital to construct the loan specific variables based on data from Loan Analytics. In column 2, we control for the average loan amount offered by each bank to borrowers in each country during the prior year. In column 3, we control for the average contracts terms (loan amount, interest rate, and loan maturity) offered by each bank to borrowers in each country during the prior year. In column 4, we exclude domestic loans from the sample. Column 5 controls for trade flows between the home country of the bank and the home country of the borrower. Column 6 controls for de jure capital account restrictions in the host country using IMF AEREAR data. Column 7 controls for the ratio of foreign bank claims per capita in the host country using BIS data. All regressions include a constant and deal nationality and time fixed effects (not reported). Standard errors in parenthesis are corrected for heteroskedasticity and are clustered at the bank parent level. *, **, and *** indicate significant at 10 percent, 5 percent and 1 percent level.

	(1) Only loans for real investment	(2) Loan amount	(3) Contract terms	(4) Foreign loans only	(5) Trade flows	(6) Capital controls	(7) Foreign bank claims
Foreign Loan	-0.495***	-0.536***	-0.498***			-0.443***	-0.599***
	(0.0296)	(0.0261)	(0.0345)			(0.0281)	(0.0345)
Shock Bank Country * Foreign Loan	-0.0528***	-0.0435**	-0.0503**	-0.0901***		-0.0886***	-0.0793***
	(0.0173)	(0.0192)	(0.0243)	(0.0299)		(0.0236)	(0.0222)
Shock Borrower Country * Foreign Loan	-0.0152	0.00404	0.0449**			0.0456**	0.0392**
	(0.00964)	(0.0163)	(0.0207)			(0.0193)	(0.0153)
Domestic Loans	0.0129*	0.618***	0.655***		0.439***	0.472***	0.481***
	(0.00754)	(0.0694)	(0.0948)		(0.0806)	(0.0691)	(0.0689)
Average Loan Amount (in US$ thousands)		-0.00198	-0.0280**				
		(0.00675)	(0.0113)				
Average Interest Rate (in %)			0.0189***				
			(0.00558)				
Average Maturity (in years)			-0.0000168				
			(0.000975)				
Shock Bank Country					-0.0664**		
					(0.0264)		
Shock Borrower Country					0.00691		
					(0.00811)		
Trade/Bank Country GDP					0.00925***		
					(0.00156)		
Capital Restrictions Index * Foreign Loan						-0.380***	
						(0.0693)	
Shock Bank Country * Foreign Loan * Capital Restrictions Index						0.0173	

	(1) Only loans for real investment	(2) Loan amount	(3) Contract terms	(4) Foreign loans only	(5) Trade flows	(6) Capital controls	(7) Foreign bank claims
						(0.0194)	
Shock Borrower Country * Foreign Loan Index * Capital Restrictions						-0.0459	
						(0.0332)	
Share Foreign Claims * Foreign Loan							0.408***
							(0.153)
Shock Bank Country * Foreign Loan * Share Foreign Claims							-0.007
							(0.005)
Shock Borrower Country * Foreign Loan * Share Foreign Claims							0.010
							(0.007)
Deal Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal Country FE* Time FE	No	No	No	Yes	No	No	No
Observations	27536	24021	6422	39982	38606	28233	30016
R-squared	0.402	0.562	0.622	0.252	0.126	0.420	0.464

Table 6. Syndicate Composition and the Flight Home Effect

In column 1, the dependent variable is the number of loans that bank i issues to country j at time t with respect to the total number of loans that bank i issues at time t. In column 2, the dependent variable is the average share of the loan retained by lead bank i for loans issued in country j at time t. In column 3, the dependent variable is the average number of participants for loans that lead bank i extends in country j at time t. The regression in column 1 controls for the number of domestic loans issued in country j at time t relative to the total number of loans issued in the syndicated loan market at time t. The regression in column 2 controls for the lead bank's share in domestic loans in the country. The regression in column 3 controls for the number of participants in domestic loans in the country. All regressions include a constant and deal nationality and time fixed effects (not reported). Standard errors in parenthesis are corrected for heteroskedasticity and are clustered at the bank parent level. *, **, and *** indicate significant at 10 percent, 5 percent and 1 percent level.

	(1) Loan Share – Number of Loans	(2) Average Lead Bank Share	(3) Number of Participants
Foreign Loan	-0.479***	-0.0709***	1.549***
	(0.0217)	(0.00872)	(0.201)
Shock Bank Country * Foreign Loan	-0.0817***	0.00353	0.00990
	(0.0222)	(0.00889)	(0.256)
Shock Borrower Country * Foreign Loan	0.0313***	0.0152*	-0.160
	(0.0108)	(0.00883)	(0.278)
Number of Domestic Loans	4.761***		
	(0.848)		
Lead Bank Share in Domestic Loans		0.415***	
		(0.0245)	
Number of Participants in Domestic Loans			0.593***
			(0.0245)
Deal Country FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	50720	12365	29791
R-squared	0.455	0.279	0.257

Table 7. Flight to Quality and the Flight Home Effect

The dependent variable is Loan Share. Column 1 estimates differential effects for emerging markets and other markets. Column 2 controls for differential impact of the protection of creditor rights in the host country. Column 3 controls for differential impact of law and order tradition in the host country. Column 4 controls for the difference between the S&P sovereign credit ratings of the bank's and the borrower's home country, respectively. Column 5 controls for the law and order tradition in the home country of the bank. In column 6 Loan Share is constructed considering only loans to rated borrowers. In column 7 Loan Share is constructed considering only loans to unrated borrowers. All regressions include a constant and deal nationality and time fixed effects (not reported). Standard errors in parenthesis are corrected for heteroskedasticity and are clustered at the bank parent level. *, **, and *** indicate significant at 10 percent, 5 percent and 1 percent level.

	(1)	(2)	(3)	(4)	(5)	(6) Rated Loans	(7) Unrated Loans
Foreign Loan	-0.505***	-0.586***	-0.899***	-0.511***	-0.520***	-0.0691***	-0.442***
	(0.0229)	(0.0562)	(0.0737)	(0.0225)	(0.0239)	(0.00900)	(0.0194)
Shock Bank Country * Foreign Loan	-0.0842***	-0.0172	-0.0710**	-0.0763***	-0.0787***	-0.0106*	-0.0649***
	(0.0216)	(0.0246)	(0.0339)	(0.0207)	(0.0220)	(0.00596)	(0.0177)
Emerging Market Loans	0.180***						
	(0.0455)						
Shock Bank Country * Emerging Market Loans	0.0611						
	(0.0775)						
Emerging Market Loans * Foreign Loan	-0.211***						
	(0.0471)						
Shock Bank Country * Emerging Market Loans * Foreign Loan	-0.0395						
	(0.0795)						
Shock Borrower Country * Foreign Loan	0.0363***	-0.0180	-0.0511	0.0451***	0.0349***	0.00650	0.0204**
	(0.0111)	(0.0207)	(0.0579)	(0.0116)	(0.0104)	(0.00419)	(0.0101)
Shock Borrower Country * Emerging Market Loans * Foreign Loan	-0.0540*						
	(0.0285)						
Domestic Loans	0.537***	0.469***	0.430***	0.548***	0.543***		
	(0.0687)	(0.0695)	(0.0681)	(0.0685)	(0.0711)		
Creditor Rights * Foreign Loan		0.0324					
		(0.0285)					
Shock Bank Country * Foreign Loan * Creditor Rights		-0.0317***					
		(0.00779)					
Shock Borrower Country * Foreign Loan * Creditor Rights		0.0333***					
		(0.00913)					
Law & Order * Foreign Loan			0.0742***				
			(0.0146)				

	(1)	(2)	(3)	(4)	(5)	(6) Rated Loans	(7) Unrated Loans
Shock Bank Country * Foreign Loan * Law & Order			-0.00286				
			(0.00628)				
Shock Borrower Country * Foreign Loan * Law & Order			0.0207*				
			(0.0123)				
Shock Bank Country * (S&P Rating Bank – S&P Rating Borrower)				-0.00211			
* Foreign Loan				(0.00136)			
Shock Borrower Country * (S&P Rating Bank – S&P Rating Borrower)				0.00528***			
* Foreign Loan				(0.00192)			
S&P Rating Borrower				0.00152*			
				(0.000860)			
Shock Bank Country * Foreign Loan * High Law & Order Home Country					0.0285		
					(0.0434)		
High Law & Order Home Country * Foreign Loan					0.0567*		
					(0.0340)		
Domestic Rated Loans						0.756***	
						(0.0667)	
Domestic Unrated Loans							0.187***
							(0.016)
Deal Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	50710	29433	30016	47982	50710	48477	48477
R-squared	0.430	0.461	0.461	0.438	0.431	0.128	0.368

Table 8. Transmission Channels of the Flight Home Effect

The dependent variable is Loan Share. All variables are defined in Table 1. Column 1 considers only loans extended to first time borrowers – borrowers that did not receive a loan from the bank before. Column 2 considers only loans extended to borrowers that have received previous loans from the banks. Column 3 controls for the impact of bank support from government interventions during the period 2006-2009. Column 4 controls for the differential effect of large banks as measured by the large bank dummy. Column 5 controls for the diversification of the parent bank using a dummy that takes value 1 for banks for which the measure of asset diversification in Laeven and Levine (2007) is above the median. Columns 6 and 7 control for the tier-1 capital ratio of the parent bank. Column 7 excludes observations from the global financial crisis years 2008 and 2009. Column 8 controls for the proportion of loans that bank i extended in domestic currency to borrowers in country j during the prior 12 months. All regressions include a constant and deal nationality and time fixed effects, whose coefficients are not reported. Standard errors in parenthesis are corrected for heteroskedasticity and are clustered at the bank parent level. *, **, and *** indicate significant at 10 percent, 5 percent and 1 percent level.

	(1) First time loans	(2) Relationship loans	(3) Government intervention	(4) Large banks	(5) Diversification	(6) Tier 1 capital– Whole sample	(7) Tier 1 capital– 1997-2007	(8) Currency composition
Foreign Loan	-0.248***	-0.261***	-0.507***	-0.462***	-0.492***	-0.569***	-0.575***	-0.511***
	(0.0122)	(0.0153)	(0.0302)	(0.0239)	(0.00564)	(0.00773)	(0.00785)	(0.0219)
Shock Bank Country * Foreign Loan	-0.0452***	-0.0385***	-0.0830**	-0.103***	-0.0230***	-0.0735***	-0.143***	-0.0878***
	(0.0146)	(0.00999)	(0.0378)	(0.0242)	(0.00841)	(0.0203)	(0.0247)	(0.0214)
Shock Borrower Country * Foreign Loan	0.0438***	0.00915	0.0793***	0.0370***	0.0348***	0.0355***	-0.0176	0.0371***
	(0.00995)	(0.00825)	(0.0161)	(0.0124)	(0.00729)	(0.00842)	(0.0123)	(0.0107)
Domestic Loans	-0.0744	0.120	0.636***	0.541***	0.487***	0.579***	0.592***	0.531***
	(0.0473)	(0.110)	(0.0848)	(0.0661)	(0.0431)	(0.0464)	(0.0529)	(0.0684)
Domestic First-Time Loans	0.715***							
	(0.120)							
Domestic Relationship Loans		0.509***						
		(0.133)						
Shock Bank Country * Foreign Loan * Government Intervention			0.0214					
			(0.0391)					
Shock Bank Country * Foreign Loan * Large Bank				0.0686***				
				(0.0217)				
Shock Bank Country * Foreign Loan * High Asset Diversification					-0.0302***			
					(0.00947)			
Shock Bank Country * Foreign Loan * Tier 1 Capital						0.285	0. 689***	
						(0. 214)	(0. 261)	
Shock Bank Country * Foreign Loan								0.0911**

	(1) First time loans	(2) Relationship loans	(3) Government intervention	(4) Large banks	(5) Diversification	(6) Tier 1 capital– Whole sample	(7) Tier 1 capital– 1997-2007	(8) Currency composition
* Proportion Loans in Domestic Currency								(0.0429)
Shock Borrower Country* Foreign Loan * Large Bank				-0.00757				
				(0.0161)				
Shock Borrower Country * Foreign Loan								-0.00647
* Proportion Loans in Domestic Currency								(0.0522)
Foreign Loan * Government Intervention			-0.0814**					
			(0.0386)					
Foreign Loan * Large Bank				-0.159***				
				(0.0300)				
Foreign Loan * High Asset Diversification					-0.0542***			
					(0.00421)			
Foreign Loan * Tier 1 Capital						0. 525***	0. 488***	
						(0. 0591)	(0. 0579)	
Foreign Loan * Proportion Loans in the Domestic Currency								-0.00724
								(0.0491)
Deal Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	50710	50710	21684	50710	24906	14283	12018	50710
R-squared	0.215	0.316	0.486	0.451	0.488	0.623	0.651	0.430

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Securitized Banking and the Run on Repo
Gary B. Gorton and Andrew Metrick
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ABSTRACT

The Panic of 2007-2008 was a run on the sale and repurchase market (the "repo" market), which is a very large, short-term market that provides financing for a wide range of securitization activities and financial institutions. Repo transactions are collateralized, frequently with securitized bonds. We refer to the combination of securitization plus repo finance as "securitized banking", and argue that these activities were at the nexus of the crisis. We use a novel data set that includes credit spreads for hundreds of securitized bonds to trace the path of crisis from subprime-housing related assets into markets that had no connection to housing. We find that changes in the "LIB-OIS" spread, a proxy for counterparty risk, was strongly correlated with changes in credit spreads and repo rates for securitized bonds. These changes implied higher uncertainty about bank solvency and lower values for repo collateral. Concerns about the liquidity of markets for the bonds used as collateral led to increases in repo "haircuts": the amount of collateral required for any given transaction. With declining asset values and increasing haircuts, the U.S. banking system was effectively insolvent for the first time since the Great Depression.

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The current financial crisis is a system-wide bank run. What makes this bank run special is that it did not occur in the traditional-banking system, but instead took place in the "securitized-banking" system. A traditional-banking run is driven by the withdrawal of deposits, while a securitized-banking run is driven by the withdrawal of repurchase ("repo") agreements. Hence, we describe the crisis as a "run on repo". The purpose of this paper is to propose a mechanism for this new kind of bank run, and to provide supporting evidence for this mechanism through analysis of a novel data set.

Traditional banking is the business of making and holding loans, with insured demand deposits as the main source of funds. Securitized banking is the business of packaging and reselling loans, with repo agreements as the main source of funds. Securitized-banking activities were central to the operations of firms formerly known as "investment banks" (e.g. Bear Stearns, Lehman Brothers, Morgan Stanley, Merrill Lynch), but they also play a role at commercial banks, as a supplement to traditional-banking activities of firms like Citigroup, J.P. Morgan, and Bank of America.[1]

We argue that the financial crisis that began in August 2007 is a "systemic event," defined in this paper to mean that the banking sector became insolvent. What happened is analogous to the banking panics of the 19th century in which depositors *en masse* went to their banks seeking to withdraw cash in exchange of demand and savings deposits. The banking system could not honor these demands because the cash had been lent out and the loans were illiquid, so instead they suspended convertibility and relied on clearinghouses to issue certificates as makeshift currency.[2] Evidence of the insolvency of the banking system in these earlier episodes is the discount on these certificates. We argue that the current crisis is similar in that contagion led to "withdrawals" in the form of unprecedented high repo haircuts and even the cessation of repo lending on many forms of collateral. Evidence of insolvency in 2008 is the bankruptcy or forced rescue of

[1] We have chosen a new term, "securitized banking", to emphasize the role of the securitization process both as the main intermediation activity and as a crucial source of the collateral used to raise funds in repo transactions. Other banking terms – "wholesale banking", "shadow banking", or "investment banking" – have broader connotations and do not completely encompass our definition of securitized banking. The closest notion to our definition of securitized banking is the model of "unstable banking" proposed by Shleifer and Vishny (2009).

[2] The clearinghouse private money was a claim on the coalition of banks, rather than a liability of any individual bank. By broadening the backing for the claim, the clearinghouse made the claim safer, a kind of insurance. Gorton (1985) and Gorton and Mullineaux (1987) discuss the clearinghouse response to panics. Also, see Gorton and Huang (2006).

several large firms, with other (even larger) firms requiring government support to stay in business.

To perform our analysis, we use a novel data set with information on 392 securitized bonds and related assets, including many classes of asset-backed securities (ABS), collateralized-debt obligations (CDOs), credit-default swaps (CDS), repo rates, and repo haircuts.[3] Using these data, we are able to provide a new perspective on the contagion in this crisis. In our exposition, we use this term "contagion" specifically to mean the spread of the crisis from subprime-housing assets to non-subprime assets that have no direct connection to the housing market.

To provide background for our analysis, we illustrate the differences between traditional banking and securitized banking in Figures 1 and 2. Figure 1 provides the classic picture of the financial intermediation of mortgages by the traditional-banking system. In Step A, depositors transfer money to the bank, in return for a checking or savings account that can be withdrawn at any time. In Step B, the bank loans these funds to a borrower, who promises to repay through a mortgage on the property. The bank then holds this mortgage on its balance sheet, along with other non-mortgage loans made to retail and commercial borrowers.

Traditional-banking runs were ended in United States in the 1930s with the introduction of deposit insurance and discount-window lending by the Federal Reserve. With deposits insured by the federal government, depositors have little incentive to withdraw their funds. Deposit insurance works well for retail investors, but still leaves a challenge for large institutions. When deposit insurance was capped at $100,000, institutions such as sovereign-wealth funds, mutual funds, and cash-rich companies did not have easy access to safe short-term investments. One solution to this problem is the securitized-banking system illustrated in Figure 2, which takes large "deposits" from investors (Step 1), and then intermediates these deposits to mortgage borrowers (Steps 2 and 3) and other debtors.

Step 1 in Figure 2 is an analogue to Step A from Figure 1, but there is one important difference. In the traditional-banking system shown in Figure 1, the deposits are insured

[3] This paper uses many terms and abbreviations that are atypical or new to the academic literature. Beginning in Section I, the first appearance of these terms is given in bold type, and definitions of bolded terms are given in Appendix A.

by the government. To achieve similar protection in Step 1 of Figure 2, the investor receives collateral from the bank. In practice, this deposit-collateral transaction takes the form of a repo agreement: the investor buys some asset (=collateral) from the bank for $X, and the bank agrees to repurchase the same asset some time later (perhaps the next day) for $Y. The percentage (Y-X)/X is the "repo rate", and is analogous to the interest rate on a bank deposit. Typically, the total amount of the deposit will be some amount less than the value of the underlying asset, with the difference called a "haircut". For example, if an asset has a market value of $100 and a bank sells it for $80 with an agreement to repurchase it for $88, then we would say that the repo rate is 10 percent (= 88-80 / 80), and the haircut is 20 percent (100 – 80 / 100). If the bank defaults on the promise to repurchase, then the investor keeps the collateral.

Turning next to the lower right corner of Figure 2, we show how the second part of the intermediation differs from traditional banking. In Figure 1, the bank did the work of underwriting the loan itself. In Figure 2, the bank outsources this function to a direct lender. Such lenders grew to prominence in the most recent housing boom, with a specialization of underwriting loans to be held for only a short time before being sold to banks. Much has been written about potential conflicts in this separation of the loan decision from the source of finance, but that is not our topic here. In principle, there is no reason that this separation must necessarily lead to poor underwriting, and in any event such problems do not imply anything about contagion or systemic events.

Another key component of securitized banking is in the "securitization" itself: the intermediation activities that transfer most of the mortgage loans to outside investors in Step 4. We will discuss this step in detail in Section I of the paper. For our purposes here, the key idea is that the outputs of this securitization are often used as collateral in Step 1, so that securitized banking is a cycle that requires all steps to keep running. In this paper, we will show how this cycle broke down in the crisis.

Figure 3 summarizes the relationships between the main elements of traditional and securitized banking. The left column lists the familiar elements of traditional banking: reserves, deposit insurance, interest rates on deposits, and the holding of loans on balance sheet. Bank solvency is promoted by requiring a fraction of deposits to be held in reserve, and in emergencies these reserves can be replenished by borrowing from the central bank. The analogue in securitized banking is the repo haircut, which forces banks to keep some fraction of their assets in reserve when they borrow money through repo markets. The next row, deposit insurance, is a promise made by the government to pay depositors in the event of default. The analogue in securitized banking is collateral. Next, a bank in need of cash can raise deposit rates to attract it; the analogues for securitized banking are the repo rates. Finally, the cash raised in traditional banking is lent out, with the resulting loans held on the balance sheet. In securitized banking, funds are lent only temporarily, with loans repackaged and resold as securitized bonds. Some of these bonds are also used as collateral to raise more funds, which completes the cycle.

The "run on repo" can be seen in Figure 4, which plots a "haircut index" from 2007 to 2008. The details of this index will be explained below in Section III; for now, just think of the index as an average haircut for collateral used in repo transactions, not including U.S. treasury securities. This index rises from zero in early 2007 to nearly 50 percent at the peak of the crisis in late 2008. During this time period, several classes of assets stopped entirely from being used as collateral, an unprecedented event that is equivalent to a haircut of 100 percent.

To see how the increase in haircuts can drive the banking system to insolvency, take as a benchmark a repo market size of, for example, $10 trillion. With zero haircuts, this is the amount of financing that banks can achieve in the repo markets. When the weighted-average haircut reaches, say, 20 percent, then banks have a shortage of $2 trillion. In the crisis, some of this amount was raised early on by issuing new securities. But, this fell far short of what was needed. Furthermore, selling the underlying collateral drives asset prices down, which then reinforces the cycle: lower prices, less collateral, more concerns about solvency, and ever increasing haircuts.

The remainder of the paper is organized as follows. In Section I, we provide institutional background for our analysis, with a discussion of the growth of securitized banking, using subprime mortgages as the case study. We use this case study to provide more detail for Step 4 in Figure 2, and to explain the mechanics of securitization and the repo market.

In Section II, we introduce and explain the two main state variables used in the paper: the ABX index – which proxies for fundamentals in the subprime mortgage market – and the LIB-OIS, which is the spread between the LIBOR rate (for unsecured interbank borrowing) and the rate on an overnight interest swap, OIS (a proxy for the risk-free rate). The LIB-OIS can be thought of as a proxy for counterparty risk in repo transactions. We then plot these state variables for 2007 and 2008 and review the timeline for the crisis. The ABX data show that the deterioration of the subprime market began in early 2007. As is now well known, this deterioration had a direct impact on banks, which had many of these securitized assets and pre-securitized mortgages on their balance sheets. This real deterioration in bank balance sheets became apparent in the interbank markets in mid-2007, as evidenced by an upward spike in the LIB-OIS in August. This state variable remained in a historically high but narrow range until September 2008, when the events at Fannie Mae, Freddie Mac, Lehman, and AIG led to a rapid deterioration in interbank markets and increase in the LIB-OIS that persisted until the end of 2008.

We posit that the increased risk at banks had several interrelated effects, all of which centered on the securitized assets used as collateral in the repo market. We provide evidence for these effects, using a data set with information on securitized bonds, credit-default swaps, and other assets used in repo transactions. These data are created by large financial institutions and are used for trading and portfolio valuation by a wide range of market participants. Section III provides summary statistics on these data and illustrates how some of these assets co-moved with the ABX and the LIB-OIS.

Section IV gives the main empirical results of the paper. Without a structural model of repo markets, we are only able to talk about co-movement of spreads on various assets, and thus we use the language of "correlation" rather than "causation" in our empirical analysis. Section IV.A explains our methodology and presents results for a few representative asset classes. Section IV.B uses the full set of asset classes to demonstrate that it was the interbank markets (LIB-OIS), and not the subprime housing market (ABX), that was correlated with increases in the spreads on non-subprime securitized assets and related derivatives. These increased spreads are equivalent to a price decrease, which represents a fall in the value of collateral used in repo transactions. Then, as lenders began to fear for the stability of the banks and the possibility that they might need to seize and sell collateral, the borrowers were forced to raise repo rates and haircuts.

Both of these increases occurred in the crisis. In Section IV.C, we find that these increases were correlated with changes in the LIB-OIS (for repo rates) and changes in the volatility of the underlying collateral (for repo haircuts). It is the rise in haircuts that constitutes the run on repo.

Section V reviews our arguments and concludes the paper. Appendix A defines some of the paper's terminology that may be unfamiliar for some readers, and also includes descriptions for each of the asset classes of securitized bonds that are used in our empirical analysis. Appendix B gives more detail on the data construction.

I. Institutional Background

This section discusses the main institutional features that intersected in the crisis: the subprime mortgage market (Section I.A), securitization (Section I.B), and repo finance (Section I.C).

A. The Subprime Mortgage Market

Home ownership for all Americans has been a long-standing national goal. This goal was behind the origins of modern housing finance during the Great Depression with the New Deal's National Housing Act of 1934 (see, e.g., Fishback, Horrace and Kantor (2001)). For example, as President Bush put it in 2004: "Not enough minorities own their own homes. … One thing I've done is I've called on private sector mortgage banks and banks to be more aggressive about lending to first-time home buyers." [4] The private sector responded.

The subprime mortgage market is a financial innovation, aimed at providing housing finance to (disproportionately poor and minority) people with some combination of spotty credit histories, a lack of income documentation, or no money for a down payment. Historically, this group was perceived by banks as too risky to qualify for the usual mortgage products, for example, a 30-year fixed rate mortgage. As explained by Gorton (2008), the innovation was to structure the mortgage to effectively make the maturity two or three years. This was accomplished with a fixed initial-period interest rate, but then at the "reset date" having the rate rise significantly, essentially requiring the

[4] See http://www.whitehouse.gov/news/releases/2004/03/20040326-15.html .

borrower to refinance the mortgage. With rising home prices, borrowers would build equity in their homes and would be able to refinance.

The innovation was a success, if measured in terms of originations. In the years 2001-2006, a total of about $2.5 trillion of subprime mortgages were originated.[5] Almost half of this total came in 2005 and 2006, a large portion of which was likely refinancings of previous mortgages.

B. Securitization

An important part of the subprime mortgage innovation was how the mortgages were financed. In 2005 and 2006, about 80 percent of the subprime mortgages were financed via securitization, that is, the mortgages were sold in **residential mortgage-backed securities (RMBS)**, which involves pooling thousands of mortgages together, selling the pool to a **special purpose vehicle (SPV)** which finances their purchase by issuing investment-grade securities (i.e., bonds with ratings in the categories of AAA, AA, A, BBB) with different seniority (called "tranches") in the capital markets. Securitization does not involve public issuance of equity in the SPV. SPVs are bankruptcy remote in the sense that the originator of the underlying loans cannot claw back those assets if the originator goes bankrupt. Also, the SPV is designed so that it cannot go bankrupt.[6]

RMBS are the largest component of the broader market for **asset-backed securities (ABS)**, which includes similar structures for student loans, credit-card receivables, equipment loans, and many others. Figure 5 shows the annual issuance of debt in the important fixed income markets in the U.S. The figure shows that: (1) the mortgage-related market is by far the largest fixed-income market in the U.S., by issuance; but further, (2), that restricting attention to non-mortgage instruments, the asset-backed securitization market is very large, exceeding the issuance of all corporate debt in the U.S. in 2004, 2005, and 2006. Overall, the figure shows that securitization is a very large, significant, part of the capital markets.

Securitization spawned a large number of new financial instruments and new usages for old instruments. Among these are asset-backed securities **credit default swaps**

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[5] See Inside Mortgage Finance, The 2007 Mortgage Market Statistical Annual, Key Data (2006), Joint Economic Committee (October 2007).
[6] On the process of securitization generally, see Gorton and Souleles (2006).

(CDS), **collateralized debt obligations** (CDOs), and **collateralized loan obligations** (CLOs).[7] Credit default swaps are derivative contracts under which one party insures another party against a loss due to default with reference to a specific corporate entity, securitization bond, or index. For our purposes, the CDS spread, which is the fixed coupon paid by the party providing the protection, is an indication of the risk premium with regard to the specified corporate entity. CDOs are securitizations of corporate bonds or asset-backed or mortgage-backed securities. CLOs are securitizations of loans to corporations. CDOs are relevant here for two reasons. First, the underlying CDO portfolios contained tranches of subprime securitizations, making their value sensitive to subprime risk. And second, like asset-backed securities generally, they too depend on the repo market.

Figure 6 shows how the pieces of the securitization process fit together. This figure is an expansion of Step 4 from the securitized-banking diagram shown in Figure 2, and also includes Step 1 from Figure 2, while omitting Steps 2 and 3. The starting point is a bank with a set of loans in its "inventory". The bank does not have the resources to keep all of these loans on its balance sheet – in securitized-banking the profit comes from the intermediation, not from holding the loans. In Step 4, these loans are transferred to the SPV and placed in one big pool. This pool is the assets of the SPV, which builds a capital structure on those assets using different layers, called **tranches**. The idea here is that the first losses on the pool will be allocated to the equity layer at the bottom, with additional losses moving up the capital structure, by seniority, until they reach the AAA tranche at the top. These layers and rating are represented by the asset-backed securities (ABS) issued by the SPV. Since the assets backing these securities are mortgages, the ABS goes by the specialized name of residential-mortgage-backed securities (RMBS) in this case.

These ABS may be sold directly to investors (Step 5), or may instead be securitized in a CDO (Step 6). A CDO will have a tranche structure similar to an ABS. The tranches of the CDO may be sold directly to investors (Step 7), or resecuritized into further levels of CDOs (not shown in figure). In some cases, the ABS or CDO tranches may return to the

[7] Other innovations, like structured investment vehicles, synthetic CDOs, and so on, are discussed in Gorton (2008). Gorton and Pennacchi (1995) discuss loan sales by banks.

balance sheets of the banks, where they may be used as collateral in the repo transaction of Step 1.

With each level of securitization, the SPV will often combine many lower-rated (BBB, BBB-) tranches into a new vehicle that has mostly AAA and AA rated tranches, a process that relies on well-behaved default models. This slicing and recombining is driven by a strong demand for highly rated securities for use as investments and collateral: essentially, there is not enough AAA debt in the world to satisfy demand, so the banking system has set out to manufacture the supply. As emphasized by Gorton (2008), it can be very difficult to pierce the veil of a CDO and learn exactly what lies behind each tranche. This opacity was a fundamental part of pre-crisis securitization, and was not limited to subprime-based assets.[8]

C. The Repo Market

A repurchase agreement (or "repo") is a financial contract used by market participants as a financing method to meet short and long-term liquidity needs.[9] A repurchase agreement is a two-part transaction. The first part is the transfer of specified securities by one party, the "bank" or "borrower," to another party, the "depositor" or "lender," in exchange for cash: the depositor holds the bond, and the bank holds the cash. The second part of the transaction consists of a contemporaneous agreement by the bank to repurchase the securities at the original price, plus an agreed upon additional amount on a specified future date. It is important to note that repurchase agreements, like derivatives, do not end up in bankruptcy court if one party defaults. The non-defaulting party has the option to simply walk away from the transaction, keeping either the cash or the bonds.[10]

[8] As explained by Gorton and Pennacchi (1990) and Dang, Gorton, and Holmström (2009), such opacity makes these instruments liquid by preventing adverse selection.

[9] For background on the repo market, see Corrigan and de Terá (2007) and Bank for International Settlements (1999).

[10] Sale and repurchase agreements, like derivatives, have a special status under the U.S. Bankruptcy Code. Repurchase agreements are exempted from the automatic stay and allows a party to a repurchase agreement to unilaterally enforce the termination provisions of the agreement as a result of a bankruptcy filing by the other party. Without this protection, a party to a repo contract would be a debtor in the bankruptcy proceedings. The safe harbor provision for repo transactions was recently upheld in court in a case involving American Home Mortgage Investment Corp. suing Lehman Brothers. See Schweitzer, Grosshandler, and Gao (2008).

While there are no official statistics on the overall size of the repo market, it may be about $12 trillion (though that may involve double counting for both lender and borrower), compared to the total assets in the U.S. banking system of $10 trillion.[11] According to Hördahl and King (2008), "the (former) top US investment banks funded roughly half of their assets using repo markets, with additional exposure due to off-balance sheet financing of their customers" (p. 39). One way to get a sense of the growth in the securitized-banking system is to compare the total assets in the traditional regulated banking system to the total assets in the dealer (investment) banks, since the latter rely more heavily on repo finance than the former. For this purpose, Federal Flow of Funds data are available, and this is shown in Figure 7, below. The figure shows that the ratio of broker-dealer total assets to banks' total assets has grown from about six percent in 1990 to a peak of 30 percent in 2007. These data do not capture the increasing share of repo in total financing for each kind of bank, which cannot be carefully measured with aggregate data: to the extent that repo has grown more important at both types of banks, Figure 7 would understate the increased role of repo finance over time.

II. State Variables: The ABX Indices and the LIB-OIS Spread

This section introduces the key "state variables" of the paper. Section II.A discusses the ABX indices, which are proxies for fundamentals of the subprime market. Section II.B discusses the LIB-OIS spread, which is a proxy for fears about bank solvency. In Section II.C, we plot these two state variables against the timeline of the crisis.

A. Subprime Fundamentals and the ABX Indices

With respect to the housing market, the fundamentals essentially are housing prices and changes in housing prices. Subprime mortgages are very sensitive to housing prices, as shown by Gorton (2008). How was information about the fundamentals in the

[11] Hördahl and King (2008) report that repo markets have doubled in size since 2002, "with gross amounts outstanding at year-end 2007 of roughly $10 trillion in each of the U.S. and euro markets, and another $1 trillion in the UK repo market" (p. 37). They report that the U.S. repo market exceeded $10 trillion in mid-2008, including double counting. See Hördahl and King (2008), p. 39. According to Fed data, primary dealers reported financing $4.5 trillion in fixed income securities with repo as of March 4, 2008.

subprime mortgage market revealed to market participants? There are no secondary markets for the securities related to subprime (mortgage-backed securities, collateralized debt obligations). But, in the beginning of 2006, the growth in the subprime securitization market led to the creation of several subprime-related indices. Specifically, dealer banks launched the ABX.HE (ABX) index in January 2006. The ABX Index is a credit derivative that references 20 equally-weighted subprime RMBS tranches. There are also sub-indices linked to a basket of subprime bonds with specific ratings: AAA, AA, A, BBB and BBB-. Each sub-index references the 20 subprime RMBS bonds with the rating level of the subindex. Every six months the indices are reconstituted based on a pre-identified set of rules, and a new vintage of the index and sub-indices are issued.[12]

Gorton (2009) argues that the introduction of the ABX indices is important because it opened a (relatively) liquid, publicly observable market that priced subprime risk. The other subprime-related instruments, RMBSs and CDOs, did not trade in publicly observable markets. In fact, securitized products generally have no secondary trading that is publicly visible. Thus, for our purposes the ABX indices are important because of the information revelation about the value of subprime mortgages, which in turn depends on house prices. Keep in mind that house price indices, like the S&P Case-Shiller Indices, are calculated with a two-month lag.[13] Furthermore, house price indices are not directly relevant because of the complicated structure of subprime securitizations.

In this paper, we will focus on the BBB ABX tranche of the first vintage of the ABX in 2006, which is representative of the riskier levels of subprime securitization. We refer to this tranche of the 2006-1 issue simply as "ABX". In the next section, we show how the ABX evolved during the crisis, and compare this evolution with deterioration in the interbank markets.

B. The Interbank Market and the LIB-OIS Spread

Our proxy for the state of the interbank market and, in particular, the repo market, is the spread between 3-month LIBOR and the overnight index swap (OIS) rate, which

[12] The index is overseen by Markit Partners. The dealers provide Markit Partners with daily and monthly marks. See http://www.markit.com/information/products/abx.html.

[13] See http://www2.standardandpoors.com/portal/site/sp/en/us/page.topic/indices_csmahp/0,0,0,0,0,0,0,0,0,1,1,0,0,0,0,0.html .

we call the LIB-OIS spread. LIBOR is the rate paid on *unsecured* interbank loans, cash loans where the borrower receives an agreed amount of money either at call or for a given period of time, at an agreed interest rate. These loans are not tradable. Basically, a cash-rich bank "deposits" money with a cash-poor bank for a period of time. The rate on such a deposit is LIBOR, which is the interest rate at which banks are willing to lend cash to other financial institutions "in size." The British Bankers' Association's (BBA) London interbank offer rate (LIBOR) fixings are calculated by taking the average of a survey financial institutions operating in the London interbank market.[14] The BBA publishes daily fixings for LIBOR deposits of maturities up to a year.

From the 3-month LIBOR rate we will subtract a measure of interest rate expectations over the same term. This rate is the **overnight index swap (OIS)** rate. The overnight index swap is a fixed-to-floating interest rate swap that ties the floating leg of the contract to a daily overnight reference rate (here, the fed-funds rate).[15] The floating rate of the swap is equal to the geometric average of the overnight index over every day of the payment period. When an OIS matures, the counterparties exchange the difference between the fixed rate and the average effective fed-funds rate over the time period covered by the swap, settling the trade on a net basis. The fixed quote on an OIS should represent the expected average of the overnight target rate over the term of the agreement. As with swaps generally, there is no exchange of principal and only the net difference in interest rates is paid at maturity, so OIS contracts have little credit risk exposure.

If there is no credit risk and no transactions costs, then the interest rate on an interbank loan should equal the overnight index swap (the expected fed funds cost of the loan). To see this consider an example: Bank 1 loans Bank 2 $10 million for three months. Bank 1 funds the loan by borrowing $10 million each day in the overnight fed-funds market. Further, Bank 1 hedges the interest-rate risk by entering into an overnight index swap under which Bank 1 agrees to pay a counterparty the difference between the contracted fixed rate and the overnight fed-funds rate over the next three months. In the past arbitrage has kept this difference below 10 bps.

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[14] The BBA eliminates the highest and lowest quartiles of the distribution and average the remaining quotes. See Gyntelberg and Wooldridge (2008).
[15] There are equivalent swaps in other currencies, which reference other rates.

If the spread between LIBOR and the OIS widens, there is an apparent arbitrage opportunity. But, at some times, banks are not taking advantage of it. Why? The answer is that there is counterparty risk: that is, Bank 1 worries that Bank 2 will default and so there is a premium between the expected interest rates over the period, the OIS rate, and the rate on the loan, LIBOR. We refer to the spread between the 3-month LIBOR and the 3-month OIS as "LIB-OIS," and think of this spread as a state variable for counterparty risk in the banking system.

C. A Timeline for the Crisis

In Figure 8, we show the ABX and LIB-OIS spreads. For the ABX, we use the 2006-1 BBB tranche in all cases. The time period is from January 1, 2007 through December 25, 2008. During the full period, the ABX makes a steady rise, whereas the LIB-OIS shows two jumps, in August 2007 and September 2008. These months are not particularly special for the ABX. Furthermore, the LIB-OIS recovers some ground at the end of 2008, while the ABX spread continues to grow. It is difficult to explain why the LIB-OIS spikes occur exactly at these times, and we are not attempting an explanation here. Instead, these figures are intended only to illustrate that the spikes are not concurrent with major changes in the ABX.

The first six months of 2007 were ordinary for the vast majority of fixed income assets. It is only when we look at subprime-specific markets that we begin to see the seeds of the crisis. The ABX begins the year at 153 basis points (bps), which is close to its historical average since the series began in January 2006, after a first year with almost no volatility. The first signs of trouble appear at the end of January, and by March 1 the spread was 552bps. The next sustained rise came in June, reaching 669bps by the end of that month. In contrast, the LIB-OIS hardly moved during the period, steady at around 8bps.

Of particular interest is the summer of 2007, where the LIB-OIS first signals danger in the interbank market. From its steady starting value of 8 bps, LIB-OIS grows to 13 bps on July 26, before exploding past its historical record to 40 bps on August 9, and to new milestones in the weeks ahead before peaking at 96 bps on September 10. This period also marked the initial shock for a wide swath of the securitization markets, particularly in high-grade tranches commonly used as collateral in the repo market. The ABX is also rising during this period, but its most significant move begins earlier, and visually appears to lead the LIB-OIS. From its starting value of 669 bps at the end of June, the spread rises to 1738 bps by the end of July, before any significant move in the LIB-OIS.

The ABX spread continued its steady rise in the first half of 2008, going from 3812 bps to 6721 bps over the six-month period from January 1 to June 30. Once again, the LIB-OIS is behaving differently from the ABX, with trading in a band between 30 and 90 bps. The reduction in the LIB-OIS in January is followed by increases through February and March, coincident – or perhaps causal – of the trouble at Bear Stearns, which reached its climax with its announced sale to JP Morgan on March 16.

In the second half of 2008, the full force of the panic hit asset markets, financial institutions, and the real economy. The ABX spread continued its steady rise, with prices of pennies on the dollar and spreads near 9000 bps by the end of the period. The LIB-OIS, after a period of stability in the summer, began to rise in early September, and then passed the 100 bps threshold for the first time on the September 15 bankruptcy filing of Lehman Brothers. The subsequent weeks heralded near collapse of the interbank market, with the LIB-OIS peaking at 364 bps on October 10, before falling back to 128 bps by the end of 2008.

With this background, we turn next to the broad set of assets included in our data set.

III. Data

Our data comes from dealer banks. The dealer banks observe market prices and convert these prices into spreads. The conversion of prices into spreads involves models of default timing and recovery amounts, and we are not privy to these models. However, one indication of the quality of the data is that it was the source for marking-to-market the books of some major institutions. The data set comprises 392 series of spreads on structured products, credit derivative indices, and a smaller set of single-company credit derivatives. In each case, the banks capture the "on-the-run" bond or tranche, which would be the spreads of interest to market participants. Fixed-rate bond spreads are spreads to Treasuries and floating-rate spreads are to LIBOR. Appendix B contains a brief discussion of spread calculation.

Some examples of the asset classes covered include spreads on credit-card securitization tranches, auto-loan securitization tranches, and all other major securitization classes. For each asset class, e.g., securitized credit-card receivables, there are spreads for each maturity, each rating category, and often for both fixed- and floating-rate bonds. For example, for fixed-rate credit-card receivables there are spreads for AAA bonds for maturities from two years to ten years. Also included are spreads on CDO and CLO tranches. Some series date back as far as January 2001, and others begin as late as 2006. Spreads are based on transactions prices, and if there are no such prices, then the series ends.

Table I provides summary statistics on various categories of asset classes. Panel A shows the spreads in basis points. Our state variable, LIB-OIS spreads, are shown first, followed by representative asset classes that were exposed to subprime: **home-equity loans (HEL)**, **mezzanine-collateralized-debt obligations (Mezzanine CDO)**, **home-equity lines-of-credit (HELOC)**; also shown are the CDS spreads for Countrywide and Washington Mutual ("Wamu"), two of the largest subprime **mortgage originators**; finally, three of the **monoline insurers'** CDS spreads are shown. These firms were alleged to have been heavily exposed to subprime risks via credit guarantees made on subprime-related bonds.

Throughout Table I there are five periods shown: the whole period (January 2007-January 2009); the first half of 2007, the second half of 2007, all of 2007, and "all of 2008" (which also includes January 2009). In general, the first half of 2007 looks "normal" in the sense that it is prior to the panic. Looking at LIB-OIS, for example, the average is about 8 basis points for the first half of 2007, consistent with no arbitrage and no counterparty risk. Also, note that AAA HELOC bonds traded at just over 15 basis points in the first half of 2007. The mortgage originators and monolines were also trading in normal spread ranges.

Looking at Panel A, it is clear that the subprime-related structured products and companies get hit in the second half of 2007. HEL, Mezzanine CDOs and HELOCs reach their peaks in the second half of 2007. Note that in the cases of HEL BBB and

HELOC AAA there are no data in 2008; these markets simply disappear.[16] This is also true of Countrywide, perhaps the largest originator of subprime mortgages. But, for WAMU and the monoline insurers the peak is in 2008.

The standard deviations are also worth noting. For the subprime-related structured asset classes, the peak of their spreads occurs in the second half of 2007, but the standard deviations are mostly highest in 2008. Thinking of standard deviations as a rough guide to uncertainty, this temporal sequence of rising uncertainty will be important later when we look at the repo market in detail.

Panel B shows asset classes that are non-subprime-related structured products based on U.S. portfolios: automobile loans, credit-card receivables, student loans, commercial mortgage-backed securities, **high-grade structured-finance CDOs (HG SF CDO)**, and **mezzanine structured-finance CDOs (Mezzanine SF CDO)**. In each case, we show the AAA tranches. In the first half of 2007, the normal state of affairs is that AAA asset-backed securities traded below LIBOR, true of auto loans, credit card receivables, and student loans. For the six categories shown, there are increases in the spreads in the second half of 2007, but the large increases are in 2008.

Figure 9 is an illustration of the time-series patterns for a few of these non-subprime asset classes: automobile loans, credit-card receivables, and student loans. In each case, the spreads appear to move closely with the LIB-OIS. These co-movements represent an important aspect of the crisis: the apparent relationship of the interbank market (LIB-OIS) with spreads on securities far removed from subprime housing. In Section IV, we will perform formal tests of these relationships.

The crisis was global. Panel C shows non-U.S. non-subprime-related asset classes, including mortgage-backed securities with portfolios of Australian, U.K., and Dutch mortgages. Also shown are U.K. credit-card receivables, European consumer loans, and European automobile loans. These categories are all trading normally in the first half of 2007, and show increases in their spreads during the second half of 2007. But, the spreads significantly widen in 2008, as do the standard deviations of their spreads.

[16] The dealer banks only use on-the-run prices to calculate spreads. If there are no on-the-run prices, no spreads are calculated.

Panel D summarizes the data on the interbank repo market.[17] Shown are different categories of collateral, in each row. The categories themselves show how far the repo market has evolved from simply being a market related to U.S. Treasuries. For each category the annualized repo rate spread to the overnight index swap rate is shown. These spreads are for overnight repo.[18] Also shown is the average haircut on the collateral during the time period. For example, looking at the first category, **BBB+/A Corporates**, the average repo rate spread to OIS in the first half of 2007 was 2 bps, and the haircut was zero. Repo spreads for AA-AAA corporate bond collateral were negative for the first half of 2007. Overall, the patterns in repo are similar to those for the non-subprime-related asset classes, that is, the spreads rise in the second half of 2007, but become dramatically higher in 2008. The haircuts also become dramatically higher in 2008. The market disappeared for **unpriced CLO/CDO**, **unpriced ABS/MBS/all subprime**, and for **AA-AAA CDOs**.

The last row in Panel E gives summary data for the **Repo-Rate Index** and the **Repo-Haircut Index** – the latter index is plotted in Figure 4 and discussed in the Introduction of this paper. During the time that all asset classes have active repo markets in 2007 and early 2008, the Repo-Rate Index is identical to the equal-weighted average for all the asset classes. As haircuts rise to 100% for any given asset class (= no trade) on date *t*, we drop that class from the index and compute the index change for period t using only the classes that traded in both period *t-1* and period *t*. The Repo-Haircut Index is always equal to the average haircut on all nine of the asset classes, with 100 percent rates included in this average.

IV. Empirical Tests

A. Methodology and Basic Tests

We want to test whether the spreads on U.S. non-subprime-related asset classes (AAA tranches) move with our state variables for the subprime market (ABX) and for interbank counterparty risk (LIB-OIS). For each asset, we want to estimate

[17] Repo rates and haircuts could be different for non-dealer bank counterparties, such as hedge funds.
[18] Though not analyzed in this paper, the full term structure of repo spreads out to one year, tells a similar story.

$$S_{i,t} = a_0 + a_1 t + b_1 \mathbf{ABX}_t + b_2 \mathbf{LIB-OIS}_t + b_3 \mathbf{X}_t + e_{i,t}\,, \tag{1}$$

where t is time a weekly time index, $S_{i,t}$ is the spread on asset i at time t, a_0 is a constant, a_1 is a time trend, $\mathbf{ABX_t}$ is a vector of the last four observations of the ABX spread including the current period, $\mathbf{LIB\text{-}OIS_t}$ is a vector of the last four observations of the LIB-OIS spread including the current period, and $\mathbf{X_t}$ is a vector of control variables. Since the $S_{i,t}$ spreads are more similar to unit-root prices than to i.i.d returns, and since these levels vary significantly over our time period, we take first differences of (1) and normalize all changes by their level in the previous period:

$$\Delta S_{i,t} = a_1 + b_1 \Delta\mathbf{ABX}_t + b_2 \Delta\mathbf{LIB-OIS}_t + b_3 \Delta\mathbf{X}_t + e_{i,t} \tag{2}$$

where the Δ prefix indicates the percentage change of the variable or vector. (Throughout our analysis, all references to "changes" will be "percentage changes".) While there is a small literature on corporate-bond spreads (see Collin-Dufresne, Goldstein, and Martin (2001), and the citations therein), there are no studies of spreads on securitized products. We follow Collin-Dufresne, Goldstein, and Martin (2001) in their choice of control variables:[19]

- The 10-year constant maturity treasury rate (10YTreasury),
- The square of 10YTreasury, (10YTreasured Squared)
- The weekly return of the SP500 Index (SP500_ret).
- The VIX index (VIX), which is a weighted average of eight implied volatilities of near-the-money options on the S&P 100 index.
- The slope of the yield curve, (YCSlope), defined as the difference between the 10-year and 2-year Treasury bond interest rates.
- The overnight swap spread (OIS).

[19] Since most of our series are not related to specific companies, we omit the company-specific control variables used by Collin-Dufresne, Goldstein, and Martin (2001).

Panel E of Table I gives summary data on these control variables. Notably, the 10-year Treasury rate and the OIS rate both decline significantly in 2008, reflecting the Fed's actions. The return on the S&P is negative in 2008. And, notably, the VIX index in 2008 is about double its level in 2007. In each case, the control variables are first-differenced for estimation of Equation (2).

Some preliminary regression results are given in Table II. Panel A shows the results for the six asset classes of U.S. non-subprime-related assets (AAA tranches) shown in Table I, Panel B. At the bottom of the table are F-tests corresponding to the hypothesis that the coefficients on the ABX variables are jointly zero and that the coefficients on the LIB-OIS variables are jointly zero. For the four securitization categories – credit cards, auto loans, student loans, and commercial mortgage-backed securities – the LIB-OIS variables are jointly significant. F-tests also show that the ABX coefficients are not jointly significant in any of the regressions.. For the two categories of CDO, high grade (HG) and mezzanine, neither the LIB-OIS nor the ABX are significant.

Panel B of Table II addresses the global aspects of the crisis. Panel B covers non-U.S. non-subprime related asset classes, the same ones displayed in Panel C of Table I. All of these asset classes are significantly affected by LIB-OIS, but not by the ABX.

B. Credit Spreads for All Categories and Tranches

Table II focuses on a subset of the available asset categories, a subset that we think is of particular interest, but nevertheless a subset. Table III summarizes the F-tests for the joint significance of the changes in LIB-OIS, for the full set of asset categories, broken down into the following categories: subprime-related, U.S.; non-subprime-related; non-U.S. non-subprime-related; financial firms (CDS spreads); and industrial firms (CDS spreads). The table has three panels, corresponding to the whole period from January 4, 2007 to January 29, 2009, and sub-periods. We also performed similar F-tests for the ABX and lags on all asset categories. These results are not tabulated, because there is nothing of interest to show: overall, changes in the ABX are no better than noise at predicting changes in spreads.

Some highlights from Table III are as follows. Subprime-related asset categories and the broad-array of financial firms are not typically correlated to the LIB-OIS. But, for the overall period, Panel A, 66 percent of the U.S. non-subprime asset classes are significantly positively correlated at the 10 percent confidence level. Similarly, 76 percent of the non-U.S. non-subprime categories are positively correlated at the 10 percent level or lower. Note that most of this occurs in 2007 for the non-U.S. structured products, but for the U.S. non-subprime structured products it is split across 2007 and 2008. Also, note that for 2008, Panel C shows that 75 percent of the industrials are significantly, positively correlated to changes in LIB-OIS, indicating the real affects hitting the economy. In 2007, Panel B, there are no such real effects.

Table IV presents the F-test results divided by rating category. Assets in all rating categories were eligible for repo, but AAA collateral was likely to be the most widely used. The table is suggestive in this regard, but not definitive. Looking at the whole period, Panel A, 62% of the AAA products were positively and significantly correlated with changes in LIB-OIS. This is about equally divided between the two sub-periods. For AA, A and BBB rated bonds, the percentages that are significantly positive for the whole period are 28, 55 and 53 percent, respectively. For A and BBB this is about equally divided between the two subperiods.

C. Repo Spreads and Haircuts

In a world with known values for collateral and no transactions costs for selling collateral, repo rates should be equal to the risk-free rate, and spreads would be zero: a lender/depositor would have no fear of default, since the collateral could be freely seized and sold. In reality, collateral pricing can be uncertain, and illiquidity and volatility in the secondary markets for this collateral can induce large transactions costs following a default. In this case, measures of bank-counterparty risk (LIB-OIS) may be relevant to lenders, and in the case of default they would be sensitive to uncertainty about collateral values. Lenders could then demand higher rates and/or higher haircuts. Higher rates would occur because the loans are no longer risk free; higher haircuts could occur to adjust for the uncertain value of the collateral, since each dollar of collateral may worth much less by the time it can be sold.

To test for the quantitative importance of these relationships, we first estimate a version of Equation (2) for repo spreads:

$$\Delta R_{j,t} = a_1 + b_1 \Delta \mathbf{ABX}_t + b_2 \Delta \mathbf{LIB - OIS}_t + b_3 \Delta \mathbf{X}_t + b_4 \Delta \mathbf{VOL}_{j,t} + e_{i,t} \tag{3}$$

where $R_{j,t}$ is the average spread of repo rates to the OIS for some class j of collateral (as in Table I, Panel D), $\mathbf{VOL_{j,t}}$ is a vector of the last four "expected volatilities" (defined below) for that class of collateral, and all other variables are defined as in Equation (2).

$VOL_{j,t}$ is a forward-looking measure, defined here as the average absolute (weekly) change in spreads over the *next* four weeks[20]:

$$VOL_{j,t} = \sum_{s=1}^{4} \left(\frac{|\Delta S_{j,t+s}|}{4} \right), \tag{4}$$

where $S_{j,t}$ is the average spread to OIS for all assets in class j:

$$S_{j,t} = \overline{S}_{i,t}, i \in j. \tag{5}$$

$\Delta VOL_{j,t}$ is defined as the difference between expected volatility today and realized volatility over the previous four weeks (not including the current week):

$$\Delta VOL_{j,t} = VOL_{j,t} - VOL_{j,t-5}. \tag{6}$$

Note that volatility uses absolute differences, and not percentage differences, because percentage differences are harder to interpret across multiple weeks. Also, since we use future information for our expected-volatility proxy, the resulting estimates could not be part of an implementable investment strategy. This restriction does not matter for our analysis, since we are not seeking to build investment portfolios from these results. In any case, we don't really have a choice here, since there is no way to extract volatility expectations from historical spread data alone.

[20] All results are qualitatively similar if we use the eight weeks or twelve weeks instead of four weeks.

We estimate (3) for all five classes of collateral that have data available to construct the VOL measure.[21] The regression results for these five classes are shown in Table V. The final rows show the results of the F-tests for the joint significance of LIB-OIS (Test 1), the ABX (Test 2) and VOL changes (Test 3), respectively. These tests show that the changes in repo spreads are significantly related to the change in LIB-OIS for all five categories, with almost all of the effect coming in the contemporaneous period. Changes in repo spreads are not significantly related to changes in the ABX or VOL or to any of the other control variables. Thus, just as we found for credit spreads in our earlier analysis, the state variable for bank-counterparty risk is the only significant correlate with repo spreads.

It seems natural that banks would have to raise repo spreads to attract funds. But, higher rates do not by themselves cause a systemic event. For a "run on repo", we need to see that even higher rates are insufficient to keep repo lenders in the market. Our simple illustrations of repo haircuts in Section III showed that this did occur. We next explore the factors related to these increases using the same regression framework as we did for repo spreads:

$$\Delta H_{j,t} = a_1 + b_1 \Delta \mathbf{ABX}_t + b_2 \Delta \mathbf{LIB-OIS}_t + b_3 \Delta \mathbf{X}_t + b_4 \Delta \mathbf{VOL}_{j,t} + e_{i,t} \ , \qquad (7)$$

where $H_{j,t}$ is the average haircut for all assets in class j, and all other variables are defined as in (3). Since haircuts are already defined as a percentage of the total value of the underlying collateral, the change in haircuts on the left-hand-side of equation (7) is already given in percentages. Table VI summarizes the results. As we have found in earlier tests, the ABX and the control variables are not significant. In contrast to previous regressions, the change in the LIB-OIS is also not significant. The only variable with any explanatory power is the proxy for expected volatility, which is significant for three of the five classes of collateral.

The key finding here is that both repo spreads and repo haircuts rose during the crisis, with these increases correlated either to concerns about counterparty risk (for

[21] For the other four classes of collateral shown in Panel D of Table I, we do not have data for the spreads of the underlying assets.

spreads), or to uncertainty about collateral values (for haircuts). While these results are somewhat different for spreads and haircuts, we suspect that this system is jointly determined, and that a disruption in the interbank market and increases in uncertainty about collateral are both necessary conditions for a run on repo. In an environment with no counterparty risk, there is no reason to expect haircuts to be affected by uncertainty about collateral; similarly, high counterparty risk by itself would be unlikely to affect repo spreads if all collateral had fixed values and liquid markets. It seems unlikely that nature will give us an example with rising VOL but no change in LIB-OIS. Instead, all of these things happened at the same time, and it is not possible to disentangle the exact causes.

V. Conclusion

How did problems in the subprime mortgages cause a systemic event? Our answer is that there was a run in the repo market. The location and size of subprime risks held by counterparties in the repo market were not known and led to fear that liquidity would dry up for collateral, in particular non-subprime related collateral. Uncertainty led to increases in the repo haircuts, which is tantamount to massive withdrawals from the banking system.

The banking system has changed, with "securitized banking" playing an increasing role alongside traditional banking. One large area of securitized banking – the securitization of subprime home mortgages – began to weaken in early 2007, and continued to decline throughout 2007 and 2008. But, the weakening of subprime per se was not the shock that caused systemic problems. The first systemic event occurs in August 2007, with a shock to the repo market that we demonstrate using the "LIB-OIS," the spread between the LIBOR and the OIS, as a proxy. The reason that this shock occurred in August 2007 – as opposed to any other month of 2007 – is perhaps unknowable. We hypothesize that the market slowly became aware of the risks associated with the subprime market, which then led to doubts about repo collateral and bank solvency. At some point – August 2007 in this telling – a critical mass of such fears led to the first run on repo, with lenders no longer willing to provide short-term finance at historical spreads and haircuts.

After August 2007, the securitized-banking model was under pressure, with small equity bases stretched by increasing haircuts on high-grade collateral. We see evidence of this pressure in the co-movement of spreads on a wide variety of AAA and AA credits. This pressure contributed to the forced rescue of Bear Stearns in March 2008 and the failure of Lehman Brothers In September 2008. The second systemic event and run on repo occurred with the failure of Lehman. In this second event, we see parallels to 19th century banking crises, with a famine of liquidity leading to significant premia on even the safest of assets.

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Appendix A: Glossary of Key Terms and Asset Classes

This glossary provides definitions for all terms given in **bold** in the body of the paper and all asset classes listed in Table 1. For the latter group, we include the panel location of that variable in parenthesis following the definition (e.g: Table I – Panel A).

AA-AAA ABS RMBS/CMBS: Residential mortgage-backed security (RMBS) or **commercial mortgage-backed security** (CMBS) with ratings between AA and AAA, inclusive. (Table I - Panel D)

<AA ABS RMBS-CMBS: **Residential mortgage-backed security** (RMBS) or **commercial mortgage-backed security** (CMBS) with ratings between AA and AAA, inclusive. (Table I - Panel D)

AA-AAA CDO: **Collateralized debt obligations (CDO)** with ratings between AA and AAA, inclusive. (Table I - Panel D)

AA-AAA CLO: **Collateralized loan obligations (CDO)** with ratings between AA and AAA, inclusive. (Table I - Panel D)

A-AAA ABS Auto/CC/SL: Asset-backed securities (ABS) comprised of auto loans, credit-card receivables, or student loans, with ratings between A and AAA, inclusive. (Table I - Panel D)

ABX, ABX Index, ABX Index Spread: The ABX Index is a credit derivative that references 20 equally-weighted subprime RMBS tranches. There are also sub-indices linked to a basket of subprime bonds with specific ratings: AAA, AA, A BBB and BBB-. Each sub-index references the 20 subprime RMBS bonds with the rating level of the subindex. Every six months the indices are reconstituted based on a pre-identified set of rules, and a new vintage of the index and sub-indices are issued. In this paper, we focus on the BBB ABX tranche of the first vintage of the ABX in 2006, which is representative of the riskier levels of subprime securitization. We refer to this tranche of the 2006-1 issue simply as "ABX".

Asset-Backed Securities (ABS): An asset-backed security is a bond which is backed by the cash flows from a pool of specified assets in a **special purpose vehicle** rather than the general credit of a corporation. The asset pools may be residential mortgages, in which case it is a **residential mortgage-backed security** (RMBS), commercial mortgages – a **commercial mortgage-backed security** (CMBS), automobile loans, credit card receivables, student loans, aircraft leases, royalty payments, and many other asset classes.

Australia RMBS AAA: AAA-rated RMBS backed by Australian mortgages. (Table I – Panel C)

Auto AAA: AAA-rated **ABS** backed by auto loans. (Table 1 – Panel B)

BBB+/A Corporates: Corporate bonds rated between BBB+ and A, inclusive. (Table I - Panel D)

Cards AAA: AAA-rated **ABS** backed by credit-card receivables. (Table I – Panel B)

CMBS AAA: AAA-rated **Commercial-mortgage-backed securities.** (Table I – Panel B)

Credit Default Swaps (CDS): A **credit default swap** is derivative contract in which one party agrees to pay the other a fixed periodic coupon for the specified life of the agreement. The other party makes no payments unless a specified credit event occurs. Credit events are typically defined to include a material default, bankruptcy or debt restructuring for a specified reference asset. If such a credit event occurs, the party makes a payment to the first party, and the swap then terminates. The size of the payment is usually linked to the decline in the reference asset's market value following the credit event.

Collateralized Debt Obligations (CDOs): A CDO is a special purpose vehicle, which buys a portfolio of fixed income assets, and finances the purchase of the portfolio via issuing different tranches of risk in the capital markets. These tranches are senior tranches, rated Aaa/AAA, mezzanine tranches, rated Aa/AA to Ba/BB, and equity tranches (unrated). Of particular interest are ABS CDOs, which have underlying portfolios consisting of **asset-backed securities** (ABS), including **residential mortgage-backed securities** (RMBS) and **commercial mortgage-backed securities** (CMBS).

Collateralized Loan Obligations (CLOs): A CLO is a securitization of commercial bank loans.

Commercial Mortgage-backed Securities (CMBS): See **asset-backed securities**, above.

Dutch RMBS AAA: AAA-rated **RMBS** backed by Dutch mortgages. (Table I – Panel C)

European Auto AAA: AAA-rated **ABS** backed by European auto loans (Table I – Panel C)

European Consumer Receivables AAA: AAA-rated **ABS** backed by European consumer receivables (Table I – Panel C)

Haircut: The collateral pledged by borrowers towards the repo has a **haircut** or "initial margin" applied, which means the collateral is valued at less than market value. This haircut reflects the perceived underlying risk of the collateral and protects the lender against a change in its value. Haircuts are different for different asset classes and ratings.

HEL BBB: BBB-rated **ABS** backed by **Home-equity loans** with BBB ratings **(**Table 1- Panel A)

HELOC AAA: AAA-rated **ABS** backed by **Home-equity lines-of-credit (**Table I- Panel A)

HG SF CDO (High-grade structured-finance CDOs): High-grade structured-finance CDOs buy collateral consisting of the AAA and AA-rated tranches of securitized bonds. (Table 1 – Panel B)

Home-equity loans (HEL): A home equity loan is a line of credit under which a home owner can borrower using the home equity as collateral.

Home-equity lines-of-credit (HELOC): A HELOC differs from a home equity loan in that the borrower does not borrower the full amount of the loan at the outset, but can draw down the line of credit over a specified period of time with a maximum amount.

LIB-OIS: The spread between the **LIBOR** and the **OIS**.

LIBOR: The London Interbank Offered Rate (LIBOR) is a series of interest rates, of different maturities and currencies, at which banks offer to lend fund to each other. These rates are calculated by the British Bankers' Association as the averages of quotes contributed by a panel of banks and announced at 11:00 Am local time in England. This is called the rate "fixing." Quotes are ranked and the top and bottom quartiles are discarded. LIBOR is fixed for 15 different maturities, from overnight to one year, and in ten international currencies. Similar fixing arrangements exist in many markets around the world. See Gyntelberg and Wooldridge (2008).

Mezzanine CDO: A Mezzanine CDO refers to a **collateralized debt obligation** where the underlying portfolio consists of tranches of different asset-backed securities that are rated between BBB and A, inclusive.

Mezzanine SF CDO: Mezzanine structured-finance CDOs buy collateral consisting of the A through BBB-rated tranches of securitized bonds. (Table I – Panel B)

Monoline Insurers, Monoline Insurance Companies ("**monolines**"): Insurance companies that are restricted by regulation to one line of the business, the business of issuing financial guarantees on bonds, that is insurance against the loss due to default of specified bonds. The first such company was AMBAC Financial Group Inc., formed in 1971, followed by MBIA formed in 1983. In 1989 a law in New York limited the sale of financial insurance products by those companies solely to bond insurance, making them "monolines."

Mortgage Originators: Financial firms that underwrite and fund residential and possibly commercial, mortgages.

OIS: See **Overnight Index Swap** (Table I – Panel E).

Overnight Index Swap (OIS): An Overnight Indexed Swap (OIS) is a fixed/floating interest rate swap where the floating leg of the swap is tied to a published index of a daily overnight rate reference. The term ranges from one week to two years (sometimes more). At maturity, the two parties agree to exchange the difference between the interest accrued at the agreed fixed rate and interest accrued through geometric averaging of the floating index rate on the agreed notional amount. This means that the floating rate calculation replicates the accrual on an amount (principal plus interest) rolled at the index rate every business day over the term of the swap. If cash can be borrowed by the swap receiver on the same maturity as the swap and at the same rate and lent back every day in the market at the index rate, the cash payoff at maturity will exactly match the swap payout: the OIS acts as a perfect hedge for a cash instrument. Since indices are generally constructed on the basis of the average of actual transactions, the index is generally achievable by borrowers and lenders. Economically, receiving the fixed rate in an OIS is like lending cash. Paying the fixed rate in an OIS is like borrowing cash. Settlement occurs net on the earliest practical date. There is no exchange of principal. The index rate used is typically the weighted average rate for overnight transactions as published by the central bank (e.g., the effective fed funds rate).

Repo-Haircut Index: The equal-weighted average haircut for all nine of the asset classes in Panel D of Table I. Haircuts of 100% (= no trade) are included in this average. (Table I, Panel D)

Repo-Rate Index: During the time that all asset classes have active **repo** markets in 2007 and early 2008, this index is identical to the equal-weighted average repo rate for all nine the asset classes in Panel D of Table I. As haircuts rise to 100% for any given asset class (= no trade) on date *t*, we drop that class from the index and compute the index change for period *t* using only the classes that traded in both period *t-1* and period *t*. (Table I, Panel D)

Repurchase Agreements (repo), **Reverse Repurchase Agreements** (reverse repo): A sale and repurchase agreement, known as a "repo" for short, is a sale of a security combined with an agreement to repurchase the same security at a specified price at the end of the contract. Economically, a repo is a secured or collateralized loan, that is, a loan of cash against a security as collateral. From the point of view of the borrower of the cash (who is putting up the security as collateral), it is a reverse repurchase agreement, or "reverse repo."

Residential Mortgage-backed Security (RMBS): See asset-backed securities, above.

Securitization: The process of financing by segregating specified cash flows, from loans originated by a firm (the "sponsor") and selling claims specifically linked to these specified cash flows. This is accomplished by setting up another company, called a **special purpose vehicle** (SPV) or special purpose entity, and then selling the specified cash flows to this company, which purchases the rights to the cash flows by issuing (rated) securities into the capital market. The sponsor services the cash flows, that is, makes sure that the cash flows are arriving, etc. The SPV is not an operating company in the usual sense. It is more of a robot company in that it is a set of rules. It has no employees or physical location.

Securitized Banking: Refers in this paper to the nexus of securitization and repurchase markets where "depositors" are able to engage in (reverse) repo by depositing money in exchange for securitized bonds as collateral.

Securitized Bonds: A general term referring to any traded and rated tranche of an ABS, RMBS, CMBS, CDO, or CLO.

Special Purpose Vehicle (SPV): An SPV or special purpose entity (SPE) is a legal entity which has been set up for a specific, limited, purpose by another entity, the sponsoring firm. An SPV can take the form of a corporation, trust, partnership, or a limited liability company. The SPV may be a subsidiary of the sponsoring firm, or it may be an "orphan" SPV, one that is not consolidated with the sponsoring firm for tax, accounting, or legal purposes (or may be consolidated for some purposes but not others). An SPV can only carry out some specific purpose, or circumscribed activity, or a series of such transactions. An essential feature of an SPV is that it be "bankruptcy remote," that is, that the SPV never be able to become legally bankrupt. The most straightforward way to achieve this would be for the SPV to waive its right to file a voluntary bankruptcy petition, but this is legally unenforceable. The only way to completely eliminate the risk of either voluntary or involuntary bankruptcy is to create the SPV in a legal form that is ineligible to be a debtor under the U.S. Bankruptcy Code.

Structured Finance: A broad term used to describe **securitized bonds**, but also more generally any bond with an embedded derivative.

Student AAA: AAA-rated **ABS** backed by student loans. (Table I – Panel B)

Tranche: A tranche (French for "cut") refers to a slice of an portfolio ordered by seniority, e.g., a senior tranche or AAA tranche is more senior than a junior tranche or BBB-rated tranche.

UK Cards AAA: AAA-rated **ABS** backed by UK credit-card receivables (Table I – Panel C)

UK RMBS AAA: AAA-rated RMBS backed by UK mortgages. (Table I – Panel C)

Unpriced ABS/MBS, All Subprime: All tranches of ABS, MBS and all subprime securitized bonds which do not have public pricing posted on Bloomberg or Reuters (two news services used by traders) (Table I - Panel D)

Unpriced CDO/CLO: All tranches of CDO and CLO securitized bonds which do not have public pricing posted on Bloomberg or Reuters (two news services used by traders) (Table I - Panel D)

VIX: VIX is the ticker symbol for a measure of implied volatility from S&P 500 index options. A high value of the VIX is associated with a more violatile market and more costly options. The VIX is calculated and traded on the Chicago Board Options Exchange. (Table I – Panel E)

Appendix B: The Spread Data

Spreads are not a common variable of analysis for financial economists, who prefer to focus on returns. As a practical matter, however, interest rate risk is frequently hedged, leaving credit risk as the focus. Credit spreads isolate the risk of default and the recovery rate. Thus, when assessing fixed income securities, investors focus on spreads as a common measure for determining how much they are being paid to bear the credit risk embedded in a security.

For fixed rate instruments, the spread is the yield spread, i.e., the difference between the yield-to-maturity of the credit risky instrument and the benchmark instrument (LIBOR) with the same maturity. Floating rate instrument prices are converted to a spreads by determining the discount margin, which is the fixed amount to be added to the current LIBOR rate that is required to reprice the bond to par. The discount margin measures the yield relative to the current LIBOR rate and so does not take into account the term structure of interest rates.

The discount margin, dm, satisfies the following relationship:

where: $P = 100 + \sum_{i=1}^{n} \frac{100(qm-dm)/m}{(1+y_i+dm)^i}$

P = Price of the floating rate note (FRN) per $100 face value;

qm = Quoted margin on FRN;

dm = discount margin;

y_i = Assumed value of the reference rate (LIBOR) in period i;

n = number of period until maturity;

m= number of period per year.

The formula shows that if the quoted margin is equal to the discount margin, then the second term is zero and the FRN is valued at par. If the current price of the floater differs from par, then the discount margin is nonzero. The discount margin assumes that the cash flows over the remaining life of the bond are determined by the current reference rate value. The margin is selected so that the present value of the cash flows is equal to the security's price. The discount margin is a measure which is similar to yield-to-maturity for fixed rate instruments. It expresses the price of an FRN relative to the current LIBOR level. See Fabozzi and Mann (2000).

Figure 1: Traditional Banking

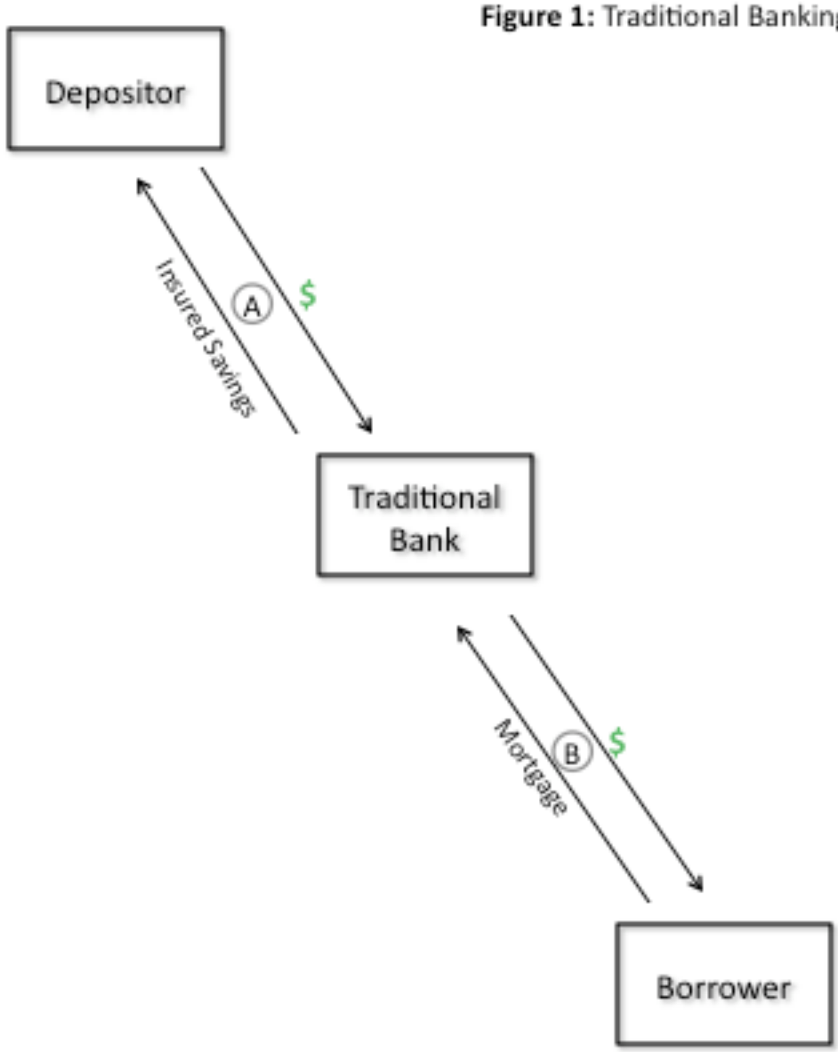


Figure 2: Securitized Banking

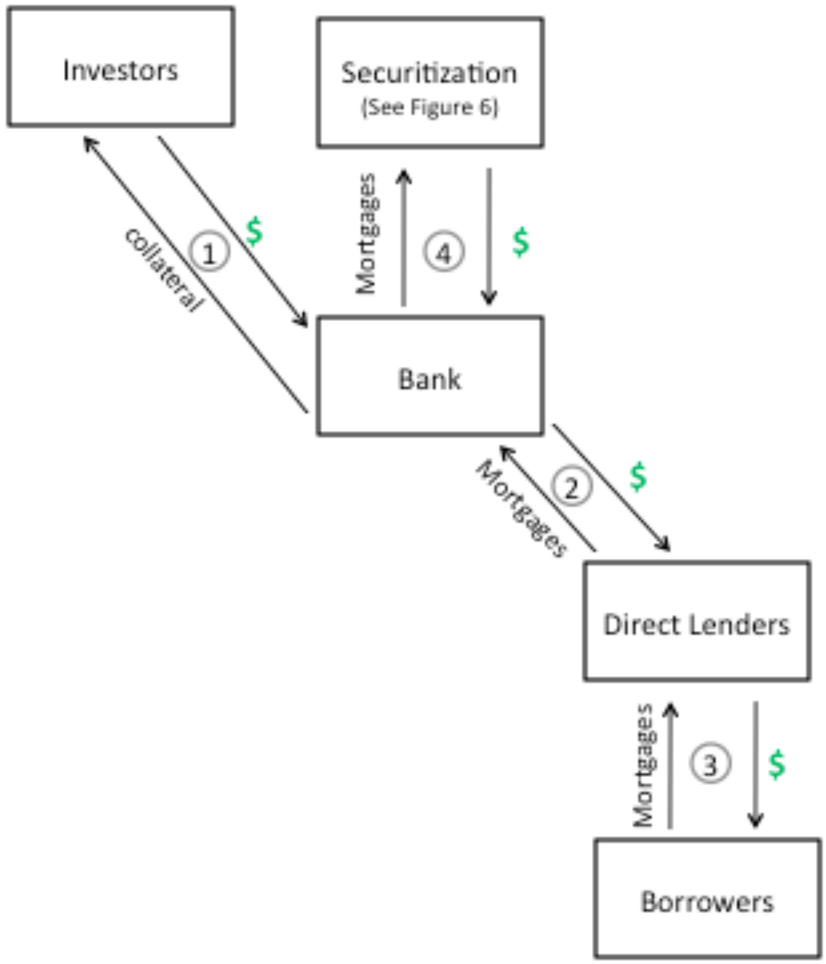


Figure 3: Traditional Banking vs. Securitized Banking

Traditional Banking

(1) Reserves
- Minimum levels set by regulators.
- Shortfalls can be borrowed from central bank.

(2) Deposit Insurance
- Guaranteed by the government

(3) Interest Rates on Deposits
- Can be raised to attract deposits when reserves are low.

(4) Loans Held on Balance Sheet

Securitized Banking

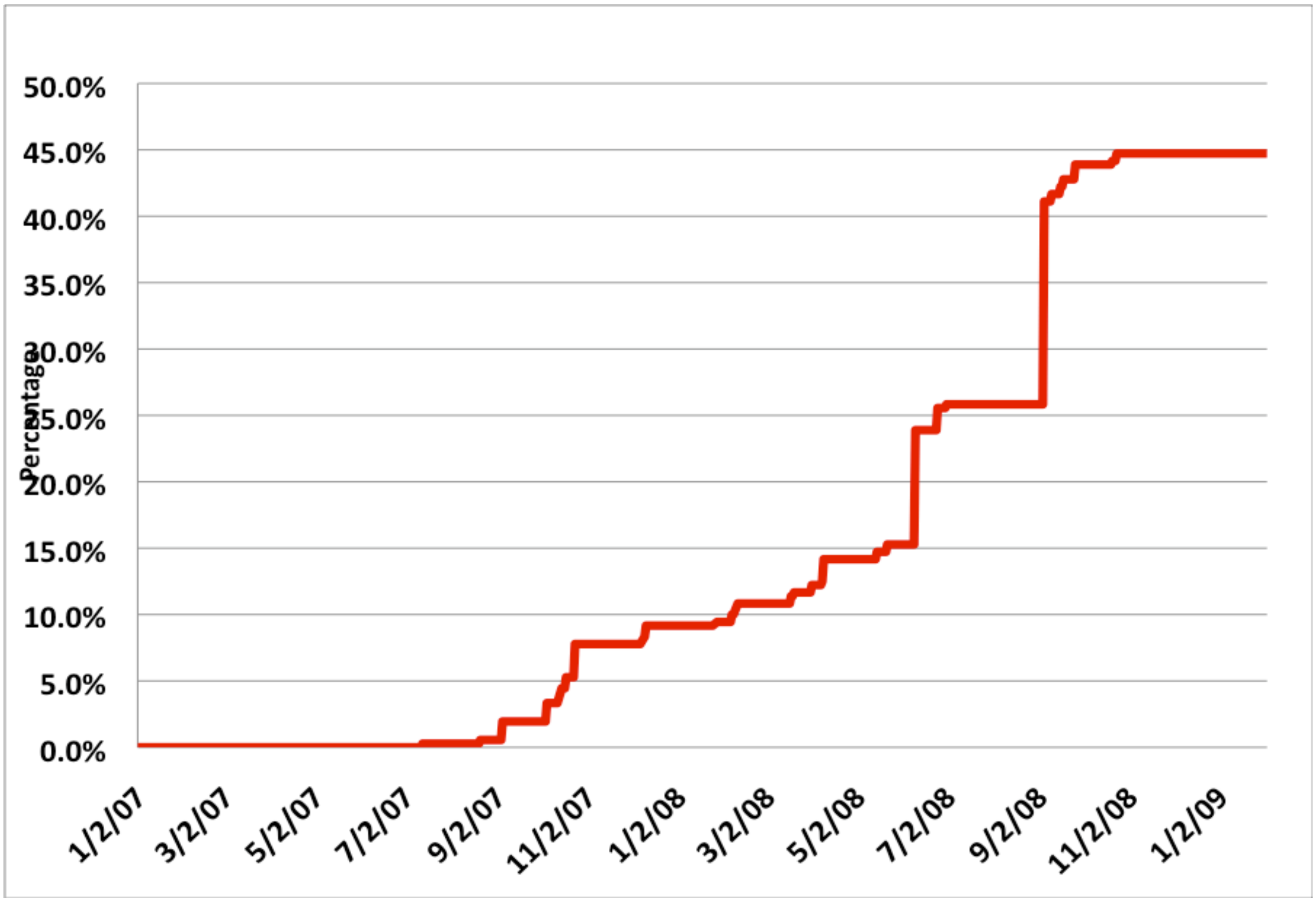
(1) Haircuts
- Minimum levels set by counterparties.
- No borrowing from central bank.

(2) Collateral
- Cash, treasury securities, loans, or securitized bonds

(3) Repo Rates
- Can be raised to attract counterparties when funds are low.

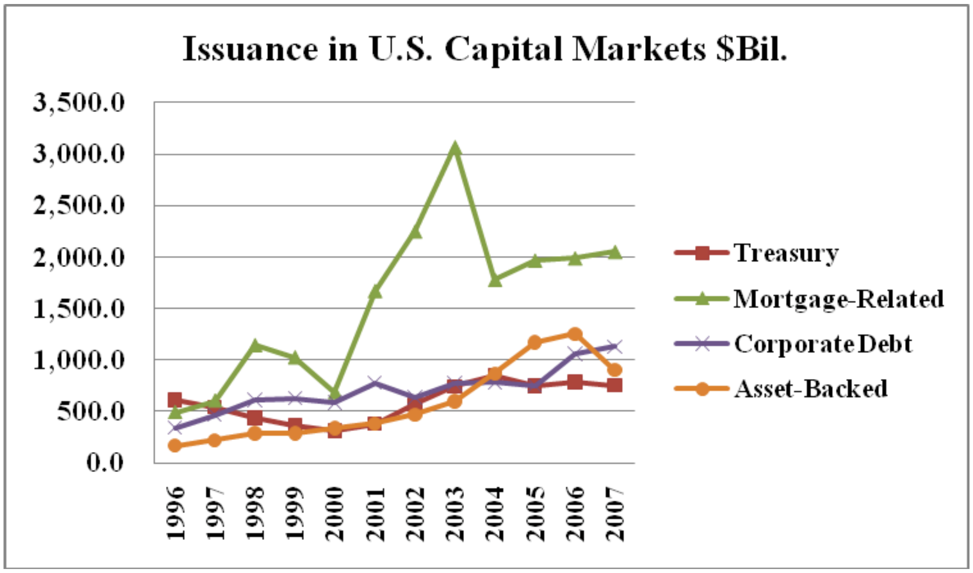
(4) Loans Securitized
- Some securitized bonds may be kept on balance sheet and used as collateral

Figure 4: The Repo-Haircut Index



Notes: The repo-haircut index is the equally-weighted average haircut for all nine asset classes included in Table I, Panel D.

Figure 5: Issuance in U.S. Capital Markets ($ billions)



Sources: U.S. Department of Treasury, Federal Agencies, Thomson Financial, Inside MBS & ABS, Bloomberg.

Figure 6: Securitization
(continuation of Figure 2)

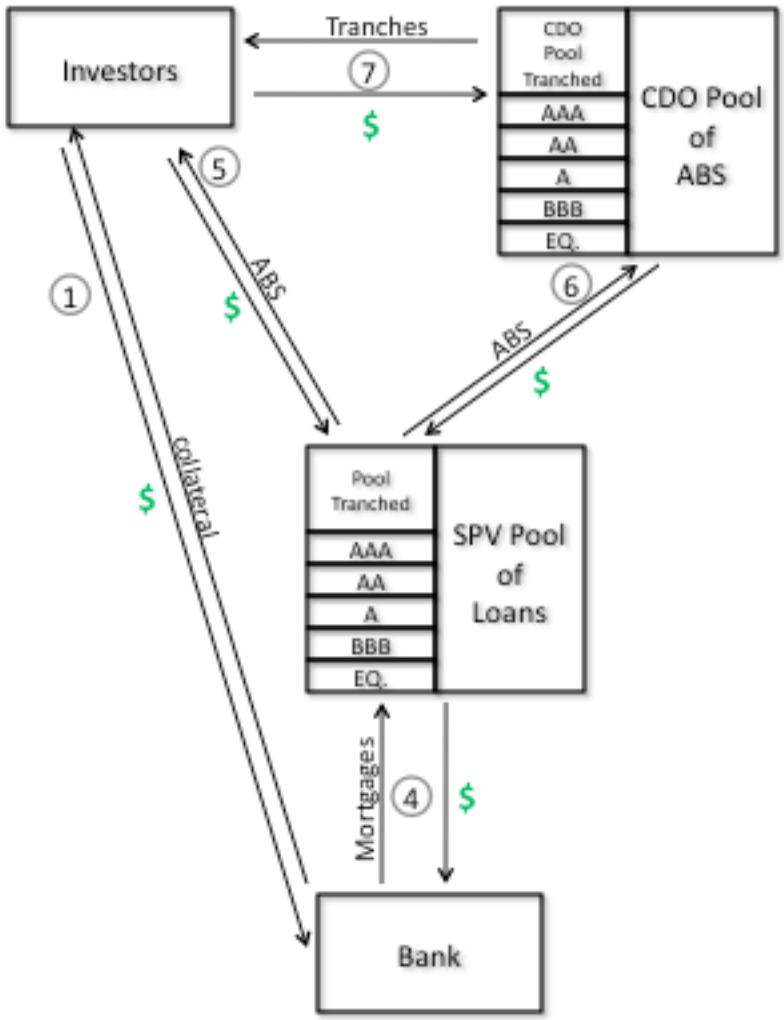
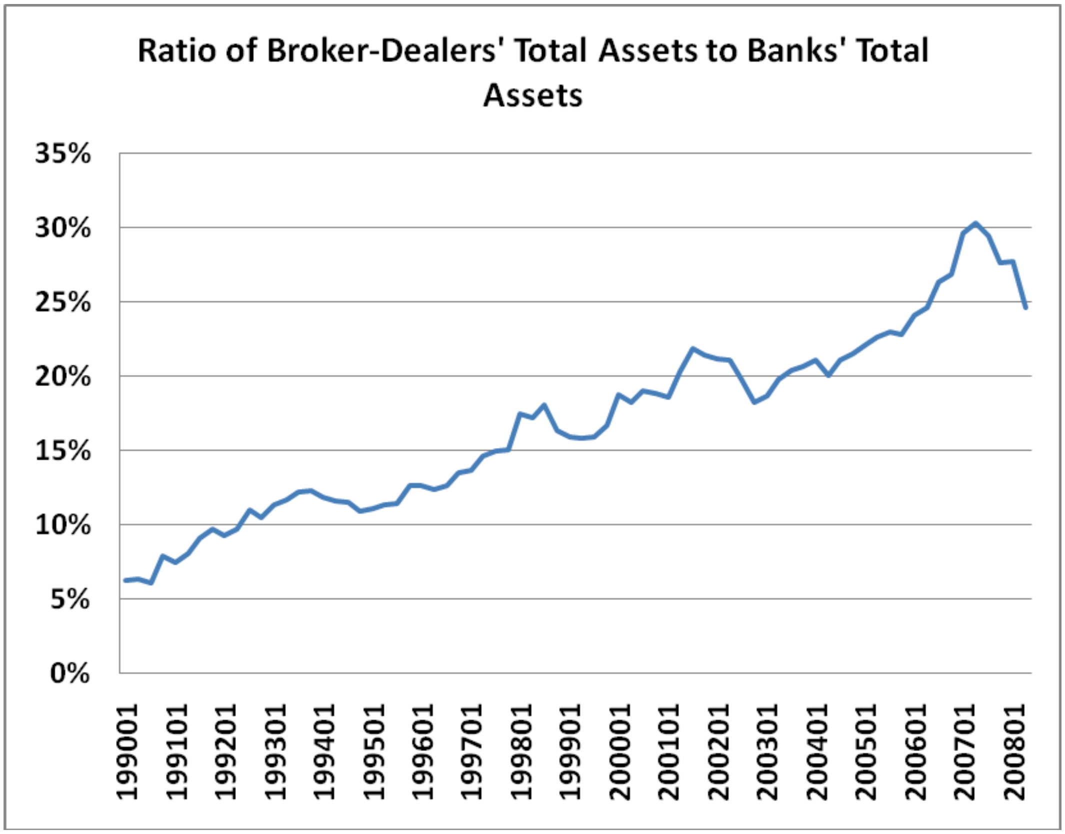
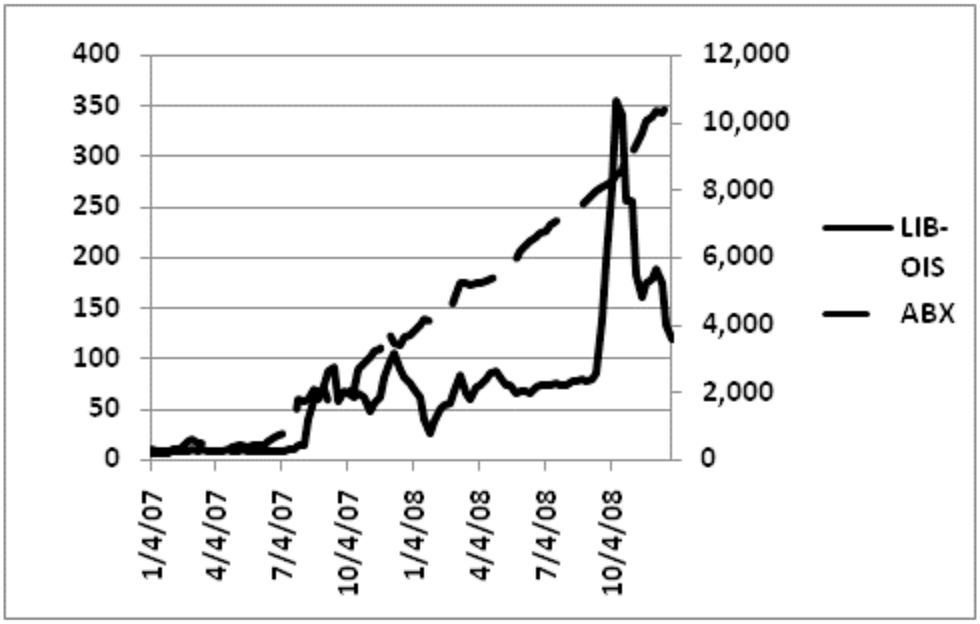


FIGURE 7



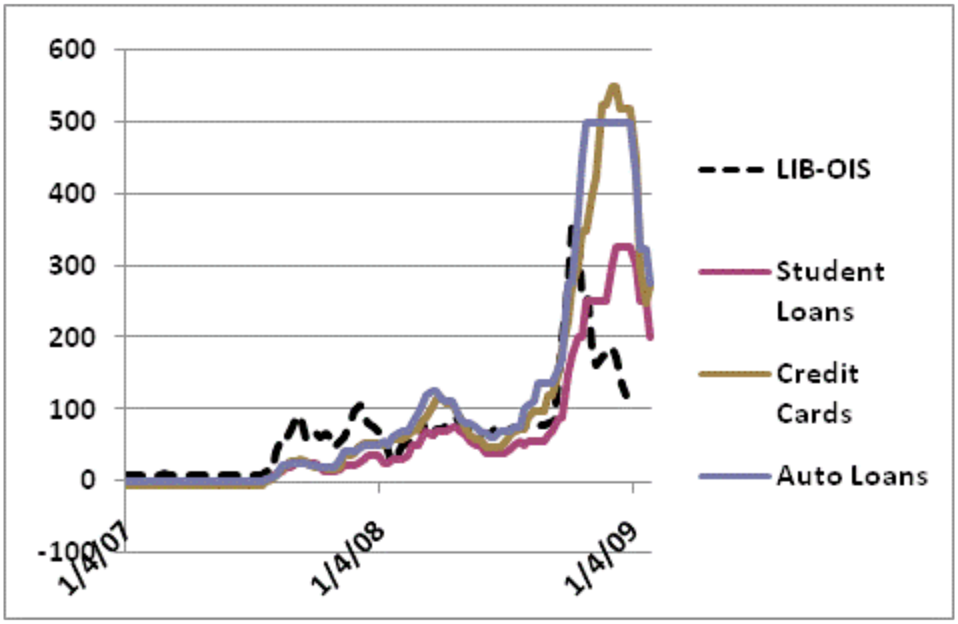
Source: Federal Flow of Funds.

FIGURE 8: ABX vs. LIB-OIS



Notes: ABX is the 2006-1 BBB tranche. LIB-OIS spreads on left-hand Y-axis, ABX spreads on right-hand y-axis. Both scales are in basis points.

Figure 9: LIB-OIS and Non-Subprime-Related Asset Classes



Notes: LIB-OIS is shown with the spreads on AAA-rated asset-backed securities: student loans, credit cards, and auto loans. The scale is in basis points.

Table I
Summary Statistics

This table reports the summary statistics for the state variable, credit spreads, repo spreads and control variables used in this paper. For each series we show summary statistics for the whole period and four subperiods. Panel A shows statistics for the state variable LIB-OIS and the credit spreads of three categories of subprime related assets. Panel B and Panel C shows statistics for the credit spreads of U.S. and non-U.S. non-subprime asset classes. Panel D reports the statistics for the spreads between three-month repo rates and OIS. Panel E shows statistics for the five control variables used in the regression analysis. All variables given in this Table are defined in Appendix A. All spreads are measured in basis points, with spread computations explained in Appendix B.

Panel A: State Variable and Subprime Related Assets Class						
Series	**Periods**	**Mean**	**Median**	**Std. Err.**	**Max**	**Min**
State Variable						
LIB-OIS Spread	Whole period	72.43	66.44	67.57	354.20	7.45
	First half of 2007	7.97	7.88	0.42	9.15	7.45
	Second half of 2007	58.71	60.78	28.64	104.73	7.70
	All of 2007	33.34	8.50	32.53	104.73	7.45
	All of 2008	108.10	77.20	71.61	354.20	24.33
Credit Spreads of Sub-prime Related Assets						
HEL BBB	Whole period	714.25	425.00	545.26	1800.00	170.00
	First half of 2007	273.27	250.00	93.54	425.00	170.00
	Second half of 2007	1113.46	1000.00	441.03	1800.00	350.00
	All of 2007	693.37	425.00	528.75	1800.00	170.00
Mezzanine CDO BBB	Whole period	2861.93	2969.42	2023.57	8421.76	365.00
	First half of 2007	627.50	650.00	152.50	950.00	365.00
	Second half of 2007	2178.47	1940.75	659.41	3063.16	1100.00
	All of 2007	1402.99	1025.00	915.27	3063.16	365.00
	All of 2008	4858.38	4687.97	1268.88	8421.76	3016.83
HELOC AAA	Whole Period	121.60	18.00	157.64	500.00	14.00
	First half of 2007	15.35	15.00	1.23	18.00	14.00
	Second half of 2007	213.31	195.00	159.59	500.00	15.00
	All of 2007	114.33	18.00	149.92	500.00	14.00
CDS Spreads of Subprime Mortgage Lenders						
Countrywide	Whole period	275.86	220.02	253.96	1185.84	22.52
	First half of 2007	51.10	50.79	17.64	77.57	22.52
	Second half of 2007	445.43	282.34	338.99	1088.00	62.53
	All of 2007	248.26	71.09	310.03	1088.00	22.52
	All of 2008	301.04	260.00	188.39	1185.84	95.67
WAMU	Whole period	413.57	318.33	643.09	4352.43	19.61
	First half of 2007	35.39	33.68	11.11	57.38	19.61
	Second half of 2007	189.27	122.03	133.36	438.47	42.55
	All of 2007	112.33	50.32	121.71	438.47	19.61
	All of 2008	815.23	438.90	818.44	4352.43	255.00
CDS Spreads of Monoline Insurers						
MBIA	Whole period	911.33	391.88	1116.88	4153.55	13.46
	First half of 2007	24.20	22.66	9.34	42.20	13.46
	Second half of 2007	164.92	121.69	89.44	322.96	45.18
	All of 2007	94.56	43.69	94.93	322.96	13.46
	All of 2008	1656.46	1391.26	1101.33	4153.55	372.55
MGIC	Whole period	520.96	453.46	406.35	1411.73	27.48
	First half of 2007	51.42	52.40	17.82	81.32	27.48
	Second half of 2007	270.97	245.95	138.90	528.53	71.21
	All of 2007	161.20	79.09	147.99	528.53	27.48
	All of 2008	849.17	885.61	262.06	1411.73	320.00
Radian	Whole period	1072.85	809.83	956.80	3164.27	28.53
	First half of 2007	56.54	55.49	18.12	93.39	28.53
	Second half of 2007	536.20	559.22	261.37	1000.32	73.26
	All of 2007	296.37	86.62	303.80	1000.32	28.53
	All of 2008	1781.22	1938.22	781.58	3164.27	704.70

Series	Periods	Mean	Median	Std. Err.	Max	Min
Panel B:U.S. Non-Subprime Asset Classes						
Auto AAA	Whole period	109.42	55.00	153.65	500.00	-1.00
	First half of 2007	-1.00	-1.00	0.00	-1.00	-1.00
	Second half of 2007	23.38	20.00	16.11	50.00	-1.00
	All of 2007	11.19	-1.00	16.70	50.00	-1.00
	All of 2008	199.04	110.00	167.75	500.00	50.00
Cards AAA	Whole period	101.92	55.00	148.93	550.00	-4.00
	First half of 2007	-3.31	-3.00	0.47	-3.00	-4.00
	Second half of 2007	24.88	23.00	17.73	55.00	-3.00
	All of 2007	10.79	-3.00	18.89	55.00	-4.00
	All of 2008	185.05	100.00	166.45	550.00	50.00
Student AAA	Whole period	65.11	30.00	90.47	325.00	-3.00
	First half of 2007	-1.12	-1.00	1.18	0.00	-3.00
	Second half of 2007	17.92	18.00	10.28	35.00	0.00
	All of 2007	8.40	0.00	12.03	35.00	-3.00
	All of 2008	116.84	65.00	99.71	325.00	25.00
CMBS AAA	Whole period	241.16	123.00	313.92	1350.00	22.00
	First half of 2007	26.27	26.50	2.79	31.00	22.00
	Second half of 2007	65.88	62.00	21.83	105.00	31.50
	All of 2007	46.08	31.25	25.25	105.00	22.00
	All of 2008	419.12	250.00	349.14	1350.00	83.00
HG SF CDO AAA	Whole period	482.24	428.32	424.87	1463.10	23.00
	First half of 2007	23.73	23.00	2.68	35.00	23.00
	Second half of 2007	177.88	108.09	135.50	450.90	42.00
	All of 2007	100.81	38.50	122.72	450.90	23.00
	All of 2008	830.22	849.77	275.79	1463.10	391.43
Mezzanine SF CDO AAA	Whole period	1094.17	1084.79	873.46	2712.79	32.00
	First half of 2007	54.38	55.00	20.99	105.00	32.00
	Second half of 2007	567.96	444.69	380.54	1084.79	115.00
	All of 2007	311.17	110.00	372.07	1084.79	32.00
	All of 2008	1808.49	1742.65	506.59	2712.79	1006.25
Panel C: Non-US Non-Subprime Asset Classes						
Australia RMBS AAA	Whole period	145.60	90.00	151.22	650.00	5.00
	First half of 2007	6.23	7.00	0.91	7.00	5.00
	Second half of 2007	48.15	50.00	24.66	90.00	5.00
	All of 2007	27.19	7.00	27.32	90.00	5.00
	All of 2008	257.55	200.00	133.86	650.00	90.00
UK RMBS AAA	Whole period	124.53	80.00	131.25	440.00	4.00
	First half of 2007	4.96	5.00	0.72	6.00	4.00
	Second half of 2007	45.15	50.00	22.23	80.00	5.00
	All of 2007	25.06	6.00	25.58	80.00	4.00
	All of 2008	218.58	180.00	121.08	440.00	80.00
Dutch RMBS AAA	Whole Period	56.56	50.00	42.40	170.00	10.00
	First half of 2007	10.69	11.00	0.74	12.00	10.00
	Second half of 2007	40.35	39.00	18.96	70.00	11.00
	All of 2007	25.52	12.00	20.02	70.00	10.00
	All of 2008	97.95	90.00	25.38	170.00	60.00
UK Cards AAA	Whole period	178.62	150.00	176.97	625.00	10.00
	First half of 2007	10.08	10.00	0.28	11.00	10.00
	Second half of 2007	44.38	40.00	25.94	90.00	11.00
	All of 2007	32.95	27.00	26.67	90.00	10.00
	All of 2008	281.91	215.00	165.05	625.00	90.00
European Consumer Receivable AAA	Whole period	206.25	200.00	176.36	600.00	15.00
	First half of 2007	15.29	15.00	0.76	17.00	15.00
	Second half of 2007	54.92	55.00	25.05	95.00	18.00
	All of 2007	46.52	50.00	27.59	95.00	15.00
	All of 2008	302.09	235.00	157.19	600.00	95.00
European Auto AAA	Whole period	120.57	85.00	119.56	450.00	7.00
	First half of 2007	7.14	7.00	0.38	8.00	7.00
	Second half of 2007	37.31	35.00	18.62	65.00	8.00
	All of 2007	30.91	30.00	20.68	65.00	7.00
	All of 2008	174.36	115.00	122.14	450.00	60.00

Panel D: Repo Rate Spreads (bps; except repo haircuts)							
Series	**Periods**	**Mean**	**Median**	**Std. Err.**	**Max**	**Min**	**Mean of Haircut**
BBB+ / A Corporates	Whole period	86.50	82.14	83.15	429.43	0.50	0.5%
	First half of 2007	2.01	1.95	0.61	5.30	0.50	0.0%
	Second half of 2007	61.85	65.49	36.29	126.35	1.70	0.0%
	All of 2007	32.28	2.70	39.53	126.35	0.50	0.0%
	All of 2008	136.19	103.63	81.61	429.43	44.33	0.9%
AA-AAA Corporates	Whole period	77.59	74.78	78.42	409.43	-3.50	0.5%
	First half of 2007	-1.69	-2.05	1.90	10.44	-3.50	0.0%
	Second half of 2007	55.27	58.95	34.53	116.35	-2.30	0.0%
	All of 2007	27.13	-1.35	37.64	116.35	-3.50	0.0%
	All of 2008	123.86	92.11	77.57	409.43	39.33	0.9%
A-AAA ABS-Auto / CC / SL	Whole period	105.22	94.76	101.00	479.43	1.70	5.2%
	First half of 2007	4.44	4.00	1.77	11.00	1.70	0.0%
	Second half of 2007	68.44	71.78	40.93	141.35	3.70	0.9%
	All of 2007	36.82	5.25	43.29	141.35	1.70	0.5%
	All of 2008	167.92	119.81	98.07	479.43	54.33	9.5%
AA-AAA ABS-RMBS / CMBS	Whole period	124.04	107.78	120.11	520.30	3.70	9.4%
	First half of 2007	6.41	6.00	1.76	13.00	3.70	0.0%
	Second half of 2007	76.35	81.78	43.92	151.35	5.70	1.8%
	All of 2007	41.80	7.00	46.92	151.35	3.70	0.9%
	All of 2008	199.44	145.08	117.27	520.30	64.33	17.1%
<AA ABS-RMBS / CMBS	Whole period	135.90	117.78	129.02	550.30	6.70	10.6%
	First half of 2007	9.41	9.00	1.76	16.00	6.70	0.0%
	Second half of 2007	84.55	88.20	48.62	166.35	8.70	3.7%
	All of 2007	47.43	10.00	51.08	166.35	6.70	1.9%
	All of 2008	217.01	153.95	125.56	550.30	69.33	18.6%
Unpriced ABS / MBS / All Sub-Prime	Whole period	108.94	109.69	84.64	295.38	7.70	37.3%
	First half of 2007	10.41	10.00	1.76	17.00	7.70	0.0%
	Second half of 2007	95.62	97.83	58.54	196.35	9.70	7.7%
	All of 2007	53.52	11.00	59.59	196.35	7.70	3.9%
	All of 2008	187.28	197.88	42.23	295.38	99.33	68.0%
AA-AAA CLO	Whole period	134.46	117.14	127.18	545.30	3.70	10.2%
	First half of 2007	6.41	6.00	1.76	13.00	3.70	0.0%
	Second half of 2007	85.93	92.65	51.27	171.35	5.70	1.8%
	All of 2007	46.64	7.00	53.98	171.35	3.70	0.9%
	All of 2008	214.96	148.76	121.61	545.30	79.33	18.7%
AA-AAA CDO	Whole period	130.09	124.69	107.46	380.38	4.70	30.0%
	First half of 2007	7.41	7.00	1.76	14.00	4.70	0.0%
	Second half of 2007	107.77	109.35	69.56	226.35	6.70	8.3%
	All of 2007	58.19	8.00	70.48	226.35	4.70	4.3%
	All of 2008	231.72	241.39	56.52	380.38	129.33	53.5%
Unpriced CLO / CDO	Whole period	148.32	142.60	123.54	413.75	6.70	32.4%
	First half of 2007	9.41	9.00	1.76	16.00	6.70	0.0%
	Second half of 2007	122.63	124.42	80.14	256.35	8.70	10.5%
	All of 2007	66.69	10.00	80.34	256.35	6.70	5.4%
	All of 2008	268.39	256.58	63.03	413.75	154.33	57.3%
Repo-Rate Index and Repo-Haircut Index (last column)	Whole period	151.36	130.89	152.79	688.10	3.81	15.1%
	First half of 2007	6.03	5.67	1.45	11.33	3.81	0.0%
	Second half of 2007	84.27	89.18	51.14	172.46	5.37	3.9%
	All of 2007	45.61	6.98	53.44	172.46	3.81	2.0%
	All of 2008	248.29	171.20	149.95	688.10	81.55	27.2%

Panel E: Control variables						
Series	**Periods**	**Mean**	**Median**	**Std. Err.**	**Max**	**Min**
ABX Index (bps)	Whole period	4090.11	3604.00	3524.76	10940.98	121.00
	First half of 2007	302.15	329.50	139.54	552.00	121.00
	Second half of 2007	1657.69	1752.00	894.91	3286.00	368.00
	All of 2007	979.92	481.50	933.01	3286.00	121.00
	All of 2008	6927.48	6938.67	2447.64	10940.98	3373.00
10Year Treasury Rate	Whole period	4.07%	4.04%	0.71%	5.19%	2.08%
	First half of 2007	4.77%	4.73%	0.20%	5.19%	4.51%
	Second half of 2007	4.52%	4.51%	0.32%	5.14%	3.96%
	All of 2007	4.64%	4.66%	0.29%	5.19%	3.96%
	All of 2008	3.56%	3.72%	0.56%	4.50%	2.08%
OIS	Whole period	3.26%	3.53%	1.79%	5.29%	0.18%
	First half of 2007	5.28%	5.28%	0.01%	5.29%	5.26%
	Second half of 2007	4.65%	4.60%	0.42%	5.28%	4.07%
	All of 2007	4.96%	5.27%	0.43%	5.29%	4.07%
	All of 2008	1.70%	2.00%	0.94%	3.96%	0.18%
Return of S&P 500	Whole period	-0.40%	0.20%	3.83%	17.97%	-18.34%
	First half of 2007	0.25%	0.18%	1.45%	3.04%	-3.65%
	Second half of 2007	-0.06%	0.01%	2.02%	3.74%	-4.53%
	All of 2007	0.09%	0.18%	1.75%	3.74%	-4.53%
	All of 2008	-0.85%	0.22%	4.98%	17.97%	-18.34%
VIX	Whole period	25.94	22.49	14.93	80.86	10.18
	First half of 2007	13.05	13.07	1.97	17.06	10.18
	Second half of 2007	21.88	21.2	4.02	30.83	15.23
	All of 2007	17.47	15.68	5.45	30.83	10.18
	All of 2008	33.68	25.59	16.59	80.86	16.3
Slope of Yield Curve	Whole period	1.01%	1.22%	0.78%	2.62%	-0.13%
	First half of 2007	-0.02%	-0.04%	0.09%	0.22%	-0.13%
	Second half of 2007	0.59%	0.55%	0.31%	1.39%	0.17%
	All of 2007	0.29%	0.18%	0.38%	1.39%	-0.13%
	All of 2008	1.66%	1.57%	0.34%	2.62%	1.08%

Table II
Credit Spreads Regression Results

For each bond i, we estimate equation (2) using weekly data from January 4, 2007 to January 29, 2009, ΔLIB-OIS is the percentage change of the spread between the 3-month LIBOR and the Overnight Index Swap (OIS). ΔABX is the parentage change of the ABX index at period t. ΔOIS is the Overnight Index Swap. Δr-10 is the change in yield on the 10-year Treasury, with its square given by (Δr-10)^2. ΔSlope is the change in 10-year minus 2-year Treasury yields. ΔVIX is the change in implied volatility of S&P 500, and ΔS&P is the return on S&P 500. t-statistics are given in parentheses below the coefficient estimates. The last two rows report F-statistics and p-values for the key state variables. The null hypothesis of the LIB-OIS F-Test is that the sum of all coefficients of ΔLIB-OIS and its lags is zero. The null hypothesis of the ABX F-Test is the sum of all coefficients of ΔABX and its lags is zero. Panel A shows the results of six U.S. non-subprime assets and Panel B shows the results of six non-US non-subprime assets.

Panel A: U.S. Non-Subprime Asset Classes						
	Credit Spreads					
	Cards	Auto	Student	CMBS	HG SF CDO	Mezz SF CDO
Intercept	0.003	0.016	-0.010	0.036	0.042	0.052
	(0.1)	(0.33)	(-0.33)	(2.41)	(2.86)	(3.96)
ΔLIB-OIS	0.341	0.079	0.461	0.025	-0.051	-0.037
	(3.24)	(0.54)	(5.23)	(0.26)	(-1.16)	(-0.94)
ΔLIB-OIS, t-1	0.264	0.486	0.131	0.078	-0.042	0.055
	(2.64)	(3.55)	(1.59)	(0.84)	(-1.00)	(1.45)
ΔLIB-OIS, t-2	0.132	0.012	0.138	-0.082	0.038	-0.081
	(1.32)	(0.08)	(1.67)	(-0.92)	(0.91)	(-2.15)
ΔLIB-OIS, t-3	0.027	0.170	-0.013	-0.030	-0.030	-0.004
	(0.27)	(1.25)	(-0.16)	(-0.33)	(-0.72)	(-0.1)
ΔABX	-0.141	-0.331	0.455	0.012	0.001	0.070
	(-0.66)	(-1.13)	(2.32)	(0.27)	(0.00)	(0.86)
ΔABX, t-1	0.079	-0.025	0.119	-0.013	0.016	0.061
	(0.36)	(-0.09)	(0.6)	(-0.32)	(0.18)	(0.74)
ΔABX, t-2	0.315	0.250	-0.202	-0.072	-0.020	-0.040
	(1.48)	(0.86)	(-1.06)	(-1.71)	(-0.23)	(-0.5)
ΔABX, t-3	-0.277	-0.351	-0.150	-0.052	0.049	-0.011
	(-1.3)	(-1.2)	(-0.69)	(-1.24)	(0.54)	(-0.14)
ΔOIS	-0.253	-0.147	-0.358	-0.096	0.156	0.106
	(-0.78)	(-0.33)	(-1.34)	(-0.69)	(1.14)	(0.85)
Δr-10	0.111	-0.092	0.059	-0.214	-0.227	-0.132
	(0.58)	(-0.36)	(0.36)	(-2.65)	(-2.87)	(-1.85)
(Δr-10)^2	0.174	0.076	0.037	-0.042	-0.094	-0.144
	(0.57)	(0.18)	(0.14)	(-0.33)	(-0.75)	(-1.26)
ΔS&P	-0.443	1.518	-0.757	-1.622	-0.580	0.592
	(-0.29)	(0.7)	(-0.57)	(-2.42)	(-0.89)	(0.99)
ΔVIX	-0.006	0.004	-0.003	0.003	0.002	0.006
	(-0.5)	(0.23)	(-0.29)	(0.56)	(0.41)	(1.26)
ΔSlope	-0.155	0.189	-0.039	0.298	0.269	0.075
	(-0.74)	(0.64)	(-0.23)	(3.29)	(3.02)	(0.92)
LIB-OIS F-test	20.16	10.26	26.13	2.99	1.38	1.08
	(<0.01)	(<0.01)	(<0.01)	(0.08)	(0.24)	(0.30)
ABX F-test	0.00	0.73	0.42	0.00	0.08	0.39
	(0.95)	(0.40)	(0.52)	(0.95)	(0.78)	(0.59)

Panel B: Non-US Non-Subprime Asset Classes						
Credit Spreads						
	Australia RMBS	UK RMBS	Dutch RMBS	UK Cards	European Consumer Receivable	European Auto
Intercept	0.014	0.017	0.014	0.031	0.032	0.037
	(0.52)	(0.93)	(1.14)	(2.4)	(3.21)	(2.35)
ΔLIB-OIS	0.126	0.240	0.100	0.109	0.049	0.081
	(1.57)	(4.38)	(2.71)	(2.86)	(1.76)	(1.8)
ΔLIB-OIS, t-1	0.575	0.237	0.071	0.136	0.021	0.019
	(7.56)	(4.57)	(2.11)	(3.72)	(0.8)	(0.45)
ΔLIB-OIS, t-2	-0.181	-0.051	0.115	0.019	0.033	0.104
	(-2.44)	(-1.01)	(3.42)	(0.52)	(1.26)	(2.51)
ΔLIB-OIS, t-3	0.138	0.067	-0.015	-0.019	0.020	0.022
	(1.86)	(1.32)	(-0.47)	(-0.55)	(0.77)	(0.53)
ΔABX	0.025	0.029	0.095	0.094	0.116	0.095
	(0.15)	(0.26)	(1.37)	(1.03)	(1.65)	(0.84)
ΔABX, t-1	-0.002	0.022	0.002	0.028	0.001	-0.010
	(-0.02)	(0.19)	(0.03)	(0.34)	(0.01)	(-0.09)
ΔABX, t-2	-0.171	-0.018	-0.037	0.011	0.037	0.044
	(-1.09)	(-0.17)	(-0.54)	(0.13)	(0.54)	(0.4)
ΔABX, t-3	0.173	0.072	-0.109	-0.084	-0.060	-0.265
	(1.09)	(0.66)	(-1.6)	(-1.05)	(-0.9)	(-2.47)
ΔOIS	0.034	-0.031	-0.237	-0.051	-0.054	-0.164
	(0.1)	(-0.15)	(-0.63)	(-0.33)	(-0.48)	(-0.91)
Δr-10	-0.207	-0.140	-0.067	-0.134	-0.106	-0.146
	(-1.36)	(-1.34)	(-0.81)	(-1.84)	(-1.97)	(-1.71)
(Δr-10)^2	0.194	-0.022	-0.058	-0.036	-0.096	-0.018
	(0.85)	(-0.15)	(-0.5)	(-0.34)	(-1.23)	(-0.15)
ΔS&P	-0.915	-0.272	-0.709	0.164	0.194	0.695
	(-0.76)	(-0.33)	(-0.86)	(0.28)	(0.45)	(1.01)
ΔVIX	-0.006	-0.001	-0.002	0.000	0.001	0.003
	(-0.64)	(-0.11)	(-0.31)	(0.07)	(0.39)	(0.6)
ΔSlope	0.179	0.077	0.051	0.133	0.091	0.190
	(1.05)	(0.66)	(0.51)	(1.64)	(1.53)	(2)
LIB-OIS	25.57	30.71	20.89	14.40	6.56	8.62
F-test	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(0.01)	(<0.01)
ABX	0.01	0.28	0.14	0.09	0.51	0.41
F-test	(0.93)	(0.60)	(0.71)	(0.77)	(0.48)	(0.52)

Table III
Summary of F-Test Results for Different Asset Categories

For each bond *i*, we estimate equation (2) using weekly data from January 4, 2007 to January 29, 2009, ΔLIB-OIS is the percentage change of the spread between the 3-month LIBOR and the Overnight Index Swap (OIS). This table summarizes the F-test results for the LIB-OIS state variable and its lags. The null hypothesis of F-test is the sum of all coefficients of ΔLIB-OIS and its lags is zero. The numbers in the table indicate how many F-tests of bonds in each category are significant at various confidence levels. Asset categories are listed in Panel A of Table I. “Negative” and “Positive” indicate the sign of the sum of coefficients for ΔLIB-OIS and its lags.

Panel A: Whole Period: January 4, 2007 to January 29,2009

		Negative			Positive		
Categories	Total Number	10%	5%	1%	10%	5%	1%
Subprime	63	1	1	0	2	1	2
Nonsubprime_US	176	3	0	0	4	7	106
Nonsubprime_Europe	59	0	0	0	0	6	39
Financial	46	0	0	0	3	2	6
Industrial	48	0	0	0	5	14	9
Total	392	4	1	0	14	30	162

Panel B: Subperiod I: January 4, 2007 to December 27,2007

		Negative			Positive		
Categories	Total Number	10%	5%	1%	10%	5%	1%
Subprime	63	2	4	2	0	2	1
Nonsubprime_US	176	4	0	1	8	21	75
Nonsubprime_Europe	59	0	0	0	5	10	24
Financial	46	3	1	0	1	2	1
Industrial	48	0	0	0	0	1	4
Total	392	9	5	3	14	36	105

Panel C: Subperiod II: January 3, 2008 to January 29,2009

		Negative			Positive		
Categories	Total Number	10%	5%	1%	10%	5%	1%
Subprime	63	1	0	0	0	0	0
Nonsubprime_US	176	8	0	0	23	26	41
Nonsubprime_Europe	59	0	0	0	0	1	0
Financial	46	0	0	0	6	10	6
Industrial	48	0	0	0	6	9	21
Total	392	9	0	0	35	46	68

Table IV

Summary of F-Test Results for Different Rating Classes

For each bond *i*, we estimate equation (2) using weekly data from January 4, 2007 to January 29, 2009, ΔLIB-OIS is the percentage change of the spread between the 3-month LIBOR and the Overnight Index Swap (OIS).This table summarizes the F-test results for the LIB-OIS state variable and its lags. The null hypothesis of F-test is the sum of all coefficients of ΔLIB-OIS and its lags is zero. The numbers in the table indicate how many F-tests of bonds in each rating class are significant at various confidence levels. "Negative" and "Positive" indicate the sign of the sum of the coefficients for ΔLIB-OIS and its lags.

Panel A: Whole Period: January 4, 2007 to January 29,2009

		Negative			Positive		
Rating	Total Number	10%	5%	1%	10%	5%	1%
AAA	157	4	0	0	4	10	83
AA	47	0	1	0	1	3	9
A	74	0	0	0	3	5	33
BBB	83	0	0	0	2	6	36
Other	31	0	0	0	4	6	1
Total	392	4	1	0	14	30	162

Panel B: Subperiod I: January 4, 2007 to December 27,2007

		Negative			Positive		
Rating	Total Number	10%	5%	1%	10%	5%	1%
AAA	157	5	1	1	9	25	47
AA	47	0	0	1	0	1	7
A	74	0	2	0	3	4	27
BBB	83	1	1	0	1	5	23
Other	31	3	1	1	1	1	1
Total	392	9	5	3	14	36	105

Panel C: Subperiod II: January 3, 2008 to January 29,2009

		Negative			Positive		
Rating	Total Number	10%	5%	1%	10%	5%	1%
AAA	157	0	0	0	4	13	44
AA	47	1	0	0	3	12	4
A	74	4	0	0	14	9	5
BBB	83	4	0	0	9	11	5
Other	31	0	0	0	5	1	10
Total	392	9	0	0	35	46	68

Table V
Repo Spreads Regression Results

For each class of securitized bonds, we estimate equation (3) using weekly data from January 4, 2007 to January 29, 2009. ΔLIB-OIS is the percentage change of the spread between the 3-month LIBOR and the Overnight Index Swap (OIS). ΔABX is the parentage change of the ABX index at period t. ΔOIS is the Overnight Index Swap. Δr-10 is the change in yield on the 10-year Treasury, with its square given by (Δr-10)^2. ΔSlope is the change in 10-year minus 2-year Treasury yields. ΔVIX is the change in implied volatility of S&P 500, and ΔS&P is the return on S&P 500. t-statistics are given in parentheses below the coefficient estimates. The last two rows report F-statistics and p-values for the key state variables. The null hypothesis of the LIB-OIS F-Test is that the sum of all coefficients of ΔLIB-OIS and its lags is zero. The null hypothesis of the ABX F-Test is the sum of all coefficients of ΔABX and its lags is zero. The null hypothesis of the VOL F-Test is the sum of all coefficients of VOL and its lags is zero.

	Repo Rate Spreads				
	A-AAA ABS-Auto / CC / SL	<AA ABS-RMBS / CMBS	AA-AAA ABS-RMBS / CMBS	AA-AAA CLO	AA-AAA CDO
Intercept	0.035	0.015	0.016	0.017	0.024
	(0.86)	(0.89)	(0.71)	(0.71)	(0.93)
ΔLIB-OIS	1.321	0.825	1.043	1.025	0.558
	(12)	(17.26)	(16.45)	(15.66)	(7.26)
ΔLIB-OIS, t-1	-0.168	-0.004	-0.056	-0.068	0.044
	(-1.58)	(-0.1)	(-0.93)	(-1.08)	(0.67)
ΔLIB-OIS, t-2	0.084	0.071	0.099	0.115	0.062
	(0.8)	(1.57)	(1.65)	(1.85)	(0.85)
ΔLIB-OIS, t-3	-0.134	0.004	-0.040	-0.021	0.010
	(-1.27)	(0.09)	(-0.66)	(-0.35)	(0.15)
ΔABX	-0.188	-0.152	-0.169	-0.183	-0.031
	(-0.86)	(-1.59)	(-1.32)	(-1.4)	(-0.23)
ΔABX, t-1	0.227	0.020	0.072	0.076	0.206
	(1.03)	(0.21)	(0.57)	(0.58)	(1.5)
ΔABX, t-2	0.435	0.007	0.092	0.086	0.037
	(1.99)	(0.07)	(0.73)	(0.66)	(0.28)
ΔABX, t-3	0.018	0.064	0.057	0.085	0.052
	(0.08)	(0.67)	(0.44)	(0.66)	(0.38)
ΔVOL	-0.002	0.000	0.000	0.000	0.000
	(-0.32)	(0.15)	(0.42)	(0.25)	(0.25)
ΔVOL, t-1	0.000	0.000	-0.001	-0.001	-0.002
	(0.03)	(-0.35)	(-0.73)	(-0.6)	(-0.84)
ΔVOL, t-2	-0.002	0.000	0.001	0.001	0.001
	(-0.32)	(0.76)	(0.98)	(0.45)	(0.26)
ΔVOL, t-3	0.001	0.000	-0.001	-0.001	0.002
	(0.18)	(-0.78)	(-1.19)	(-1.3)	(0.8)
ΔOIS	0.060	-0.044	-0.078	-0.005	0.184
	(0.11)	(-0.19)	(-0.21)	(-0.01)	(0.21)
Δr-10	0.085	0.023	0.085	0.028	0.142
	(0.4)	(0.27)	(0.73)	(0.23)	(0.79)
(Δr-10)^2	-0.178	-0.019	0.010	0.019	-0.082
	(-0.52)	(-0.13)	(0.05)	(0.09)	(-0.35)
ΔS&P	-0.374	0.136	-0.158	0.430	-2.373
	(-0.21)	(0.17)	(-0.15)	(0.39)	(-1.38)
ΔVIX	0.004	0.000	0.001	0.006	0.000
	(0.29)	(-0.01)	(0.09)	(0.64)	(-0.01)
ΔSlope	-0.218	-0.080	-0.122	-0.027	-0.196
	(-0.98)	(-0.81)	(-0.92)	(-0.2)	(-0.99)
LIB-OIS F-Test	32.56	129.61	100.87	96.07	30.37
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
ABX F-Test	1.44	0.12	0.05	0.07	1.07
	(0.23)	(0.73)	(0.82)	(0.79)	(0.3)
VOL F-Test	0.53	0.01	0.34	1.80	0.14
	(0.47)	(0.93)	(0.56)	(0.18)	(0.71)

Table VI
Haircut Regression Results

For each class of securitized bonds, we estimate equation (7) using weekly data from January 4, 2007 to January 29, 2009, ΔLIB-OIS is the percentage change of the spread between the 3-month LIBOR and the Overnight Index Swap (OIS). ΔABX is the parentage change of the ABX index at period t. ΔOIS is the Overnight Index Swap. Δr-10 is the change in yield on the 10-year Treasury, with its square given by (Δr-10)^2. ΔSlope is the change in 10-year minus 2-year Treasury yields. ΔVIX is the change in implied volatility of S&P 500, and ΔS&P is the return on S&P 500. t-statistics are given in parentheses below the coefficient estimates. The last two rows report F-statistics and p-values for the key state variables. The null hypothesis of the LIB-OIS F-Test is that the sum of all coefficients of ΔLIB-OIS and its lags is zero. The null hypothesis of the ABX F-Test is the sum of all coefficients of ΔABX and its lags is zero. The null hypothesis of the VOL F-Test is the sum of all coefficients of VOL and its lags is zero.

Panel A: Haircut Regression with Lags					
	Change of Haircuts				
	A-AAA ABS- Auto / CC / SL	<AA ABS- RMBS / CMBS	AA-AAA ABS- RMBS / CMBS	AA-AAA CDO	AA-AAA CLO
Intercept	0.00096	0.00266	0.00194	-0.00514	0.00311
	(0.69)	(1.19)	(1.08)	(-0.34)	(1.59)
ΔLIB-OIS	-0.00010	0.00009	0.00010	0.00121	0.00003
	(-1.44)	(0.89)	(1.25)	(0.85)	(0.27)
ΔLIB-OIS, t-1	-0.00010	0.00001	-0.00002	0.00079	0.00008
	(-1.53)	(0.07)	(-0.24)	(0.55)	(0.67)
ΔLIB-OIS, t-2	0.00005	0.00008	0.00011	-0.00053	-0.00016
	(0.75)	(0.75)	(1.31)	(-0.41)	(-1.45)
ΔLIB-OIS, t-3	-0.00001	-0.00014	-0.00010	0.00073	0.00006
	(-0.12)	(-1.2)	(-1.18)	(0.62)	(0.74)
ΔABX	0.00001	0.00000	0.00001	0.00004	0.00000
	(1.05)	(0.33)	(1.19)	(0.69)	(-0.34)
ΔABX, t-1	0.00000	-0.00001	0.00000	0.00001	0.00000
	(0.06)	(-1.05)	(-0.64)	(0.2)	(0.18)
ΔABX, t-2	0.00000	0.00001	0.00001	0.00002	0.00000
	(0.12)	(0.67)	(0.86)	(0.32)	(0.43)
ΔABX, t-3	0.00000	-0.00001	-0.00001	0.00003	-0.00001
	(-0.79)	(-1.4)	(-1.58)	(0.44)	(-1.34)
ΔVOL	0.00036	0.00001	0.00000	0.00311	0.00015
	(2.31)	(0.52)	(-0.06)	(3.19)	(2.05)
ΔVOL, t-1	-0.00049	-0.00001	-0.00001	-0.00345	0.00000
	(-2.01)	(-0.24)	(-0.12)	(-2.37)	(0.04)
ΔVOL, t-2	0.00049	0.00002	0.00003	0.00235	-0.00016
	(2.09)	(0.36)	(0.34)	(1.57)	(-1.61)
ΔVOL, t-3	-0.00005	-0.00001	-0.00004	0.00006	0.00017
	(-0.28)	(-0.52)	(-0.69)	(0.05)	(1.99)
ΔOIS	0.00476	-0.01801	-0.01655	-0.09061	-0.01967
	(0.4)	(-0.92)	(-1.02)	(-0.67)	(-1.2)
Δr-10	0.00413	-0.01072	-0.00689	0.04610	0.00241
	(0.6)	(-1.02)	(-0.82)	(0.51)	(0.26)
(Δr-10)^2	0.00703	-0.00617	-0.00882	-0.13209	-0.00100
	(0.64)	(-0.36)	(-0.62)	(-0.97)	(-0.06)
ΔS&P	0.03663	-0.02488	-0.06200	0.07360	-0.00699
	(0.66)	(-0.28)	(-0.89)	(0.09)	(-0.09)
ΔVIX	0.00037	-0.00014	-0.00042	0.00098	-0.00074
	(0.77)	(-0.18)	(-0.68)	(0.14)	(-1.07)
ΔSlope	0.01253	0.01069	0.00682	-0.07066	-0.00906
	(1.63)	(0.85)	(0.67)	(-0.7)	(-0.85)
LIB-OIS F-Test	1.47	0.06	0.69	0.89	0.01
	(0.23)	(0.81)	(0.41)	(0.35)	(0.91)
ABX F-Test	0.05	0.58	0.01	0.64	0.32
	(0.83)	(0.45)	(0.92)	(0.43)	(0.57)
VOL F-Test	4.66	0.07	0.29	5.33	5.53
	(0.03)	(0.80)	(0.60)	(0.02)	(0.02)

Gropp, Reint; Lo Duca, Marco; Vesala, Jukka

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Abstract

This paper analyses cross-border contagion in a sample of European banks from January 1994 to January 2003. We use a multinomial logit model to estimate the number of banks in a given country that experience a large shock on the same day ("coexceedances") as a function of variables measuring common shocks and coexceedances in other countries. Large shocks are measured by the bottom 95th percentile of the distribution of the first difference in the daily distance to default of the bank. We find evidence in favour of significant cross-border contagion. We also find some evidence that since the introduction of the euro cross-border contagion may have increased. The results seem to be very robust to changes in the specification.

JEL codes: G21, F36, G15

Keywords: Banking, Contagion, Distance to default, Multinomial logit model

1. **Introduction**

Contagion is widely perceived to be an important element of banking crises and systemic risk. Very prominently, for example, the private sector rescue operation of LTCM in 1998, co-ordinated by the Federal Reserve Bank of New York was justified by the risk of contagion. Similarly, contagion transmitted through the interbank market played a major role in the failure of a number of Japanese Securities houses in the early 1990s (Padoa-Schioppa, 2003). The aim of this paper is to estimate the extent of cross-border contagion among the banking sectors of the largest EU countries. It is intended to contribute to a better understanding of the degree to which European banking systems have become interconnected and how banking problems could spread across borders.

When we use the term "contagion", we mean the transmission of a shock affecting one bank or possibly a group of banks and how this shock is transmitted to other banks or banking sectors. Defined in this way, contagion is a subset of the broader concept of a systemic crisis, which may be the result of contagion or of a common shock affecting all banks simultaneously. In this paper, we use the distance to default (e.g. KMV, 2002), a market based indicator of the soundness of the bank. The distance to default is defined as the difference between the current market value of assets of a firm and its estimated default point, divided by the volatility of assets[1]. In order to investigate contagion among banking systems we focus on the behaviour of the tail of the distribution of the change in the distance to default[2]. For each country we construct an indicator variable named "coexceedances" by counting the number of banks that experience a large shock in the distance to default on a given day. Large shocks are measured by large negative (in the bottom 95th percentile of the distribution) percentage changes in the daily distance to default of the bank. We then estimate the probability of several bank simultaneously experiencing a large shock in country j as a function of systemic risk emanating from domestic and international risk factors and from coexceedances in the other large EU countries. Econometrically, our approach builds on a recent papers by Bae et al. (2003) which uses a similar methodology to study contagion among stock market returns in emerging economies.

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[1] We give a detailed description of the distance to default in the next section.

[2] Our choice of focusing on the tails of the distribution has already been adopted in the literature. Gropp and Moerman (2004) use the co-incidence of extreme shocks in banks' distance to default to examine contagion. They employ Monte Carlo simulations to show that standard distributional assumptions (multivariate Normal, Student t) cannot replicate the patterns of observed in tails of the data. This implies that not only the distribution of distances to default of individual banks exhibit fat tails, but also that the correlation among banks' distances to default is substantially higher for larger shocks. Bae et al. (2003) do the same for emerging market stock returns and conclude, as Gropp and Moerman (2004) that it may be justified to examine the tails of the distribution of returns (in our case of the distance to default) only.

For our sample of (predominately) large banks[3] for January 1994 to January 2003 that are stock market listed, we find evidence of significant cross border contagion. We also find some evidence that cross-border contagion increased in importance after the introduction of the euro. We subject the results to a battery of robustness checks and find them to be quite robust to changes in specification, method of estimation, selection of banks and other considerations.

The theoretical banking literature has focussed on contagion among banks via the interbank market. Allen and Gale (2000) show that, in a Diamond/Dybvig (1983) liquidity framework an “incomplete” market structure, with only unilateral exposure chains across banks, is the most vulnerable to contagion. In contrast, a “complete” structure, with banks transacting with all other banks, contains less risk of contagion.[4] A “tiered structure” of a “money centre” bank (or banks), where all banks have relations with the centre bank, but not with each other, is also susceptible to contagion (Freixas, Parigi and Rochet, 2000). In both papers, contagion arises from unforeseen liquidity shocks, i.e. banks withdrawing interbank deposits at other banks. Alternatively, contagion conceivably could arise from credit risk in the interbank market, namely deposits at other banks not being repaid.[5]

There may be contagion even in the absence of explicit financial links between banks. In the presence of asymmetric information difficulties in one bank may be perceived as a signal of possible difficulties in others, especially if one thinks that banks’ assets may be opaque and balance sheet data and other publicly available information may be uninformative (Morgan, 2002).[6] In Freixas, Parigi and Rochet (2000) if a liquidity shock hits one bank, depositors may run on other banks as well, even if they are perfectly solvent, if they fear that there may be insufficient liquid assets in the banking system. Recently, Cifuentes et al. (2004) have proposed that there may be contagion through fire sales of illiquid assets. If banks use fair value accounting to value at least some of their illiquid assets at imputed market prices and the demand for illiquid assets is less than perfectly elastic, sales by distressed institutions depress the market prices of such assets. Prices fall, inducing a further round of sales and so forth.

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3 We use the largest stock listed banks in Germany, France, Italy, The Netherlands, Spain and the United Kingdom.

4 The intuition is that in the case of an “incomplete” market (or "tiered structure"), the effects of a shock hitting one bank are concentrated, while in the case of a “complete” market the shock is distributed among a large number of banks and, thus, it can be more easily absorbed.

5 Iyer and Peydro-Alcalde (2005a) model the mechanism of contagion through the money market and show how the reactions of banks initially unaffected by the shock can result in an endogenous reduction in liquidity, which in turn results in further stress on the banking system.

6 For recent evidence to the contrary see Flannery et al. (2004).

In their model, relatively small shocks can result in contagious failures in the banking system.[7]

There is a vast previous empirical literature on within-country contagion. First, evidence of contagion has been estimated using autocorrelation and survival time tests using historical data on bank failures. A number of papers have tested for autocorrelation in bank failures, controlling for macroeconomic conditions, generally in historical samples during which bank failures were common occurrences in the US.[8] Most of these studies find some evidence of contagion, i.e. bank failures tend to be autocorrelated controlling for macro variables. Similarly, using survival time tests, Calomiris and Mason (2000) find that bank-level, regional and national fundamentals can explain a large portion of the probability of survival of banks during the Great Depression. They also find some evidence of contagion, which, however, is limited to specific regions of the US. Inherently, both approaches are limited to times of sweeping bank failures.

In this paper, we examine the spill over effects during calm times using a stock market-based default risk indicator (distance to default). In this way, we hope to uncover information that may still be indicative of the links during times of actual crisis. In this sense, studies examining the reaction of stock prices to news and studies using actual interbank data and simulating the failure of one or more banks are more closely related to our work. The literature examining the reaction of stock prices to news suggests that stock price reactions vary proportionally to the degree of the news' extent of affecting the bank and banks' share prices react to problems of other banks. However, the findings could also be consistent with no contagion, as the results may be driven by common shocks, rather than contagion.[9]

A large number of papers for different countries have used actual or estimated interbank links to simulate contagion. Generally, the evidence of contagion resulting in significant bank failures is mixed. While Furfine (2003) for the US and Sheldon and Maurer (1998) for Switzerland find relatively benign effects, Upper and Worms (2003) estimate a matrix of interbank loans for German banks and find some stronger evidence of contagion risk. Degryse and Nguyen (2004) for Belgium find that the patterns of linkages changed from a structure with complete links among banks to one in which

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[7] Other channels of contagion could be the payment system, where difficulties in one bank may lead to credit losses to other banks (in netting systems) or gridlock in the entire system or ownership links among banks.

[8] Grossman (1993) looks at U.S. data for 1875-1914, Hasan and Dwyer (1994) consider the U.S. free banking era (1837-1863), and Schoenmaker (1996) the years 1880-1936, again in the U.S.

[9] For a survey see De Bandt and Hartmann (2001).

there are multiple money centre banks. Overall, the change in structure suggests a decrease in the risk of contagion. While Degryse and Nguyen discuss the possibility of cross-border contagion, generally the simulations studies concentrate on contagion risk within one country, rather than across countries.

Most closely related to the approach in this paper and the only other paper we are aware of that examines cross-border contagion among banking systems, Hartmann et al. (2004b) use multivariate extreme value theory to estimate contagion in Europe and the US. They find that contagion may have increased from the mid-1990s onwards both in Europe and the US. Overall, however, the level of contagion risk in the US remains higher than in the EU. Iyer and Peydro-Alcalde (2005b) estimate in a unique dataset for India the effect of the failure of one large regional bank (due to fraud). They find that banks' exposures with the failed bank in the interbank market as an important determinant of depositor withdrawals of the banks. The evidence is strongly supportive of contagion in interbank markets.

The remainder of the paper is organised as follows. In the next Section, we describe the data used in the paper and give some descriptive statistics. Section III explains our primary econometric approach, the multinomial logit model. Section IV presents our econometric results. Section V discusses a few issues related to the robustness of our findings. Finally, Section VI concludes the paper.

2. Sample, definition of variables and descriptive statistics

In our sample selection, we started with all banks in France, Germany, Italy, The Netherlands, Spain and the United Kingdom that are listed at a stock exchange and whose stock price and total debt are available from Datastream during January 1994 to January 2003 (50 banks). We limited ourselves to these countries, as almost all largest internationally active European banks are headquartered in these countries (see Table 1). We deleted all banks that had trading volume below one thousand stocks in more than 30% of all trading days and banks which had less than 100 weeks of stock data available (7 banks). We deleted three additional banks where we had serious concerns about data quality.[10] For those banks where the distant to default was not available for the entire period under review (5 banks), we imputed a total of 342 missing values using linear interpolation and random numbers (for details see the notes to table 2). In this

[10] The banks showed zero equity returns on a high number of trading days, resulting in extremely volatile distances to default.

way, we ensure that the "coexceedances" (see below) for each country are built using the same banks during the entire period under analysis. This yields a complete data set for 40 banks. For each bank the sample contains 2263 daily observations, i.e. a total of 94,520 observations.

The banks in the sample are generally quite large relative to the population of banks in the EU (Table 1). On average, their total assets amount to EUR 178 billion (median: EUR 132 billion). The relatively large average size is an outcome of the requirement that the bank be traded at a stock exchange. Nevertheless, the size variation is considerable within the sample. For example, the largest bank, Deutsche Bank, is more than 300 times the size of the smallest. The degree of coverage in each country depends on the number of banks traded at a stock exchange and the structure of the banking system, but despite the relatively low number of banks the coverage is quite high. The fraction of the total assets of commercial banks covered in our data varies from 36% for France to 68% for Spain.[11]

The distance to default (KMV, 2002), is defined as the difference between the current market value of assets of a firm and its estimated default point, divided by the volatility of assets. In order to compute the distance to default some assumptions must be made. Intuitively, the value of equity of a company can be seen as a call option, since at the time of the repayment of the debt the value of equity is the maximum between zero and the difference between total assets and total debt. Equity is therefore modelled as a call option on the assets of the company. The level and the volatility of assets are calculated with the Black and Scholes model using the observed market value and volatility of equity and the balance sheet data on debt. A detailed description of the method used to compute the distance to default is in Appendix 1. The distance to default increases either when the values of assets increases or/and when volatility of assets goes down. An increase in the distance to default means that the firm is moving away from the default point and that the bankruptcy event becomes less likely. Being a market based measure of distress, the distance to default has the advantage that it contains expectations of market participants and therefore it is forward looking. Gropp et al. (2004, 2006) argue that, specifically with respect to banks, the distance to default may be a particularly suitable and all-encompassing measure of default risk. In particular, its ability to measure default risk correctly is not affected by the potential incentives of the stock holders to prefer increased risk taking (unlike e.g. in the case of unadjusted equity returns) or by the presence of explicit or implicit safety nets (unlike e.g. subordinated

[11] The total assets of commercial banks in a country were taken from the OECD's Bank Profitability data.

debt spreads). Further, it combines information about stock returns with leverage and volatility information, thus encompassing the most important determinants of default risk (unlike e.g. unadjusted stock returns).

In order to obtain our dependent variable, we calculated the daily distance to default for each bank in the sample and for each time period, t,. We then defined large shocks as the negative 95th percentile of the common distribution of the percentage change in distance to default ($\Delta dd_{it} / | dd_{it} |$) across all banks.[12] Choosing the bottom 95th percentile was a compromise between the need for "large" shocks in the spirit of extreme value theory (Straetmans, 2000) and maintaining adequate sample size for the estimation. Finally, we counted the number of banks in a given country that were simultaneously in the tail, which we, following Bae et al. (2003), labelled the coexceedances of banks in a given country.

In order to control for common shocks we rely on the existing literature on financial crises and contagion (Forbes and Rigobon, 2002, and Rigobon, 2003). Our model is basically a factor model in which the occurrence of coexceedances is a function of some domestic and international common factors and coexceedances in other countries. In our model, coexceedances in other countries are the source of potential contagion. We use four variables to control for common shocks. The main selection criterion was that the variables can be measured at a daily frequency. This is essential, as we want to model daily innovations in the distance to default.[13]

The first common factor, which we label "systemic risk", is an indicator measuring the number of stock markets that are experiencing a large shock at time t. We construct this variable as follows: Emulating our approach to modelling large shocks in banks, we use indicator variables that we set equal to one if a stock market of a given country experienced a shock large enough to be in the bottom 95th percentile of the distribution of daily returns. Equivalently, we calculate indicator variables for the Euro Area stock market index, the US and Emerging market stock indices. We use total market indices as provided by Datastream; except for emerging markets the MSCI Emerging Market Index is used. "Systemic risk" is then the sum of indicator variables measuring whether or not the domestic stock market, the US stock market, the European

[12] This definition relies on the assumption that the stochastic process governing the distance to default at different banks is the same. This assumption turns out to be reasonable, however, as redoing the analyisis reported below with bank-specific tail occurrences yields quantitatively very similar results.

[13] As a consequence, many other variables available at lower frequency that might have explanatory power as common shocks do not enter into the model directly. We don't think this is a problem. Since financial variables incorporate news and expectations regarding several factors affecting the business scenario, we believe that any relevant information we might want to include regarding economic growth, monetary policy or other shocks, is discounted in financial prices.

stock market and the index of emerging market stock markets are in the tail on a given day. Hence, it ranges from 0 to 4.[14] This variables measures something that we would label a "global shock", i.e. if many markets experience large shocks simultaneously. This distinguishes it from a domestic shock, which we measure using the domestic conditional stock market volatility (see below). "Systemic risk" should be positively related to the number of coexceedances.

The second factor ("yield curve") is the daily change in absolute value of the slope of the yield curve. The slope is defined as the difference between the yield of the 10 year government bond and the yield of the 1 year note in a given country.[15] This variable is a commonly used measure of expectations on economic growth and monetary policy. One view of banks suggests that they transform short-term liabilities (deposits) into long term assets (loans). A flattening of the yield curve results in an increase of the interest rate banks have to pay on their short term liabilities without a corresponding increase in the rates they can charge on their loans. We would, thus, expect this variable to be positively related to the number of coexceedances.

The third factor ("volatility own") is the daily change in the volatility of the domestic stock market. Bae et al. (2003) found this variable to be particularly important when explaining emerging market coexceedances and we follow their approach here. Stock market volatility has been estimated using a GARCH(1,1) model of the form

(1) $$\sigma_{tc}^2 = \alpha + \beta_1 \varepsilon_{c,t-1}^2 + \beta_2 \sigma_{c,t-1}^2$$

using maximum likelihood, where σ_{tc}^2 represents the conditional variance of the stock market index in country c in period t and ε represents the error term. The estimated parameters are reported in Appendix 2. We obtain, depending on the country, values of between 0.06 and 0.11 for β_1 and between 0.89 and 0.93 for β_2. While we are interested in contagion among European banks, it is possible that there are volatility spill-overs from other parts of the world as well. To control for these, we also control for the stock market volatility from the US in the regressions, estimated also with a GARCH (1,1) ("volatility US"). [16] As US markets open later than European markets, we used data from the previous day to estimate US volatility. Further, we include one lag of the domestic coexceedances, as we suspect that first-differencing and using only the large

[14] We also experimented with including the indicator variables for each market separately. However, their correlation is generally above 0.5 within the EU and around 0.2 and 0.3 with the US and emerging markets, respectively.

[15] If the yield of the 1 year treasury note was not available, we used the interbank rate for the same maturity. The source of the data are Datastream and the BIS.

[16] "Volatility own" and "volatility US" were rescaled by multiplying the estimated values by 1000.

negative tail events of the distance to default may not have removed all autocorrelation in the dependent variable.

Table 2 shows that the banks in the sample on average are just above four standard deviations away from the default point (mean distance to default of 4.13). However, this hides substantial variation in the health of banks. Only one bank shows distances to default below one. At the other end of the spectrum, there were a number of banks with a maximal distance to default of above 10. As expected, the mean of the first difference in the distance to default is approximately zero, the largest negative change is 77%, which can truly be considered a sizeable daily shock. The negative 95th percentile is at about -1%.

Tables 3 and 4 present some additional descriptive statistics on the variable of interest, the number of banks simultaneously in the tail on a given day, i.e. the number of coexceedances. The number of banks per country differs somewhat: In Italy there are 12 banks in the sample, while in France and the Netherlands there are only three. The UK, Spain and Germany are also well represented with 8, 7 and 7 banks, respectively. Table 3 also shows that there is at least one day on which all, or almost all banks, experienced a large adverse shock simultaneously. This is explored in more detail in Table 4.

As we will estimate a multinomial logit model, which implies that we will estimate one coefficient per outcome, we follow Bae et al. (2003) and limit the number of outcomes to 0,1,2, and 3 or more coexceedances, except for France and The Netherlands where we limit the number of outcomes to 2 or more. Table 4 shows, for example, that in Spain, there were 50 days with three or more coexceedances, in the United Kingdom there were 88 such days and in Italy 125 such days, while in The Netherlands and France there were 78 and 75 days with 2 or more coexceedances, respectively. The number of coexceedances is a function of the number of banks included in the sample and does not necessarily reflect the strength or weakness of the banking sector per se. Still, comparing countries with an equal number of banks in the sample suggests that Spanish banks tend to experience fewer shocks compared to German banks and that Dutch banks tend to be about equally frequently subject to large shocks compared to French banks. Of the total of 40 banks in the sample, a maximum of 20 are simultaneously in the tail (on October 2, 1998) and there are 14 days with more than 15 coexceedances (not reported in Tables).

3. Econometric model

We study whether contagion is one factor associated with negative large movements in banks' default risk. These events can be identified from the negative tail of the distribution of the innovations in our preferred market-based indicator of default risk, the distance to default.

Our dependent variable is the number of coexceedances of banks on a given day, which is a count variable. There are many methods to estimate a model with count data as the dependent variable, including tobit models, Poisson models, negative binomial models, multinomial and ordered logit models. A tobit model is clearly inappropriate as it relies on the assumption that the dependent variable is truncated normal, an assumption, which Gropp and Moerman (2004) also show to be rejected in the data used in this paper. Poisson models rely on the assumption of equality between mean and variance of the dependent variable, an assumption, also rejected in our sample. The negative binomial model is essentially a generalised Poisson model, which avoids this restrictive assumption of mean/variance equality. Nevertheless, it still makes the restrictive assumption that the dependent variable was drawn from a mixture of Poisson random variables. Given the evidence and arguments in Gropp and Moerman (2004) and Bae et al. (2003) we do not think that the estimation of this model would be advisable. This leaves ordered logit and multinomial logit models as the preferred method. The main difference between a multinomial logit model and an ordered logit model is that the ordered logit restricts the marginal effects at each outcome to be the same. This means that the effect of coexceedances in another country on going from 1 to 2 bank coexceedances in the dependent variable is restricted to be the same as going from 3 to 4 banks, while the multinomial logit model permits for full flexibility in this regard. The trade-off is that in a multinomial logit model, there are many more parameters to estimate and one may loose degrees of freedom.

Given these considerations, we decided to use a multinomial logit model as our primary specification and use the results from an ordered logit model as a robustness check (see section V). Hence, we estimate the number of coexceedances in one country (the number of banks simultaneously in the tail) as a function of the number of coexceedances in the other countries, controlling for common shocks:

$$\Pr_c[Y = j] = \frac{e^{\left[\alpha'_j F_c + \beta_j C_{ct-1} + \gamma'_j C_{dt}\right]}}{\sum_k^J e^{\left[\alpha'_k F_c + \beta_k C_{ct-1} + \sum_{d \neq c} \gamma_{dk} C_{dt}\right]}} \quad (2)$$

,

where j = 1,2,3…J represents the number of banks in the tail simultaneously ("coexceedances") in country c, F_c the common shocks in country c, C_{ct-1} the lagged number of coexceedances in country c, and C_{dt} represents the coexceedances in period t in country d. As common shocks are controlled for, the significant coefficients of C_{dt} would signal cross-border contagion.

In order to remove the indeterminacy associated with the model, we follow the convention and define Y=0 (zero coexceedances) as the base category. All coefficients, hence, are estimated relative to this base. Still, the coefficients from this model are difficult to interpret and, therefore, it is useful to also report the marginal effect of the regressors. The marginal effects are obtained from the probability for each outcome j

$$\Pr[Y = j] = \frac{e^{\left[\alpha_j' F_c + \beta_j C_{ct-1} + \gamma_j' C_{dt}\right]}}{1 + \sum_k^J e^{\left[\alpha_k' F_c + \beta_k C_{ct-1} + \gamma_k' C_{dt}\right]}} \quad (3)$$

Differentiating with respect to C_{dt} yields

$$\frac{\partial \Pr_c[Y = j]}{\partial C_{dt}} = \Pr[Y = j] * \left[\gamma_j - \sum_{k=1}^{J} P_k \gamma_k \right], \quad (4)$$

which can be computed from the parameter estimates, with the independent variables evaluated at suitable values, along with its standard errors.[17] In all tables we will report the estimated coefficients alongside the marginal probabilities obtained from (5).

4. Estimation results

4.1. Base model

The results for the basic contagion estimation are given in Table 5. For each country we first report the results for a specification in which the controls for systemic risk and common factors are the only explanatory variables. Subsequently, we add the coexceedances from other countries. Recall that the dependent variable is the number of banks whose first-differenced distance to default was in the negative 95th tail in a given week in a given country. In all countries with more than 3 banks (DE, ES, IT, UK), we limited the model to estimating four outcomes, 0, 1, 2 and 3 or more coexceedances, while in FR and NL we estimated three outcomes, 0,1 and 2 or more coexceedances.

[17] The computation of the standard errors is exceedingly time consuming and most studies do not report them. However, both the significance and even the sign could differ between the coefficients and their marginal effects (Greene, 2000).

First consider the base model without contagion variables for the five countries (Table 5, first columns for each country). Recall that in a multinomial logit model we estimate coefficients for each outcome. Following the convention, we take the outcome of coexceedances equal to zero as the base case. Overall we are able to explain between 9 percent (IT) and 17 percent (NL) of the variation in the dependent variable using variables measuring common shocks only.[18]

The notion that the number of coexceedances are autocorrelated is supported: The lagged (by one day) number of coexceedances tends to be positive and significant for all countries. Further, global systemic risk (as measured by the number of stock markets in the tail) tends to be positive and significant. A steepening of the yield curve tends to be only weakly associated with a higher number of coexceedances in most countries; the effect is somewhat stronger in DE and FR. As in Bae et al. (2003), increases in conditional volatility are very important in our specification and are always significantly (at the 1 percent level) positively related to a higher number of coexceedances. All these results conform to expectations. We also checked whether conditional volatility in the US stock market matters for coexceedances among European banks, but the coefficients tend to be insignificant, except in case of German and Italian banks and not for UK banks, where we would have expected US volatility to be particularly important.[19]

In order to aide the interpretability of the results, we also report marginal probabilities for each coefficients (reported in the second column). We see, for example, that a one percent increase in the conditional volatility of the stock market in Germany increases the probability of one exceedance by 0.02 percent, the probability of two coexceedances by 0.01 percent and of three or more coexceedances by 0.001 percent. All of these marginal probabilities are significant at the one percent level. Similar magnitudes are found for all six countries.

Now consider the evidence on contagion. We measure contagion by including the one-day lagged coexceedances in the other five countries. If, controlling for common shocks, as we have done, any of these variables turn out to be positive and significant, we interpret this as contagion from that country. We also report significance tests for the sum of the contagion variables from each country, as well as the sum of all contagion variables. We find that the contagion variables are jointly significant at least

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[18] As a comparison: in the context of emerging markets, Bae et al. (2003) find pseudo R^2 of around 0.1 in a similar type of model, using three explanatory variables (conditional volatility, exchange rates and interest rates).

[19] Given that there is ample evidence for stock market spill overs from the US to Europe (see Hartmann et al. (2003), these may be captured by our “systemic risk” variable.

at the five percent level for explaining the number of coexceedances in all six countries. This is also reflected in an increase in Pseudo R^2 of generally about 1 to 2 percentage points. It is important to note that adding the one-day lagged coexceedances from other countries does not result in large changes in the level or significance of the controls, suggesting that adding foreign coexceedances adds information to the specification.

The patterns of contagion among countries can be more easily examined using Chart 2. In this chart, we represented the joint significance of the lagged coexceedance variable in country A in the specification for country B as an arrow from country A to country B. A few observations can be made. One, we only find one country pair where we have evidence in favour of bi-lateral contagion, namely UK and DE. This means that adverse shocks affecting German banks have an impact upon UK banks and vice versa. Second, aside from being exposed to contagion from the UK, German banks are also exposed to contagion from Spanish and Dutch banks. Second, Spanish banks tend to be particularly important for the banking systems in other countries, which may be somewhat surprising. In addition to German banks, also French, UK and Dutch banks have been exposed to contagion from the Spanish banking system. Third, Spanish banks themselves are exposed to contagion from Italian banks only.

While we find the contagion variables to be econometrically highly significant, their economic magnitude is difficult to interpret. Hence, in order to shed some light on this, we have plotted the probability of one or more banks being in the tail (experiencing a large shock) conditional on the number of banks in other countries being in the tail on the previous day, setting all other control variables to their unconditional mean. Bae et al. (2003) in a similar exercise have labelled these types of curves "coexceedance response curves" and report that these curves have their origin in epidemiology, where they were used to show the spread of infectious disease across regions.

First let us examine the effect of conditional volatility of the stock market ("volatility own") on coexceedances of banks. In Chart 1 we plotted coexceedances in each country as a function of conditional volatility increasing from the lowest 5th percentile (i.e. conditional volatility strongly decreasing) to the highest 5th percentile. Hence, the charts show the effect of the most important common shock on coexceedances. We find that the curves are highly non-linear, supporting our use of a multinomial logit model. In general, if conditional volatility increases strongly (i.e. above the 75th percentile), the probability of more than one coexceedance increases to between 20% (FR) and 50% (IT) from 3% and 20%, respectively. Three or more coexceedances increase from essentially zero at negative changes in volatility to 2% (ES) to 10% (IT). These results give use a benchmark against which we can evaluate the effects of contagion.

Now in comparison consider the effect of contagion. First consider the upper left hand panel of Chart 3, which shows contagion from French banks to German banks. The Chart shows that the probability of 3 or more German banks being in the tail is 1.1 percent if no French banks are in the tail. If three French banks are in the tail, this probability increases to 2.8 percent. In the econometric analysis we found this effect to be insignificant. Now consider the case of contagion from The Netherlands to Germany (depicted in the fourth panel from the left in Chart 3). The probability that three or more German banks are in the tail remains unchanged at just above 1 percent no matter how many Dutch banks are in the tail, but the probability that at least one German bank is in the tail increases from 20 percent in the case of no Dutch banks in the tail to 42 percent in the case of three Dutch banks in the tail. In the econometric analysis we found this effect is significant at the 5 percent level. Contagion from Dutch banks to the German banking system is significantly stronger than contagion from French banks, but it tends to affect only one or two banks, rather than a large number of banks. The opposite is true for contagion from Spain to Germany (panel 2 in Chart 3). In this case, the probability of one or more coexceedances in Germany is not a function of coexceedances in Spain, but the probability three or more coexceedances increases from less than one percent to 3.5%. Contagion from Spain tends to affect many banks, rather than just one.

In the case of France (Chart 4), we only found statistically significant contagion from Spain, where the probability of two or more coexceedances increases from 0.2% to 5%. Contagion to Italian banks is also important (Chart 6). For example, in the case of no German coexceedances the probability of three or more coexceedances in Italy is 2.4%; for three or more German coexceedances this probability increases to 5.4%. This change is significant at the one percent level. It is also interesting to note that the probability that only one bank in Italy is in the tail is not affected by German coexceedances. Finally consider the case of contagion to the UK. The case of the UK is particularly interesting, because it is the only country in the sample that did not introduce the euro in 1999. We find that there is significant contagion to the UK from German and Spanish banks. If there are no coexceedances in Germany the probability of three or more coexceedances in the UK is 1.1%, which increases to 6.7% if there are three or more German coexceedances (the change is significant at the one percent significance level). The contagion effects from Spain to the UK, although also statistically significant is much smaller: the increase is from 1.2% to 3.5%.[20] Given the size and importance of its banking system it may be at first glance surprising that we do not find evidence of stronger contagion from the UK to euro area countries. UK coexceedances are only significantly related to German coexceedances. The relationship between UK banks and the unified euro area money market after 1999 will be explored in more detail in the next section.

4.2. Extension: Effect of the introduction of the euro

The effect of the introduction of the common currency on cross-border contagion risk among EU countries is ambiguous ex ante. One could argue that the common currency on 1 January 1999 would give rise to further cross-border contagion risk, since it has led to a single money market for liquid reserves in euro, strengthening the cross-border interbank links among banks. This would be the case, especially, if cross-border transactions are mainly conducted by money centre banks. On the other hand, Allen and Gale (2000) have argued that in a system, in which interbank liabilities and assets are very well diversified across many banks, cross-border contagion risk should decrease. Hence, the integration of the money market in the wake of the introduction of the common currency may have resulted in a reduction in contagion risk. It is also interesting to see the effect of the introduction of the euro on contagion risk to and from the UK, as the UK has not joined the euro.

In order to analyse this issue we estimate the model separately for the pre- and a post-euro periods. For the pre-euro period we have 1302 daily observations in the sample and for the post euro period we have 1058 observations, i.e. the sample is split about in half. The results are reported in Table 6. Before we discuss the results regarding contagion, there may be a few issues worth noting about the results more generally. One, the fit of the model is better in almost all countries for the post-euro period. The pseudo R^2 is higher by 2 percentage points (UK, IT) to 7 percentage points (FR). Only in Germany and Spain does it remain the same.

This result is consistent with the idea that idiosyncratic factors explain less of the coexceedances after the euro was introduced and may be suggestive of financial integration (see for example Baele et al., 2004). Second, the coefficients on some of the

[20] It is quite in line with our priors that we find that German and Spanish banks have contagious effects on the UK. German banks have large interbank exposures to the UK and Spanish banks have quite close ties with UK banks, as e.g. evidenced by the recent merger between Banco Santander and Abbey National.

control variables change substantially, both in terms of economic magnitude and in terms of econometric significance, although conditional volatility remains the most important variable explaining coexceedances.

Charts 9 and 10 represent graphically the estimated patterns of cross-border contagion for the two periods. Overall, the introduction of the euro appears to have increased cross-border contagion. In order to systematise the discussion, let us distinguish three cases: (i) contagion between two countries exists before and after the introduction of the euro; (ii) contagion exists only before the introduction of the euro and (iii) contagion exists only after the introduction of the euro. In the first category, we find that contagion from ES to UK and FR and the bilateral contagion between UK and DE have prevailed. As to the second category, we find that there is no longer contagion from NL to DE, from FR to IT and from ES to DE. In the third case of new contagion patterns, we find that after the euro there is evidence of contagion from FR to UK, UK to ES and bilateral contagion between DE and IT.

In our view, this evidence is consistent not only with somewhat overall higher cross-border contagion risk, but also with the idea that this higher cross-border contagion risk may be related to the integration of the money market in the euro area.

We now turn to the question whether the economic magnitude of contagion has also changed. To examine this, we prepared the conditional probability charts for the two periods separately (see Charts 11-16). We conclude from the charts that, overall, the economic magnitude of contagion before and after the introduction of the euro has remained largely unchanged. Hence, we would conclude that the main change relates to the greater presence of contagion after the euro, rather than, given its presence, that its effect is stronger. One exception to this may be contagion to and from the UK, which we find to possibly have somewhat increased in magnitude, in particular to and from IT, NL and ES. Again, we would interpret this as evidence that UK banks may have increased their exposure to the common euro area money market.

5. Robustness

As we are estimating a large number of coefficients, we were concerned that some of our results may be spurious. Hence, we subjected the results to five robustness checks: (i) we excluded from the sample well-identified systemic crisis periods; (ii) we re-estimated the model using ordered logit, rather than multinomial logit models; (iii) we added foreign country conditional volatilities to the specification; (iv) we re-estimated the model for the largest and smallest banks in the sample separately and (v) we relax the assumption of a common stochastic process driving the returns across banks.[21] Rather than report a full set of results for each specification, we summarised the robustness checks in simple matrix tables reported in Appendix III.

As a first robustness check, we re-estimated the base model with contagion effects (Table 5) excluding the following periods: the week of September 11 (US terror attacks), the July and October of 1997 (Asia and Hong Kong crisis) and the first two weeks of October 1998 (Russia's default). The results are reported in the second panel in Appendix III. During these time periods, the number of coexceedances was particularly high and we were concerned that our results could in part be driven by the inability of the control variables to properly account for either event, given that they are clearly identified as common shocks, rather than contagion. Comparing the results to the first panel of Appendix III, which summarises the base specification in Table 5, however, reveals that the results are unaffected by the exclusion of these episodes of systemic financial stress. Indeed, the only difference is that we find additional contagion risk, namely from ES to IT and from UK to ES.

As we discussed in section II, there are a number of alternatives for the estimation of count data. While we would consider Poisson models and tobit models inappropriate for reasons specified above, an ordered logit model seems to represent a useful robustness check. As discussed above the main difference is that the ordered logit model relies on the assumption of constant marginal effects across the different outcomes, while the multinomial logit model permits full flexibility in this regard. The advantage of the ordered logit model is that we gain degrees of freedom, as we have to estimate each covariate only once and not once for each outcome in the dependent variable. When performing this estimation, the results of which are reported in the third panel of Appendix III, we found almost identical patterns of contagion compared to the base line. The only difference is that we are no longer able to detect any contagion from ES to DE.

Next, it is possible that our results are at least in part driven by volatility spill-overs from other countries rather than contagion. In order to examine this, we re-estimated the base model and included also the conditional volatility variables of the

[21] We also estimated the model with domestic stock market tail events as a separate explanatory variable (rather than subsumed in "systemic risk"). The contagion patterns obtained are broadly unchanged and the domestic stock market variable is generally insignificant, suggesting that domestic systemic risk is picked up by the conditional volatility variable. The results are available from the authors upon request.

other countries in cases where we found significant contagion. For example, we detect contagion from the UK to Germany. It is possible that the coexceedances in the UK only proxy for large changes in conditional volatility in the UK, which in turn have an effect on coexceedances in Germany. The results of this exercise are reported in panel 4 of Appendix III and are identical to our baseline results.

As documented earlier, our sample of banks is very heterogeneous in size. This permits a check of whether our results are primarily driven by large banks or whether the presence of relatively small banks has introduced some error or noise into the estimation. In general, large banks can be expected to be more important in cross-border contagion simply because they are large, but also because interbank money market links tend to be primarily through these banks. There is evidence that in the euro area at least, tiered structures have emerged in which smaller banks conduct their international business through a few large banks. This has resulted in a tiered interbank market structure with respect international operations (see e.g. Degryse and Nguyen, 2004).

To test whether large banks play a disproportionate role in our results we split the sample in small and large banks and re-estimated the basic model. An such sample split is somewhat arbitrary. In this paper we use all banks larger than EUR 170 billion (the median). The results (reported in panel 5 of Appendix III) suggest that the patterns when estimating the model with large banks are again very similar to those reported earlier, while we find very little contagion from small banks to small banks across borders (Appendix III, panel 6). These results are consistent with a tiered interbank structure, in which only large banks operate across borders in the interbank market and act as money centres for smaller domestic banks.

Finally, we also re-defined our threshold for exceedances. In the base specifications, we used the five percent tail of the joint distribution of all banks in the sample. This means that each individual banks may be more or less frequently in the tail, depending upon the frequency with which it was hit by a large adverse shock. More fundamentally, the approach implicitly relies on the idea that the stochastic process governing the distance to default of individual banks is the same. This, given the definition of the distance to default (see Appendix I) seems reasonable; however, to check the robustness of the results with respect to this assumption we re-estimated the models taking bank-specific cut off points at the five percent negative tail. The results are essentially identical to the base line, which supports the assumption that the stochastic process governing the distance to default of individual banks is similar and more generally enhances the confidence in the robustness of the results.

6. Conclusions

In this paper, we analyse cross-border contagion in the EU banking sector using a multinomial logit approach, focussing on the tail observations in a measure derived from financial market data. Applying this approach to bank contagion, we modelled banks' default risk using the stock market-based distance to default and examined the occurrence of large changes in this measure as depicting major shocks in banks' financial condition. We argued that contagion can be identified, when the incidence of such tail events is significantly influenced by a lagged measure of coexceedances of banks from another country. In order to distinguish between common shocks affecting more than one bank and contagion, we control for tail events in domestic stock markets, changes in the yield curve and changes in conditional volatility in the home and the US stock market.

We feel we are able to present fairly strong evidence in favour cross-border contagion. Cross-border contagion was found to be significant and economically relevant. Moreover the patterns of contagion were robust across a wide variety of specifications. This suggests an important pan-European dimension in the monitoring of systemic risk; a conclusion which is even strengthened by the fact that we also find the relevance of cross-border contagion after the introduction of the euro to have increased. While in this paper we do not take a position on the channel of contagion (i.e. payment systems, money markets, ownership links, pure contagion), the results suggest that the integrated money market may have resulted in an increase in contagion risk. We would take this as evidence, that the interbank market is not fully integrated in the sense of Allen and Gale's (2000) complete set of linkages among banks. Instead, the results indicate, combined with our finding that there is virtually no contagion among small banks, a "tiered" interbank structure at the cross-border level such that small banks only deal with domestic counterparties, leaving foreign operations to major international banks.

Overall we would argue that our results should be viewed as a lower bound to the true existing contagion risk in the euro area. One, we estimate the model for a relatively calm period without major financial disruptions in any of the banking systems or in any of the major banks. If contagion risk increases during crises, this is not reflected in our estimates. Second, we use lagged coexceedances (by one day) as our measure of contagion. If financial markets are semi-efficient and incorporate information very quickly, we will miss those cases of contagion taking place within one day. Third, in some countries in the sample (e.g. Spain) banks play a dominant role in the available stock market indices, suggesting that our common shock variables, such as conditional volatility, may in fact pick up effects that are related to contagion.

Finally, there may be a puzzle related to the fact that bank by bank interbank exposures are not available to the market as a whole (as they are not available to the authors). The way we interpret our results implicitly relies on the assumption that markets have this data or if they do not, at least use estimates. Alternatively, our results could be driven by market participants that do have the data, which are the banks themselves. From our perspective this would be a very interesting avenue for further research.

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Table 1. Sample banks (sorted by total assets in 2000, millions of euro)

1	Deutsche Bank AG	DE	927,900
2	Bayerische Hypo- und Vereinsbank	DE	694,300

3	BNP Paribas	FR	693,053
4	ABN AMRO Bank N.V.	NL	543,200
5	Barclays	UK	486,936
6	Societe Generale	FR	455,881
7	Commerzbank	DE	454,500
8	ING Bank NV	NL	406,393
9	Banco Santander Central Hispano	ES	347,288
10	Banca Intesa	IT	331,364
11	Abbey National plc	UK	293,395
12	Banco Bilbao Vizcaya Argentaria	ES	292,557
13	HSBC	UK	288,339
14	Royal Bank of Scotland	UK	206,176
15	Bankgesellschaft Berlin	DE	203,534
16	UniCredito Italiano	IT	202,649
17	Sanpaolo IMI	IT	171,046
18	Standard Chartered	UK	161,934
19	DePfa Group	DE	156,446
20	Banca di Roma	IT	132,729
21	Natexis Banques Populaires	FR	113,131
22	BHF-BANK	DE	53,863
23	Banco Espanol de Credito	ES	44,381
24	Banca Pop Bergamo	IT	37,670
25	IKB Deutsche Industriebank	DE	32,359
26	Banco Popular Espanol	ES	31,288
27	Banca Popolare di Milano	IT	28,282
28	Banca Lombarda	IT	26,816
29	Banca Popolare di Novara	IT	20,959
30	Credito Emiliano	IT	15,148
31	Banca Agricola Mantovana	IT	10,190
32	Banco Pastor	ES	9,404
33	Credito Valtellinese	IT	7,416
34	Banco Guipuzcoano	ES	5,518
35	Kas-Associatie N.V.	NL	5,417
36	Banco Zaragozano	ES	5,175
37	Schroders	UK	4,180
38	Banca Popolare di Intra	IT	3,929
39	Close Brothers	UK	3,241
40	Singer & Friedlander Group	UK	2,792

Table 2. Variable definitions and summary statistics

Variable	Definition	n	Mean	Median	Std Dev	Min	Max
	Bank specific variables						
dd_{it}	Distance to default of bank *i* in week t (see Appendix I)	94,520	4.13	3.73	1.73	0.55	16.59
$\Delta dd_{it}/ \lvert dd_{it-1} \rvert$	Percentage change in the distance to default	94,520	0.00	0	0.01	-0.77	0.69**
	(of which missing values replaced) 1/	343	/	/	/	/	/
tail	takes value 1 if bank *i* is in the 95th percentile negative tail of the distribution of $\Delta dd_{it}/dd_{it-1}$	94,520	0.05	0	0.22	0	1
Country specific variables							
Coexceedances DE	Number of banks in the 95th percentile negative tail of $\Delta dd_{it}/dd_{it-1}$ in DE	2363	0.34	0	0.75	0	7
Coexceedances ES	Number of banks in the 95th percentile negative tail of $\Delta dd_{it}/dd_{it-1}$ in ES	2363	0.34	0	0.71	0	6
Coexceedances FR	Number of banks in the 95th percentile negative tail of $\Delta dd_{it}/dd_{it-1}$ in FR	2363	0.16	0	0.48	0	3
Coexceedances IT	Number of banks in the 95th percentile negative tail of $\Delta dd_{it}/dd_{it-1}$ in IT	2363	0.56	0	1.12	0	11
Coexceedances NL	Number of banks in the 95th percentile negative tail of $\Delta dd_{it}/dd_{it-1}$ in NL	2363	0.16	0	0.47	0	3
Coexceedances UK	Number of banks in the 95th percentile negative tail of $\Delta dd_{it}/dd_{it-1}$ in UK	2363	0.48	0	0.90	0	7
Systemic risk DE	Number of markets in the 95th percentile negative tail among US, Emerging, Europe and DE	2363	0.2014	0	0.6104	0	4
Systemic risk ES	Number of markets in the 95th percentile negative tail among US, Emerging, Europe and ES	2363	0.2014	0	0.6034	0	4
Systemic risk FR	Number of markets in the 95th percentile negative tail among US, Emerging, Europe and FR	2363	0.2014	0	0.6146	0	4
Systemic risk IT	Number of markets in the 95th percentile negative tail among US, Emerging, Europe and IT	2363	0.2014	0	0.5935	0	4
Systemic risk NL	Number of markets in the 95th percentile negative tail among US, Emerging, Europe and NL	2363	0.2014	0	0.6062	0	4
Systemic risk UK	Number of markets in the 95th percentile negative tail among US, Emerging, Europe and UK	2363	0.2014	0	0.6048	0	4
Yield curve DE	Change in the slope of the yield curve in DE	2363	0.0004	0.0000	0.0385	-0.1900	0.3800
Yield curve ES	Change in the slope of the yield curve in ES	2363	0.0006	-0.0020	0.0682	-0.5400	0.4840
Yield curve FR	Change in the slope of the yield curve in FR	2363	0.0006	-0.0046	0.0645	-0.8000	0.3198
*Yield curve IT**	Change in the slope of the yield curve in IT	2363	0.0002	-0.0010	0.1511	-2.5580	2.5960
Yield curve NL	Change in the slope of the yield curve in NL	2363	0.0003	0.0000	0.0512	-0.3000	0.3210
Yield curve UK	Change in the slope of the yield curve in UK	2363	0.0013	0.0000	0.0814	-0.8740	0.5460
*Volatility DE**	Change in the volatility of the stock market in DE	2362	0.0072	-0.3141	3.0809	-10.5551	47.7505
*Volatility ES**	Change in the volatility of the stock market in ES	2362	0.0011	-0.3486	2.4996	-9.2267	32.1450
*Volatility FR**	Change in the volatility of the stock market in FR	2362	0.0044	-0.2951	1.9286	-4.8973	47.0638
*Volatility IT**	Change in the volatility of the stock market in IT	2362	0.0045	-0.6004	4.1482	-15.1464	63.3724
*Volatility NL**	Change in the volatility of the stock market in NL	2362	0.0060	-0.2482	2.8988	-10.9020	32.1924
*Volatility UK**	Change in the volatility of the stock market in UK	2362	0.0045	-0.1762	1.5277	-6.5127	21.0707
*Volatility US**	Change in the volatility of the stock market in US	2362	0.0054	-0.2353	2.1676	-5.2696	34.7094
	Memo items						
Cut off point of the 95th percentile of $\Delta dd_{it}/\lvert dd_{it-1} \rvert$		-0.0085					

1/ Number of observations imputed by linear interpolation: Close Brothers (20 observations), ING(1 observation), Natexis (1 observation). Number of observations added with random number generator: BHF (113 observations), BNP (208 observations).

* This variable has been multiplied by 1000.

Table 3. Description of the sample by countries

	Number of observations	Number of banks	Percentage of total assets of commercial banks	Number of observations per bank	Maximum number of coexceedances
France	7,089	3	36.0	2363	3
Germany	16,541	7	46.5	2363	7
	28,356	12	52.1	2363	11
The Netherlands	7,089	3	58.9	2363	3
Spain	16,541	7	68.3	2363	6
UK	18,904	8	56.1	2363	7
Total	94,520	40	/	/	20

Table 4. Coexceedances by countries

	France* (FR)	Germany (DE)	Italy (IT)	The Netherlands* (NL)	Spain (ES)	United Kingdom (UK)
Coexceedances = 0	2085	1822	1591	2066	1795	1628
Coexceedances = 1	203	385	495	219	407	486
Coexceedances = 2	75	89	152	78	111	161
Coexceedances ≥ 3	-	67	125	-	50	88
Total	2363	2363	2363	2363	2363	2363

*Due to the small number of banks in the sample, for France and The Netherlands the analysis is limited to coexceedances ≥ 2.

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Table 5. Multinomial logit model: Contagion in daily coexceedances of the first differenced distance to default, large EU countries, January 1993-January 2003

*Dependent variable: number of domestic banks simultaneously in the tai ("coexceedances"). Base case: Zero coexceedances. *, ** indicate statistical significance at the 5% and 1% levels, respectively. All models estimated with 2362 daily observations. Robust standard errors are used.*

	France				**Germany**				**Italy**			
	Model 1		**Model 2**		**Model 1**		**Model 2**		**Model 1**		**Model 2**	
	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb
Coexceedances=1												
Constant	-2.47***		-2.57***		-1.78***		-1.92***		-1.35***		-1.41***	
Coexceedances lagged	0.40**	0.030**	0.28*	0.021*	0.61***	0.078***	0.51***	0.065***	0.36***	0.045***	0.31***	0.039***
Systemic risk	0.24**	0.018**	0.21*	0.016*	0.15	0.020	0.11	0.014	0.24***	0.034**	0.22**	0.031**
Yield curve	0.40	0.032	0.36	0.028	1.97	0.241	1.96	0.241	-0.01	-0.010	-0.19	-0.012
Volatility own	0.29***	0.022***	0.29***	0.022***	0.15***	0.018***	0.16***	0.020***	0.10***	0.013***	0.10***	0.013***
Volatility US	-0.01	-0.001	-0.02	-0.002	0.02	0.002	0.01	0.000	0.02	0.002	0.01	0.001
Contagion DE			0.03	0.002							-0.01	-0.007
Contagion FR							0.07	0.009			0.05	0.010
Contagion IT			-0.09	-0.007			0.11	0.016*				
Contagion NL			-0.08	-0.006			0.40***	0.053***			0.12	0.017
Contagion ES			0.29***	0.022***			-0.10	-0.017			0.01	0.001
Contagion UK			0.15	0.011			0.16**	0.020*			0.14**	0.023*
Coexceedances=2												
Constant	-4.35***		-4.62***		-3.59***		-3.87***		-2.81***		-2.94***	
Coexceedances lagged	0.90***	0.012***	0.68***	0.009**	0.95***	0.024***	0.77***	0.018***	0.70***	0.034***	0.62***	0.030***
Systemic risk	0.39**	0.005**	0.35**	0.004**	0.09	0.002	0.01	-0.000	0.36***	0.017***	0.31***	0.015**
Yield curve	-0.27	-0.004	-0.31	-0.0044	6.39***	0.178***	6.44***	0.168***	0.55	0.032	0.57	0.032
Volatility own	0.64***	0.009***	0.65***	0.008***	0.30***	0.008***	0.31***	0.008***	0.15***	0.007***	0.15***	0.007***
Volatility US	0.08*	0.001*	0.07	0.001	0.05	0.001	0.02	0.001	-0.00	-0.000	-0.01	-0.001
Contagion DE			0.28	0.004							0.23*	0.012*
Contagion FR							0.09	0.002			-0.08	-0.005
Contagion IT			-0.07	-0.001			-0.14	-0.004				
Contagion NL			-0.25	-0.003			0.48**	0.011**			0.11	0.005
Contagion ES			0.54***	0.007**			0.29*	0.008*			0.09	0.005
Contagion UK			0.09	0.001			0.37***	0.009***			0.12	0.005

Table 5 (continued). Multinomial logit model: Contagion in daily coexceedances of the first differenced distance to default, large EU countries, January 1993-January 2003

	France				Germany				Italy			
	Model 1		Model 2		Model 1		Model 2		Model 1		Model 2	
	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb
Coexceedances=3												
Constant					-4.61***		-5.01***		-3.91***		-3.99***	
Coexceedances lagged					1.28***	0.015***	1.07***	0.011***	1.15***	0.026***	1.11***	0.025***
Systemic risk					0.39***	0.005**	0.22	0.002	0.39***	0.008**	0.37***	0.007**
Yield curve					0.12	-0.005	0.54	0.000	0.09	0.001	0.15	0.003
Volatility own					0.39***	0.005***	0.41***	0.004***	0.29***	0.007***	0.30***	0.007***
Volatility US					0.12**	0.002**	0.09*	0.001*	0.09***	0.002**	0.08**	0.002**
Contagion DE											0.30**	0.007**
Contagion FR							0.32	0.004			0.09	0.002
Contagion IT							0.26	0.003				
Contagion NL							0.10	0.000			0.20	0.004
Contagion ES							0.42**	0.005**			-0.00	-0.000
Contagion UK							0.20	0.002			-0.12	-0.004
Pseudo R2	0.14		0.15		0.10		0.12		0.09		0.10	
Log-likelihood	-878		-867		-1523		-1493		-1982		-1972	
N	2361		2361		2361		2361		2361		2361	
ΣContagion DE			1.36								4.21**	
ΣContagion FR							1.07				0.03	
ΣContagion IT			0.66				0.81					
ΣContagion NL			0.56				5.30**				1.34	
ΣContagion ES			11.08***				4.08**				0.14	
ΣContagion UK			0.92				9.01***				0.33	
ΣContagion			4.69**				25.91***				6.47**	

Table 5 (continued). Multinomial logit model: Contagion in daily coexceedances of the first differenced distance to default, large EU countries, January 1993-January 2003

	The Netherlands				Spain				United Kingdom			
	Model 1		Model 2		Model 1		Model 2		Model 1		Model 2	
	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb
Coexceedances=1												
Constant	-2.54***		-2.72***		-1.72***		-1.82***		-1.48***		-1.60***	
Coexceedances lagged	0.77***	0.060***	0.55***	0.043***	0.59***	0.079***	0.54***	0.073***	0.42***	0.057***	0.33***	0.044***
Systemic risk	0.49***	0.039***	0.43***	0.034***	0.23**	0.029**	0.21**	0.027**	0.61***	0.092***	0.58***	0.089***
Yield curve	0.78	0.064	0.65	0.053	0.11	0.007	0.03	-0.002	-0.35	-0.052	-0.42	-0.062
Volatility own	0.25***	0.019***	0.26***	0.020***	0.27***	0.035***	0.27***	0.036***	0.29***	0.041***	0.33***	0.046***
Volatility US	0.02	0.001	0.00	0.0002	0.04	0.005	0.03	0.005	0.02	0.003	0.00	0.001
Contagion DE			0.14	0.011			0.07	0.010			0.12	0.017
Contagion FR			0.28*	0.022*			0.02	0.000			0.02	0.007
Contagion IT			0.24***	0.019***			0.21***	0.030***			0.07	0.012
Contagion NL							-0.07	-0.011			0.14	0.022
Contagion ES			-0.01	-0.001							0.24***	0.035**
Contagion UK			0.00	0.000			0.01	-0.001				
Coexceedances=2												
Constant	-4.39***		-4.76***		-3.51***		-3.71***		-3.00***		-3.16***	
Coexceedances lagged	1.16***	0.016***	0.65***	0.008**	0.91***	0.030***	0.73***	0.021***	0.87***	0.043***	0.76***	0.037***
Systemic risk	0.38*	0.005	0.25	0.003	0.55***	0.020***	0.48***	0.015***	0.70***	0.030***	0.68***	0.029***
Yield curve	-0.76	-0.012	-1.44	-0.020	0.76	0.024	0.46	0.015	-0.71	-0.036	-0.89	-0.044
Volatility own	0.47***	0.006***	0.48***	0.006***	0.46***	0.014***	0.47***	0.014***	0.54***	0.0326**	0.56***	0.026***
Volatility US	0.08**	0.001**	0.05	0.001	-0.03	-0.001	-0.06	-0.002	-0.01	-0.001	-0.03	-0.002
Contagion DE			0.08	0.001			0.08	0.002			0.15	0.006
Contagion FR			0.23	0.003			0.30	0.010			-0.22	-0.012
Contagion IT			0.30**	0.004**			0.10	0.002			0.00	-0.001
Contagion NL							0.04	0.002			0.25	0.012
Contagion ES			0.47***	0.006***							0.43***	0.020***
Contagion UK			0.07	0.001			0.28**	0.010**				

Table 5 (continued). Multinomial logit model: Contagion in daily coexceedances of the first differenced distance to default, large EU countries, January 1993-January 2003

	The Netherlands				Spain				United Kingdom			
	Model 1		Model 2		Model 1		Model 2		Model 1		Model 2	
	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb
Coexceedances=3												
Constant					-5.04***		-5.37***		-4.50***		-4.92***	
Coexceedances lagged					1.11***	0.008***	0.82***	0.006***	1.01***	0.015***	0.94***	0.011***
Systemic risk					0.78***	0.006***	0.68***	0.005***	1.01***	0.013***	0.95***	0.011***
Yield curve					2.55	0.021	2.12	0.017	0.43	0.009	0.24	0.005
Volatility own					0.56***	0.004***	0.57***	0.004***	0.82***	0.011***	0.88***	0.010***
Volatility US					0.07*	0.001	0.04	0.000	0.07	0.001	0.05	0.001
Contagion DE							0.30*	0.002*			0.65***	0.008***
Contagion FR							0.27	0.002			-0.52*	-0.007*
Contagion IT							0.32*	0.002			0.24	0.003
Contagion NL							0.03	0.000			-0.26	-0.004
Contagion ES											0.47***	0.005**
Contagion UK							0.20	0.001				
Pseudo R2	0.17		0.18		0.12		0.13		0.12		0.13	
Log-likelihood	-881		-866		-1531		-1516		-1848		-1821	
N	2361		2361		2361		2361		2361		2361	
ΣContagion DE			0.97				2.19				13.35***	
ΣContagion FR			2.84*				1.91				2.21	
ΣContagion IT			10.38***				5.77**				1.82	
ΣContagion NL							0.00				0.10	
ΣContagion ES			4.47**								17.31***	
ΣContagion UK			0.12				2.65					
ΣContagion			18.44***				13.40***				9.61***	

Table 6. Multinomial logit model: Contagion in daily coexceedances of the first differenced distance to default, large EU countries, January 1993-January 2003, pre and post euro

	France				Germany				Italy			
	Pre euro		Post euro		Pre euro		Post euro		Pre euro		Post euro	
	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb
Coexceedances=1												
Constant	-2.36***		-3.01***		-1.96***		-1.88***		-1.15***		-1.77***	
Coexceedances lagged	0.40*	0.034*	0.28	0.015	0.38***	0.050***	0.74***	0.096***	0.31***	0.040***	0.22*	0.0232
Systemic risk	0.07	0.005	0.45***	0.024***	0.41**	0.056**	-0.08	-0.012	0.35**	0.053*	0.22*	0.030*
Yield curve	-0.08	-0.006	3.78	0.205	4.36**	0.575**	-2.07	-0.286	-0.10	-0.024	0.30	0.033
Volatility own	0.54***	0.046***	0.18**	0.009**	0.26***	0.032***	0.13***	0.017***	0.11***	0.015***	0.10***	0.013***
Volatility US	-0.16	-0.014	0.01	0.001	0.01	0.001	-0.00	-0.000	-0.02	-0.005	0.01	0.001
Contagion DE	-0.00	-0.001	-0.01	-0.001					-0.23**	-0.046**	0.32**	0.045**
Contagion FR					0.10	0.013	0.08	0.010	0.20	0.028	-0.20	-0.021
Contagion IT	-0.07	-0.006	-0.25	-0.014	0.14*	0.023*	0.02	0.001				
Contagion NL	0.07	0.007	-0.92**	-0.050**	0.64***	0.086***	0.05	0.008	0.19	0.032	0.03	-0.001
Contagion ES	0.25*	0.021*	0.41**	0.022**	-0.15	-0.025	-0.04	-0.007	-0.11	-0.018	0.22	0.030
Contagion UK	0.04	0.003	0.37**	0.020**	0.17	0.021	0.18	0.023	0.09	0.021	0.20*	0.027
Coexceedances=2												
Constant	-4.56***		-4.76***		-3.66***		-4.23***		-2.58***		-3.51***	
Coexceedances lagged	0.82**	0.009**	0.46	0.005	0.43**	0.009**	1.24***	0.026***	0.53***	0.028***	0.71***	0.027***
Systemic risk	0.46**	0.005*	0.31	0.003	0.34	0.007	-0.09	-0.002	0.48**	0.025**	0.26*	0.009
Yield curve	-1.07	-0.012	2.50	0.028	8.68***	0.209***	-1.52	-0.028	0.2	0.017	1.45	0.058
Volatility own	0.91***	0.010***	0.59***	0.007***	0.59***	0.014***	0.25***	0.005***	0.15***	0.008***	0.16***	0.006***
Volatility US	0.02	0.000	0.10*	0.001*	0.05	0.001	-0.04	-0.001	-0.03	-0.002	-0.01	-0.001
Contagion DE	0.31	0.004	0.22	0.003					0.17	0.016	0.37*	0.012
Contagion FR					-0.10	-0.003	0.11	0.002	0.33	0.018	-0.96**	-0.038**
Contagion IT	-0.15	-0.002	0.04	0.001	-0.55***	-0.015***	0.22	0.005				
Contagion NL	-1.02**	-0.012**	0.38	0.005	0.68***	0.015**	0.00	-0.000	0.08	0.001	0.38	0.016
Contagion ES	0.48*	0.005*	0.72**	0.008**	0.38*	0.010**	0.38	0.009	-0.16	-0.009	0.42**	0.016**
Contagion UK	0.12	0.001	-0.20	-0.003	0.39**	0.009**	0.28	0.006	-0.06	-0.005	0.33*	0.012*

Table 6 (continued). Multinomial logit model: Contagion in daily coexceedances of the first differenced distance to default, large EU countries, January 1993-January 2003, pre and post euro

	France				Germany				Italy			
	Pre euro		Post euro		Pre euro		Post euro		Pre euro		Post euro	
	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb
Coexceedances=3												
Constant					-4.78***		-5.69***		-3.68***		-4.58***	
Coexceedances lagged					0.89***	0.010***	1.40***	0.008***	1.00***	0.028***	1.26***	0.019***
Systemic risk					0.24	0.002	0.35*	0.002	0.56***	0.014**	0.32	0.004
Yield curve					-1.45	-0.031	5.04	0.037	0.04	0.002	0.55	0.007
Volatility own					0.73***	0.009***	0.34***	0.002***	0.32***	0.009***	0.29***	0.004***
Volatility US					-0.09	-0.001	0.15**	0.001**	0.12***	0.004***	0.03	0.000
Contagion DE									0.08	0.004	0.62**	0.001**
Contagion FR					0.50	0.006	0.08	0.000	0.32	0.008	-0.36	-0.005
Contagion IT					-0.06	-0.001	0.68**	0.005*				
Contagion NL					0.20	0.001	-0.21	-0.002	0.31	0.008	0.16	0.002
Contagion ES					0.67***	0.009***	-0.12	-0.001	0.03	0.002	-0.12	-0.003
Contagion UK					0.06	0.000	0.34	0.002	-0.21	-0.007	0.11	0.001
Pseudo R2	0.14		0.21		0.15		0.14		0.10		0.12	
Log-likelihood	-506		-332		-808		-639		-1168		-766	
N	1302		1058		1302		1058		1302		1058	
ΣContagion DE	0.76		0.17						0.01		9.40***	
ΣContagion FR					0.47		0.14		3.77*		4.47** 1/	
ΣContagion IT	0.66		0.44		2.10		3.97**					
ΣContagion NL	2.73* 1/		0.53		6.94***		0.04		1.67		0.62	
ΣContagion ES	4.98**		8.27***		5.80**		0.17		0.60		0.98	
Σcontagion UK	0.23		0.20		3.28*		3.75*		0.27		2.42	
Σcontagion	0.00		1.28		8.33***		5.98**		2.83*		3.29*	

1/ The sum of the coefficients is significantly negative. Not represented as an arrow in Charts 9 and 10.

Table 6 (continued). Multinomial logit model: Contagion in daily coexceedances of the first differenced distance to default, large EU countries, January 1993-January 2003, pre and post euro

	The Netherlands				Spain				United Kingdom			
	Pre euro		Post euro		Pre euro		Post euro		Pre euro		Post euro	
	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb
Coexceedances=1												
Constant	-2.40***		-3.16***		-1.58***		-2.10***		-1.51***		-1.79***	
Coexceedances lagged	0.56***	0.050***	0.52*	0.033*	0.46***	0.064***	0.66***	0.087***	0.39***	0.058***	0.32**	0.039*
Systemic risk	0.51***	0.050***	0.46***	0.029***	-0.14	-0.025	0.34***	0.044***	0.63***	0.100***	0.64***	0.094***
Yield curve	-0.67	-0.060	2.14	0.135	-0.47	-0.080	1.09	0.162	-1.21	-0.212	1.04	0.176
Volatility own	0.28***	0.024***	0.25***	0.015***	0.42***	0.059***	0.21***	0.026***	0.84***	0.134***	0.20***	0.026***
Volatility US	-0.01	-0.001	0.00	0.000	0.02	0.007	0.02	0.002	-0.02	-0.004	-0.00	0.000
Contagion DE	0.05	0.004	0.24	0.016	0.02	0.002	0.17	0.022	0.16	0.027	0.10	0.009
Contagion FR	0.33*	0.030*	0.15	0.009	0.05	0.005	-0.17	-0.024	0.22	0.046*	-0.31	-0.044
Contagion IT	0.15	0.014	0.34**	0.021**	0.20**	0.030**	0.21*	0.028*	0.05	0.010	0.08	0.012
Contagion NL					-0.23	-0.035	0.11	0.015	0.07	0.011	0.30	0.044
Contagion ES	-0.14	-0.013	0.19	0.012					0.14	0.017	0.42***	0.062***
Contagion UK	-0.11	-0.010	0.10	0.006	-0.20	-0.030*	0.20*	0.026				
Coexceedances=2												
Constant	-4.69***		-5.04***		-3.51***		-4.26***		-3.00***		-3.37***	
Coexceedances lagged	0.62*	0.007	0.48	0.005	0.67***	0.019***	0.93***	0.020***	0.71***	0.034***	0.89***	0.044***
Systemic risk	0.44*	0.005	0.16	0.001	0.32	0.011	0.65***	0.014***	0.84***	0.038***	0.66***	0.027***
Yield curve	-0.14	-0.001	0.42	0.003	1.07	0.038	-2.24	-0.06	-0.05	0.016	-1.47	-0.095
Volatility own	0.66***	0.008***	0.42***	0.004***	0.69***	0.020***	0.40***	0.009***	1.06***	0.047***	0.43***	0.020***
Volatility US	0.03	0.000	-0.06	0.001	-0.65***	-0.022***	-0.00	-0.000	-0.07	-0.003	-0.04	-0.002
Contagion DE	0.21	0.003	-0.24	-0.003	0.08	0.003	0.13	0.002	0.00	-0.002	0.36*	0.018*
Contagion FR	0.18	0.002	0.38	0.004	0.30	0.009	0.15	0.004	-0.24	-0.016	-0.41	-0.018
Contagion IT	0.08	0.001	0.63**	0.006**	0.07	0.001	0.02	-0.000	-0.05	-0.004	0.00	-0.001
Contagion NL					-0.06	-0.001	0.21	0.005	0.21	0.011	0.35	0.015
Contagion ES	0.56***	0.008***	0.12	0.001					0.44***	0.022**	0.43**	0.019*
Contagion UK	-0.04	-0.000	0.32	0.003	0.05	0.003	0.49***	0.011**				

Table 6 (continued). Multinomial logit model: Contagion in daily coexceedances of the first differenced distance to default, large EU countries, January 1993-January 2003, pre and post euro

	The Netherlands				Spain				United Kingdom			
	Pre euro		Post euro		Pre euro		Post euro		Pre euro		Post euro	
	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb	Coeff	ΔProb
Coexceedances=3												
Constant					-5.12***		-5.78***		-5.38***		-5..02***	
Coexceedances lagged					0.66**	0.004*	1.02***	0.006**	1.18***	0.009***	1.01***	0.012***
Systemic risk					0.86***	0.007***	0.50**	0.003*	1.06***	0.007***	1.03***	0.011***
Yield curve					1.95	0.016	-1.12	-0.008	-2.87	-0.022	4.10**	0.053*
Volatility own					0.88***	0.006***	0.43***	0.002***	1.87***	0.014***	0.63***	0.007***
Volatility US					0.09	0.001	0.01	0.000	0.05	0.001	0.05	0.001
Contagion DE					0.17	0.001	0.57**	0.003*	0.48**	0.004**	1.01***	0.013***
Contagion FR					0.24	0.002	0.01	0.000	-0.82*	-0.007*	-0.59	-0.007
Contagion IT					0.21	0.001	0.28	0.002	0.25	0.002	0.08	0.001
Contagion NL					0.13	0.001	-0.07	-0.001	-0.43	-0.004	-0.10	-0.002
Contagion ES									0.68***	0.005**	0.07	-0.001
Contagion UK					-0.08	-0.000	0.51	0.003				
Pseudo R2	0.18		0.23		0.15		0.15		0.14		0.16	
Log-likelihood	-509		-334		-837		-632		-991		-780	
N	1302		1058		1302		1058		1302		1058	
ΣContagion DE	0.84		0.00		0.49		2.98*		3.24*		11.98***	
ΣContagion FR	1.84		1.20		1.12		0.00		1.50		3.02*	
ΣContagion IT	1.32		8.41***		1.94		1.52		0.69		0.14	
ΣContagion NL					0.08		0.13		0.06		0.65	
ΣContagion ES	2.41		0.55						13.49***		3.40*	
ΣContagion UK	0.28		1.51		0.30		7.04***					
ΣContagion	4.06**		12.47***		1.27		9.11***		1.54		4.12**	

Chart 1. Response curves to volatility shocks.

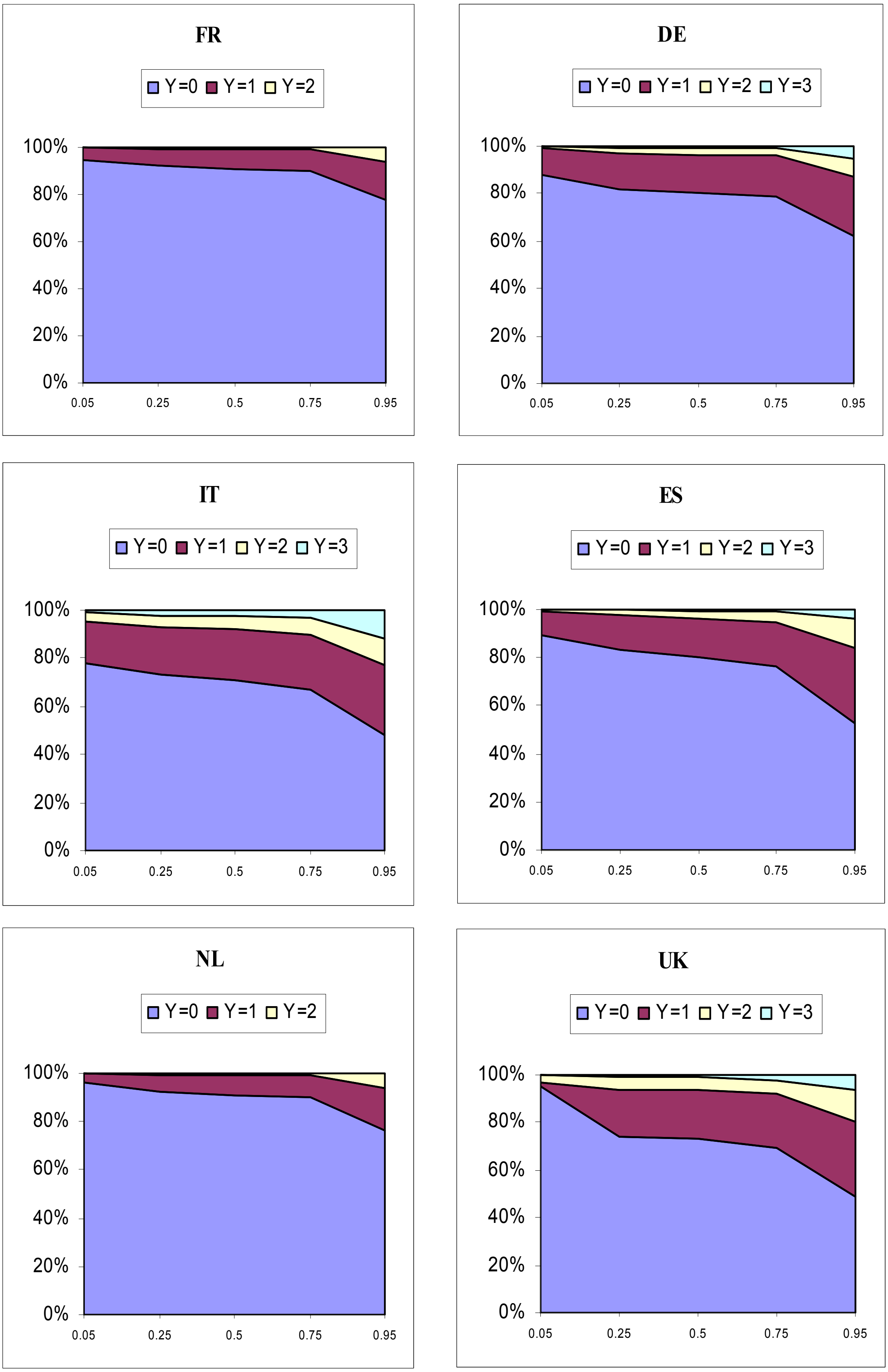


Chart 2. Contagion directions (dotted line indicate significance of contagion parameters at 10% level)

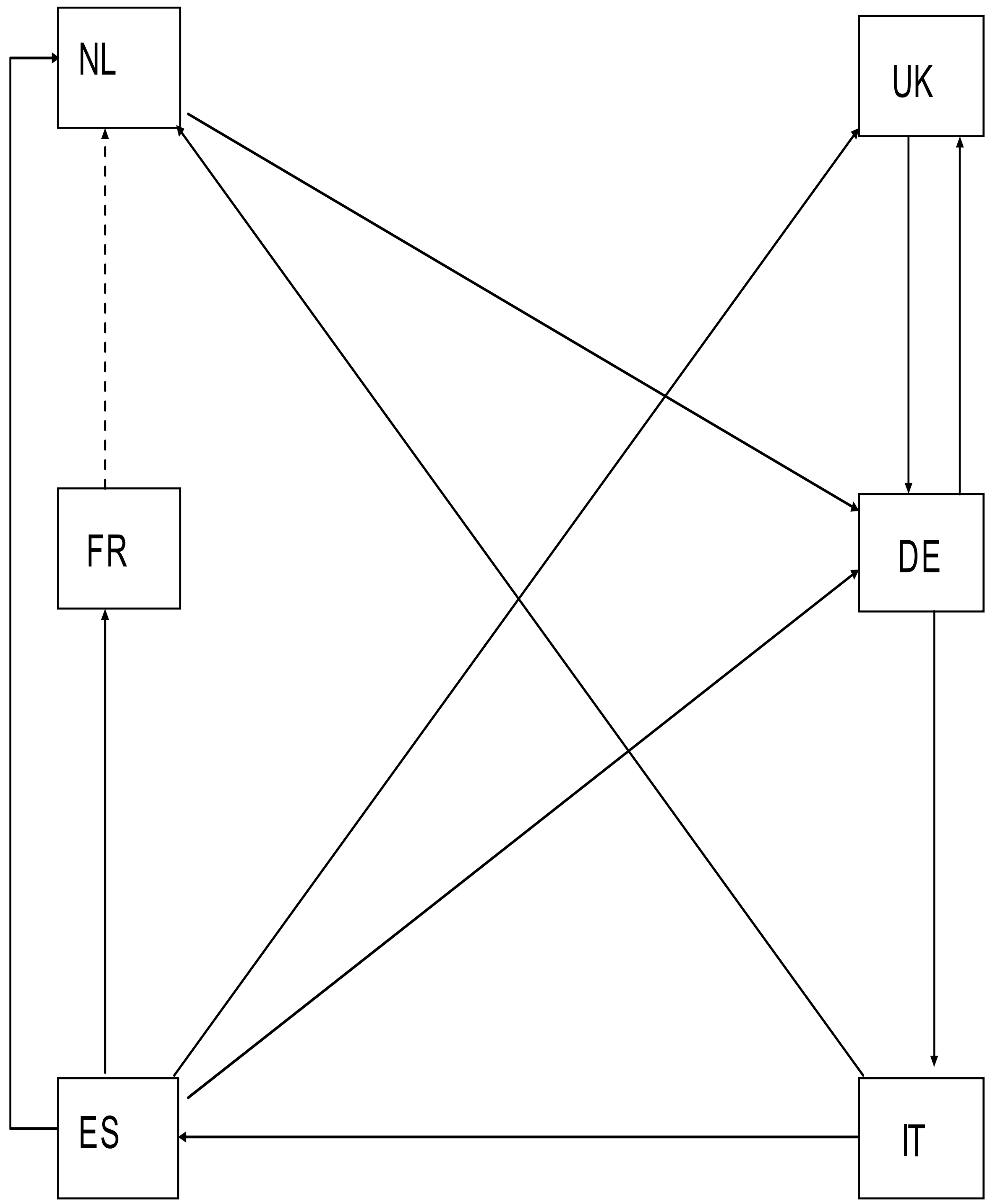


Chart 3. contagion to Germany

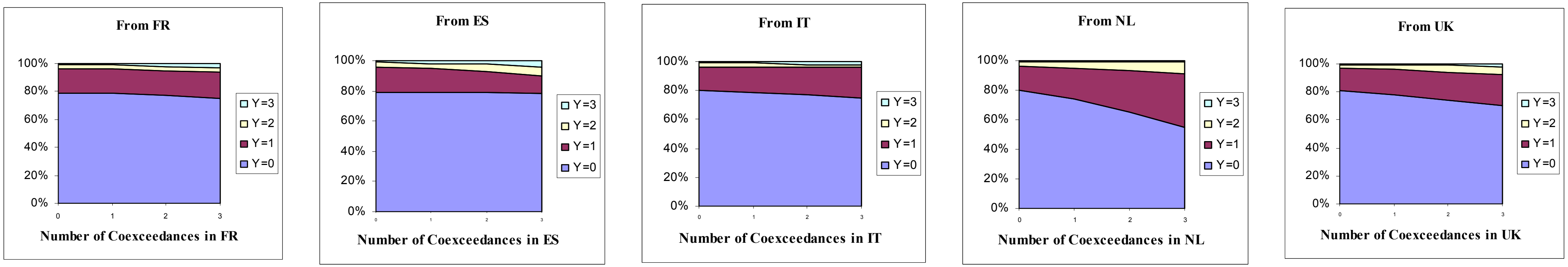


Chart 4. contagion to France

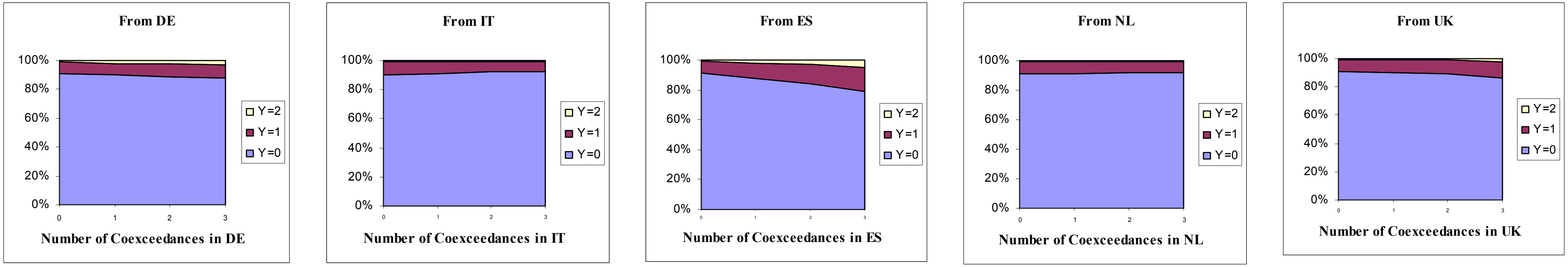


Chart 5. contagion to Spain

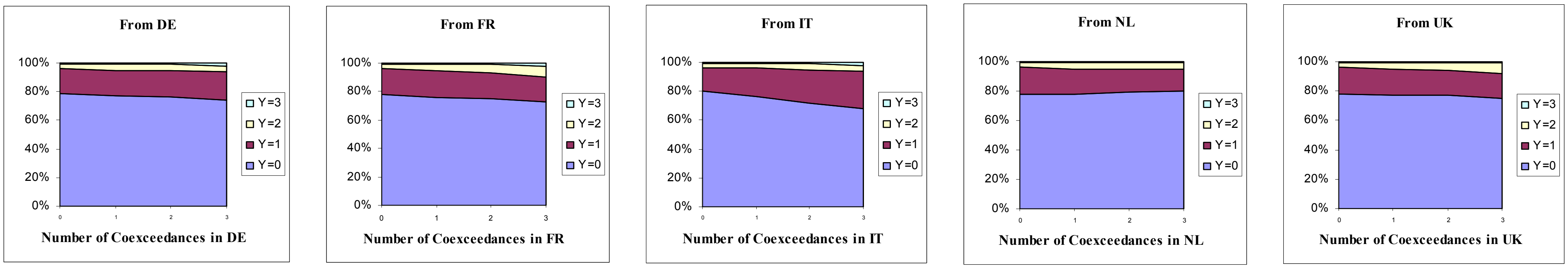


Chart 6. Contagion to Italy

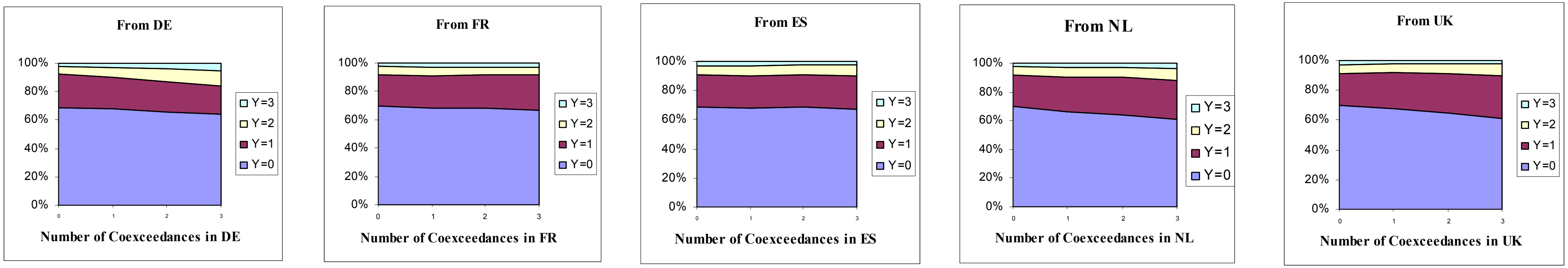


Chart 7. Contagion to the Netherlands

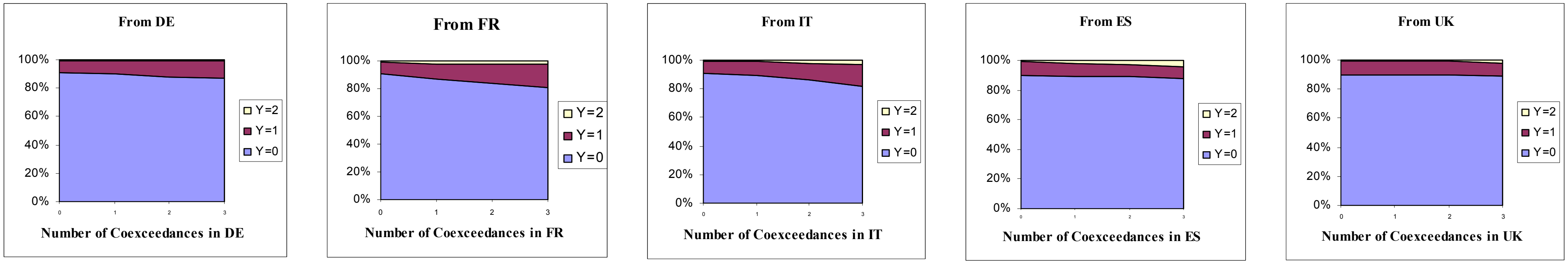


Chart 8. Contagion to the United Kingdom

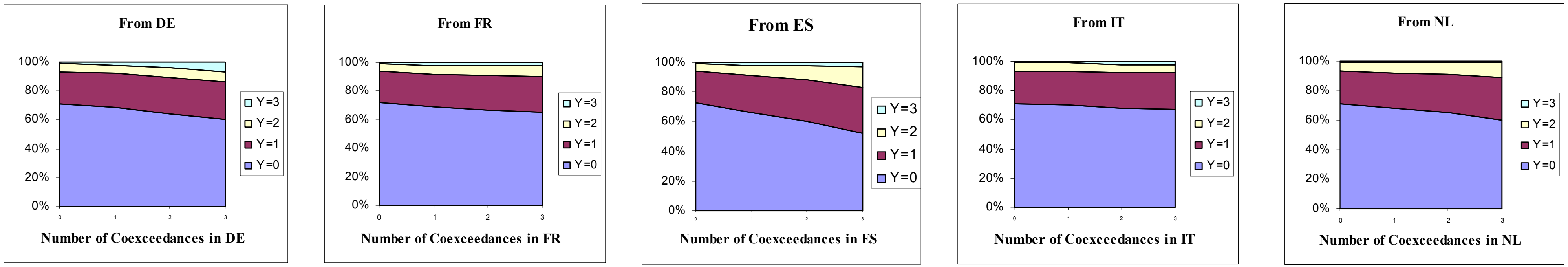


Chart 9. Contagion directions – pre euro (dotted line indicate significance of contagion parameters at 10% level)

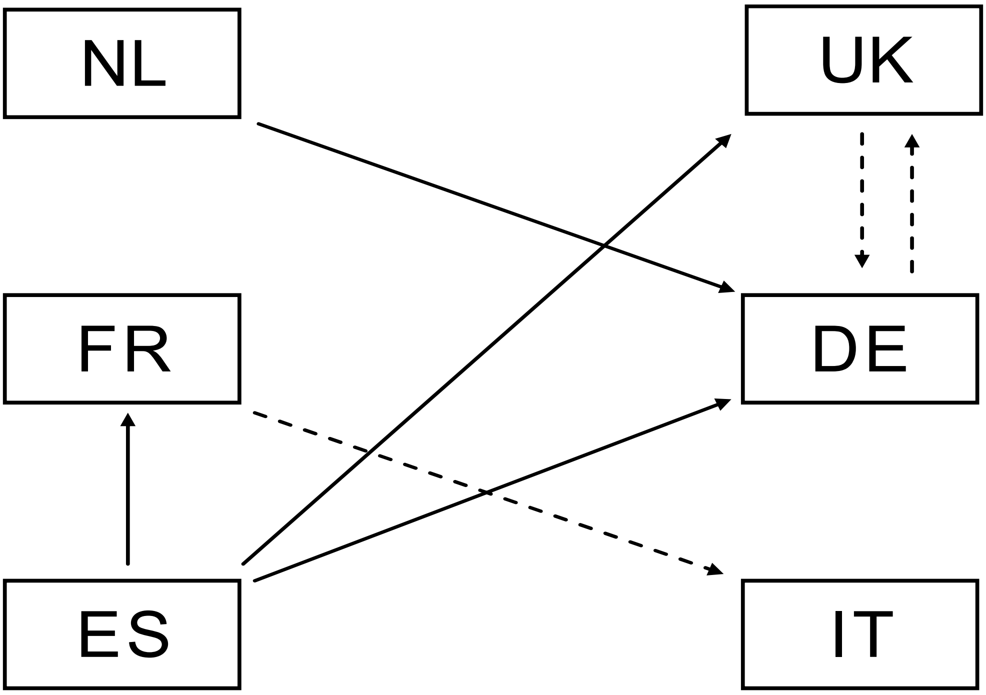


Chart 10. Contagion directions - post euro (dotted line indicate significance of contagion parameters at 10% level)

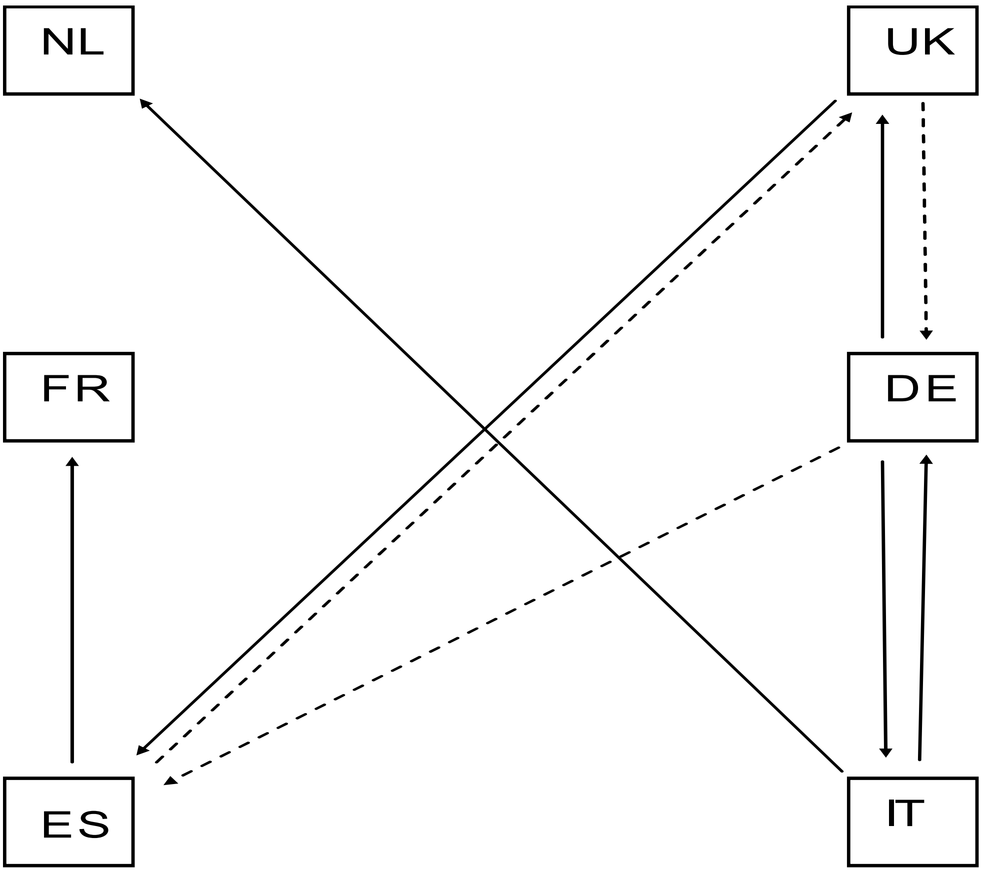


Chart 11. Response curves pre and post euro for Germany.

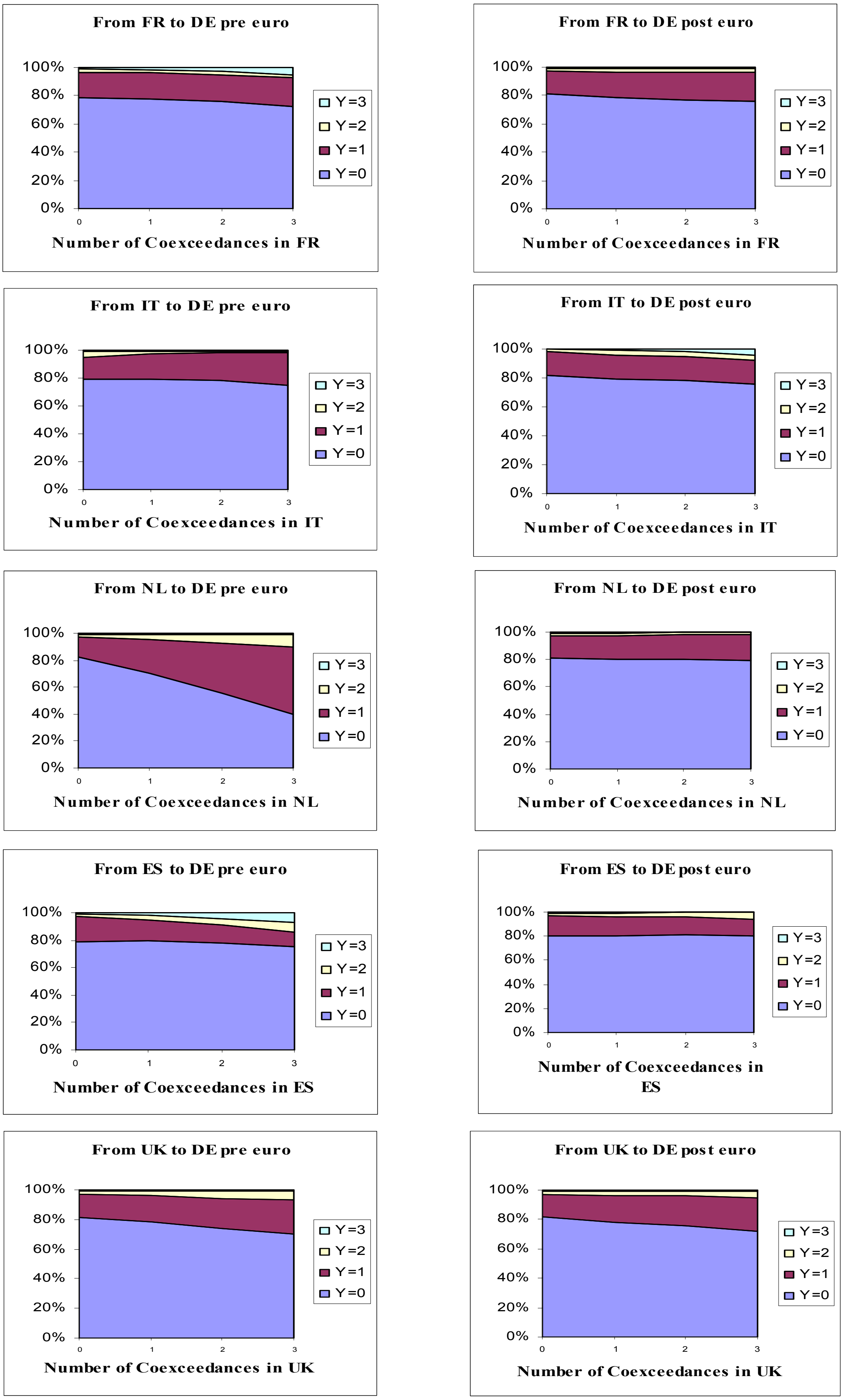


Chart 12. Response curves pre and post euro for France.

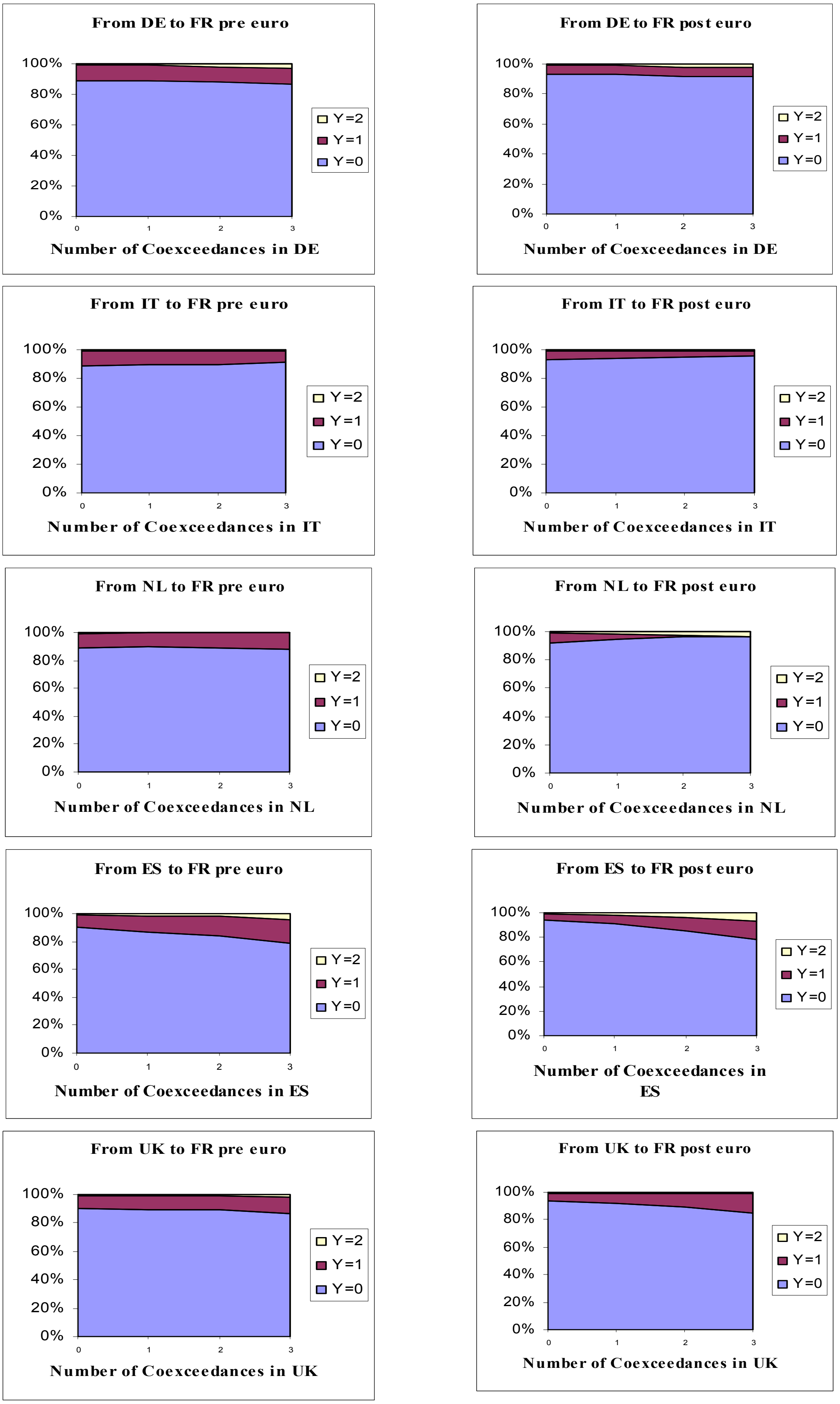


Chart 13. Response curves pre and post euro for Italy.

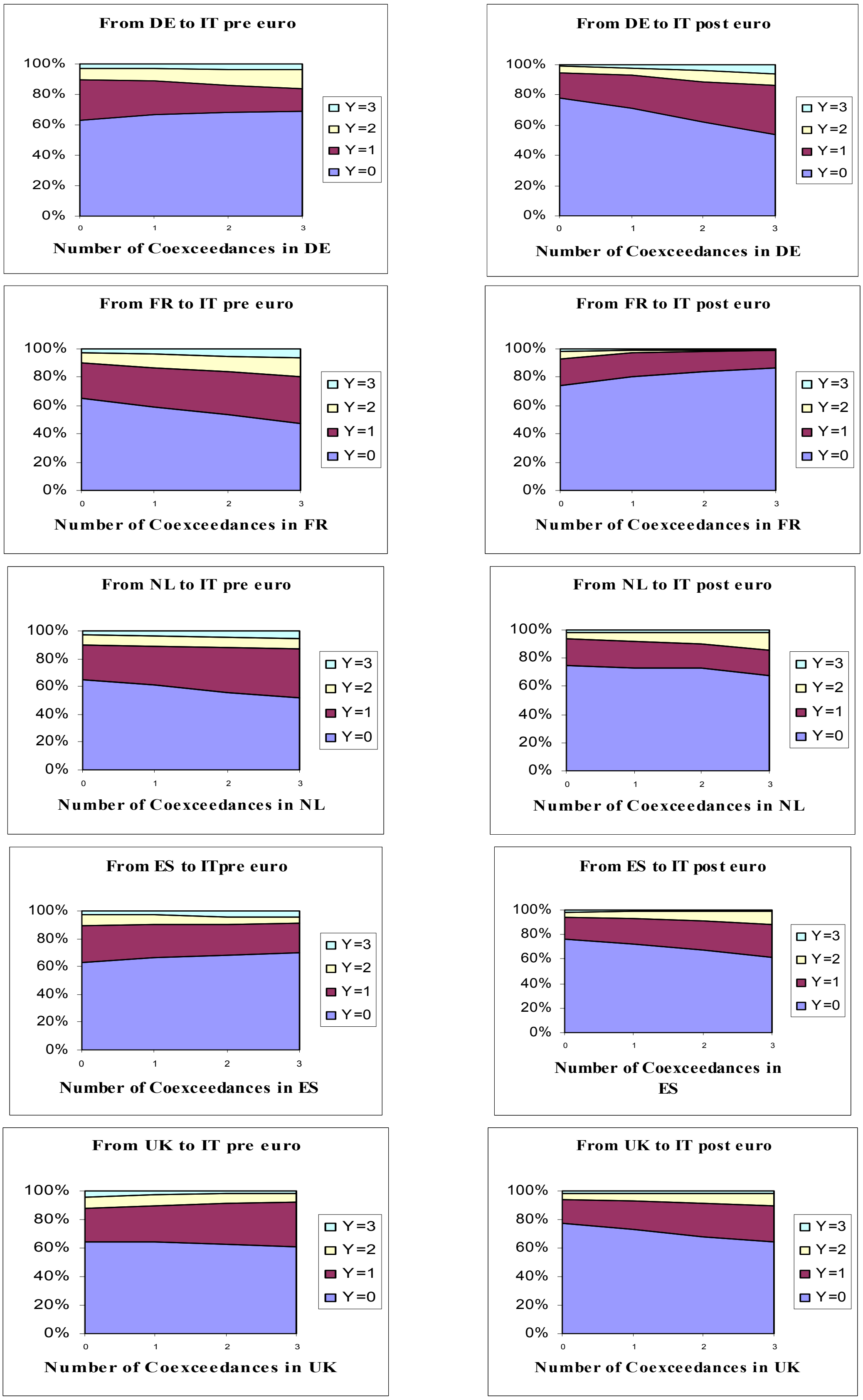


Chart 14. Response curves pre and post euro for the Netherlands.

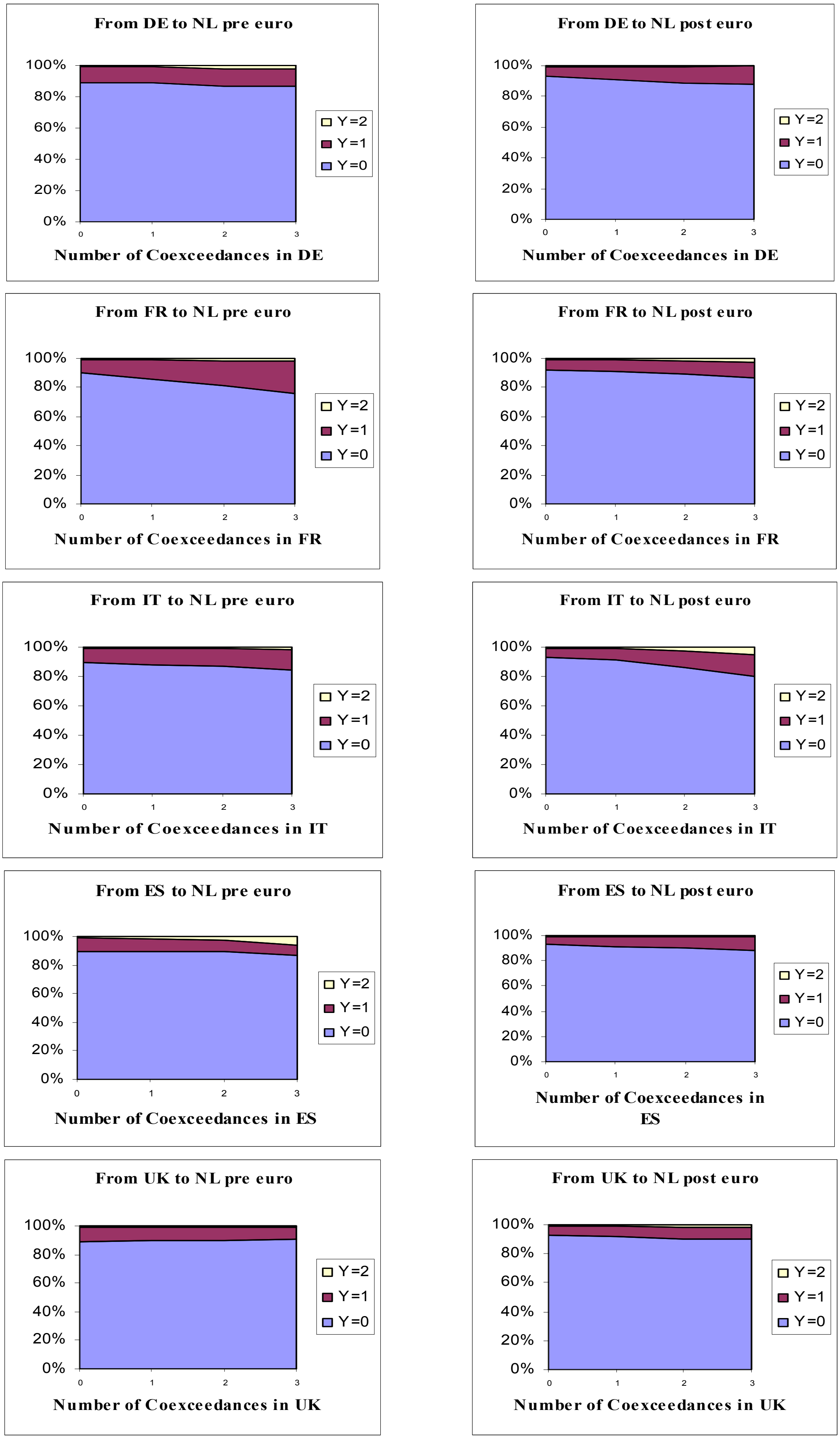


Chart 15. Response curves pre and post euro for Spain.

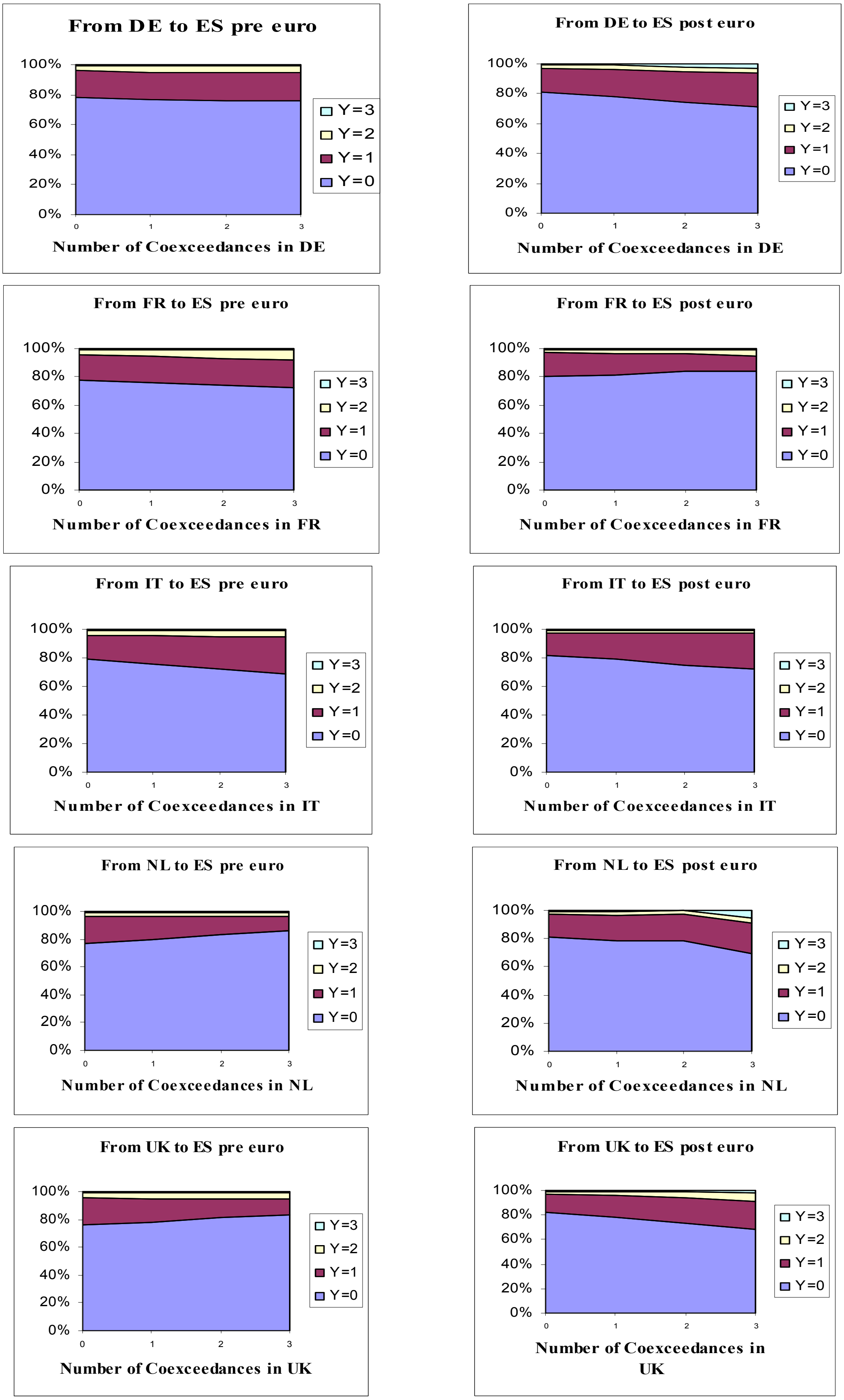
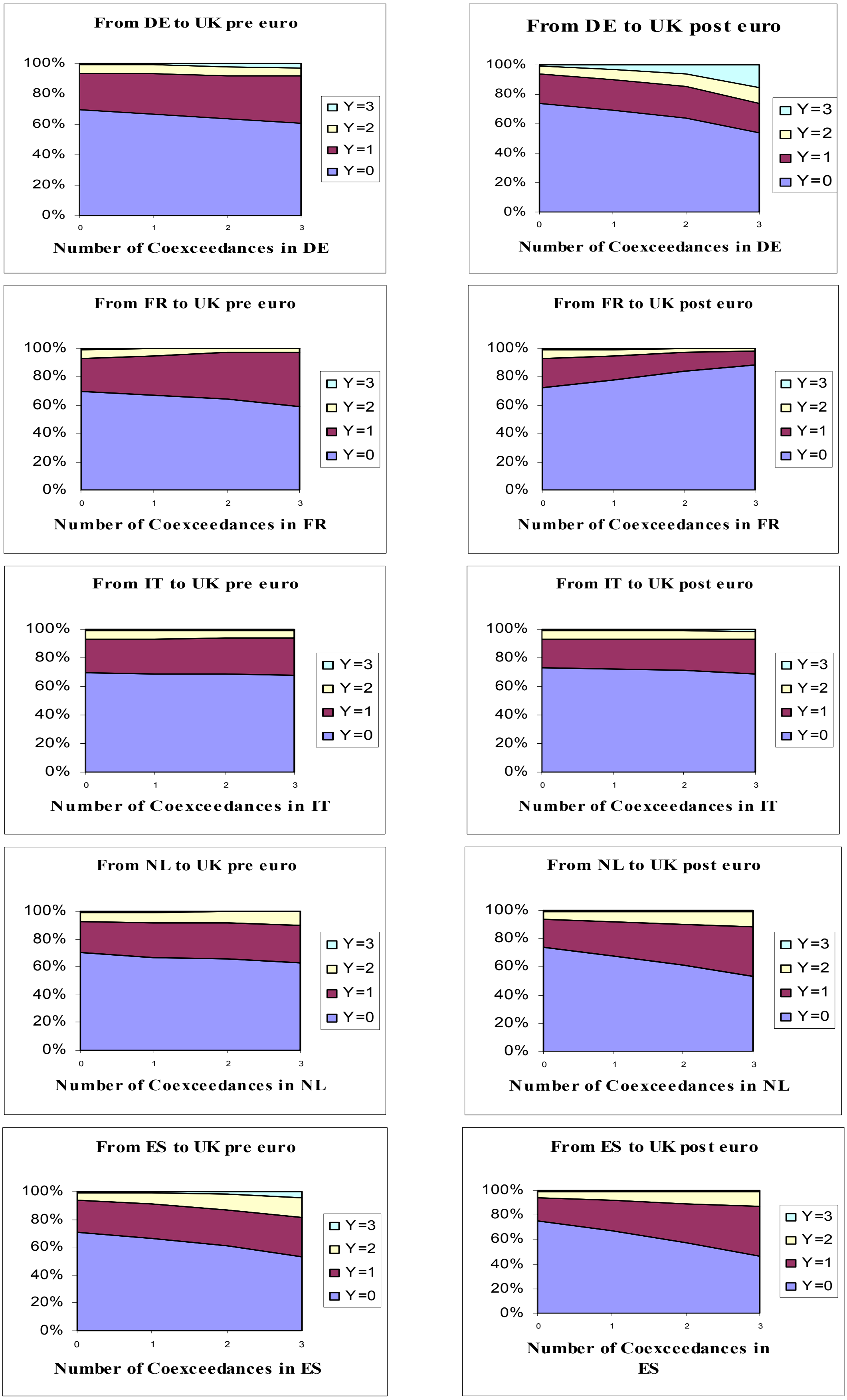


Chart 16. Response curves pre and post euro for UK.



Appendix I. Calculation of distances to default

The distance of default is derived by starting with the Black-Scholes model, in which the time path of the market value of assets follows a stochastic process:

$$\ln V^T = \ln V + \left(r - \frac{\sigma^2}{2}\right)T + \sigma\sqrt{T}\varepsilon, \tag{A1}$$

which gives the asset value at time T (i.e. maturity of debt), given its current value (V). ε is the random component of the firm's return on assets, which the Black-Scholes model assumes is normally distributed, with zero mean and unit variance, N(0,1).

Hence, the current distance d from the default point (where $\ln V = \ln D$) can be expressed as:

$$d = \ln V^d - \ln D = \ln V + (r - \frac{\sigma^2}{2})T + \sigma\sqrt{T}\varepsilon - \ln D <=>$$

$$\frac{d}{\sigma\sqrt{T}} = \frac{\ln\left(\frac{V}{D}\right) + \left(r - \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}} + \varepsilon. \tag{A2}$$

That is, the distance to default, *dd*

$$dd \equiv \frac{d}{\sigma\sqrt{T}} - \varepsilon = \frac{\ln\left(\frac{V}{D}\right) + \left(r - \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}} \tag{A3}$$

represents the number of asset value standard deviations (σ) that the firm is from the default point. The inputs to *dd, V* and σ, can be calculated from observable market value of equity capital (V_E), volatility of equity σ_E, and D (total debt liabilities) using the system of equations below:

$$\begin{aligned} &\mathrm{V_E} = \mathrm{VN(d1)} - \mathrm{D}\,e^{-\mathrm{rT}}\mathrm{N(d2)} \\ &\sigma_\mathrm{E} = \left(\frac{\mathrm{V}}{\mathrm{V_E}}\right)\mathrm{N(d1)}\sigma, \\ &\mathrm{d1} \equiv \frac{\ln\left(\frac{\mathrm{V}}{\mathrm{D}}\right) + \left(\mathrm{r} + \frac{\sigma^2}{2}\right)\mathrm{T}}{\sigma\sqrt{\mathrm{T}}} \\ &\mathrm{d2} \equiv \mathrm{d1} - \sigma\sqrt{\mathrm{T}}, \end{aligned} \tag{A4}$$

The system of equations was solved by using the generalised reduced gradient method to yield the values for V and σ, which in turn entered into the calculation of the distance to default.. [1] The results were found robust with respect to the choice of starting values. The measure of bank risk used in this paper is then

---

[1] See KMV Corporation (2002), Vassalou and Xing (2004), Eom et al. (2004), Delianedis and Geske (2003), Bharath and Shumway (2004) for a similar derivation and more ample discussions. Duan (1994, 2000) proposes an alternative way to calculate the distance to default, which is based on maximum likelihood estimation of the parameters. We feel that our choice of the "traditional" approach is justified by the fact that the distance to default does not enter directly in our model. Instead, we use it to build a count variable that takes value 1 if the change in distance to default falls in the bottom 95th percentile and 0 elsewhere. In our opinion, this transformation smoothes differences between different computations methods of distance to default. In order to make this point clear, it must be kept in mind that one of the main differences between the traditional method and the Duan's approach is that in the former stock volatility is estimated using historical data. Duan (1994, 2000), hence, corrects that in periods of increasing prices, the traditional approach tends to overestimate the default probability, while the opposite happens in period of decreasing prices. As we do not consider the level of the distance to default but the change, the distortion is essentially spread out through the sample. It is also important to stress that in our study we use data at relatively high frequency and therefore any movements in the distance to default will largely be driven by changes in equity prices under either approach.

obtained by first differencing (A3), yielding the change in the number of standard deviations away from the default point, which is denoted as Δdd.

As underlying data we used daily values for the equity market capitalisation, V_E from Datastream. The equity volatility, σ_E, was estimated as the standard deviation of the daily absolute equity returns and, as proposed in Marcus and Shaked (1984), we took the 6-month moving average (backwards) to reduce noise. The presumption is that the market participants do not use the very volatile short-term estimates, but more smoothed volatility measures. This is not an efficient procedure as it imposes the volatility to be constant. However, equity volatility is accurately estimated for a specific time interval, as long as leverage does not change substantially over that period (see for example Bongini et. al., 2001). The total debt liabilities, D, are obtained from published accounts and are interpolated (using a cubic spline) to yield daily observations. this suggests that our variation in the dependent variable arises from either changes in the value of the bank or in changes in volatility. The time to the maturing of the debt, T was set to one year, which is the common benchmark assumption without particular information about the maturity structure. Finally, we used the government bond rates as the risk-free rates, r.

Appendix II. Results from a GARCH (1,1) model

Estimated coefficients of the Garch (1,1) model for the daily stock market returns in the analysed countries. Equation and variable definitions given in text.

	coef	*std err*	*z-stat*	*prob*
FR				
Const	0.00	0.00	3.03	0.00
ε^2_{t-1}	0.06	0.01	9.60	0.00
σ^2_{t-1}	0.93	0.01	125.21	0.00
DE				
Const	0.00	0.00	5.64	0.00
ε^2_{t-1}	0.10	0.01	10.47	0.00
σ^2_{t-1}	0.89	0.01	97.08	0.00
IT				
Const	0.00	0.00	5.00	0.00
ε^2_{t-1}	0.11	0.01	9.84	0.00
σ^2_{t-1}	0.86	0.01	58.21	0.00
NL				
Const	0.00	0.00	3.68	0.00
ε^2_{t-1}	0.09	0.01	10.11	0.00
σ^2_{t-1}	0.91	0.01	102.81	0.00
ES				
Const	0.00	0.00	5.67	0.00
ε^2_{t-1}	0.08	0.01	10.08	0.00
σ^2_{t-1}	0.91	0.01	108.16	0.00
UK				
Const	0.00	0.00	3.61	0.00
ε^2_{t-1}	0.08	0.01	9.17	0.00
σ^2_{t-1}	0.91	0.01	99.71	0.00
US				
Const	0.00	0.00	4.61	0.00
ε^2_{t-1}	0.07	0.01	11.80	0.00
σ^2_{t-1}	0.92	0.01	144.88	0.00

Appendix III. Robustness checks

Panel 1: Results of the basic contagion model (see table 5)

to from	DE	FR	IT	NL	ES	UK
DE	X			**	**	***
FR		X			***	
IT	**		X			
NL		*	***	X	**	
ES			**		X	
UK	***				***	X

Panel 2: Results after excluding major crises from the sample (Asia, July 1997, Russia, October 1998 and September 11, 2001)

to from	DE	FR	IT	NL	ES	UK
DE	X				***	**
FR		X			***	
IT	*		X		** *	
NL		*	***	X	**	
ES			**		X	*
UK	***				***	X

Panel 3: Results using an ordered logit model

to from	DE	FR	IT	NL	ES	UK
DE	X			***		***
FR		X			***	
IT	*		X			
NL		**	***	X		
ES			***		X	
UK	***				***	X

Panel 4: Adding the volatilities of the countries with significant contagion coefficients

to from	DE	FR	IT	NL	ES	UK
DE	X			**	**	***
FR		X			***	
IT	**		X			
NL		*	***	X	*	
ES			**		X	
UK	***				***	X

Panel 5: Results using large banks only

to from	DE	FR	IT	NL	ES	UK
DE	X			***		***
FR		X			***	
IT	**		X			
NL		**		X	***	
ES			**		X	*
UK	***		***			X

Panel 6: Results using small banks only

to from	DE	FR	IT	NL	ES	UK
DE	X					
FR		X				
IT			X	**		
NL				X		
ES			**		X	
UK				*	***	X

Note: We find a negative impact of From French and Dutch banks on German banks and from French banks on UK banks.

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Bank Lending During the Financial Crisis of 2008

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Abstract

This paper documents that new loans to large borrowers fell by 37% during the peak period of the financial crisis (September-November 2008) relative to the prior three-month period and by 68% relative to the peak of the credit boom (Mar-May 2007). New lending for real investment (such as capital expenditures) fell to the same extent as new lending for restructuring (LBOs, M&A, share repurchases). Banks that have access to deposit financing cut their lending less than banks with less access to deposit financing. In addition, there is a large overhang of revolving credit facilities, which may also have curtailed lending. We document an increase in drawdowns of revolving credit facilities. Many of these drawdowns were undertaken by low credit quality firms concerned about their access to funding. While helpful to these borrowers, they may limit the ability of banks to make other loans. Banks with more revolving lines outstanding relative to deposits reduced their lending more than those with less revolving line exposure.

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1. Introduction

The global financial crisis that erupted in September, 2008 has thrown economies around the world into recession. The seeds of this crisis were sown in the credit boom that peaked in mid-2007, followed by the meltdown of sub-prime mortgages and securitized products. The resulting concerns about the health of financial institutions became a full-blown banking panic following the failures of Lehman Brothers and Washington Mutual, and government takeovers of Fannie Mae, Freddie Mac, and AIG. Although the panic subsided in the first half of October after a variety of government actions to promote the liquidity and solvency of the financial sector, prices across most asset classes and commodities fell drastically, the cost of corporate and bank borrowing rose substantially, and financial market volatility rose to levels that have rarely, if ever, been seen.

The goal of this paper is to understand a key mechanism through which financial crises can affect the real economy, namely the supply of credit to the corporate sector. Towards this end, we examine data on loan syndications, which is the primary source of loans for large corporations. In these syndications a lead bank "originates" a loan and lines up other financial institutions to buy a portion of the loan. This market has evolved over the last twenty years as the main vehicle through which banks and other financial institutions lend to large corporations.

We start by documenting that syndicated lending started falling in mid-2007 and that it accelerated with the onset of the financial crisis in September 2008. During the September-November 2008 period, lending was 37% lower than the prior three-month period and it was 68% lower than the three-month period at the peak of the credit boom, March-May 2007. Lending fell across all types of loans – those used to finance buyouts and takeovers as well as those for real investment.   New revolving credit facilities and new term loans also fell. The decline in lending was particularly steep for below-investment-grade loans.

Our finding of a decline in lending is ostensibly at odds with Chari, Chistiano and Kehoe (2008) who document that commercial and industrial (C&I) loans reported on the balance sheet of U.S. banks rose by about $100 billion from September to mid-October, 2008. However, their finding can be reconciled with ours if the rise in C&I loans on bank balance sheets reflects an increase in drawdowns of *existing* revolving credit facilities. Indeed, we document that this was likely the case. From news accounts alone, we are able to document $16 billion of credit line drawdowns (Table II), which would account for approximately 15.5% of the increase in C&I loans reported on bank balance sheets. In almost all instances, the firms state that they are drawing on their credit lines because of concerns about the financial markets. Thus, these drawdowns are likely to be crisis-related, not drawdowns for usual business purposes.   Given our estimate of roughly $3,500 billion in outstanding revolving credit lines, the drawdowns were likely much larger than what we find in news reports.

A reduction in lending does not, by itself, show that there was a decline in the supply of credit. It is possible that the recession and general economic uncertainty reduced the demand for credit by corporate borrowers. To separate supply and demand effects, we relate bank lending to a bank's willingness or ability to lend during the crisis. In particular, we focus on the role of deposits and revolving credit lines in mitigating and exacerbating the effects of the turmoil in financial markets.

We argue that banks that have a strong base of deposits will likely cut their lending less during the crisis. Concerns about bank solvency made it difficult for banks to roll over short-term debt and raise additional long-term debt. Commercial paper issuance by financial institutions fell dramatically, and commercial paper that was issued was very short term. Thus, banks with a large and stable base of deposits (particularly if they are insured) should be less dependent on financing from short-term debt markets, and therefore less credit-constrained. In addition, as concerns about general credit quality rose during the crisis, investors pulled their money from uninsured money market funds and the commercial paper market, and redeployed their funds to banks in the form of insured deposits. Therefore, banks that were in a better position to attract deposits, were likely less credit-constrained and thus in a better position to lend than banks without a strong deposit base.

Although a strong deposit base could help a bank to continue lending, Kashyap, Rajan and Stein (2002) show that banks that finance more with deposits also extend more credit lines. When credit markets freeze and it is difficult to raise capital, firms tap their unused credit lines. If banks are themselves credit-constrained, then drawdowns of existing lines limit the ability of banks to make new loans. Gatev and Strahan (2006) argue, however, that when there are systemic shocks that lead firms to draw on their credit facilities, those same shocks may also lead to an increase in bank deposits. Specifically, if there is concern about credit quality in commercial paper markets, as occurred after the Enron collapse, firms will tap their backup commercial paper lines. At the same time, investors will withdraw from money market funds that invest in commercial paper, and instead place their money in insured deposits. Thus, banks with deposits are in a better position to withstand the effects of credit line drawdowns. These observations suggest that banks that have more credit line exposure relative to deposits may be in a worse position to continue lending during the financial crisis.

We explore these factors by estimating the cross-sectional determinants of the change in bank lending during the financial crisis. We first establish that banks with more deposit financing (scaled by assets) had a smaller percentage reduction in lending. The median bank cuts its lending by 39% in August-November 2008, relative to the prior year, August 2007-July 2008. However, a bank with deposits one standard deviation below the mean cuts lending by 51%, while a bank with deposits one standard deviation above the mean cuts lending by only 14%.

Similarly, we look at exposure to revolving lines net of deposits (both scaled by bank assets). This variable, which we call net revolving line exposure, is negatively related to loan growth; banks with more credit line exposure cut lending more during the financial crisis. This regression has somewhat more explanatory power than the regression with deposits. A bank with net revolving line exposure one standard deviation above the mean cuts lending by 47%, while a bank with net exposure one standard deviation below the mean cuts lending by only 10%.

This paper is organized as follows. Section 2 briefly describes the data. Section 3 presents the basic facts about aggregate bank lending for a variety of loan types, and it documents the importance of credit line drawdowns. Section 4 presents the cross-sectional regressions and Section 5 concludes.

2. Data

The data for our analysis come from Reuters' DealScan database of large bank loans. Almost all these loans are syndicated, i.e., originated by one or more banks and sold to a syndicate of banks and other investors, notably to those structuring collateralized debt obligations (CDOs), as well as insurance companies, pension funds, mutual funds, and hedge funds. Although CDOs were a large buyer of loans, by the fourth quarter of 2007, they effectively disappeared as buyers after the meltdown in securitized mortgages.

The mean size of the loans in 2008 was $425 million, the median was $125 million, and 90% were larger than $21 million. The average borrower had sales of $5.9 billion. While we do not have data on small loans, the loans in our sample account for a large share of outstanding bank loans. In fact, the value of the outstanding loans in our sample *exceeds* the value of C&I loans on commercial bank balance sheets.[1]

A difficulty with using DealScan to analyze such a recent period is that there are lags in reporting. Some loans are reported within a day of origination, while others may not be reported for several months. These reporting lags will lead to significant underestimation of loan volume for recent months. Using information on reporting dates in the DealScan database, we calculate that for the period November 1, 2006 through October 31, 2007, 21% of loans are reported within a day, 36% within 7 days, 49% within 14 days, 57% within 21 days, and 95% within a year.

We use this information to scale up the data for more recent months, which was collected on December 1, 2008. For example, we identified $1.89 billion of loans originated in the week ending November, 2008. However, we conservatively estimate that only 28.5% of loans made during this week would have been reported by December 1, 2008. This is the average of thee one-day and seven day reporting rate.[2] Thus, we scale up the $1.89 billion of loans to $6.64

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[1] This is possible because Federal Reserve Board's C&I figure corresponds to U.S. commercial banks while our sample includes all banks and financial companies. In addition, approximately 48 percent of the loans in our sample are estimated to be held outside the banking sector (http://www.federalreserve.gov/newsevents/press/bcreg/20081008a.htm.)

[2] This is conservative because the average is a linear approximation of the reporting hazard function which approximately logarithmic in shape.

billion (i.e., $1.89 billion divided by 28.5%). We do this for all weeks prior to December 1, 2008 up to 76 weeks using the relevant reporting rates for each week.

3. Basic Facts

Panel A of Figure 1 graphs the dollar volume of loan issues in three-month periods from December 1, 2006 through November 30, 2008. Because we wanted the last period to encompass the peak period of the financial crisis, we defined it as September to November 2008, and defined the other three-month periods accordingly. The dotted line is the actual reported loan originations during the period. The solid line above the dashed line is our estimate of loan originations taking into account reporting lags. Panel B of Figure 1 graphs the number of loan issues, again adjusting for reporting lags.

[FIGURE 1]

Fact 1: New lending in 2008 was significantly below new lending in 2007, even before the peak period of the financial crisis (September-November 2008).

As can easily be seen from both panels of Figure 1, new lending to large corporate borrowers peaked in the period, March-May 2007. In summer of 2007, concerns about the credit risk of all types of collateralized debt obligations (CDOs), led to a drop in institutional demand for syndicated loans, many of which were put in CDOs. By June-August 2008, the dollar volume of lending was 49% lower than the peak of the credit boom, and the number of loans was down 32%.[3]

[3] The drop in lending was not just due to financial services firms, which were in significant trouble, but was equally to non-financial borrowers.

Fact 2: The decline in new loans accelerated during the financial crisis, falling by 37% in dollar volume and 22% in number of issues in the September-November 2008 period relative to the prior three-month period.

The dollar volume of bank loans fell from $726.03 billion in March – May 2007, the peak of the credit boom, to $372.28 15 months later, and then to $233.31 billion three months later in the September-November 2008 period. The drop in October, 2008 was particularly steep. The dollar volume of lending during the peak financial crisis period was less than one third of peak lending 18 months earlier. The number of issues was less than half. This drop was not just due to the collapse in large LBOs or contraction in the institutional investors demand for corporate loans.

Fact 3: Real investment loans (working capital or general corporate purposes) and restructuring loans (those for M&A, LBOs, and stock repurchases) have decreased to a similar extent.

Table I breaks out the loan data by the stated use of the funds. One can see that a large portion of the loans were used for various types of restructuring: leveraged buyouts (LBOs); mergers and acquisitions (M&A); and stock repurchases. These loans have the effect of increasing leverage or changing ownership, but do not fund real investments in physical or working capital. Thus, a reduction in lending for restructuring purposes might be less troubling than a reduction in loans for real investment.

Figure 2 graphs restructuring and real investment loans through time. We define “real investment loans” as those where funds are to be used for general corporate purposes (e.g. capital expenditures) or working capital, while “restructuring loans” are those used to fund LBOs, M&A, or stock repurchases.

It is apparent that restructuring loans and real investment loans both experienced a significant decline.[4] Although restructuring lending contraction since the peak lending period of March-May 2007 was somewhat bigger than real investment lending contraction (78% vs. 65%), bank loans have fallen not just because LBO and M&A activity has dried up.

[TABLE I & FIGURE 2]

Fact 4: During the peak period of the financial crisis (September-November 2008), non-investment grade loans fell by 54% relative to the prior period, while investment grade loans fell by 22%.

Figure 3 graphs dollar volume of new issues of investment grade and non-investment grade loans. This figure is based on the 33% of the sample for which ratings are available.

During the peak of the credit boom, 50% of all loan syndication and 76% of non-investment-grade syndications were funded by institutional investors, i.e. non-bank financial institutions including CDOs. However, as the credit boom turned into a bust in mid-2007, institutional loan demand dropped drastically, and CDO demand went to zero (Ivashina and Sun, 2007). Thus, the drop in non-investment-grade loans during the September-November period is not driven by the exit of institutional investors; that occurred earlier. The drop in investment-grade lending is also not driven by the drop in institutional demand, as institutional investors were never a large part of that market in the first place

[4] Lumpiness in LBO and M&A loans is likely to reflect a lag in financing of deals committed during the pre-crisis period. We only observe the day of financing, but typically a takeover funding is committed before the board of directors and regulatory approvals. As a result, observed LBO financing could be less responsive to the market conditions than other types of loans.

[FIGURE 3]

Fact 5: During the peak period of the financial crisis (September-November 2008), revolving credit facilities and term loans both declined, but the decline in revolving credit facilities (39%) was somewhat larger than the decline in term loans (26%).

Figure 4 breaks out the sample into term loans and revolving credit facilities. These facilities allow firms to borrow up to a certain amount at a pre-set interest rate (usually a spread over LIBOR). For this right, the firm pays an additional annual fee on all unused portions of the loan. Revolving lines are traditionally funded by banks.

Here too, terms loans and revolving credit facilities track each other. One can see a big drop in 2008 relative to 2007, leading to the low point in September-November 2008. The decline in revolving credit facilities with a maturity greater than one year was even larger. These facilities, which comprise a large portion of originations, require banks to allocate more regulatory capital than do facilities with a maturity of less than one year. Thus, it is not surprising that there has been a bigger drop in the longer term facilities.

[FIGURE 4]

As noted above, it is important to reconcile our findings with those of Chari et. al. (2008), who have documented that C&I loans on bank balance sheets were trending slightly upward for much of 2008, until they rose substantially in following the collapse of Lehman Brothers before stabilizing in the middle of October 2008. Figure 5 shows this graphically.

To reconcile our findings with theirs, it is useful to note the following identity:

$$OutstandingLoans_t =$$

$$OutstandingLoans_{t-1} + NewLoans_t + Drawdowns_t - LoanRetirements_t$$

Thus, outstanding loans will increase more if there are more new loans, more drawdowns, or fewer loan retirements. Since new loans appear to be decreasing, this means that there are either more draw-downs or fewer loan retirements.

[FIGURE 5]

Loan Retirements. Firms may choose to retire debt early with excess cash flow or a stock issue. In fact, in many LBOs, there are explicit plans to pay down debt early with excess cash flow. Though we have no direct evidence of a reduction in loan retirements, it would not be surprising if firms increasingly chose not to repay debt early. This would be the case for LBOs that are running into trouble, firms that want the security of having more cash on their balance sheets, or those that are reluctant to repay debt by issuing equity in a down market..[5]

Revolving Credit Facility Drawdowns. Firms could be increasing their drawdowns of existing credit lines. These would not count as new loans in our data, but would count as new loans in the Federal Reserve data.

Figure 6 plots the total outstanding amount of revolving credit facilities. It rose dramatically through 2006 and 2007, peaking in early 2008 and falling slightly during 2008 to the current level of $3,373 billion. While only a fraction of the total has been drawn, there may have been a recent increase in drawdowns. The only way to know for sure is to look at firms' quarterly filings, but these have only been released for the third quarter. Nevertheless, we have some indication from news reports, that firms may have increased their revolver drawdowns.

[FIGURE 6]

[5] The flip side of a reduction in loan retirements is an increase in loan roll-overs. Some bank debt used to finance LBOs had "PIK toggles" which allowed firms to opt out of paying cash interest, but instead to increase the principal outstanding on the loan (i.e. interest was "payment-in-kind"). Harrah's recently opted for the toggle on its $1.4 billion bank loan, as have a number of other firms. This would show up as increase in loans outstanding.

Table II lists 24 credit line drawdowns reported by the media since mid-August 2008. There were no equivalent announcements in the prior three-month period, which suggests that there has been an increase in drawdowns. The drawdowns total $16 billion. Sixteen of the 22 rated companies are currently below investment grade. At the time of the drawdowns, the average credit default swap spread for the eight companies for which data were available was over 1,500 basis points. Nevertheless, twelve of the sixteen firms were able to draw down and pay interest rates that were below current rates for non-investment-grade debt (LIBOR + 275 basis points). Although violation of the financial covenants could prevent companies from drawing down the lines, most of the loans originated in the past two years were “covenant-lite;” they had loose covenants, which would not prevent them from drawing down their credit lines as their financial condition worsened.[6]

[TABLE II]

The reasons given for the drawdowns are also instructive. In forteen cases, firms state that they are drawing down to enhance liquidity and financial flexibility during the credit crisis. For example, in an 8-K filing with the SEC, the Tribune Company notes that it “is borrowing under the revolving credit facility to increase its cash position to preserve its financial flexibility in light of the current uncertainty in the credit markets.” While Tribune’s recent bankruptcy filing and the credit problems of the other firms list in Table II make clear that financial market turmoil was not the only reason for an increase in drawdowns, it is likely that that a combination

[6] A typical loan contract included Material Adverse Change (MAC) provision that would allow the lender to terminate the deal under the terms of covenants negotiated under the agreement. As the provision’s title indicates, the borrower would need to be facing *material* changed in it its financial performance. Thus, it has nothing to do with the financial health of the bank, and it has everything to do with the financial health of the borrower. However, based on the firm’s public announcements, the latter appears to be the reason for revolvers drawdowns. In addition, the effectiveness of the MAC provision would be hampered by the “covenant-lite” terms.

of firm-specific credit problems and market-wide financial turmoil led to an acceleration of drawdowns.

While C&I loans on bank balance sheets rose from September to mid-October, Figure 5 shows that they leveled off just after October 14, 2008 when the Treasury bought equity in nine large banks and the FDIC offered to guarantee new issues of bank debt. Veronesi and Zingales (2008) have documented that this led to a large drop in the perceived probability of default as measured by bank credit default swap spreads. Thus, as concerns about bank solvency diminished, firms slowed their drawdowns of revolving lines.

Figure 5 also shows that as C&I loans rose so did deposits until they started declining in mid-October. Funds that would otherwise have been invested in commercial paper and money market funds moved over to insured deposits with concerns about credit quality in those markets. They moved back to commercial paper and money market funds after a variety of interventions in those markets. These patterns lend support to our claim that banks with greater access to insured deposits would have had less financing trouble and would have been in a better position to lend.

4. Determinants of Bank Lending During the Crisis

We now examine the characteristics of banks that affected their lending behavior during the crisis. We start by examining the role of deposits. We argue that deposits, particularly insured deposits, are a more stable source of capital than short-term debt. With concerns about bank solvency, interbank lending dried up and banks found it difficult to roll over short-term debt. As discussed by Diamond and Rajan (2001), this is a common feature of financial crises.

Thus, we predict that firms with a larger amount of deposits relative to assets would cut lending by less in the financial crisis.

To examine this prediction, we start by calculating total deposits as a fraction of assets measured as of December 2007. Ideally, we would also use insured deposits; however, we were not able to get these data for the several foreign banks in our sample (e.g., Royal Bank of Scotland, Societe Generale). As Table III indicates, 52% of the median bank's liabilities are deposits. At the 25th percentile, the bank has no deposits. This is because 10 of the 38 firms in our sample are investment banks (such as Goldman Sachs) or finance companies (CIT Group and GE Capital). Bear Stearns, which failed in March, 2008 is dropped from the sample. We keep Lehman Brothers, which failed in September 2008, and Merrill Lynch and Wachovia, both of which were acquired in October 2008. None of the results depend on to their inclusion.

[TABLE III]

The empirical analysis looks at the percentage change in bank lending during the August – November 2008 period relative to a base period before the crisis. We use two base periods. One base period is August 2007-July 2008, the year before the August-November 2008. As shown in the prior section, this base period was a credit crisis of its own, with a big decline in bank lending. We call this base period Crisis I, and the later period Crisis II. We also compare Crisis II to the period August 2006-July 2007, which was a period of robust loan growth. We refer to this period at Pre-Crisis.

As can be seen from Table III, in Crisis II the median bank cuts lending drastically. For example, in Crisis II, there is a 39% decrease in the number of monthly loan syndications in which the median bank participates relative to Crisis I; there is a 55% decrease relative to Pre-

Crisis. There is a 49% drop in the dollar volume of loans relative to Crisis I and a 62% drop relative to Pre-Crisis.

The question we take up now is whether these reductions are related to deposits. Table IV reports the results of regressing percentage change in loan growth on deposits (normalized by assets). In odd columns we calculate the change in loans relative to Crisis I as the base period and in even columns the base period is Pre-Crisis. In Panel A we measure loans in three different ways: the total number of loans in which the bank participates either as a lead bank or syndicate member (columns 1 and 2); the total number of loans in which the bank acts as the lead bank (columns 3 and 4); the dollar amount of loans in which in which the bank acts as the lead bank (columns 5 and 6)   Note that we do not observe the actual amount of a loan, only the amount lent by the syndicate and whether a bank is a lead lender or other syndicate member.

[TABLE IV]

Regardless of how we define the change in loans, the coefficient on deposits is positive, and statistically significant in most of the specifications. For example, in column 3 of Table IV, Panel A, the dependent variable is the percentage change from Crisis I to Crisis II in the number of loans in which the bank plays the lead role. The average bank experiences a 32% drop in the number of lead syndications; however, the estimated coefficients imply that banks with deposits one standard deviation above the mean experience a 14% drop, while banks one standard deviation below the mean experience a 51% drop in dollar lending volume.

Banks with low deposits experience the biggest declines in lending. It is possible, however, that these banks, many of which are investment banks or finance companies, specialize in loan types that experience an especially sharp drop in demand. In particular, there was a big drop in LBO and M&A activity during Crisis I and Crisis II. If investment banks made more of these loans before the crisis (perhaps to support their private equity and M&A advisory businesses), it could generate the pattern we observe. Panel B addresses this concern by focusing on real investment loans – those intended to be used for "corporate purposes" or working capital. Here too we observe the same basic pattern of results, with positive and often statistically significant coefficients on deposits.

Another concern might be that less deposit-dependent banks, particularly investment banks, experienced a greater increase in lending during the credit boom. It would therefore not be surprising if they experienced a steeper fall. We performed three tests to rule out this possibility. First, we documented that less deposit-dependent banks did not increase their lending more during the credit boom. Second, we excluded investment banks from the sample, with no effect on the results. Third, we included the growth in loans during the credit boom as a control in our regression analysis. This control did not affect the estimated coefficient of deposits on loan growth.

The analysis uses total deposits as our main explanatory variable. Since insured deposits are an even more stable supply of capital, it would be useful to verify that the same relationship holds with this variable. Unfortunately, we do not have reliable information on insured deposits from many of the foreign banks in the sample. Nevertheless, for those we do have, we have found that there is a positive relationship between loan growth and insured deposits.

As a final test we examined the effect of deposits on loan growth in a panel data set where a bank's month lending is the unit of observation. We find the same basic pattern of results using that approach. However, since our main interest is in how different types of banks respond to the crisis, the panel structure does not add much and risks understating standard errors. Thus, we reported only the cross-sectional results, with its conservatively estimated standard errors.

We now move to our analysis of the effect of potential drawdowns of outstanding revolving credit facilities on lending behavior of banks. As noted in the introduction and as demonstrated in Table II, firms have been drawing on their credit lines both because of their own financial troubles and because of concerns about the ability of banks fund these commitments. One way to examine this effect would be to estimate the relationship between loan growth and the existing stock of outstanding revolving lines. The problem with this approach is that revolving lines and deposits are highly positively correlated as theory suggests (Kashyap, Rajan and Stein, 2002 and Gatev and Strahan, 2006). Thus, estimating an independent effect with few observations is difficult, if not impossible.

Instead, we calculate a variable that measures the mismatch between revolving lines and deposits, i.e. the stock of outstanding revolving lines less deposits normalized by bank assets. We will refer to this variable as net revolving line exposure. Gatev and Strahan (2006) show that deposits tend to rise when there are abnormally high credit lines drawdowns. These drawdowns are likely to occur when credit risk associated with commercial paper is perceived to be high. But at those times, would-be commercial paper investors will move their funds to insured deposits. We saw a similar phenomenon between September 2008 and mid-October 2008, as shown in Figure 5. Thus, banks with large revolver exposure but few deposits will not see an offsetting increase in deposits as credit lines are drawn down. This drains the bank of liquidity, and leads it to lend less. By contrast, a bank that has limited revolver exposure and a large deposit base does not face the prospect of drawdowns and has a stable funding base. Such a bank should be in a better position to make new loans during the financial crisis.

Table III indicates that the average firm's deposits exceeds its revolving lines by 26% of assets. It is important to keep in mind that this is a crude estimate as we have a very imprecise measure of revolving line exposure both because we can only crudely estimate actual allocations in loan syndications and because we do not know whether there were prior drawdowns on existing credit lines.

Table V shows that, in general, the net revolving line exposure is negatively related to the percent change in loans, measured in the same way as Table IV. Banks with greater net exposure, lend less. For example, the estimated coefficients reported in a column 3, which estimates the effect on the change in the number of lead syndications, predicts that a bank with net revolving line exposure one standard deviation above the mean cuts lending by 47%, while a bank one standard deviation below the mean cuts lending by only 10%.

[TABLE V]

Of course, one has to be careful interpreting our results since our measure subtracts out deposits, which is positively related to lending. Thus, it is not surprising that our net exposure measure has an estimated negative effect. However, it is worth noting that in most specifications the net revolving line exposure measure has a higher R^2 than the comparable regressions with deposits as the dependent variable. These findings should be interpreted as suggestive of an effect of revolving lines, but they are admittedly not conclusive.

Conclusion

New lending declined substantially during the financial crisis across all types of loans. Some of this decline could reflect a drop in demand as firms scale back expansion plans during a recession. However, we show that there may be a supply effect as well: banks with less access to deposit financing and more revolving line exposure reduced their lending more than other banks. While this is consistent with the existence of a supply effect at the bank level, it is possible that there was a shifted in lending from one set of banks to another without affecting the aggregate supply of credit. If, however, bank-borrower relationships matter for the lending process, then borrowers may not be able to easily switch from one lender to another. Ultimately, to determine the real effects of the financial crisis, researchers will need to examine the investment and performance of potential borrowers, not just lenders.

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Figure 1: Total Loan Issuance, US Corporate Loans

Compiled from DealScan database of loan originations. Reported corresponds to loans reported in DealScan as of December 1, 2008.

Panel A: Total amount of loans issued (Billion USD)

Panel B: Total number of loan issued

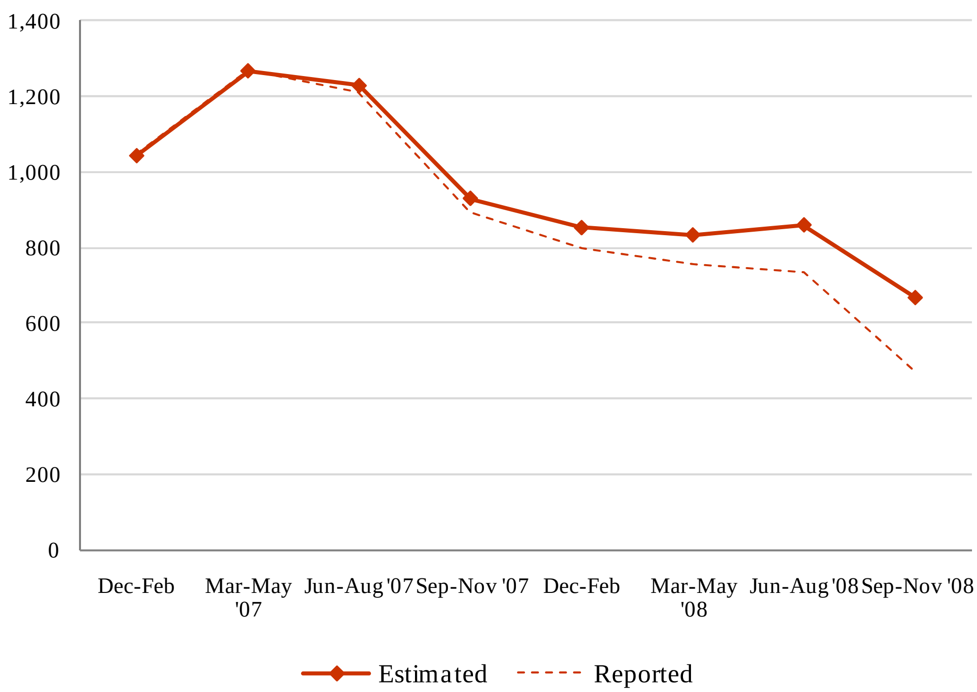


Figure 1 - *continued*

Month	Loan amount		Number of loans	
	Reported	Estimated	Reported	Estimated
Dec-Feb	419.05	419.05	1,043	1,043.00
Mar-May '07	726.03	726.03	1,267	1,267.00
Jun-Aug '07	640.21	648.84	1,211	1,228.02
Sep-Nov '07	526.41	548.89	892	930.46
Dec-Feb	279.80	299.51	797	853.06
Mar-May '08	306.34	339.09	754	833.88
Jun-Aug '08	319.00	372.28	733	860.37
Sep-Nov '08	162.49	233.31	467	668.42

Figure 2: Real Investment Loans vs. Restructuring Loans (Billion USD)

Compiled from DealScan database of loan originations. Real Investment Loans are defined as those that are intended for general corporate purposes, capital expenditure or working capital. Restruturing Loans are defined as those that are intended for leveraged buyouts, mergers and acquisitions, or share repurchases. The numbers correspond to pro-rated figures.

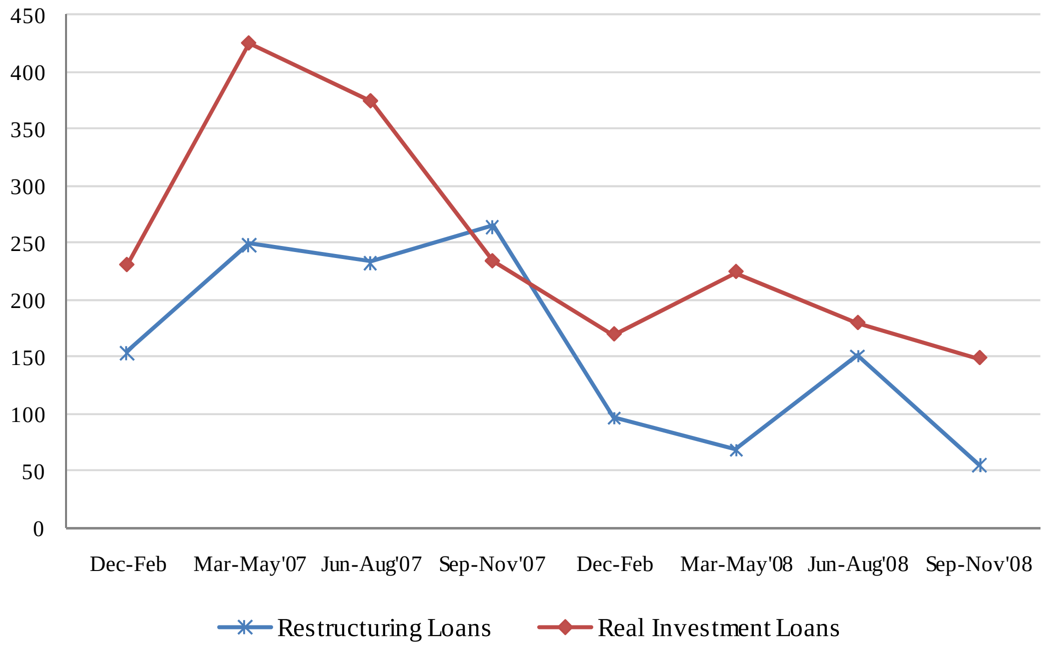
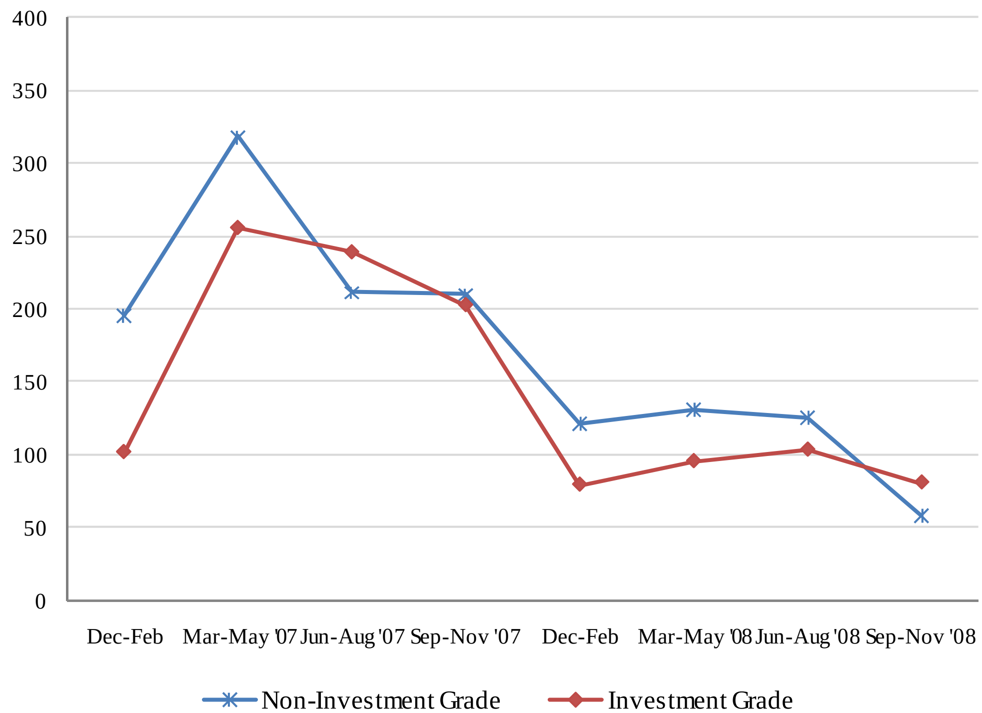


Figure 3: Total Loan Issuance, by Corporate Rating (Billion USD)

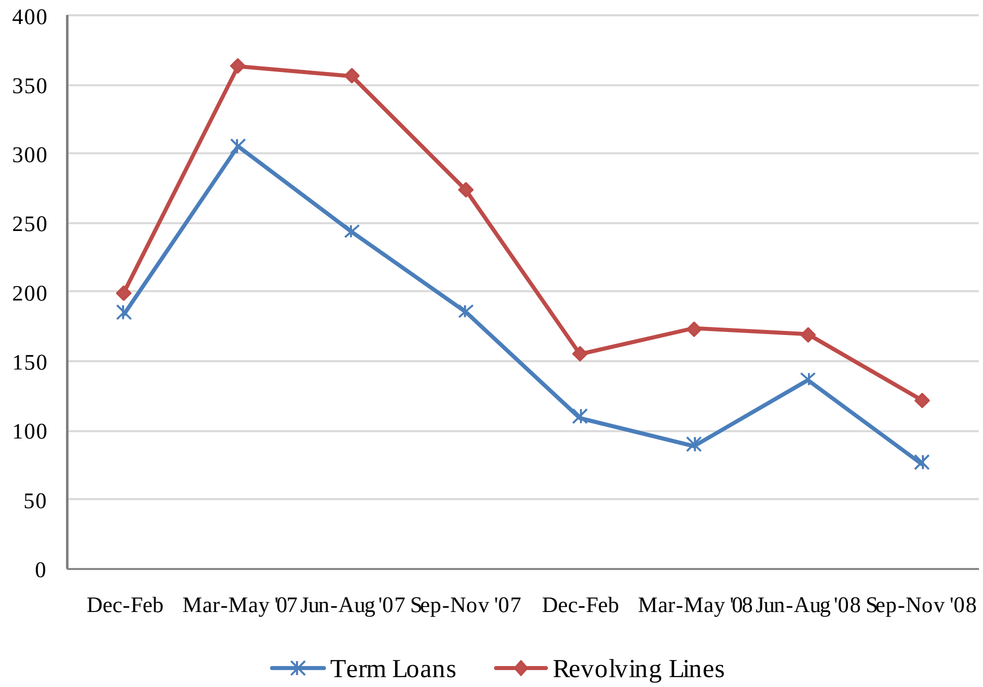
Compiled from DealScan database of loan originations. This figure is based on a sub-sample of loans for which credit ratings are available.



Month	Investment Grade	Non-Investment Grade
Dec-Feb	101.62	195.30
Mar-May '07	255.66	318.07
Jun-Aug '07	238.93	211.13
Sep-Nov '07	202.63	209.81
Dec-Feb	79.25	120.71
Mar-May '08	95.41	130.82
Jun-Aug '08	103.31	124.96
Sep-Nov '08	80.78	57.54

Figure 4: Total Issuance of Revolving Credit Facilities vs. Term Loans (Billion USD)

Compiled from DealScan database of loan originations. The numbers correspond to pro-rated figures.



Month	Term Loans	Revolving Lines	Revolving Lines <1 Yr.	Revolving Lines =>1 Yr.
Dec-Feb	184.44	199.23	26.83	172.40
Mar-May '07	305.08	363.75	61.25	302.49
Jun-Aug '07	243.20	356.65	83.48	273.17
Sep-Nov '07	185.44	274.07	52.29	221.78
Dec-Feb	109.62	155.35	21.26	134.09
Mar-May '08	89.61	173.08	63.26	109.82
Jun-Aug '08	136.55	169.04	59.08	109.96
Sep-Nov '08	76.31	121.54	51.61	69.93

Figure 5: Commercial and Industrial Bank Credit and Deposits (Billion USD)

Compiled from Federal Reserve Statistical Release, includes commercial banks in United States (seasonally adjusted).

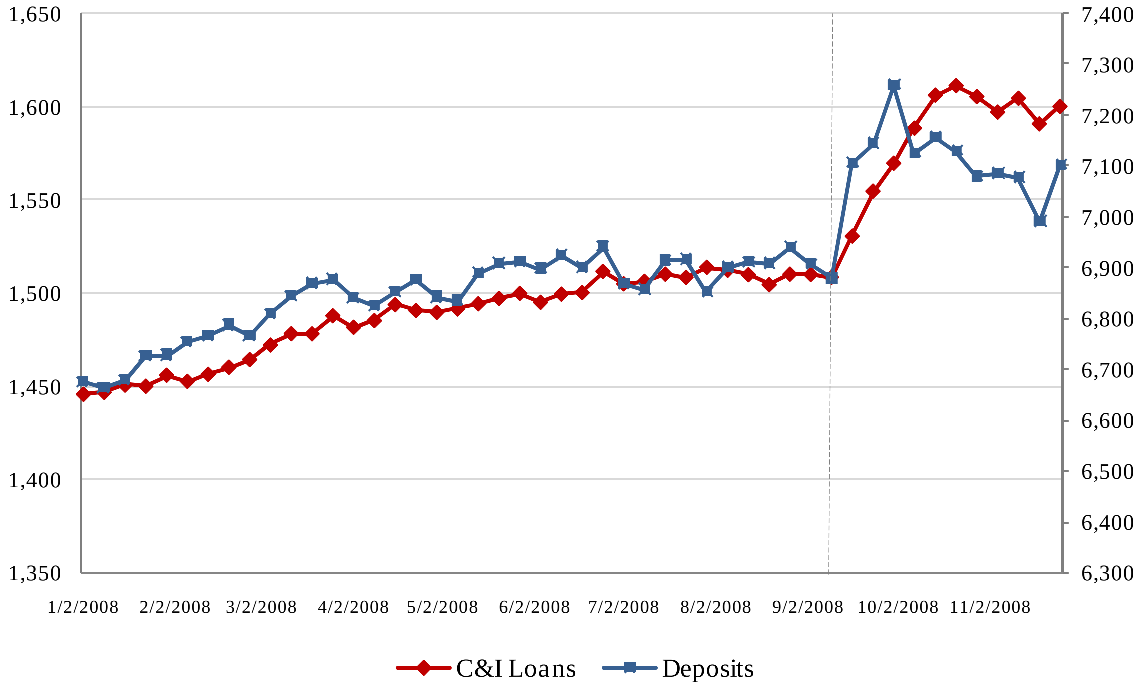


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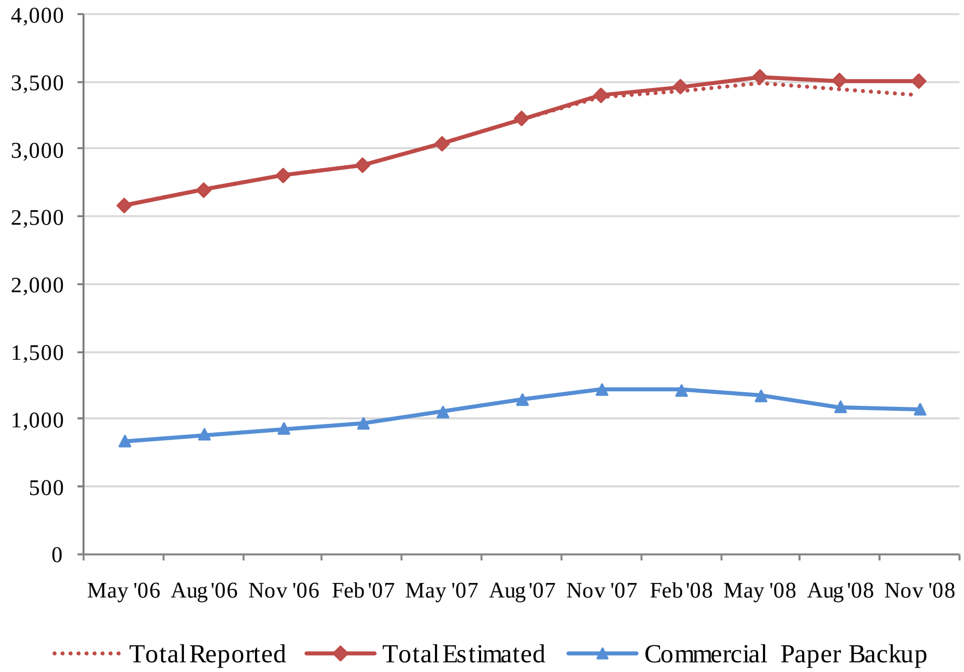
Figure 6: Total Exposure to Revolving Credit Facilities (Billion USD)

Compiled from DealScan database of loan originations.



Month	Total Reported	Total Estimated	Commercial Paper Backup
May '06	2,589.90	2,589.90	831.34
Aug '06	2,703.01	2,703.01	882.07
Nov '06	2,811.21	2,811.21	926.15
Feb '07	2,887.09	2,887.09	964.25
May '07	3,044.89	3,044.89	1,048.54
Aug '07	3,227.35	3,232.13	1,142.97
Nov '07	3,385.89	3,401.65	1,218.29
Feb '08	3,440.65	3,466.29	1,210.85
May '08	3,493.13	3,538.72	1,170.38
Aug '08	3,444.54	3,512.43	1,088.77
Nov '08	3,405.45	3,506.73	1,070.13

Table I: Total Loan Issuance by Loan Purpose, US Corporate Loans (Billion USD)

Compiled from DealScan database of loan originations. The numbers correspond to pro-rated figures.

Year	Month	Corp. purposes	Work. Capital	CP backup	LBO	M&A	Recap.	Debtor-in-poss.	Exit financing	Proj. finance	Real estate	Other	Total
2005	Mar-May	237.45	53.79	43.94	15.89	38.04	47.23	1.18	4.99	0.86	12.10	2.90	458.38
2005	Jun-Aug	208.08	56.87	31.85	21.14	39.89	36.31	2.38	10.80	1.75	13.44	2.58	425.08
2005	Sep-Nov	177.23	54.95	20.26	22.61	85.72	21.06	1.31	2.87	0.22	17.67	4.10	407.99
2005-06	Dec-Feb	196.20	69.43	15.57	33.08	74.03	17.98	3.02	24.37	0.44	11.03	0.72	445.87
2006	Mar-May	281.78	52.41	27.79	27.74	95.01	39.86	2.07	3.75	1.07	13.37	0.00	544.85
2006	Jun-Aug	258.96	61.53	22.35	30.86	122.59	22.54	1.43	8.93	12.29	14.54	1.71	557.71
2006	Sep-Nov	205.32	36.62	16.50	49.96	66.17	14.81	1.21	13.17	1.93	14.55	1.18	421.41
2006-07	Dec-Feb	199.67	30.47	11.22	69.50	59.43	25.17	0.20	5.18	2.68	15.52	0.00	419.05
2007	Mar-May	369.65	54.93	6.15	93.11	111.44	43.74	1.65	13.77	14.88	16.72	0.00	726.03
2007	Jun-Aug	330.72	43.09	13.00	87.18	104.94	40.25	0.30	6.84	3.59	18.93	0.00	648.84
2007	Sep-Nov	205.05	28.33	27.86	140.55	115.66	8.38	0.87	6.73	2.37	10.62	2.46	548.89
2007-08	Dec-Feb	119.57	49.73	1.33	34.72	57.47	4.46	1.51	15.20	6.34	9.18	0.00	299.51
2008	Mar-May	206.22	17.84	2.35	12.78	53.22	2.96	1.19	12.66	14.99	13.57	1.32	339.09
2008	Jun-Aug	148.81	30.46	5.77	50.14	95.76	5.51	3.84	14.71	4.78	11.64	0.88	372.28
2008	Sep-Nov	135.71	12.77	3.37	7.55	45.87	1.88	3.66	0.92	13.10	7.58	0.92	233.31

Table II: Revolving Lines Drawdonws, US Corporate Loans (Billion USD)

Compiled from SEC filings and Reuters. Exposure to Lehman Brothers identifies loans with Lehman in the original lending syndicate.

Date drawn	Company	Current credit rating	Amount drawn ($MM)	Credit line ($MM)	Maturity	Spread (Undrawn/ Drawn)	Lead bank	Exposure to Lehman Brothers	Comment (SEC filings)
08/25/2008	Delta Air Lines	BB-/Ba2	1,000	1,000	2012	50/ L+200	JPM	Yes	Simply put, we have taken this action to increase our cash balance as we approach the closing of the merger. We believe this will provide us with the utmost in flexibility – at minimal cost – as we prepare for this critical transition.
09/15/2008	FairPoint Communications	BB+/Ba3	200	200	2014	37.5/ L+275	Lehman Brothers	Yes	The Company believes that these actions were necessary to preserve its availability to capital due to Lehman Brothers' level of participation in the Company's debt facilities and the uncertainty surrounding both that firm and the financial markets in general.
9/19/2008	Michaels Stores	B	120	1,000	2011	25/ L+150	Bank of America	No	The Company took this proactive step to ensure that it had adequate liquidity to meet its cash needs while there are disruptions in the debt markets.
9/22/2008	General Motors	B-/Caa3	3,400	4,100	2011	30/ L+205	Citigroup, JPM	No	The company said it was drawing down the credit in order to maintain a high level of financial flexibility in the face of uncertain credit markets.
9/26/2008	Goodyear Rubber & Tire Co.	BB+/ Baa3	600	1,500	2013	37.5/ L+125	JPM	No	Temporary delay in the company's ability to access $360 million currently invested with The Reserve Primary Fund, Goodyear said in a statement. The funds also will be used to support seasonal working capital needs and to enhance the company's liquidity position.
9/26/2008	AMR Corp	B-	255	225	2013	50/ L+425	GE Capital Corp.	No	Cash balance
9/30/2008	Duke Energy	A-/ Baa2	1,000	3,200	2012	9/ L+40	Wachovia, JPM	Yes	In light of the uncertain market environment, we made this proactive financial decision to increase our liquidity and cash position and to bridge our access to the debt capital markets. This improves our flexibility as we continue to execute our business plans.
10/1/2008	GameStop	BB+/Ba1	150	400	2012	25/ L+100	Bank of America	No	Acquisition
10/2/2008	Dana Corp	BB+/Ba3	200	650	2013	37.5/ L+200	Citibank	Yes	Drawing down these funds is a prudent liquidity measure. Ensuring access to our liquidity to the fullest extent possible at a time of ambiguity in the capital markets is in the best interest of our customers, suppliers, shareholders, and employees.
Oct-2008	Six Flags	B/B2	244	275	2013	50/ L+250	JPM	Yes	(W)e borrowed $244.2 million under the revolving facility portion of the Credit Facility to ensure we would have sufficient liquidity to fund our off-season expenditures given difficulties in the global credit markets.
Oct-2008	Saks	B+/B2	80.6	500	2011	25/L+100	Bank of America	No	Cash balance
Oct-2008	Monster Worldwide		247	250	2012	8/L+30	Bank of America	No	"We have always viewed our revolving credit as an insurance policy, and given the events in the market, we felt that it was appropriate to access that insurance," CFO Timothy Yates said in an Oct. 30 earnings call.

10/9/2008	CMS Energy	BB+/ Baa3	420	550	2012	20/ L+100	Citigroup	No	Cash balance
10/10/2008	American Electric Power	BBB/ Baa2	2,000	3,000	2012	9/ L+45	JPM, Barclays	No	AEP took this proactive step to increase its cash position while there are disruptions in the debt markets. The borrowings provide AEP flexibility and will act as a bridge until the capital markets improve.
10/15/2008	Lear Corp	BB/B1	400	1,000	2012	50/ L+200	Bank of America	No	Given the recent volatility in the financial markets, we believe it is also prudent to temporarily increase our cash on hand by borrowing under our revolving credit facility.
10/16/2008	Southwest Airlines	BBB+/ Baa1	400	1,200	2010	15/ L+75	JPM	No	Although our liquidity is healthy, we have made the prudent decision in today's unstable financial markets to access $400 million in additional cash through our bank revolving credit facility.
10/16/2008	Chesapeake Energy	BB/Ba2	460	3,000	2012	20/ L+100	Union Bank of California	Yes	Cash balance
10/16/2008	Ebay		1,000	1,840	2012	4/ L+24	Bank of America	Yes	Acquisition
10/20/2008	Tribune Co.	B/Caa1	250	750	2013	75/ L+300	JPM	Yes	Tribune is borrowing under the revolving credit facility to increase its cash position to preserve its financial flexibility in light of the current uncertainty in the credit markets.
10/23/2008	FreeScale Semiconductor	BB/B-	460	750	2012	50/ L+200	Citibank	Yes	We made this proactive financial decision to further enhance our liquidity and cash position. This improves the company's financial flexibility as we continue to execute our business plans.
10/24/2008	Idearc	BBB-/ Ba3	249	250	2011	37.5/ L+150	JPM	No	The company made this borrowing under the revolver to increase its cash position to preserve its financial flexibility in light of the current uncertainty in the credit markets.
11/13/2008	Genworth Financial	A/A2	930	1,700	2012	5/ L+20	Bank of America, JPM	Yes	The Company intends to use the borrowings along with other sources of liquidity for the repayment of outstanding holding company debt (including the Company's senior notes maturing in 2009) at maturity and/or the purchase and retirement of outstanding debt prior to maturity or for other general corporate purposes.
11/23/2008	Computer Sciences	A-/Baa1	1,500	1,500	2012	7/L+25	Citibank	No	The Company took the action due to the current instability of the commercial paper market and to ensure the Company's liquidity position in light of the ongoing credit market dislocation.
11/25/2008	NXP Semiconductors	B	400	600	2012	50/ L+275	Morgan Stanley	No	In view of the current global financial turmoil we are drawing USD 400 million under our revolving credit facility. This is a proactive financial decision in order to secure availability of this facility in a turbulent financial market environment.

Table III

Summary Statistics

Deposits and Assets correspond to the Call reports figures as of the end of 2007. Revolving lines committed is the sum of all revolvers outstanding as of the end of 2007 calculated using DealScan. Pre-crisis, Crisis I, and Crisis II are respectively defined as periods August 2006 through July 2007, August 2007 through July 2008, and August 2008 through November 2008. The dependent variable is in percentage changes; e.g. %Δ Total number of loans (Crisis II vs. Crisis I) = [Mean (Monthly number of loans issued between Aug'08 and Nov'08)/Mean (Monthly number of loans issued between Aug'07 and Jul'08) – 1]. (Lead bank) indicates variables calculated using only loans where the bank is the lead arranger; based on pro-rata credit and estimated retained share of the loans. All the other variables just count the total number of loans with the bank participation. Real investment loans are defined as those that are intended for general corporate purposes, capital expenditure or working capital. To account for reporting bias, all loan numbers correspond to pro-rated figures.

		Full sample						Excluding outliers					
		Obs.	P25	P50	P75	Mean	Std	Obs.	P25	P50	P75	Mean	Std
Deposits/Assets		38	0	0.52	0.65	0.38	0.30	36	0	0.47	0.63	0.36	0.30
(Revolving lines committed – Deposits)/Assets		38	-0.46	-0.28	0.02	-0.26	0.24	36	-0.37	-0.25	0.02	-0.24	0.23
All loans:													
%Δ Total number of loans	Crisis II vs. Crisis I	38	-0.48	-0.39	-0.21	-0.03	1.44	35	-0.50	-0.41	-0.26	-0.41	0.20
%Δ Total number of loans	Crisis II vs. Pre-Crisis	38	-0.71	-0.55	-0.31	0.14	2.51	35	-0.72	-0.58	-0.34	-0.52	0.27
%Δ Total number of loans (lead bank)	Crisis II vs. Crisis I	38	-0.53	-0.39	-0.06	-0.32	0.39	36	-0.53	-0.39	0.00	-0.30	0.38
%Δ Total number of loans (lead bank)	Crisis II vs. Pre-Crisis	38	-0.77	-0.46	-0.25	-0.37	0.56	36	-0.77	-0.46	-0.24	-0.36	0.57
%Δ Total amount of loans (lead bank)	Crisis II vs. Crisis I	38	-0.67	-0.49	-0.31	-0.48	0.32	36	-0.67	-0.49	-0.31	-0.48	0.31
%Δ Total amount of loans (lead bank)	Crisis II vs. Pre-Crisis	38	-0.83	-0.64	-0.32	-0.51	0.49	36	-0.83	-0.64	-0.32	-0.50	0.50
Real investment loans:													
%Δ Total number of loans	Crisis II vs. Crisis I	36	-0.42	-0.33	-0.15	-0.06	1.10	35	-0.49	-0.36	-0.21	-0.36	0.24
%Δ Total number of loans	Crisis II vs. Pre-Crisis	36	-0.62	-0.49	-0.30	-0.21	1.19	35	-0.67	-0.53	-0.36	-0.50	0.26
%Δ Total number of loans (lead bank)	Crisis II vs. Crisis I	37	-0.53	-0.30	0.05	-0.27	0.51	35	-0.53	-0.30	0.18	-0.25	0.51
%Δ Total number of loans (lead bank)	Crisis II vs. Pre-Crisis	37	-0.76	-0.48	-0.20	-0.32	0.67	35	-0.76	-0.48	-0.14	-0.31	0.68
%Δ Total amount of loans (lead bank)	Crisis II vs. Crisis I	38	-0.72	-0.50	-0.22	-0.24	1.35	36	-0.71	-0.50	-0.23	-0.23	1.38
%Δ Total amount of loans (lead bank)	Crisis II vs. Pre-Crisis	38	-0.85	-0.67	-0.30	-0.52	0.48	36	-0.84	-0.67	-0.29	-0.51	0.48

Table IV

Change in Lending and Deposits

Deposits and Assets correspond to the Call reports figures as of the end of 2007. Pre-crisis, Crisis I, and Crisis II are respectively defined as periods August 2006 through July 2007, August 2007 through July 2008, and August 2008 through November 2008. The dependent variable is in percentage changes; e.g. %Δ Total number of loans (Aug'08-Nov'08 vs. Aug'07-Jul'08) = [Mean (Monthly number of loans issued between Aug'08 and Nov'08)/Mean (Monthly number of loans issued between Aug'07 and Jul'08) – 1]. (Lead bank) indicates variables calculated using only loans where the bank is the lead arranger; based on pro-rata credit and estimated retained share of the loans. All the other variables just count the total number of loans with the bank participation. Real investment loans are defined as those that are intended for general corporate purposes, capital expenditure or working capital. To account for reporting bias, all loan numbers correspond to pro-rated figures. Estimates excluding outliers are reported in italics. Robust standard errors are reported in brackets. ***, **, * indicate statistical significance at 1%, 5%, and 10%.

	(1)	(2)	(3)	(4)	(5)	(6)
	%Δ Total number of loans	%Δ Total number of loans	%Δ Total number of loans (lead bank)	%Δ Total number of loans (lead bank)	%Δ Total amount of loans (lead bank)	%Δ Total amount of loans (lead bank)
	Crisis II vs. Crisis I	Crisis II vs. Pre-Crisis	Crisis II vs. Crisis I	Crisis II vs. Pre-Crisis	Crisis II vs. Crisis I	Crisis II vs. Pre-Crisis
	Panel A: All loans					
Deposits/Assets	1.29**	2.42*	0.62***	0.93***	0.29*	0.61**
	[0.62]	[1.26]	[0.21]	[0.27]	[0.17]	[0.25]
	*0.27***	*0.52****	*0.69****	*1.05****	*0.33**	*0.69****
Constant	-0.55***	-0.86***	-0.56***	-0.75***	-0.59***	-0.76***
	[0.13]	[0.24]	[0.09]	[0.07]	[0.08]	[0.07]
Observations	38	38	38	38	38	38
R-squared	0.07	0.08	0.20	0.23	0.07	0.13
	Panel B: Real investment loans					
Deposits/Assets	0.45*	0.65***	0.49	0.98***	0.22	0.43
	[0.26]	[0.22]	[0.31]	[0.32]	[0.25]	[0.29]
	0.14	*0.41****	*0.58**	*1.12****	*0.27*	*0.51**
Constant	-0.46***	-0.69***	-0.47***	-0.72***	-0.54***	-0.69***
	[0.10]	[0.06]	[0.15]	[0.08]	[0.11]	[0.12]
Observations	37	37	37	37	37	38
R-squared	0.09	0.19	0.08	0.18	0.02	0.07

Table V

Change in Lending and Revolvers Overhang

Deposits and Assets correspond to the Call reports figures as of the end of 2007. Revolving lines committed is the sum of all revolvers outstanding as of the end of 2007 calculated using DealScan. Pre-crisis, Crisis I, and Crisis II are respectively defined as periods August 2006 through July 2007, August 2007 through July 2008, and August 2008 through November 2008. The dependent variable is in percentage changes; e.g. %Δ Total number of loans (Aug'08-Nov'08 vs. Aug'07-Jul'08) = [Mean (Monthly number of loans issued between Aug'08 and Nov'08)/Mean (Monthly number of loans issued between Aug'07 and Jul'08) – 1]. (Lead bank) indicates variables calculated using only loans where the bank is the lead arranger; based on pro-rata credit and estimated retained share of the loans. All the other variables just count the total number of loans with the bank participation. Real investment loans are defined as those that are intended for general corporate purposes, capital expenditure or working capital. To account for reporting bias, all loan numbers correspond to pro-rated figures. Estimates excluding outliers are reported in italics. Robust standard errors are reported in brackets. ***, **, * indicate statistical significance at 1%, 5%, and 10%.

	(1)	(2)	(3)	(4)	(5)	(6)
	%Δ Total number of loans	%Δ Total number of loans	%Δ Total number of loans (lead bank)	%Δ Total number of loans (lead bank)	%Δ Total amount of loans (lead bank)	%Δ Total amount of loans (lead bank)
	Crisis II vs. Crisis I	Crisis II vs. Pre-Crisis	Crisis II vs. Crisis I	Crisis II vs. Pre-Crisis	Crisis II vs. Crisis I	Crisis II vs. Pre-Crisis
	Panel A: All loans					
(Revolving lines committed – Deposits)/Assets	-2.19*	-4.27*	-0.79***	-0.83**	-0.41*	-0.66
	[1.18]	[2.36]	[0.26]	[0.37]	[0.21]	[0.42]
	*-0.33***	*-0.68****	*-0.78****	*-1.13****	*-0.36**	*-0.89**
Constant	-0.65***	-1.04***	-0.49***	-0.59***	-0.56***	-0.68***
	[0.15]	[0.32]	[0.08]	[0.09]	[0.07]	[0.07]
Observations	37	37	37	38	37	38
R-squared	0.15	0.18	0.23	0.13	0.09	0.11
	Panel B: Real investment loans					
(Revolving lines committed – Deposits)/Assets	-0.50	-0.65***	-0.72*	-1.02**	-0.46	-0.63
	[0.36]	[0.21]	[0.41]	[0.43]	[0.31]	[0.37]
	-0.16	*-0.52***	*-0.73**	*-1.36****	*-0.42*	*-0.85***
Constant	-0.44***	-0.64***	-0.43***	-0.58***	-0.55***	-0.68***
	[0.09]	[0.05]	[0.14]	[0.10]	[0.09]	[0.11]
Observations	36	36	36	37	36	38
R-squared	0.13	0.31	0.12	0.14	0.07	0.10

DID SECURITIZATION LEAD TO LAX SCREENING? EVIDENCE FROM SUBPRIME LOANS*

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A central question surrounding the current subprime crisis is whether the securitization process reduced the incentives of financial intermediaries to carefully screen borrowers. We examine this issue empirically using data on securitized subprime mortgage loan contracts in the United States. We exploit a specific *rule of thumb* in the lending market to generate exogenous variation in the ease of securitization and compare the composition and performance of lenders' portfolios around the *ad hoc* threshold. Conditional on being securitized, the portfolio with greater ease of securitization defaults by around 10%–25% more than a similar risk profile group with a lesser ease of securitization. We conduct additional analyses to rule out differential selection by market participants around the threshold and lenders employing an optimal screening cutoff unrelated to securitization as alternative explanations. The results are confined to loans where intermediaries' screening effort may be relevant and soft information about borrowers determines their creditworthiness. Our findings suggest that existing securitization practices *did* adversely affect the screening incentives of subprime lenders.

I. Introduction

Securitization, converting illiquid assets into liquid securities, has grown tremendously in recent years, with the universe of securitized mortgage loans reaching \$3.6 trillion in 2006. The

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option to sell loans to investors has transformed the traditional role of financial intermediaries in the mortgage market from "buying and holding" to "buying and selling." The perceived benefits of this financial innovation, such as improving risk sharing and reducing banks' cost of capital, are widely cited (e.g., Pennacchi [1988]). However, delinquencies in the heavily securitized subprime housing market increased by 50% from 2005 to 2007, forcing many mortgage lenders out of business and setting off a wave of financial crises, which spread worldwide. In light of the central role of the subprime mortgage market in the current crisis, critiques of the securitization process have gained increased prominence (Blinder 2007; Stiglitz 2007).

The rationale for concern over the "originate-to-distribute" model during the crisis derives from theories of financial intermediation. Delegating monitoring to a single lender avoids the duplication, coordination failure, and free-rider problems associated with multiple lenders (Diamond 1984). However, for a lender to screen and monitor, it must be given appropriate incentives (Hölmstrom and Tirole 1997), and this is provided by the illiquid loans on its balance sheet (Diamond and Rajan 2003). By creating distance between a loan's originator and the bearer of the loan's default risk, securitization may have potentially reduced lenders' incentives to carefully screen and monitor borrowers (Petersen and Rajan 2002). On the other hand, proponents of securitization argue that reputation concerns, regulatory oversight, or sufficient balance sheet risk may have prevented moral hazard on the part of lenders. What the effects of existing securitization practices on screening were thus remains an empirical question.

This paper investigates the relationship between securitization and screening standards in the context of subprime mortgage loans. The challenge in making a causal claim is the difficulty of isolating differences in loan outcomes independent of contract and borrower characteristics. First, in any cross section of loans, those that are securitized may differ on observable and unobservable risk characteristics from loans that are kept on the balance sheet (not securitized). Second, in a time-series framework, simply documenting a correlation between securitization rates and defaults may be insufficient. This inference relies on establishing the optimal level of defaults at any given point in time. Moreover, this approach ignores macroeconomic factors and policy initiatives that may be independent of lax screening and yet may induce compositional differences in mortgage borrowers over time. For instance, house price appreciation and the changing role of government-sponsored enterprises (GSEs) in the subprime market may also have accelerated the trend toward originating mortgages to riskier borrowers in exchange for higher payments.

We overcome these challenges by exploiting a specific *rule of thumb* in the lending market that induces exogenous variation in the ease of securitization of a loan compared to another loan with similar observable characteristics. This *rule of thumb* is based on the summary measure of borrower credit quality known as the FICO score. Since the mid-1990s, the FICO score has become the credit indicator most widely used by lenders, rating agencies, and investors. Underwriting guidelines established by the GSEs, Fannie Mae and Freddie Mac, standardized purchases of lenders' mortgage loans. These guidelines cautioned against lending to risky borrowers, the most prominent rule of thumb being not lending to borrowers with FICO scores below 620 (Avery et al. 1996; Loesch 1996; Calomiris and Mason 1999; Freddie Mac 2001, 2007; Capone 2002).[1] Whereas the GSEs actively securitized loans when the nascent subprime market was relatively small, since 2000 this role has shifted entirely to investment banks and hedge funds (the nonagency sector). We argue that persistent adherence to this *ad hoc* cutoff by investors who purchase securitized pools from nonagencies generates a differential increase in the ease of securitization for loans. That is, loans made to borrowers which fall just above the 620 credit cutoff have a higher unconditional likelihood of being securitized and are therefore more liquid than loans below this cutoff.

To evaluate the effect of securitization on screening decisions, we examine the performance of loans originated by lenders around this threshold. As an example of our design, consider two borrowers, one with a FICO score of 621 (620^+) and the other with a FICO score of 619 (620^-), who approach the lender for a loan. Screening to evaluate the quality of the loan applicant involves collecting both "hard" information, such as the credit score, and "soft" information, such as a measure of future income stability of the borrower. Hard information, by definition, is something that is easy to contract upon (and transmit), whereas the lender has to exert an unobservable effort to collect soft information (Stein 2002). We argue that the lender has a weaker incentive to base

1. We discuss the 620 rule of thumb in more detail in Section III and in reference to other cutoffs in the lending market in Section IV.G.

origination decisions on both hard and soft information, less carefully screening the borrower, at 620^{+}, where there is an increase in the relative ease of securitization. In other words, because investors purchase securitized loans based on hard information, the cost of collecting soft information is internalized by lenders when screening borrowers at 620^{+} to a lesser extent than at 620^{-}. Therefore, by comparing the portfolio of loans on either side of the credit score threshold, we can assess whether differential access to securitization led to changes in the behavior of lenders who offered these loans to consumers with nearly identical risk profiles.

Using a sample of more than one million home purchase loans during the period 2001–2006, we empirically confirm that the number of loans securitized varies systematically around the 620 FICO cutoff. For loans with a potential for significant soft information—*low documentation* loans—we find that there are more than twice as many loans securitized above the credit threshold at 620^{+} than below the threshold at 620^{-}. Because the FICO score distribution in the population is smooth (constructed from a logistic function; see Figure I), the underlying creditworthiness and demand for mortgage loans (at a given price) are the same for prospective buyers with a credit score of either 620^{-} or 620^{+}. Therefore, these differences in the number of loans confirm that the unconditional probability of securitization is higher above the FICO threshold; that is, it is easier to securitize 620^{+} loans.

Strikingly, we find that although 620^{+} loans should be of slightly better credit quality than those at 620^{-}, low-documentation loans that are originated above the credit threshold tend to default within two years of origination at a rate 10%–25% higher than the mean default rate of 5% (which amounts to roughly a 0.5%–1% increase in delinquencies). As this result is conditional on observable loan and borrower characteristics, the only remaining difference between the loans around the threshold is the increased ease of securitization. Therefore, the greater default probability of loans above the credit threshold must be due to a reduction in screening by lenders.

Because our results are conditional on securitization, we conduct additional analyses to address selection on the part of borrowers, lenders, or investors as explanations for differences in the performance of loans around the credit threshold. First, we rule out borrower selection on observables, as the loan terms and borrower characteristics are smooth across the FICO score threshold. Next, selection of loans by investors is mitigated because the

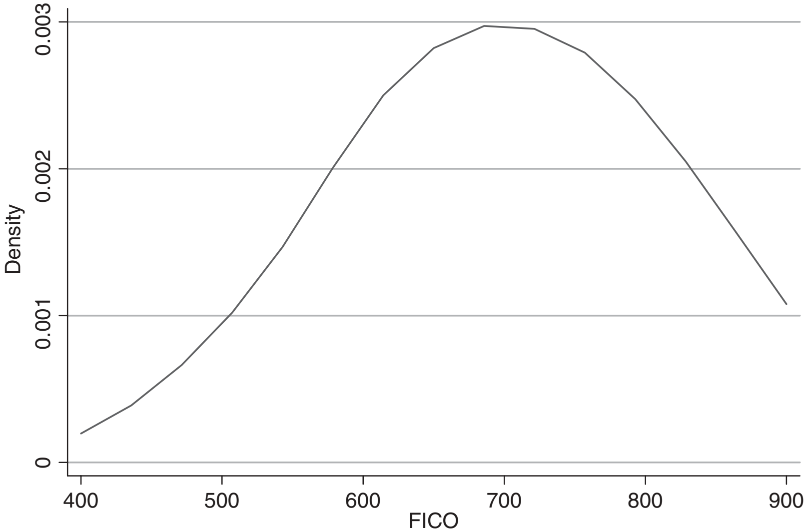


FIGURE I
FICO Distribution (U.S. Population)

The figure presents the FICO distribution in the U.S. population for 2004. The data are from an anonymous credit bureau, which assures us that the data exhibit similar patterns during the other years of our sample. The FICO distribution across the population is smooth, so the number of prospective borrowers in the local vicinity of a given credit score is similar.

decisions of investors (special purpose vehicles, SPVs) are based on the same (smooth–through the threshold) loan and borrower variables as in our data (Kornfeld 2007).

Finally, strategic adverse selection on the part of lenders may also be a concern. However, lenders offer the entire pool of loans to investors, and, conditional on observables, SPVs largely follow a randomized selection rule to create bundles of loans out of these pools, suggesting that securitized loans would look similar to those that remain on the balance sheet (*Comptroller's Handbook* 1997; Gorton and Souleles 2006). Furthermore, if at all present, this selection will tend to be more severe below the threshold, thereby biasing the results against our finding any screening effect. We also constrain our analysis to a subset of lenders who are not susceptible to strategic securitization of loans. The results for these lenders are qualitatively similar to the findings using the full sample, highlighting that screening is the driving force behind our results.

Could the 620 threshold be set by lenders as an optimal cutoff for screening that is unrelated to differential securitization? We investigate further using a natural experiment in the passage and subsequent repeal of antipredatory laws in New Jersey (2002) and Georgia (2003) that varied the ease of securitization around the threshold. If lenders used 620 as an optimal cutoff for screening unrelated to securitization, we would expect the passage of these laws to have no effect on the differential screening standards around the threshold. However, if these laws affected the differential ease of securitization around the threshold, our hypothesis would predict an impact on the screening standards. Our results confirm that the discontinuity in the number of loans around the threshold diminished during a period of strict enforcement of antipredatory lending laws. In addition, there was a rapid return of a discontinuity after the law was revoked. Importantly, our performance results follow the same pattern, that is, screening differentials attenuated only during the period of enforcement. Taken together, this evidence suggests that our results are indeed related to differential securitization at the credit threshold and that lenders did not follow the rule of thumb in all instances. Importantly, the natural experiment also suggests that prime-influenced selection is not at play.

Once we have confirmed that lenders are screening more rigorously at 620^- than 620^+, we assess whether borrowers were aware of the differential screening around the threshold. Although there is no difference in contract terms around the cutoff, borrowers may have an incentive to manipulate their credit scores in order to take advantage of differential screening around the threshold (consistent with our central claim). Aside from outright fraud, it is difficult to strategically manipulate one's FICO score in a targeted manner and any actions to improve one's score take relatively long periods of time, on the order of three to six months (Fair Isaac). Nonetheless, we investigate further using the same natural experiment evaluating the performance effects over a relatively short time horizon. The results reveal a rapid return of a discontinuity in loan performance around the 620 threshold, which suggests that rather than manipulation, our results are largely driven by differential screening on the part of lenders.

As a test of the role of soft information in screening incentives of lenders, we investigate the *full documentation* loan market. These loans have potentially significant hard information because complete background information about the borrower's ability to repay is provided. In this market, we identify another credit cutoff, a FICO score of 600, based on the advice of the three credit repositories. We find that twice as many full documentation loans are securitized above the credit threshold at 600^+ as below the threshold at 600^-. Interestingly, however, we find no significant difference in default rates of full documentation loans originated around this credit threshold. This result suggests that despite a difference in ease of securitization across the threshold, differences in the returns to screening are attenuated due to the presence of more hard information. Our findings for full documentation loans suggest that the role of soft information is crucial to understanding what worked and what did not in the existing securitized subprime loan market. We discuss this issue in more detail in Section VI.

This paper connects several strands of the literature. Our evidence sheds new light on the subprime housing crisis, as discussed in the contemporaneous work of Doms, Furlong, and Krainer (2007), Gerardi, Shapiro, and Willen (2007), Dell'Ariccia, Igan, and Laeven (2008), Mayer, Piskorski, and Tchistyi (2008), Rajan, Seru, and Vig (2008), Benmelech and Dlugosz (2009), Mian and Sufi (2009), and Demyanyk and Van Hemert (2010).[2] This paper also speaks to the literature that discusses the benefits (Kashyap and Stein 2000; Loutskina and Strahan 2007), and the costs (Morrison 2005; Parlour and Plantin 2008) of securitization. In a related line of research, Drucker and Mayer (2008) document how underwriters exploit inside information to their advantage in secondary mortgage markets, and Gorton and Pennacchi (1995), Sufi (2006), and Drucker and Puri (2009) investigate how contract terms are structured to mitigate some of these agency conflicts.[3]

The rest of the paper is organized as follows. Section II provides a brief overview of lending in the subprime market and describes the data and sample construction. Section III discusses the framework and empirical methodology used in the paper, whereas Sections IV and V present the empirical results in the paper. Section VI concludes.

2. For thorough summaries of the subprime mortgage crisis and the research which has sought to explain it, see Mayer and Pence (2008) and Mayer, Pence, and Sherlund (2009).

3. Our paper also sheds light on the classic liquidity/incentives trade-off that is at the core of the financial contracting literature (see Coffee [1991], Diamond and Rajan [2003], Aghion, Bolton, and Tirole [2004], and DeMarzo and Urosevic [2006]).

II. Lending in the Subprime Mortgage Market

II.A. Background

Approximately 60% of outstanding U.S. mortgage debt is traded in mortgage-backed securities (MBS), making the U.S. secondary mortgage market the largest fixed-income market in the world (Chomsisengphet and Pennington-Cross 2006). The bulk of this securitized universe ($3.6 trillion outstanding as of January 2006) is composed of agency pass-through pools—those issued by Freddie Mac, Fannie Mae, and Ginnie Mae. The remainder, approximately, $2.1 trillion as of January 2006, has been securitized in nonagency securities. Although the nonagency MBS market is relatively small as a percentage of all U.S. mortgage debt, it is nevertheless large on an absolute dollar basis. The two markets are separated based on the eligibility criteria of loans that the GSEs have established. Broadly, agency eligibility is established on the basis of loan size, credit score, and underwriting standards.

Unlike the agency market, the nonagency (referred to as "subprime" in the paper) market was not always this size. This market gained momentum in the mid- to late 1990s. Inside B&C Lending—a publication that covers subprime mortgage lending extensively—reports that total subprime lending (B&C originations) grew from $65 billion in 1995 to $500 billion in 2005. Growth in mortgage-backed securities led to an increase in securitization rates (the ratio of the dollar value of loans securitized divided by the dollar value of loans originated) from less than 30% in 1995 to over 80% in 2006.

From the borrower's perspective, the primary feature distinguishing between prime and subprime loans is that the up-front and continuing costs are higher for subprime loans.[4] The subprime mortgage market actively prices loans based on the risk associated with the borrower. Specifically, the interest rate on the loan depends on credit scores, debt-to-income ratios, and the documentation level of the borrower. In addition, the exact pricing may depend on loan-to-value ratios (the amount of equity of the borrower), the length of the loan, the flexibility of the interest rate (adjustable, fixed, or hybrid), the lien position, the property

4. Up-front costs include application fees, appraisal fees, and other fees associated with originating a mortgage. The continuing costs include mortgage insurance payments, principal and interest payments, late fees for delinquent payments, and fees levied by a locality (such as property taxes and special assessments).

type, and whether stipulations are made for any prepayment penalties.[5]

For investors who hold the eventual mortgage-backed security, credit risk in the agency sector is mitigated by an implicit or explicit government guarantee, but subprime securities have no such guarantee. Instead, credit enhancement for nonagency deals is in most cases provided internally by means of a deal structure that bundles loans into "tranches," or segments of the overall portfolio (Lucas, Goodman, and Fabozzi 2006).

II.B. Data

Our primary data set contains individual loan data leased from LoanPerformance. The database is the only source that provides a detailed perspective on the nonagency securities market. The data include information on issuers, broker dealers/deal underwriters, servicers, master servicers, bond and trust administrators, trustees, and other third parties. As of December 2006, more than eight thousand home equity and nonprime loan pools (over seven thousand active) that include 16.5 million loans (more than seven million active) with over $1.6 trillion in outstanding balances were included. LoanPerformance estimates that as of 2006, the data cover over 90% of the subprime loans that are securitized.[6] The data set includes all standard loan application variables such as the loan amount, term, LTV ratio, credit score, and interest rate type—*all* data elements that are disclosed and form the basis of contracts in nonagency securitized mortgage pools. We now describe some of these variables in more detail.

For our purpose, the most important piece of information about a particular loan is the creditworthiness of the borrower. The borrower's credit quality is captured by a summary measure called the FICO score. FICO scores are calculated using various measures of credit history, such as types of credit in use and

5. For example, the rate and underwriting matrix of Countrywide Home Loans Inc., a leading lender of prime and subprime loans, shows how the credit score of the borrower and the loan-to-value ratio are used to determine the rates at which different documentation-level loans are made (www.countrywide.com).

6. Note that only loans that are securitized are reported in the LoanPerformance database. Communication with the database provider suggests that the roughly 10% of loans that are not reported are for privacy concerns from lenders. Importantly for our purpose, the exclusion is not based on any selection criteria that the vendor follows (e.g., loan characteristics or borrower characteristics). Moreover, based on estimates provided by LoanPerformance, the total number of nonagency loans securitized relative to all loans originated has increased from about 65% in early 2000 to over 92% since 2004.

amount of outstanding debt, but do *not* include any information about a borrower's income or assets (Fishelson-Holstein 2005). The software used to generate the score from individual credit reports is licensed by the Fair Isaac Corporation to the three major credit repositories—TransUnion, Experian, and Equifax. These repositories, in turn, sell FICO scores and credit reports to lenders and consumers. FICO scores provide a ranking of potential borrowers by the probability of having some negative credit event in the next *two years*. Probabilities are rescaled into a range of 400–900, though nearly all scores are between 500 and 800, with a higher score implying a lower probability of a negative event. The negative credit events foreshadowed by the FICO score can be as small as one missed payment or as large as bankruptcy. Borrowers with lower scores are proportionally more likely to have all types of negative credit events than are borrowers with higher scores.

FICO scores have been found to be accurate even for low-income and minority populations (see Fair Isaac website www.myfico.com; also see Chomsisengphet and Pennington-Cross [2006]). More importantly, the applicability of scores available at loan origination extends reliably up to two years. By design, FICO measures the probability of a negative credit event over a two-year horizon. Mortgage lenders, on the other hand, are interested in credit risk over a much longer period of time. The continued acceptance of FICO scores in automated underwriting systems indicates that there is a level of comfort with their value in determining lifetime default probability differences.[7] Keeping this as a backdrop, most of our tests of borrower default will examine the default rates up to 24 months from the time the loan is originated.

Borrower quality can also be gauged by the level of documentation collected by the lender when taking the loan. The documents collected provide historical and current information about the income and assets of the borrower. Documentation in the market (and reported in the database) is categorized as full, limited, or no documentation. Borrowers with full documentation provide verification of income as well as assets. Borrowers with limited documentation provide no information about their income but do

7. An econometric study by Freddie Mac researchers showed that the predictive power of FICO scores drops by about 25% once one moves to a three to five–year performance window (Holloway, MacDonald, and Straka 1993). FICO scores are still predictive, but do not contribute as much to the default rate probability equation after the first two years.

provide some information about their assets. "No-documentation" borrowers provide no information about income or assets, which is a very rare degree of screening lenience on the part of lenders. In our analysis, we combine limited and no-documentation borrowers and call them low-documentation borrowers. Our results are unchanged if we remove the very small portion of loans that are no-documentation.

Finally, there is also information about the property being financed by the borrower, and the purpose of the loan. Specifically, we have information on the type of mortgage loan (fixed rate, adjustable rate, balloon, or hybrid) and the loan-to-value (LTV) ratio of the loan, which measures the amount of the loan expressed as a percentage of the value of the home. Typically loans are classified as either for purchase or refinance, though for convenience we focus exclusively on loans for home purchases.[8] Information about the geography where the dwelling is located (ZIP code) is also available in the database.[9]

Most of the loans in our sample are for owner-occupied single-family residences, townhouses, or condominiums (single-unit loans account for more than 90% of the loans in our sample). Therefore, to ensure reasonable comparisons, we restrict the loans in our sample to these groups. We also drop nonconventional properties, such as those that are FHA- or VA-insured or pledged properties, and also exclude buy down mortgages. We also exclude Alt-A loans, because the coverage for these loans in the database is limited. Only those loans with valid FICO scores are used in our sample. We conduct our analysis for the period January 2001 to December 2006, because the securitization market in the subprime market grew to a meaningful size post-2000 (Gramlich 2007).

III. Framework and Methodology

When a borrower approaches a lender for a mortgage loan, the lender asks the borrower to fill out a credit application. In addition, the lender obtains the borrower's credit report from the three credit bureaus. Part of the background information on the application and report could be considered "hard" information (e.g.,

8. We find similar rules of thumb and default outcomes in the refinance market.

9. See Keys et al. (2009) for a discussion of the interaction of securitization and variation in regulation, driven by the geography of loans and the type of lender.

the FICO score of the borrower), whereas the rest is "soft" (e.g., a measure of future income stability of the borrower, how many years of documentation were provided by the borrower, joint income status) in the sense that it is less easy to summarize on a legal contract. The lender expends effort to process the soft and hard information about the borrower and, based on this assessment, offers a menu of contracts to the borrower. Subsequently, the borrower decides to accept or decline the loan contract offered by the lender.

Once a loan contract has been accepted, the loan can be sold as part of a securitized pool to investors. Notably, only the hard information about the borrower (FICO score) and the contractual terms (e.g., LTV ratio, interest rate) are used by investors when buying these loans as part of a securitized pool.[10] In fact, the variables about the borrowers and the loan terms in the LoanPerformance database are identical to those used by investors and rating agencies to rate tranches of the securitized pool. Therefore, although lenders are compensated for the hard information about the borrower, the incentive for lenders to process soft information critically depends on whether they have to bear the risk of loans they originate (Gorton and Pennacchi 1995; Parlour and Plantin 2008; Rajan, Seru, and Vig 2008). The central claim in this paper is that lenders are less likely to expend effort to process soft information as the ease of securitization increases.

We exploit a specific *rule of thumb* at the FICO score of 620 that makes securitization of loans more likely if a certain FICO score threshold is attained. Historically, this score was established as a minimum threshold in the mid-1990s by Fannie Mae and Freddie Mac in their guidelines on loan eligibility (Avery et al. 1996; Capone 2002). Guidelines by Freddie Mac suggest that FICO scores below 620 are placed in the *Cautious Review Category*, and Freddie Mac considers a score below 620 "as a strong indication that the borrower's credit reputation is not acceptable" (Freddie Mac 2001, 2007).[11] This is also reflected in Fair Isaac's statement, "... those agencies [Fannie Mae and Freddie Mac], which buy mortgages from banks and resell them to investors,

10. See Testimony of Warren Kornfeld, Managing Director of Moodys Investors Service, before the subcommittee on Financial Institutions and Consumer Credit, U.S. House of Representatives, May 8, 2007.

11. These guidelines appeared at least as far back as 1995 in a letter by the Executive Vice President of Freddie Mac (Michael K. Stamper) to the CEOs and credit officers of all Freddie Mac sellers and servicers (see Online Appendix Exhibit 1).

have indicated to lenders that any consumer with a FICO score above 620 is good, while consumers below 620 should result in further inquiry from the lender. . . . " Although the GSEs actively securitized loans when the nascent subprime market was relatively small, this role shifted entirely to investment banks and hedge funds (the nonagency sector) in recent times (Gramlich 2007).

We argue that adherence to this cutoff by subprime MBS investors, following the advice of GSEs, generates an increase in demand for securitized loans that are just above the credit cutoff relative to loans below this cutoff. There is widespread evidence that is consistent with 620 being a rule of thumb in the securitized subprime lending market. For instance, rating agencies (Fitch and Standard and Poor's) used this cutoff to determine default probabilities of loans when rating mortgage-backed securities with subprime collateral (Loesch 1996; Temkin, Johnson, and Levy 2002). Similarly, Calomiris and Mason (1999) survey the high-risk mortgage loan market and find 620 as a rule of thumb for subprime loans. We also confirmed this view by conducting a survey of origination matrices used by several of the top fifty originators in the subprime market (a list obtained from *Inside B&C Lending*; these lenders amount to about 70% of loan volume). The credit threshold of 620 was used by nearly all the lenders.

Because investors purchase securitized loans based on hard information, our assertion is that the cost of collecting soft information is internalized by lenders when screening borrowers at 620^- to a greater extent than at 620^+. There is widespread anecdotal evidence that lenders in the subprime market review both soft and hard information more carefully for borrowers with credit scores below 620. For instance, the website of Advantage Mortgage, a subprime securitized loan originator, claims that ". . . all loans with credit scores below 620 require a second level review. . . . There are no exceptions, regardless of the strengths of the collateral or capacity components of the loan."[12] By focusing on the lender as a unit of observation, we attempt to learn about the differential impact ease of securitization had on the behavior of lenders around the cutoff.

To begin with, our tests empirically identify a statistical discontinuity in the distribution of loans securitized around the credit threshold of 620. In order to do so, we show that the number

12. This position for loans below 620 is reflected in lending guidelines of numerous other subprime lenders.

of loans securitized dramatically increases when we move along the FICO distribution from 620^- to 620^+. We argue that this is equivalent to showing that the unconditional probability of securitization increases as one moves from 620^- to 620^+. To see this, denote $N_s^{620^+}$ and $N_s^{620^-}$ as the numbers of loans securitized at 620^+ and 620^-, respectively. Showing that $N_s^{620^+} > N_s^{620^-}$ is equivalent to showing that $N_s^{620^+}/N_p > N_s^{620^-}/N_p$, where N_p is the number of prospective borrowers at 620^+ or 620^-. If we assume that the numbers of prospective borrowers at 620^+ and 620^- are similar, that is, $N_p^{620^-} \approx N_p^{620^+} = N_p$ (a reasonable assumption, as discussed below), then the unconditional probability of securitization is higher at 620^+. We refer to the difference in these unconditional probabilities as the differential *ease of securitization* around the threshold. Notably, our assertion of differential screening by lenders does not rely on knowledge of the proportion of prospective borrowers that applied, were rejected, or were held on the lenders' balance sheet. We simply require that lenders are aware that a prospective borrower at 620^+ has a higher likelihood of eventual securitization.

We measure the extent of the jump by using techniques that are commonly used in the literature on regression discontinuity (e.g., see DiNardo and Lee [2004]; Card, Mas, and Rothstein [2008]). Specifically, we collapse the data on each FICO score (500–800) i and estimate equations of the form

$$Y_i = \alpha + \beta T_i + \theta f(\text{FICO}(i)) + \delta T_i \cdot f(\text{FICO}(i)) + \epsilon_i, \tag{1}$$

where Y_i is the number of loans at FICO score i, T_i is an indicator that takes a value of 1 at FICO ≥ 620 and a value of 0 if FICO < 620 and ϵ_i is a mean-zero error term. f(FICO) and $T \cdot f$(FICO) are flexible seventh-order polynomials, with the goal of these functions being to fit the smoothed curves on either side of the cutoff as closely to the data presented in the figures as possible.[13] f(FICO) is estimated from 620^- to the left, and $T \cdot f$(FICO) is estimated from 620^+ to the right. The magnitude of the discontinuity, β, is estimated by the difference in these two smoothed functions evaluated at the cutoff. The data are *re-centered* such that FICO = 620 corresponds to "0," thus at the

13. We have also estimated these functions of the FICO score using third-order and fifth-order polynomials in FICO, as well as relaxing parametric assumptions and estimating using local linear regression. The estimates throughout are not sensitive to the specification of these functions. In Section IV, we also examine the size and power of the test using the seventh-order polynomial specification following the approach of Card, Mas, and Rothstein (2008).

cutoff the polynomials are evaluated at 0 and drop out of the calculation, which allows β to be interpreted as the magnitude of the discontinuity at the FICO threshold. This coefficient should be interpreted locally in the immediate vicinity of the credit score threshold.

After documenting a large jump at the ad-hoc credit thresholds, we focus on the performance of the loans around these thresholds. We evaluate the performance of the loans by examining the default probability of loans—that is, whether or not the loan defaulted t months after it was originated. If lenders screen similarly for the loan of credit quality 620^+ and the loan of 620^- credit quality, there should not be any discernible differences in default rates of these loans. Our maintained claim is that any differences in default rates on either side of the cutoff, after controlling for hard information, should be only due to the impact that securitization has on lenders' screening standards.

This claim relies on several identification assumptions. First, as we approach the cutoff from either side, any differences in the characteristics of prospective borrowers are assumed to be random. This implies that the underlying creditworthiness and the demand for mortgage loans (at a given price) is the same for prospective buyers with a credit score of 620^- or 620^+. This seems reasonable as it amounts to saying that the calculation Fair Isaac performs (using a logistic function) to generate credit scores has a random error component around any specific score. Figure I shows the FICO distribution in the U.S. population in 2004. These data are from an anonymous credit bureau that assures us that the data exhibit similar patterns during the other years of our sample. Note that the FICO distribution across the population is smooth, so the number of prospective borrowers across a given credit score is similar (in the example above, $N_p^{620^-} \approx N_p^{620^+} = N_p$).

Second, we assume that screening is costly for the lender. The collection of information—hard systematic data (e.g., FICO score) as well as soft information (e.g., joint income status) about the creditworthiness of the borrower—requires time and effort by loan officers. If lenders did not have to expend resources to collect information, it would be difficult to argue that the differences in performance we estimate are a result of ease of securitization around the credit threshold affecting banks incentives to screen and monitor. Again, this seems to be a reasonable assumption (see Gorton and Pennacchi [1995]).

Note that our discussion thus far has assumed that there is no explicit manipulation of FICO scores by the lenders or borrowers.

TABLE I
SUMMARY STATISTICS

Panel A: Summary statistics by year

	Low documentation			Full documentation		
	Number of loans	Mean loan-to-value	Mean FICO	Number of loans	Mean loan-to-value	Mean FICO
2001	35,427	81.4	630	101,056	85.7	604
2002	53,275	83.9	646	109,226	86.4	613
2003	124,039	85.2	657	194,827	88.1	624
2004	249,298	86.0	658	361,455	87.0	626
2005	344,308	85.5	659	449,417	86.9	623
2006	270,751	86.3	655	344,069	87.5	621

Panel B: Summary statistics of key variables

	Low documentation		Full documentation	
	Mean	Std. dev.	Mean	Std. dev.
Average loan size ($000)	189.4	132.8	148.5	116.9
FICO score	656.0	50.0	621.5	51.9
Loan-to-value ratio	85.6	9.8	87.1	9.9
Initial interest rate	8.3	1.8	8.2	1.9
ARM (%)	48.5	50.0	52.7	49.9
Prepayment penalty (%)	72.1	44.8	74.7	43.4

Notes. Information on subprime home purchase loans comes from LoanPerformance. Sample period is 2001–2006. See text for sample selection.

However, the borrower may have incentives to do so if loan contracts or screening differ around the threshold. Our analysis in Section IV.F focuses on a natural experiment and shows that the effects of securitization on performance are not being driven by strategic manipulation.

IV. MAIN EMPIRICAL RESULTS

IV.A. Descriptive Statistics

As noted earlier, the nonagency market differs from the agency market on three dimensions: FICO scores, loan-to-value ratios, and the amount of documentation asked of the borrower. We next look at the descriptive statistics of our sample, with special emphasis on these dimensions. Our analysis uses more than one million loans across the period 2001 to 2006. As mentioned earlier, the nonagency securitization market has grown dramatically since 2000, which is apparent in Panel A of Table I, which shows the number of subprime loans securitized across years. These patterns are similar to those described in Gramlich (2007) and Demyanyk and Van Hemert (2010). The market has witnessed an increase in the number of loans with reduced hard information in the form of limited or no documentation. Note that whereas limited documentation provides no information about income but does provide some information about assets, a no-documentation loan provides information about neither income nor assets. In our analysis we combine both types of limited-documentation loans and denote them as *low*-documentation loans. The full-documentation market grew by 445% from 2001 to 2005, whereas the number of low-documentation loans grew by 972%.

We find similar trends for loan-to-value ratios and FICO scores in the two documentation groups. LTV ratios have gone up over time, as borrowers have put less and less equity into their homes when financing loans. This increase is consistent with better willingness of market participants to absorb risk. In fact, this is often considered the bright side of securitization—borrowers are able to borrow at better credit terms because risk is being borne by investors who can bear more risk than individual banks. Panel A also shows that average FICO scores of individuals who access the subprime market have been increasing over time. The mean FICO score among low-documentation borrowers increased from 630 in 2001 to 655 in 2006. This increase in average FICO scores is consistent with the rule of thumb leading to a larger expansion of the market above the 620 threshold. Average LTV ratios are lower and FICO scores higher for the low-documentation as compared to the full-documentation sample. This possibly reflects the additional uncertainty lenders have about the quality of low-documentation borrowers.

Panel B compares the low- and full-documentation segments of the subprime market on a number of the explanatory variables used in the analysis. Low-documentation loans are on average larger and are given to borrowers with higher credit scores than loans where full information on income and assets is provided. However, the two groups of loans have similar contract terms such as interest rate, loan-to-value, prepayment penalties, and whether the interest rate is adjustable or not. Our analysis below focuses first on the low-documentation segment of the market; we explore the full-documentation market in Section V.

IV.B. Establishing the Rule of Thumb

We first present results that show that large differences exist in the number of low-documentation loans that are securitized around the credit threshold we described earlier. We then examine whether this jump in securitization has any consequences on the subsequent performance of the loans above and below this credit threshold.

As mentioned in Section III, the rule of thumb in the lending market impacts the ease of securitization around a credit score of 620. We therefore expect to see a substantial increase in the number of loans just above this credit threshold as compared to number of loans just below this threshold. In order to examine this, we start by plotting the number of loans at each FICO score in the two documentation categories around the credit cutoff of 620 across years starting with 2001 and ending in 2006. As can be seen from Figure II, there is a marked increase in number of low-documentation loans at 620^+ relative to the number of loans at 620^-. We do not find any such jump for full-documentation loans at FICO of 620.[14] Given this evidence, we focus on the 620 credit threshold for low-documentation loans.

From Figure II, it is clear that the number of loans see roughly a 100% jump in 2004 for low-documentation loans across the credit score of 620—there are twice as many loans securitized at 620^+ at 620^-. Clearly, this is consistent with the hypothesis that the ease of securitization is higher at 620^+ than at scores just below this credit cutoff.

To estimate the jumps in the number of loans, we use the methods described above in Section III using the specification provided in equation (1). As reported in Table II, we find that low-documentation loans see a dramatic increase above the credit threshold of 620. In particular, the coefficient estimate (β) is significant at the 1% level and is on average around 110% (from 73% to 193%) higher for 620^+ as compared to 620^- for loans during the sample period. For instance, in 2001, the estimated discontinuity in Panel A is 85. The mean average number of low-documentation loans at a FICO score for 2001 is 117. The ratio is around 73%. These jumps are plainly visible from the yearly graphs in Figure I.

In addition, we conduct permutation tests (or "randomization" tests), where we vary the location of the discontinuity (T_i)

14. We will elaborate more on full-documentation loans in Section V.

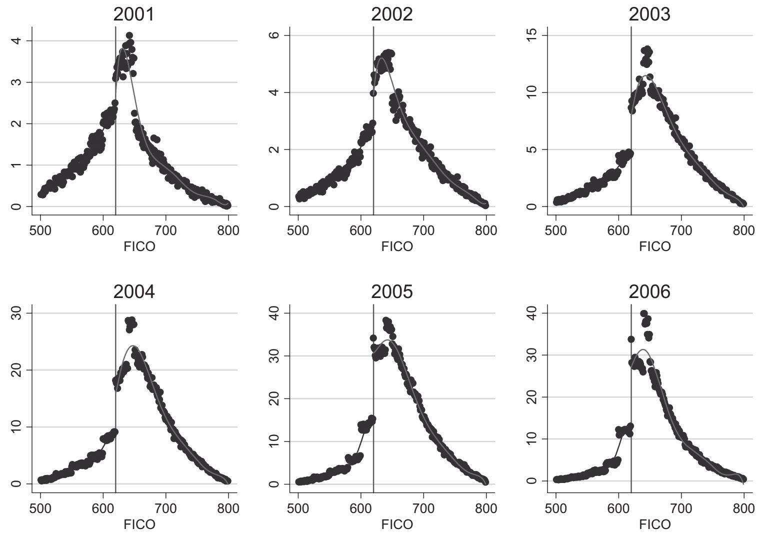


FIGURE II
Number of Loans (Low-Documentation)

The figure presents the data for number of low-documentation loans (in '00s). We plot the average number of loans at each FICO score between 500 and 800. As can be seen from the graphs, there is a large increase in the number of loans around the 620 credit threshold (i.e., more loans at 620^+ as compared to 620^-) from 2001 onward. Data are for loans originated between 2001 and 2006.

TABLE II
DISCONTINUITY IN NUMBER OF LOW-DOCUMENTATION LOANS

Year	FICO $\geq$ 620 (β)	t-stat	Observations	R^2	Mean
2001	36.83	(2.10)	299	.96	117
2002	124.41	(6.31)	299	.98	177
2003	354.75	(8.61)	299	.98	413
2004	737.01	(7.30)	299	.98	831
2005	1,721.64	(11.78)	299	.99	1,148
2006	1,716.49	(6.69)	299	.97	903
Pooled estimate (t-stat) [permutation test p-value]			781.87 (4.14) [.003]		

Notes. This table reports estimates from a regression that uses the number of low-documentation loans at each FICO score as the dependent variable. In order to estimate the discontinuity (FICO $\geq$ 620) for each year, we collapse the number of loans at each FICO score and estimate flexible seventh-order polynomials on either side of the 620 cutoff, allowing for a discontinuity at 620. We report t-statistics in parentheses. Permutation tests, which allow for a discontinuity at every point in the FICO distribution, confirm that jumps for each year are significantly larger than those found elsewhere in the distribution (see Section IV.B for more details). For brevity, we report a permutation test estimate from pooled regressions with time fixed effects removed to account for vintage effects. FICO = 620 has the smallest permutation test p-value (and is thus the largest outlier) among *all* the visible discontinuities in our sample.

across the range of all possible FICO scores and reestimate equation (1). The test treats every value of the FICO distribution as a potential discontinuity, and estimates the magnitude of the observed discontinuity at each point, forming a counter factual distribution of discontinuity estimates. This is equivalent to a bootstrapping procedure that varies the cutoff but does not resample the order of the points in the distribution (Johnston and DiNardo 1996). We then compare the value of the estimated discontinuity at 620 to the counterfactual distribution and construct a test statistic based on the asymptotic normality of the counterfactual distribution and report the p-value from this test. The null hypothesis is that the estimated discontinuity at a FICO score of 620 is the mean of the 300 possible discontinuities.[15]

The precision of the permutation test is limited by the number of observations used at each FICO score. As a result, regressions that pool across years provide the greatest power for statistical testing. While constructing the counterfactuals, we therefore use pooled specifications with year fixed effects removed to account for differences in vintage. The result of this test is shown in Table II and shows that the estimate at 620 for low-documentation loans is a strong outlier relative to the estimated jumps at other locations in the distribution. The estimated discontinuity when the years are pooled together is 780 loans with a permutation test p-value of .003. In summary, if the underlying creditworthiness and the demand for mortgage loans are the same for potential buyers with a credit score of 620^{-} or 620^{+}, this result confirms that it is easier to securitize loans above the FICO threshold.

IV.C. Contract Terms and Borrower Demographics

Before examining the subsequent performance of loans around the credit threshold, we first assess whether there are any differences in hard information—either in contract terms or in other borrower characteristics—around this threshold. The endogeneity of contractual terms based on the riskiness of borrowers may lead to different contracts and hence different types of borrowers obtaining loans around the threshold in a systematic way.

15. In unreported tests, we also conduct a falsification simulation exercise following Card, Mas, and Rothstein (2008). In particular, we apply our specification to data generated by a continuous process. We reject the null hypothesis of no effect (using a two-sided 5% test) in 6.0% of the simulations, indicating that the size of our test is reasonable. A similar test with data generated by a discontinuous process suggests that the power of our test is also reasonable. We reject the null of no effect about 92% of the times (in a two-sided 5% test) in this case.

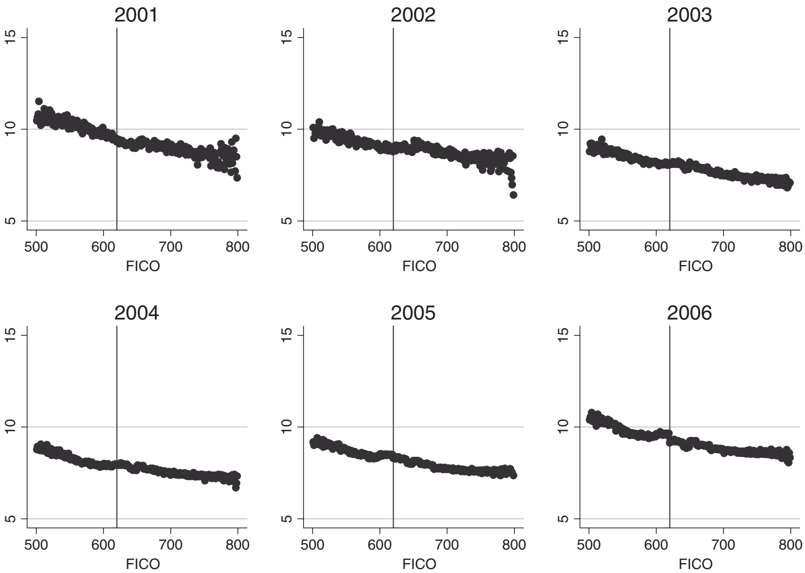


FIGURE III
Interest Rates (Low-Documentation)

The figure presents the data for interest rate (in %) on low-documentation loans. We plot average interest rates on loans at each FICO score between 500 and 800. As can be seen from the graphs, there is no change in interest rates around the 620 credit threshold (i.e., more loans at 620^+ as compared to 620^-) from 2001 onward. Data are for loans originated between 2001 and 2006.

Though we control for the possible contract differences when we evaluate the performance of loans, it is a source of insight to examine whether borrower and contract terms also systematically differ around the credit threshold.

We start by examining the contract terms—LTV ratio and interest rates—across the credit threshold. Figures III and IV show the distributions of interest rates and LTV ratios offered on low-documentation loans across the FICO spectrum. As is apparent, we find these loan terms to be very similar—that is, we find no differences in contract terms for low-documentation loans above and below the 620 credit score. We test this formally using an approach equivalent to equation (1), replacing the dependent variable Y_i in the regression framework with contract terms (loan-to-value ratios and interest rates) and present the results in Appendix I.A. Our results suggest that there is no difference in loan terms across the credit threshold. For instance, for low-documentation loans originated in 2006, the average loan-to-value ratio across the

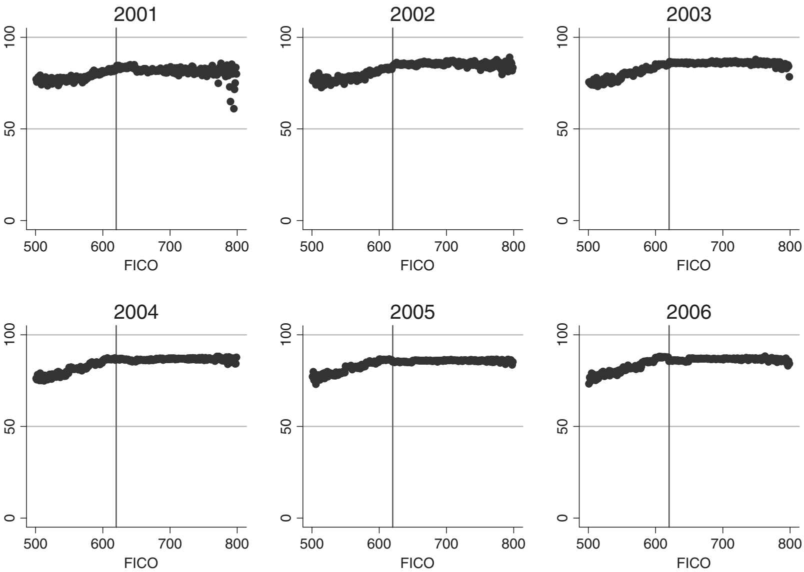


FIGURE IV
Loan-to-Value Ratio (Low-Documentation)

The figure presents the data for loan-to-value ratio (in %) on low-documentation loans. We plot average loan-to-value ratios on loans at each FICO score between 500 and 800. As can be seen from the graphs, there is no change in loan-to-value around the 620 credit threshold (i.e., more loans at 620^+ as compared to 620^-) from 2001 onward. Data are for loans originated between 2001 and 2006.

collapsed FICO spectrum is 85%, whereas our estimated discontinuity is only −1.05%, a 1.2% difference. Similarly for the interest rate, for low-documentation loans originated in 2005, the average interest rate is 8.2%, and the difference on either side of the credit score cutoff is only about −0.091%, a 1% difference. Permutation tests reported in Appendix I.D confirm that these differences are not outliers relative to the estimated jumps at other locations in the distribution.

Additional contract terms, such as the presence of a prepayment penalty, or whether the loan is ARM, FRM, or interest only/balloon are also similar across the 620 threshold (results not shown). In addition, if loans have second liens, then a combined LTV (CLTV) ratio is calculated. We find no difference in the CLTV ratios around the threshold for those borrowers with more than one lien on the home. Finally, low-documentation loans often do not require that borrowers provide information about their

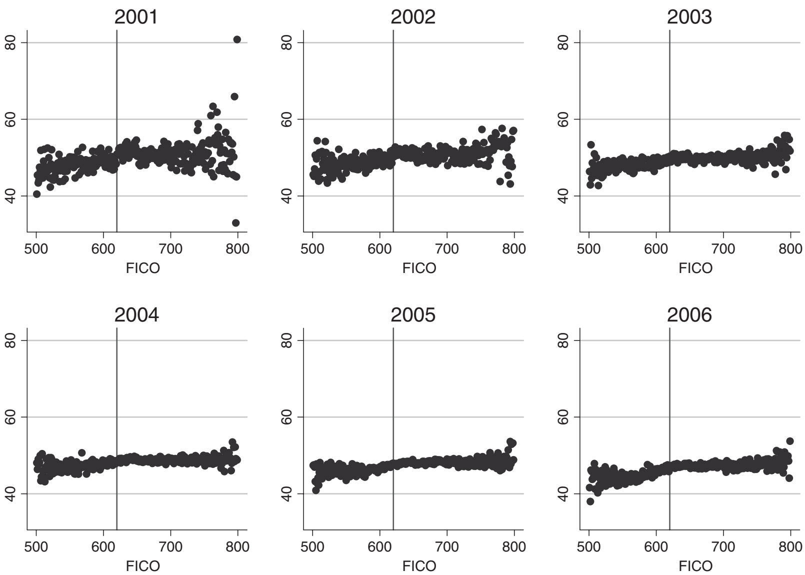


FIGURE V
Median Household Income (Low-Documentation)

The figure presents median household income (in ’000s) of ZIP codes in which loans are made at each FICO score between 500 and 800. As can be seen from the graphs, there is no change in median household income around the 620 credit threshold (i.e., more loans at 620^+ as compared to 620^-) from 2001 onward. We plotted similar distributions for average percent minorities taking loans and average house size and found no differences around the credit thresholds. Data are for loans originated between 2001 and 2006.

income, so only a subset of our sample provides a debt-to-income (DTI) ratio for the borrowers. Among this subsample, there is no difference in DTI across the 620 threshold in low-documentation loans. For brevity, we report only the permutation tests for these contract terms in Appendix I.D.

Next, we examine whether the characteristics of borrowers differ systematically across the credit threshold. In order to evaluate this, we look at the distribution of the population of borrowers across the FICO spectrum for low-documentation loans. The data on borrower demographics come from Census 2000 and are at the ZIP code level. As can be seen from Figure V, median household incomes of the ZIP codes of borrowers around the credit thresholds look very similar for low-documentation loans. We plotted similar distributions for average percent minorities residing in the ZIP code and average house value in the ZIP code across the FICO spectrum (unreported) and again find no differences across the credit threshold.[16]

We use the same specification as equation (1), this time with the borrower demographic characteristics as dependent variables and present the results formally in Appendix I.B. Consistent with the patterns in the figures, permutation tests (unreported) reveal no differences in borrower demographic characteristics around the credit score threshold. Overall, our results indicate that observable characteristics of loans and borrowers are not different around the credit threshold.

IV.D. Performance of Loans

We now focus on the performance of loans that are originated close to the credit score threshold. Note that our analysis in Section IV.C suggests that there is no difference in terms of observable hard information about contract terms or about borrower demographic characteristics across the credit score thresholds. Nevertheless, we will control for these differences when evaluating the subsequent performance of loans in our logit regressions. If there is any remaining difference in the performance of the loans above and below the credit threshold, it can be attributed to differences in unobservable soft information about the loans.

We estimate the differences in default rates on either side of the cutoff using the same framework as equation (1), using the dollar-weighted fraction of loans defaulted within ten to fifteen months of origination as the dependent variable, Y_i. This fraction is calculated as the dollar amount of unpaid loans in default divided by the total dollar amount originated in the same cohort. We classify a loan as under default if any of the conditions is true: (a) payments on the loan are 60^+ days late as defined by the Office of Thrift Supervision; (b) the loan is in foreclosure; or (c) the loan is real estate owned (REO), that is, the bank has retaken possession of the home.[17]

16. Of course, because the census data are at the ZIP code level, we are to some extent smoothing our distributions. We note, however, that when we conduct our analysis on differences in number of loans (from Section IV.B), aggregated at the ZIP code level, we still find jumps across the credit threshold within each individual ZIP code.

17. Although two different definitions of delinquency are used in the industry (Mortgage Bankers Association (MBA) definition and Office of Thrift Supervision (OTS) definition), we have followed the more stringent OTS definition. Whereas MBA starts counting days a loan has been delinquent from the time a payment is missed, OTS counts days a loan is delinquent one month *after* the first payment is missed.

We collapse the data into one-point FICO bins and estimate seventh-order polynomials on either side of the threshold for each year. By estimating the magnitude of β in each year separately, we ensure that no one cohort (or vintage) of loans is driving our results. As shown in Figures VI.A to VI.F, the low-documentation loans exhibit discontinuities in default rates at the FICO score of 620. A year-by-year estimate is presented in Panel A of Table III. Contrary to what one might expect, around the credit threshold, we find that loans with higher credit scores actually default *more often* than lower credit loans in the post-2000 period. In particular, for loans originated in 2005, the estimate of β is 0.023 (t-stat $= 2.10$), and the mean delinquency rate is 0.078, suggesting a 29% increase in defaults to the right of the credit score cutoff. Similarly, in 2006, the estimated size of the jump is 0.044 (t-stat $= 2.68$), and the mean delinquency rate for all FICO bins is 0.155, which is again a 29% increase in defaults around the FICO score threshold.

Panel B presents results of permutation tests, estimated on the residuals obtained after pooling delinquency rates across years and removing year effects. Besides the 60^+ late delinquency definition used in Panel A, we also classify a loan as in default if it is 90^+ late in payments and if it is in foreclosure or REO. Our approach yields similar, if not stronger, results. Compared to 620^- loans, 620^+ loans are on average 2.8% more likely to be in arrears of 90^+ days and 2.5% more likely to be in foreclosure or REO. Permutation test p-values confirm that the jump in defaults at 620 using all the definitions of default are extreme outliers to the rest of the delinquency distribution. For instance, with default defined as foreclosure/REO, the p-value for the discontinuity at 620 is .004. That we find similar results using different default definitions is consistent with high levels of rollover, whereby loans that are delinquent continue to reach deeper levels of delinquency. As shown in Online Appendix Table 1, more than 80% of loans that are 60 days delinquent reach 90^+ days delinquent within a year, and 66% of loans that are 90 days delinquent reach foreclosure twelve months after in the low documentation market.

Although previous default definitions were dollar-weighted, we also use the raw number of loans in default to estimate the magnitude of the discontinuity in loan performance around the FICO threshold. The unweighted results with 60^+ delinquency are also presented in Panel B, and continue to exhibit a pattern of higher credit scores leading to higher default rates across the

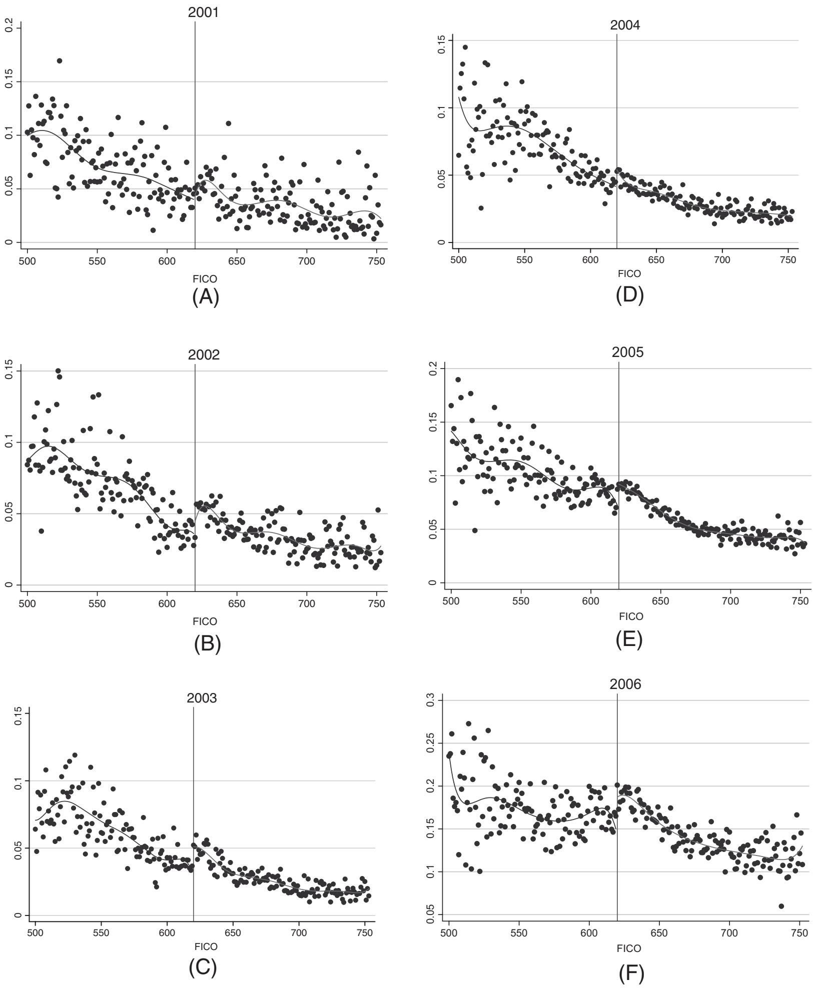


FIGURE VI

Annual Delinquencies for Low-Documentation Loans Originated in 2001–2006

The figures present the percentage of low-documentation loans originated in 2001(A), 2002(B), 2003(C), 2004(D), 2005(E), and 2006(F) that became delinquent. We plot the dollar-weighted fractions of the pools that become delinquent for one-point FICO bins between scores of 500 and 750. The vertical lines denote the 620 cutoff, and a seventh-order polynomial is fitted to the data on either side of the threshold. Delinquencies are reported between ten and fifteen months for loans originated in the year.

TABLE III
DELINQUENCIES IN LOW-DOCUMENTATION LOANS AROUND THE CREDIT THRESHOLD

Panel A: Dollar-weighted fraction of loans defaulted (60+ delinquent)

Year	FICO $\geq$ 620 (β)	t-stat	Observations	R^2	Mean
2001	0.005	(0.44)	254	.58	0.053
2002	0.010	(2.24)	254	.75	0.051
2003	0.022	(3.47)	254	.83	0.043
2004	0.013	(1.86)	254	.79	0.049
2005	0.023	(2.10)	254	.81	0.078
2006	0.044	(2.68)	253	.57	0.155

Panel B: Permutation tests for alternative default definitions (pooled 2001–2006 with time fixed effects)

Dependent variable (default definition)	FICO$\geq$ 620 (β)	t-stat	Permutation test p-value	Observations	R^2	Mean
60+ (dollar-weighted)	0.019	(3.32)	.020	1523	.66	0.072
90+ (dollar-weighted)	0.028	(4.67)	.006	1525	.70	0.065
Foreclosure+ (dollar-weighted)	0.025	(6.25)	.004	1525	.71	0.048
60+ (unweighted)	0.025	(5.00)	.004	1525	.65	0.073

Panel C: Delinquency status of loans

	Pr(delinquency)=1			
	(1)	(2)	(3)	(4)
FICO $\geq$ 620	0.12	0.48	0.12	0.48
	[0.004]	[0.011]	[0.004]	[0.011]
	(3.42)	(2.46)	(2.10)	(2.48)
Observations	1,393,655	1,393,655	1,393,655	1,393,655
Pseudo R^2	.088	.116	.088	.116
Other controls	Yes	Yes	Yes	Yes
FICO $\geq$ 620 $*$ other controls	No	Yes	No	Yes
Time fixed effects	No	Yes	No	Yes
Clustering unit	Loan ID	Loan ID	Vintage	Vintage
Mean delinquency (%)	4.45			

Notes. In Panel A, we estimate the differences in default rates using a flexible seventh-order polynomial on either side of the 620 cutoff, allowing for a discontinuity at 620. The 60^+ dollar-weighted fraction of loans defaulted within 10–15 months is the dependent variable. In Panel B, we present estimates from permutation tests from pooled regressions with time fixed effects removed to account for vintage effects using specification similar to Panel A. Permutation tests confirm that the discontinuity at 620 has the smallest p-value (and is thus largest outlier) in our sample. We use alternative definitions of defaults as the dependent variable. In Panel C, we estimate differences in default rates on either side of the 620 FICO cut off using a logit regression. The dependent variable is the delinquency status of a loan in a given month that takes a value 1 if the loan is classified as under default, as defined in the text. Controls include borrower and loan terms discussed in Section IV. t-statistics are reported in parentheses (marginal effects are reported in square brackets).

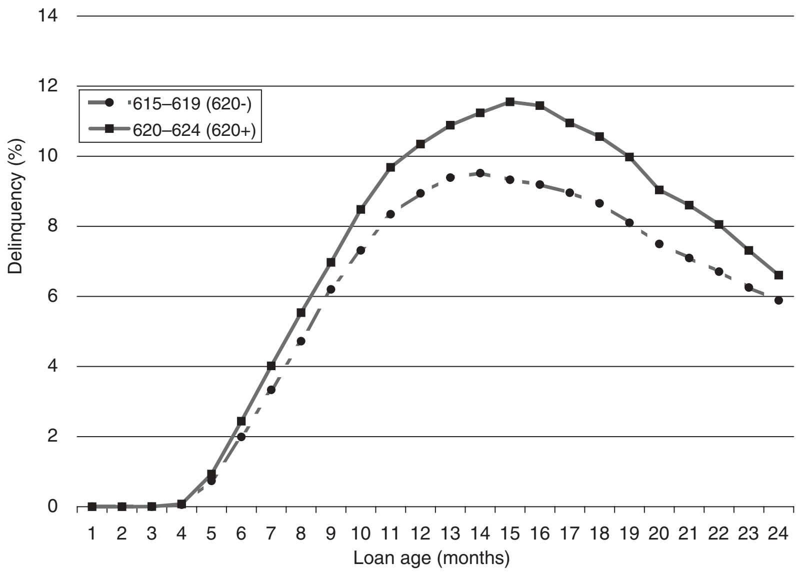


FIGURE VII
Delinquencies for Low-Documentation Loans (2001–2006)
The figure presents the percent of low-documentation loans (dollar-weighted) originated between 2001 and 2006 that subsequently became delinquent. We track loans in two FICO buckets—615–619 (620^-) dashed and 620–624 (620^+) solid—from their origination date and plot the average loans that become delinquent each month after the origination date. As can be seen, the higher credit score bucket defaults *more* than the lower credit score bucket for the post-2000 period. For brevity, we do not report plots separately for each year of origination. The effects shown here in the pooled 2001–2006 plot are apparent in every year.

620 threshold. In fact, the results are statistically stronger than the 60^+ weighted results, with a permutation test p-value based on the pooled estimates of .004 and the discontinuity estimate being significant in all the years (unreported; see Online Appendix Figure 4).

To show how delinquency rates evolve over the age of the loan, in Figure VII we plot the delinquency rates of 620^+ and 620^- for low-documentation loans (dollar-weighted) by loan age. As discussed earlier, we restrict our analysis to about two years after the loan has been originated. As can be seen from the figure, the differences in the delinquency rates are stark. The differences begin around four months after the loans have been originated and persist up to two years. Differences in default rates also seem quite large in terms of magnitudes. Those with a credit score of

620^- are about 20% less likely to default after a year as compared to loans with credit score 620^+.[18]

An alternative methodology is to measure the performance of each unweighted loan by tracking whether or not it became delinquent and estimate logit regressions of the following form:

$$Y_{ikt} = \Phi\left(\alpha + \beta T_{it} + \gamma_1 X_{ikt} + \delta_1 T_{it} * X_{ikt} + \mu_t + \epsilon_{ikt}\right). \tag{2}$$

This logistic approach complements the regression discontinuity framework, as we restrict the sample to the ten FICO points in the immediate vicinity of 620 in order to maintain the same local interpretation of the RD results. Moreover, we are also able to directly control for the possibly endogenous loan terms around the threshold. The dependent variable is an indicator variable (*Delinquency*) for loan i originated in year t that takes a value of 1 if the loan is classified as under default in month k after origination as defined above. We drop the loan from the regression once it is paid out after reaching the REO state. T takes the value 1 if FICO is between 620 and 624, and 0 if it is between 615 and 619 for low-documentation loans, thus restricting the analysis to the immediate vicinity of the cutoffs. Controls include FICO scores, the interest rate on the loan, loan-to-value ratio, and borrower demographic variables, as well as interaction of these variables with T. We also include a dummy variable for the type of loan (adjustable or fixed rate mortgage). We control for the possible nonlinear effect of age of the loan on defaults by including three dummy variables—which take a value of 1 if the month since origination is 0–10, 11–20, and more than 20 months, respectively. Year of origination fixed effects are included in the estimation and standard errors are clustered at the loan level to account for multiple loan delinquency observations in the data.

As can be seen from the logit coefficients in Panel C of Table III, results from this regression are qualitatively similar to those reported in the figures. In particular, we find that β is positive when we estimate the regressions for low-documentation loans. The economic magnitudes are similar to those in the

18. Note that Figure VII does not plot cumulative delinquencies. As loans are paid out, say after a foreclosure, the unpaid balance for these loans falls relative to the time when they entered into a 60^+ state. This explains the dip in delinquencies in the figure after about twenty months. Our results are similar if we plot cumulative delinquencies, or delinquencies that are calculated using the unweighted number of loans. Also note that the fact that we find no delinquencies early on in the duration of the loan is not surprising, given that originators are required to take back loans on their books if the loans default within three months.

figures as well. For instance, keeping all other variables at their mean levels, low-documentation loans with credit score 620^- are about 10%–25% less likely to default after a year than low-documentation loans with credit score 620^+. These are large magnitudes—for instance, note that the mean delinquency rate for low-documentation loans is around 4.45%; the economic magnitude of the effects in column (2) suggests that the difference in the absolute delinquency rate between loans around the credit threshold is around 0.5%–1% for low documentation loans.[19]

To account for the possibility that lax screening might be correlated across different loans within the same vintage, we cluster the loans for each vintage and report the results in columns (3) and (4). Note that the RD regressions (Panel A) estimated separately by year also alleviate concerns about correlated errors across different loans with the same vintage.

In the mortgage market, the other way for loans to leave the pool is to be repaid in full through refinancing or outright purchase, known as prepayment. This prepayment risk decreases the return to investing in mortgage-backed securities in a manner similar to default risk (see, e.g., Gerardi, Shapiro, and Willen [2007] and Mayer, Piskorski, and Tchistyi [2008]). To assess whether there are any differences in actual prepayments around the 620 threshold, we plot the prepayment seasoning curve for all years 2001–2006 in Figure VIII. As can be observed, prepayments of 620^+ and 620^- borrowers in the low-documentation market are similar (also see permutation test in Appendix I.D). Nevertheless, to formally account for prepayment rates, we also estimate a competing risk model using both prepayment and default as means for exiting the sample. We use the Cox proportional hazard model based on the econometric specification following Deng, Quigley, and Van Order (2000). In unreported tests (Online Appendix Table 6), we find results that are similar to our logistic specification.

Finally, the reported specification uses five-point bins of FICO scores around the threshold, but the results are similar (though less precise) if we restrict the bins to fewer FICO scores on either side of 620 (Online Appendix Table 2). This issue is also fully addressed by the regression discontinuity results reported in Panels A and B, which use individual FICO score bins as the units of

19. Our logistic specification is equivalent to a hazard model if we drop loans as soon as they hit the first indicator of delinquency (sixty days in default) and include a full set of duration dummies. Doing so does not change the nature of our results.

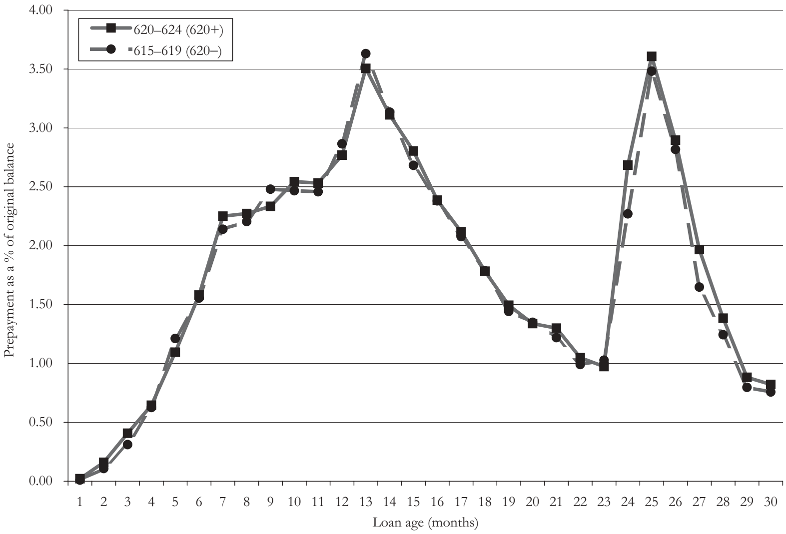


FIGURE VIII

Actual Prepayments for Low-Documentation Loans (2001–2006)

The figure presents the percentage of low-documentation loans (dollar weighted) originated between 2001 and 2006 that subsequently were prepaid. We track loans in two FICO buckets—615–619 (620^-) dashed and 620–624 (620^+) solid—from their origination dates and plot the average loans that prepaid each month after the origination date. As can be seen, there are no differences in prepayments between the higher and lower credit score buckets. For brevity, we do not report plots separately for each year of origination. The effects shown here in the pooled 2001–2006 plot are apparent in every year.

observation. In sum, we find that even after controlling for all observable characteristics of the loan contracts or borrowers, loans made to borrowers with *higher* FICO scores perform *worse* around the credit threshold.

IV.E. Selection Concerns

Because our results are conditional on securitization, we conduct additional analyses to address selection explanations on account of borrowers, investors, and lenders for the differences in the performance of loans around the credit threshold. First, contract terms offered to borrowers above the credit threshold might differ from those below the threshold and attract a riskier pool of borrowers. If this were the case, it would not be surprising if the loans above the credit threshold performed worse than those below it. As shown in Section IV.C, loan terms are smooth through the FICO score threshold. We also investigate the loan terms in more detail than in Section IV.C by examining the distribution of interest rates and loan-to-value ratios of contracts offered around 620 for low-documentation loans.

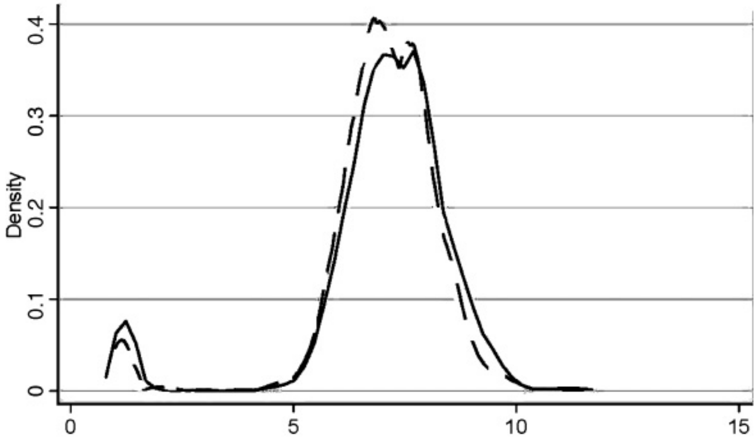
Figure IX.A depicts the Epanechnikov kernel density of the interest rate on low documentation loans in the year 2004 for two FICO groups—620^- (615–619) and 620^+ (620–624). The distributions of interest rates observed in the two groups lie directly on top of one another. A Kolmogorov–Smirnov test for equality of distribution functions cannot be rejected at the 1% level. Similarly, Figure IX.B depicts the density of LTV ratios on low documentation loans in the year 2004 for 620^- and 620^+ groups. Again, a Kolmogorov–Smirnov test for equality of distribution functions cannot be rejected at the 1% level. The fact that we find that the borrowers characteristics are similar around the threshold (Section IV.C) also confirms that selection based on observables is unlikely to explain our results.[20]

Second, there might be concerns about selection of loans by investors. In particular, our results could be explained if investors could potentially cherry pick better loans below the threshold. The loan and borrower variables in our data are identical to the data upon which investors base their decisions (Kornfeld 2007). Furthermore, as shown in Section IV.C, these variables are smooth through the threshold, mitigating any concerns on selection by investors.[21]

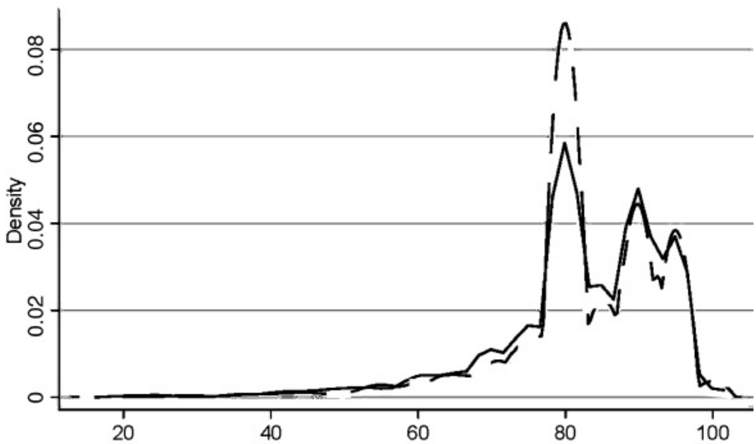
Finally, strategic adverse selection on the part of lenders may also be a concern. Lenders could, for instance, keep loans of better quality on their balance sheet and offer only loans of worse quality to the investors. This concern is mitigated for several reasons.

20. The equality of interest rate distributions also rules out differences in the expected cost of capital across the threshold as an alternative explanation. For instance, lenders could originate riskier loans above the threshold only because the expected cost of capital was lower due to easier securitization. However, in a competitive market, the interest rates charged for these loans should reflect the riskiness of the borrowers. In that case, as mean interest rates above and below the threshold would be the same (Section IV.C), lenders must have added riskier borrowers above the threshold—resulting in a more dispersed interest rate distribution above the threshold. Our analysis in Figure IX.A shows that this is not the case.

21. An argument might also be made that banks screen similarly around the credit threshold but are able to sell portfolios of loans above and below the threshold to investors with different risk tolerance. If this were the case, it could potentially explain our results in Section IV.D. This does not seem likely. Because all the loans in our sample are securitized, our results on performance on loans around the credit threshold are *conditional* on securitization. Moreover, securitized loans are sold to investors in pools that contain a mix of loans from the entire credit score spectrum. As a result, it is difficult to argue that loans of 620^- are purchased by different investors as compared to loans of 620^+.



(A)



(B)

FIGURE IX

Dispersion of (A) Interest Rates and (B) Loan-to-Value (Low-Documentation)

The figure depicts the Epanechnikov kernel density of interest rate (A) and loan-to-value ratio (B) for two FICO groups for low-documentation loans—620^- (615–619) as the solid line and 620^+ (620–624) as the dashed line. The bandwidth for the density estimation is selected using the plug-in formula of Sheather and Jones (1991). The figures show that the densities of interest rates on loans are similar for both the groups. A Kolmogorov–Smirnov test for equality of distribution functions cannot be rejected at the 1% level. Data for loans originated in 2004 are reported here. We find similar patterns for 2001–2006 originations. We do not report those graphs, for brevity.

First, the securitization guidelines suggest that lenders offer the entire pool of loans to investors and that conditional on observables, SPVs largely follow a randomized selection rule to create bundles of loans. This suggests that securitized loans would look similar to those that remain on the balance sheet (*Comptroller's Handbook* 1997; Gorton and Souleles 2006).[22] In addition, this selection, if at all present, will tend to be more severe below the credit threshold, thereby biasing us against finding any effect of screening on performance.

We conduct an additional test that also suggests that our results are not driven by selection on the part of lenders. Although banks may screen and then strategically hold loans on their balance sheets, independent lenders do not keep a portfolio of loans on their books. These lenders finance their operations entirely out of short-term warehouse lines of credit, have limited equity capital, and have no deposit base to absorb losses on loans that they originate (Gramlich 2007). Consequently, they have limited motives for strategically choosing which loans to sell to investors. However, because loans below the threshold are more difficult to securitize and thus are less liquid, these independent lenders still have strong incentives to differentially screen these loans to avoid losses. We focus on these lenders to isolate the effects of screening in our results on defaults (Section IV.D).

To test this, we classify the lenders into two categories—banks (banks, subsidiaries, thrifts) and independents—and examine the performance results only for the sample of loans originated by independent lenders. It is difficult to identify all the lenders in the database because many of the lender names are abbreviated. In order to ensure that we are able to cover a majority of our sample, we classify the top fifty lenders (by origination volume) across the years in our sample period, based on a list from the publication "Inside B&C Mortgage." In unreported results, we confirm that independent lenders also follow the rule of thumb for low-documentation loans. Moreover, low-documentation loans securitized by independents with credit scores of 620^{-} are about 15% less likely to default after a year as

22. We confirmed this fact by examining a subset of loans held on the lenders' balance sheets. The alternative data set covers the top ten servicers in the subprime market (more than 60% of the market) with details on performance and loan terms of loans that are securitized or held on the lenders' balance sheet. We find no differences in the performance of loans that are securitized relative to those kept by lenders, around the 620 threshold. Results of this analysis are available upon request.

compared to low-documentation loans securitized by them with credit scores 620^+.[23] Note that the results in the sample of loans originated by lenders without a strategic selling motive are similar in magnitude to those in the overall sample (which includes other lenders that screen and then may strategically sell). This finding highlights that screening is the driving force behind our results.

IV.F. Additional Variation from a Natural Experiment

Unrelated Optimal Rule of Thumb. So far we have worked under the assumption that the 620 threshold is related to securitization. One could plausibly argue, in the spirit of Baumol and Quandt (1964), that this rule of thumb could have been set by lenders as an optimal cutoff for screening that was unrelated to differential securitization. Ruling this alternative out requires an examination of the effects of the threshold when the ease of securitization varies, everything else equal. To achieve this, we exploit a natural experiment that involves the passage of anti–predatory lending laws in two states which reduced securitization in the subprime market drastically. Subsequent to protests by market participants, the laws were substantially amended and the securitization market reverted to prelaw levels. We use these laws to examine how the main effects vary with the time series variation in the ease of securitization likelihood around the threshold in the two states.

In October 2002, the Georgia Fair Lending Act (GFLA) went into effect, imposing anti–predatory lending restrictions that at the time were considered the toughest in the United States. The law allowed unlimited punitive damages when lenders did not comply with the provisions, and that liability extended to holders in due course. Once GFLA was enacted, the market response was swift. Fitch, Moody's, and S&P were reluctant to rate securitized pools that included Georgia loans. In effect, the demand for the securitization of mortgage loans from Georgia fell drastically during the same period. In response to these actions, the Georgia legislature amended the GLFA in early 2003. The amendments removed many of the GFLAs ambiguities and eliminated covered loans. Subsequent to April 2003, the market revived in Georgia.

23. More specifically, in a specification similar to column (2) in Panel C of Table III, we find that the coefficient on the indicator $T(\text{FICO} \geq 620)$ is 0.67 ($t = 3.21$).

Similarly, New Jersey enacted its law, the New Jersey Homeownership Security Act of 2002, with many provisions similar to those of the Georgia law. As in Georgia, lenders and ratings agencies expressed concerns when the New Jersey law was passed and decided to substantially reduce the number of loans that were securitized in these markets. The Act was later amended in June 2004 in a way that relaxed requirements and eased lenders' concerns.

If lenders use 620 as an optimal cutoff for screening unrelated to securitization, we expect the passage of these laws to have no effect on the differential screening standards around the threshold. However, if these laws affect the differential ease of securitization around the threshold, our hypothesis would predict an impact on the screening standards. As 620^{+} loans became relatively more difficult to securitize, lenders would internalize the cost of collecting soft information for these loans to a greater degree. Consequently, the screening differentials we observed earlier should attenuate during the period of enforcement. Moreover, we expect the results described in Section IV.D to appear only during the periods when the differential ease of securitization around the threshold was high, that is, before the law was passed and after the law was amended.

Our experimental design examines the ease of securitization and performance of loans above and below the credit threshold in both Georgia and New Jersey during the period when the securitization market was affected and compares it with the period before the law was passed and the period after the law was amended. To do so, we estimate equations (1) and (2) with an additional dummy variable that captures whether or not the law is in effect (*NoLaw*). We also include time fixed effects to control for any macroeconomic factors independent of the laws.

The results are striking. Panel A of Table IV confirms that the discontinuity in the number of loans around the threshold diminishes during a period of strict enforcement of anti–predatory lending laws. In particular, the difference in number of loans securitized around the credit thresholds fell by around 95% during the period when the law was passed in Georgia and New Jersey. This effectively nullified any meaningful difference in the ease of securitization above the FICO threshold. Another intuitive way to see this is to compare these jumps in the number of loans with jumps in states that had housing profiles similar to those of Georgia and New Jersey before the law was passed (e.g., Texas in 2001). For instance, relative to the discontinuity in Texas, the jump during

TABLE IV
NUMBER OF LOANS AND DELINQUENCIES IN LOW-DOCUMENTATION LOANS ACROSS THE CREDIT THRESHOLD: EVIDENCE FROM A NATURAL EXPERIMENT

Year	FICO $\geq$ 620 (β)	t-stat	Observations	R^2	Mean
Panel A: Number of low-documentation loans					
During law	10.71	(2.30)	294	.90	16
Pre and post law	211.50	(5.29)	299	.96	150

Panel B: Delinquency status of low-documentation loans

	Pr(delinquency)=1			
	Entire period 2001–2006		During law and six months after	
	(1)	(2)	(3)	(4)
FICO $\geq$ 620	−0.91	−0.91	−1.02	−1.02
	[0.043]	[0.043]	[0.030]	[0.030]
	(1.78)	(2.00)	(1.69)	(2.12)
FICO $\geq$ 620 $*$ *NoLaw*	0.88	0.88	1.13	1.13
	[0.040]	[0.040]	[0.034]	[0.034]
	(1.90)	(1.94)	(1.79)	(1.93)
Observations	109,536	109,536	14,883	14,883
Other controls	Yes	Yes	Yes	Yes
FICO $\geq$ 620 $*$ other controls	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Pseudo R^2	.06	.06	.05	.05
Clustering unit	Vintage	Loan ID	Vintage	Loan ID
Mean delinquency (%)	6.1		4.2	

Notes. This table reports estimates of the regressions on differences in number of loans and performance of loans across the credit thresholds. We use specifications similar to these Table II, Panel A, to estimate the number of loans regressions and Table III, Panel C, to estimate delinquency regressions. We restrict our analysis to loans made in Georgia and New Jersey. *NoLaw* is a dummy that takes a value of 1 if the anti–predatory lending law was not passed in a given year or was amended and a value of 0 during the time period when the law was passed. Permutation tests confirm that the discontinuity in number of loans at 620 when the law is not passed has the smallest p-value (and is thus the largest outlier) in the Georgia and New Jersey sample. We report t-statistics in parentheses (marginal effects are reported in square brackets).

the period when the law was passed is about 5%, whereas the jumps are of comparable size both before the law was passed and after the law was amended. In addition, the results also indicate the rapid return of a discontinuity after the law is revoked. It is notable that this time horizon is too brief for any meaningful change in the housing stock (Glaeser and Gyourko 2005) or in the underlying demand for home ownership.

Importantly, our performance results follow the same pattern as well. Columns (1) and (2) of Panel B show that the default rates for 620^+ loans were below that of 620^- loans in both Georgia and New Jersey *only* when the law was in effect. In addition, when the law was either not passed or was amended, we find that default rates for loans above the credit threshold are similar to those for loans below the credit threshold. This upward shift in the default curve above the 620 threshold is consistent with the results reported in Section IV.D. Taken together, these results suggest that our findings are indeed related to differential securitization at the credit threshold and that lenders were not blindly following the rule of thumb in all instances.

Manipulation of Credit Scores. Having confirmed that lenders are screening more at 620^{-} than at 620^{+}, we assess whether borrowers were aware of the differential screening around the threshold. Even though there is no difference in contract terms around the cutoff, screening is weaker above the 620 score than below it, and this may create an incentive for borrowers to manipulate their credit score. If FICO scores could be manipulated, lower quality borrowers might artificially appear at higher credit scores. This behavior would be consistent with our central claim of differential screening around the threshold. Note that per the rating agency (Fair Isaac), it is difficult to strategically manipulate one's FICO score in a targeted manner. Nevertheless, to examine the response of borrowers more closely, we exploit the variation generated from the same natural experiment.

If FICO scores tend to be quite sticky and it takes relatively long periods of time (more than three to six months) to improve credit scores, as Fair Isaac claims, we should observe that the difference in performance around the threshold should take time to appear after the laws are reversed. Restricting our analysis to loans originated within six months after the laws were reversed, columns (3) and (4) of Panel B (Table IV) show that the reversal of anti–predatory lending laws has immediate effects on the performance of loans that are securitized. This result suggests that borrowers might not have been aware of the differential screening around the threshold or were unable to quickly manipulate their FICO scores. Overall, the evidence in this section is consistent with Mayer and Pence (2008), who find no evidence of manipulation of FICO scores in their survey of the subprime market.[24]

24. As a further check, we obtained another data set of subprime loans that continues to track the FICO scores of borrowers after loan origination. Borrowers who manipulate their FICO scores before loan issuance should experience a decline in FICO score shortly after receiving a loan (because a permanent change in the credit score cannot be considered manipulation). Consistent with evidence for no

IV.G. Additional Confirmatory Tests

GSE Selection. Although the subprime market is dominated by the nonagency sector, one might worry that the GSEs may differentially influence the selection of borrowers into the subprime market through their actions in the prime market. For instance, the very best borrowers above the 620 threshold might select out of the subprime market in search of better terms in the prime market. We establish several facts to confirm that this is not the case.

First, the natural experiment we discuss in Section IV.F suggests that prime-influenced selection is not at play. The anti–predatory lending laws were targeted primarily toward the subprime part of the market (Bostic et al. 2008), leaving the prime part of the market relatively unaffected. To confirm the behavior of the prime market during the enforcement of anti–predatory lending laws, we rely on another data set of mortgages in the United States that covers the agency loan market. The data are collected from the top U.S. servicers, are primarily focused on the agency market, and covers the period 2001 to 2006. As reported in Panel A of Table V, during the natural experiment, it was no more difficult to obtain an agency loan (comparable to a subprime loan in our sample) than before or after the law was in effect. Similarly, in unreported tests we find that contractual terms (such as LTV ratios and interest rates) around 620 see no change across time periods. Furthermore, in the prime market, there were no differences in defaults around the 620 threshold across the time periods (Table V, Panel B). Because borrower quality in the prime market did not change across the 620 threshold across the two time periods, if there was indeed selection, the very best 620^{+} subprime borrowers should have selected out into the prime market even while the laws were in place. As a result, we should have found that 620^{+} borrowers in subprime market continued to default more than 620^{-} borrowers even when the law is in place. As we showed earlier in Table IV, this is not the case.

Second, the data set confirms that Freddie Mac and Fannie Mae primarily do not buy subprime loans (especially low-documentation loans) with credit scores around FICO of 620. This is consistent with anecdotal evidence that the role of active

manipulation around the threshold, we find that both 620^{+} and 620^{-} borrowers are as likely to experience such a reduction within a quarter of obtaining a loan. Results of this analysis are available upon request.

TABLE V
NUMBER OF LOANS AND DELINQUENCIES IN AGENCY (GSE/PRIME) LOANS ACROSS THE CREDIT THRESHOLD: EVIDENCE FROM A NATURAL EXPERIMENT

Year	FICO $\geq$ 620 (β)	t-stat	Observations	R^2	Mean
	Panel A: Number of prime loans				
During law	4.80	(2.70)	249	.88	20.30
Pre and post law	2.33	(1.02)	268	.92	22.80

Panel B: Delinquency status of prime loans

	Pr(delinquency)=1	
	60+ delinquent 2001–2006 (1)	90+ delinquent 2001–2006 (2)
FICO $\geq$ 620	−0.026	−0.029
	[0.001]	[0.001]
	(0.19)	(0.10)
FICO $\geq$ 620 $*$ *NoLaw*	−0.004	−0.003
	[0.0004]	[0.0004]
	(0.03)	(0.05)
Observations	56,300	56,300
Other controls	Yes	Yes
FICO $\geq$ 620 $*$ other controls	Yes	Yes
Time fixed effects	Yes	Yes
Clustering unit	Vintage	Vintage
Pseudo R^2	.01	.02
Mean delinquency (%)	5.2	3.1

Notes. This table reports estimates of the regressions on differences in number of loans and performance of loans across the credit thresholds. The analysis is restricted to prime loans made in Georgia and New Jersey. The data are for GSE loans that are first mortgages, that are either single-family or condo or a townhouse, that are only purchase loans, that are conventional mortgages without private insurance, and that are primary residents for the borrower. *NoLaw* is a dummy that takes a value 1 if the anti–predatory lending law was not passed in a given year or was amended and a value 0 during the time period when the law was passed. Permutation tests confirm that the discontinuity in number of loans at 620 when the law is not passed or passed is no different from estimated jumps at other locations in the distribution in the Georgia and New Jersey sample. We report t-statistics in parentheses (marginal effects are reported in square brackets).

subprime securitization in recent years had shifted to the non-agency sector (Gramlich 2007). In unreported permutation tests (see Online Appendix Table 4, Panel A), we also find a very small jump in the number of loans in the agency market across the 620 threshold. In addition, the loan terms and default rates are also smooth. Together these results suggest that, in general, there seems to be no differential selection in terms of number of loans or quality of loans across the 620 cutoff.

Third, if our results in the low-documentation market around the 620 threshold are driven by differential GSE selection, we should observe no differences in defaults when we combined the loans from agencies with low-documentation subprime loans around the 620 threshold. If it were purely selection, lower performance above the threshold in the low-documentation subprime loans would be offset by differentially higher quality loans selected into the agency market. Unreported results (Online Appendix Table 5) show that there are still differences in default rates across the 620 threshold when we examine the agency loans and low-documentation subprime loans together.

Finally, we examine the set of borrowers in the subprime market (around 620) who are offered contractual terms similar to those offered in the prime market. If there is indeed selection into the prime market, it is likely based on contractual terms offered to borrowers. By examining borrowers who are offered similar contractual terms in the subprime market, we are able to isolate our analysis to borrowers of similar quality as those who are possibly attracted by GSEs (i.e., the good-quality borrowers). For this subset of subprime borrowers, we are able to show that 620^{+} loans still default more than 620^{-} loans (Online Appendix Table 4, Panel B). This evidence further suggests that selection by GSEs is unlikely to explain our results.

Other Thresholds. In the data, we also observe smaller jumps in other parts of the securitized loan FICO distribution as other *ad hoc* cutoffs have appeared in the market in the past three years (e.g., 600 for low documentation in 2005 and 2006). We remain agnostic as to why or how these other cutoffs have appeared: due to greater willingness to lend to riskier borrowers, or to changing use of automated underwriting, which generally included a matrix of qualifications and loan terms including FICO buckets. Several comments about why we focus on the 620 threshold are therefore in order.

First, the 620 cutoff is the only threshold that is actively discussed by the GSEs in their lending guidelines, where the ease of securitization is higher on the right side of the threshold (see Online Appendix Exhibit 1). This feature is essential for us to disentangle the effect of lax screening on defaults from what a change in FICO score might predict. As increasing FICO scores predict decreasing default rates, performing our analysis with any cutoff where ease of securitization is lower on the right side of the threshold would not allow us to use this identification. For instance, consider the cutoff of 660 that is also discussed in the

GSE guidelines and where we observe a jump in securitization. The ease of securitization is lower on the right-hand side of this cutoff; that is, the unconditional probability of securitization is lower at 660^+ relative to 660^-, suggesting that 660^+ loans would be more intensively screened and would default less frequently than 660^-. However, it would be impossible to disentangle this effect from just a mechanical effect of 660^+ FICO loans being more creditworthy and thus defaulting less often than 660^- loans (by construction). This subtle advantage of the 620 cutoff is crucial to our identification strategy and rules out the use of several other *ad hoc* thresholds. In general, our methodology could extend to any cutoff that had greater ease of securitization on the right side of the threshold.

Moreover, to identify the effects of securitization on screening by lenders, the liquidity differential for the loan portfolios around the threshold has to be large enough. Because 620 is the largest jump we observe in the loan distribution, it is a natural choice. This is confirmed in the permutation tests, which show that FICO = 620 has the smallest p-value (and is thus the largest outlier) among *all* the visible discontinuities for *each year* in our sample. Although other cutoffs may also induce slight differences in screening effort in some years, these differences may be too small to make any meaningful inferences. In results not shown, we analyzed some of these other thresholds and found results for delinquencies that are consistent with those reported for the predominant cutoff (620), but are indeed quite small in magnitude.

Other Tests. We also conduct several falsification tests, repeating our analysis at other credit scores where there is no jump in securitization. In sharp contrast to the results reported in Section IV.D, the higher credit score bucket defaults *less* than the lower credit score bucket. This is consistent with the results of the permutation tests reported above, which estimate *every* false discontinuity and compare it to the discontinuity at 620. Moreover, as we will show in Section V, full-documentation loans do not see any jumps at this threshold. We plot the delinquency rates of 620^+ and 620^- for full-documentation loans (2001–2006) in Figure X and find that loans made at lower credit scores are more likely to default.[25]

25. This test can also provide insight into the issue of GSE selection discussed earlier. Because 620^+ full documentation loans do not default more than 620^- loans, differential selection into the agency market must account for this

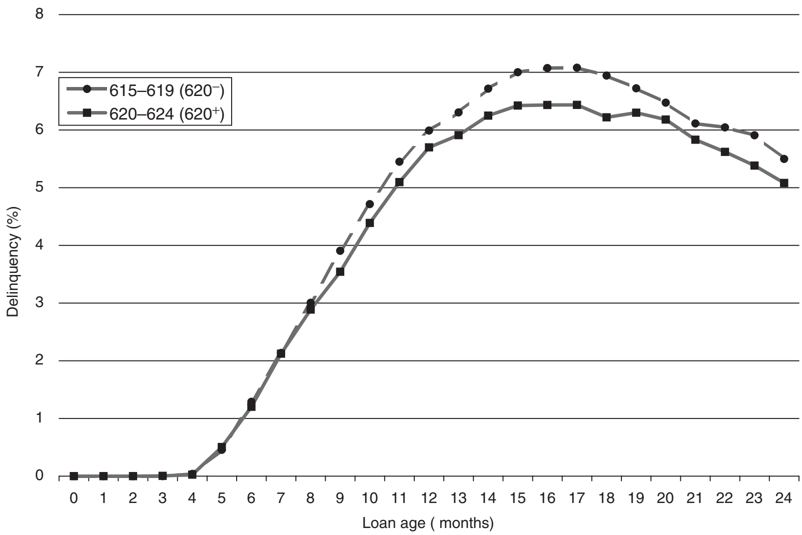


FIGURE X
Falsification Test—Delinquencies for Full-Documentation Loans around FICO of 620

The figure presents the falsification test by examining the percentage of full-documentation loans (dollar-weighted) originated between 2001 and 2006 that became delinquent. We track loans in two FICO buckets—615–619 (620^-) dashed and 620–624 (620^+) solid—from their origination date and plot the average loans that become delinquent each month after the origination date. As can be seen, the higher credit score bucket defaults *less* than the lower credit score bucket for the post-2000 period. For brevity, we do not report plots separately for each year of origination. The effects shown here in the pooled 2001–2006 plot show up for every year.

As further tests of our hypothesis, we also conducted our tests in the refinance market, and find a similar rule of thumb and similar default outcomes around the 620 threshold in this market. Finally, we reestimated our specifications with state, lender, and pool fixed effects to account for multiple levels of potential variation in the housing market and find qualitatively similar results.[26]

fact as well. One possibility is selection on the basis of debt-to-income ratios. To examine this, we compare DTI ratios in the full- and low-documentation markets. Unreported tests (Online Appendix Table 3) show that the DTI ratios are similar around the threshold and thus cannot entirely explain results across the two types of loans.

26. For additional information on tests across types of lenders and states, see Keys et al. (2009).

V. Did Hard Information Matter?

The results presented above are for low-documentation loans, which necessarily have an unobserved component of borrowers' creditworthiness. In the full-documentation loan market, on the other hand, there is no omission of hard information on the borrower's ability to repay. In this market, we identify a credit threshold at the FICO score of 600, the score that Fair Isaac (and the three credit repositories) advises lenders as a bottom cutoff for low risk borrowers. They note that "anything below 600 is considered someone who probably has credit problems that need to be addressed..." (see www.myfico.com). Similarly, Fannie Mae in its guidelines notes that "a borrower with credit score of 600 or less has a high primary risk..." (see www.allregs.com/efnma/doc/). The Consumer Federation of America along with Fair Isaac (survey report in March 2005) suggests that "FICO credit scores range from 300–850, and a score above 700 indicates relatively low credit risk, while scores below 600 indicate relatively high risk which could make it harder to get credit or lead to higher loan rates." Einav, Jenkins and Levin (2008) make a similar observation when they note that "a FICO score above 600 [is] a typical cut-off for obtaining a standard bank loan."

Figure XI reveals that there is a substantial increase in the number of full documentation loans above the credit threshold of 600. This pattern is consistent with the notion that lenders are more willing to securitize at a lower credit threshold (600 vs. 620) for full-documentation loans because there is less uncertainty about these borrowers relative to those who provide less documentation. The magnitudes are again large—around 100% higher at 600^+ than at 600^- in 2004—for full-documentation loans. In Panel A of Table VI, we estimate regressions similar to equation (1) and find that the coefficient estimate is also significant at 1% and is on average around 100% (from 80% to 141%) higher for 600^+ as compared to 600^- for post-2000 loans. Again, if the underlying creditworthiness and the demand for mortgage loans (at a given price) are the same for potential buyers with a credit score of 600^- or 600^+, as the credit bureaus claim, this result confirms that it is easier to securitize full-documentation loans above the 600 FICO threshold. We repeated a similar analysis for loan characteristics (LTV and interest rates) and borrower demographics and find no differences for full documentation loans above and below the credit score of 600. Appendix I.C presents the estimates from the

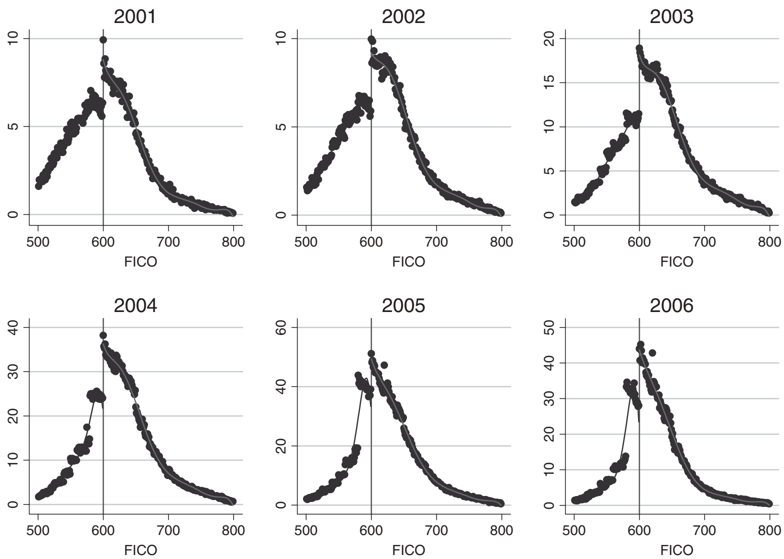


FIGURE XI

Number of Loans (Full-Documentation)

The figure presents the data for the number of full-documentation loans (in '00s). We plot the average number of loans at each FICO score between 500 and 800. As can be seen from the graphs, there is a large increase in number of loans around the 600 credit threshold (i.e., more loans at 600^+ as compared to 600^-) from 2001 onward. Data are for loans originated between 2001 and 2006.

regressions (Appendix I.D provides permutation test estimates corresponding to these loan terms).

Interestingly, we find that full-documentation loans with credit scores of 600^- (FICO between 595 and 599) are about as likely to default after a year as loans with credit scores of 600^+ (FICO between 601 and 605) for the post-2000 period. Both Figures XII and XIII and results in Panels B, C, and D of Table VI support this conjecture. Following the methodology used in Figures VI and VII, we show the default rates annually across the FICO distribution (Figure XII) and across the age of the loans (Figure XIII). The estimated effects of the *ad hoc* rule on defaults are negligible in all specifications.

The absence of differences in default rates across the credit threshold, while the same magnitude of the jump in the number of loans is maintained, is consistent with the notion that the pattern of delinquencies around the low-documentation threshold are primarily due to the soft information of the borrower. With so much

TABLE VI
NUMBER OF LOANS AND DELINQUENCIES ACROSS THE CREDIT THRESHOLD FOR FULL-DOCUMENTATION LOANS

Year	FICO $\geq$ 600 (β)	t-stat	Observations	R^2	Mean
		Panel A: Number of full-documentation loans			
2001	306.85	(5.70)	299	.99	330
2002	378.49	(9.33)	299	.99	360
2003	780.72	(11.73)	299	.99	648
2004	1,629.82	(8.91)	299	.99	1,205
2005	1,956.69	(4.72)	299	.98	1,499
2006	2,399.48	(6.97)	299	.98	1,148
Pooled estimate (t-stat) [permutation test p-value]			1,241.75 (3.23) [.000]		
		Panel B: Dollar weighted fraction of loans defaulted			
2001	0.005	(0.63)	250	.87	0.052
2002	0.018	(1.74)	250	.87	0.041
2003	0.013	(1.93)	250	.94	0.039
2004	0.006	(1.01)	254	.94	0.040
2005	0.008	(1.82)	254	.96	0.059
2006	0.010	(0.89)	254	.86	0.116

Panel C: Permutation tests for alternative default definitions (pooled 2001–2006 with time fixed effects)

Dependent variable (Default definition)	FICO $\geq$ 600 (β)	t-stat	Permutation test p-value	Observations	R^2	Mean
60+ (dollar-weighted)	0.010	(1.66)	.240	1,512	.84	0.058
90+ (dollar-weighted)	0.006	(1.00)	.314	1,525	.75	0.046
Foreclosure+ (dollar-weighted)	0.005	(1.25)	.265	1,525	.77	0.032
60+ (unweighted)	0.011	(1.50)	.150	1,525	.70	0.056

Panel D: Delinquency status of loans

	Pr(delinquency)=1			
	(1)	(2)	(3)	(4)
FICO $\geq$ 600	−0.06	−0.02	−0.06	−0.02
	[0.002]	[0.0006]	[0.002]	[0.0006]
	(2.30)	(0.15)	(1.21)	(0.18)
Observations	3,125,818	3,125,818	3,125,818	3,125,818
Pseudo R^2	.073	.084	.073	.084
Other controls	Yes	Yes	Yes	Yes
FICO $\geq$ 600 $*$ other controls	No	Yes	No	Yes
Time fixed effects	No	Yes	No	Yes
Clustering unit	Loan ID	Loan ID	Vintage	Vintage
Mean delinquency (%)	4.54			

Notes. This table reports estimates of the regressions on differences in number of loans and performance of loans around the credit threshold of 600 for full-documentation loans. We use specifications similar to these in Table II, Panel A, to estimate the number of loan regressions and Table III, Panels A, B, and C, to estimate delinquency regressions. Permutation tests confirm that FICO = 600 has the smallest permutation test p-value (and is thus the largest outlier) among *all* the visible discontinuities in the full-documentation loan sample. We report t-statistics in parentheses (marginal effects are reported in square brackets).

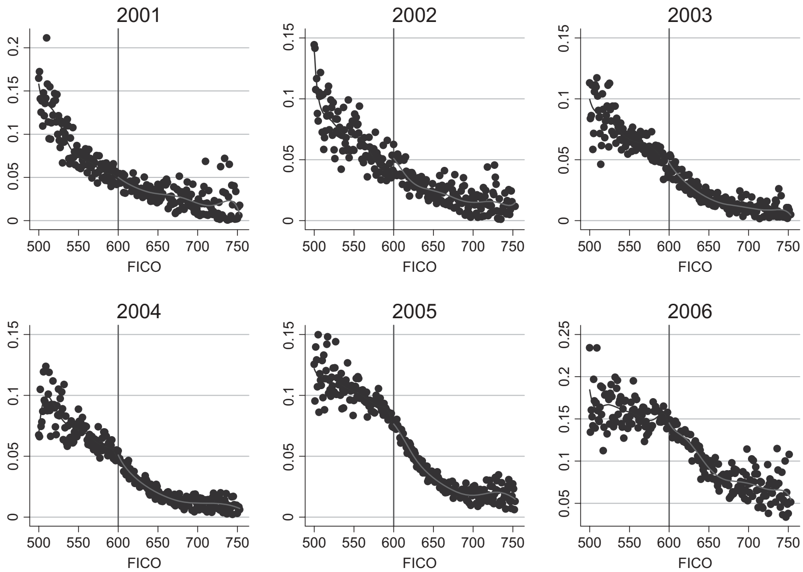


FIGURE XII

Annual Delinquencies for Full-Documentation Loans

The figure presents the percentage of full-documentation loans originated between 2001 and 2006 that became delinquent. We plot the dollar-weighted fraction of the pool that becomes delinquent for one-point FICO bins between scores of 500 and 750. The vertical line denotes the 600 cutoff, and a seventh-order polynomial is fitted to the data on either side of the threshold. Delinquencies are reported between 10 and 15 months for loans originated in all years.

information collected by the lender for full-documentation loans, there is less value to collecting soft information. Consequently, for full-documentation loans there is no difference in how the loans perform subsequently after hard information has been controlled for. Put another way, differences in returns to screening are attenuated due to the presence of more hard information.

VI. Discussion

In the wake of the subprime mortgage crisis, a central question confronting market participants and policy makers is whether securitization had an adverse effect on the *ex ante* screening effort of loan originators. Comparing characteristics of the loan market above and below the *ad hoc* credit threshold, we show that a doubling of securitization volume is on average associated with about a 10%–25% increase in defaults. Notably, our empirical strategy delivers only inferences on differences in the performance

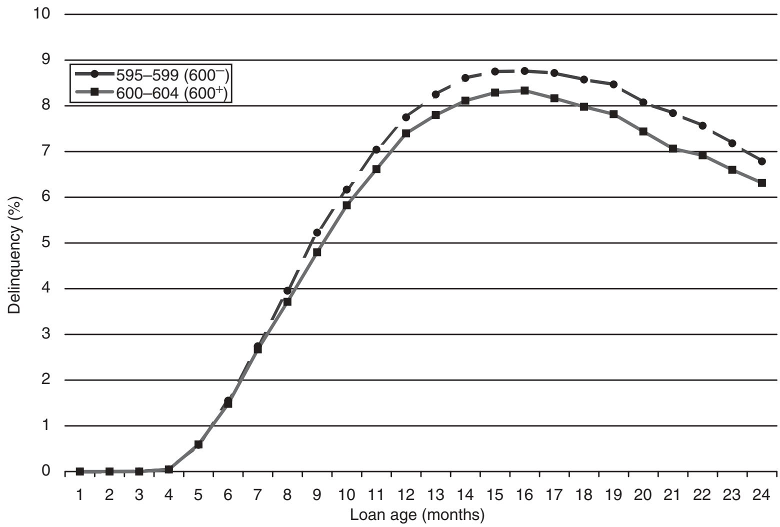


FIGURE XIII

Delinquencies for Full-Documentation Loans (2001–2006)

The figure presents the percentage of full-documentation loans (dollar-weighted) originated between 2001 and 2006 that became delinquent. We track loans in two FICO buckets—595–599 (600^-) dashed and 600–604 (600^+) solid—from their origination date and plot the average loans that become delinquent each month after the origination date. As can be seen, the higher credit score bucket defaults *more* than the lower credit score bucket for the post-2000 period. For brevity, we do not report plots separately for each year of origination. The effects shown here in the pooled 2001–2006 plot show up for every year.

of loans around this threshold. Although we cannot infer what the optimal level of screening at each credit score ought to be, we conclude from our empirical analysis that there was a causal link between ease of securitization and screening. That we find any effect on default behavior in one portfolio compared to another with virtually identical risk profiles, demographic characteristics, and loan terms suggests that the ease of securitization may have had a direct impact on incentives elsewhere in the subprime housing market. Understanding whether the ease of securitization had a similar impact on other securitized markets requires more research.

The results of this paper, in particular from the anti–predatory lending laws' natural experiment, confirm that lender behavior in the subprime market did change based on the ease of securitization. This suggests that existing securitization practices did not ensure that a decline in screening standards would be counteracted by requiring originators to hold more of the loans' default risk. If lenders were in fact holding on to optimal risk where it was easier to securitize, there should have been no differences in defaults around the threshold. This finding resonates well with concerns surrounding the subprime crisis that, in an environment with limited disclosure on who holds what in the originate-to-distribute chain, there may have been insufficient "skin in the game" for some lenders (Blinder 2007; Stiglitz 2007). At the same time, the results further suggest that the breakdown in the process only occurred for loans where soft information was particulary important. With enough hard information, as in the full-documentation market, there may be less value in requiring market participants to hold additional risk to counteract the potential moral hazard of reduced screening standards.

In a market as competitive as the market for mortgage-backed securities, our results on interest rates are puzzling. Lenders' compensation on either side of the threshold should reflect differences in default rates, and yet we find that the interest rates to borrowers are similar on either side of 620. The difference in defaults, despite similar compensation around the threshold, suggests that there may have been some efficiency losses. Of course, it is possible that from the lenders' perspective, a higher propensity to default above the threshold could have exactly offset the benefits of additional liquidity—resulting in identical interest rates around the threshold.

Our analysis remains agnostic about whether investors priced the moral hazard aspects of securitization accurately. It may have been the case that moral hazard existed in this market, though investors appropriately priced persistent differences in performance around the threshold (see Rajan, Seru, and Vig [2008]). On the other hand, developing an arbitrage strategy for exploiting this opportunity may have been prohibitively difficult, given that loans are pooled across the FICO spectrum before they are traded. In addition, these fine differences in performance around the FICO threshold could have been obscured by the performance of other complex loan products in the pool. Understanding these aspects of investor behavior warrants additional investigation.

It is important to note that we refrain from making any welfare claims. Our conclusions should be directed at securitization practices, as they were during the subprime boom, rather than at the optimally designed originate-to-distribute model. We believe securitization is an important innovation and has several merits. It is often asserted that securitization improves the efficiency of credit markets. The underlying assumption behind this assertion is that there is no information loss in transmission, even though securitization increases the distance between borrowers and investors. The benefits of securitization are limited by information loss, and in particular the costs we document in the paper. More generally, what types of credit products should be securitized? We conjecture that the answer depends crucially on the information structure: loans with more hard information are likely to benefit from securitization relative to loans that involve soft information. A careful investigation of this question is a promising area for future research.

More broadly, our findings caution against policy that emphasizes excessive reliance on default models. Our research suggests that by relying entirely on hard information variables such as FICO scores, these models ignore essential elements of strategic behavior on the part of lenders which are likely to be important. The formation of a rule of thumb, even if optimal (Baumol and Quandt 1964), has an undesirable effect on the incentives of lenders to collect and process soft information. As in Lucas (1976), this strategic behavior can alter the relationship between observable borrower characteristics and default likelihood, rather than moving along the previous predicted relationship. Incorporating these strategic elements into default models, although challenging, is another important direction for future research.

APPENDIX I.A
LOAN CHARACTERISTICS AROUND DISCONTINUITY IN LOW-DOCUMENTATION LOANS

	Loan to value					Interest rate				
Year	FICO $\geq$ 620 (β)	t-stat	Obs.	R^2	Mean (%)	FICO $\geq$ 620 (β)	t-stat	Obs.	R^2	Mean (%)
2001	0.67	(0.93)	296	.76	80.3	0.06	(0.59)	298	.92	9.4
2002	1.53	(2.37)	299	.91	82.6	0.15	(1.05)	299	.89	8.9
2003	2.44	(4.27)	299	.96	83.4	0.10	(1.50)	299	.97	7.9
2004	0.30	(0.62)	299	.96	84.5	0.03	(0.39)	299	.97	7.8
2005	−0.33	(0.96)	299	.95	84.1	−0.09	(1.74)	299	.98	8.2
2006	−1.06	(2.53)	299	.96	84.8	−0.21	(2.35)	299	.98	9.2

Notes. This table reports estimates from a regression that uses the mean interest rate and LTV ratio of low-documentation loans at each FICO score as the dependent variables. In order to estimate the discontinuity (FICO $\geq$ 620) for each year, we collapse the interest rate and LTV ratio at each FICO score and estimate flexible seventh-order polynomials on either side of the 620 cutoff, allowing for a discontinuity at 620. Because the measures of the interest rate and LTV are estimated means, we weight each observation by the inverse of the variance of the estimate. We report t-statistics in parentheses. Permutation tests, which allow for a discontinuity at every point in the FICO distribution, confirm that these jumps are *not* significantly larger than those found elsewhere in the distribution. For brevity, we report permutation test estimates from pooled regressions (with time fixed effects removed to account for vintage effects) and report them in Appendix I.D.

APPENDIX I.B
BORROWER DEMOGRAPHICS AROUND DISCONTINUITY IN LOW-DOCUMENTATION LOANS

Year	FICO $\geq$ 620 (β)	t-stat	Observations	R^2	Mean (%)
		Panel A: Percent black in ZIP code			
2001	1.54	(1.16)	297	.79	11.2
2002	0.32	(0.28)	299	.63	10.6
2003	1.70	(2.54)	299	.70	11.1
2004	0.42	(0.53)	299	.72	12.2
2005	−0.50	(0.75)	299	.69	13.1
2006	0.25	(0.26)	299	.59	14.7
		Panel B: Median income in ZIP code			
2001	1,963.23	(2.04)	297	.33	49,873
2002	−197.21	(0.13)	299	.35	50,109
2003	154.93	(0.23)	299	.50	49,242
2004	699.90	(1.51)	299	.46	48,221
2005	662.71	(1.08)	299	.64	47,390
2006	−303.54	(0.34)	299	.68	46,396
		Panel C: Median house value in ZIP code			
2001	3,943.30	(0.44)	297	.66	163,151
2002	−599.72	(0.11)	299	.79	165,049
2003	−1,594.51	(0.36)	299	.89	160,592
2004	−2,420.01	(1.03)	299	.91	150,679
2005	−342.04	(0.14)	299	.93	143,499
2006	−3,446.06	(1.26)	299	.92	138,556

Notes. This table reports estimates from a regression that uses the mean demographic characteristics of low-documentation borrowers at each FICO score as the dependent variables. In order to estimate the discontinuity (FICO $\geq$ 620) for each year, we collapse the demographic variables at each FICO score and estimate flexible seventh-order polynomials on either side of the 620 cutoff, allowing for a discontinuity at 620. Because the demographic variables are estimated means, we weight each observation by the inverse of the variance of the estimate. We obtain the demographic variables from Census 2000, matched using the ZIP code of each loan. Permutation tests, which allow for a discontinuity at every point in the FICO distribution, confirm that these jumps are *not* significantly larger than those found elsewhere in the distribution. We report t-statistics in parentheses.

APPENDIX I.C
LOAN CHARACTERISTICS AND BORROWER DEMOGRAPHICS AROUND DISCONTINUITY IN FULL-DOCUMENTATION LOANS

Panel A: Loan characteristics

	Loan to value					Interest rate				
Year	FICO $\geq$ 600 (β)	t-stat	Obs.	R^2	Mean (%)	FICO $\geq$ 600 (β)	t-stat	Obs.	R^2	Mean (%)
2001	0.820	(2.09)	299	.73	85.1	−0.097	(0.87)	299	.97	9.5
2002	−0.203	(0.65)	299	.86	85.8	−0.279	(3.96)	299	.97	8.6
2003	1.012	(3.45)	299	.95	86.9	−0.189	(3.42)	299	.99	7.7
2004	0.755	(2.00)	299	.96	86	−0.244	(6.44)	299	.99	7.3
2005	0.354	(1.82)	299	.93	86.2	−0.308	(5.72)	299	.99	7.7
2006	−0.454	(1.96)	299	.94	86.7	−0.437	(9.93)	299	.99	8.6

Panel B: Percent black in ZIP code

Year	FICO $\geq$ 600 (β)	t-stat	Observations	R^2	Mean (%)
2001	2.32	(2.03)	299	.86	13.6
2002	−0.79	(1.00)	299	.82	12.5
2003	0.40	(0.48)	299	.87	12.5
2004	0.54	(0.96)	299	.92	12.9
2005	−0.38	(0.85)	299	.86	13.4
2006	−0.86	(1.40)	299	.81	14.3

Notes. This table reports the estimates of the regressions on loan characteristics and borrower demographics around the credit threshold of 600 for full-documentation loans. We use specifications similar to Appendices I.A and I.B for estimation. We report t-statistics in parentheses. Permutation tests, which allow for a discontinuity at every point in the FICO distribution, confirm that these jumps are *not* significantly larger than those found elsewhere in the distribution. For brevity, we report permutation test estimates from pooled regressions (with time fixed effects removed to account for vintage effects) and report them in Appendix I.D.

APPENDIX I.D
PERMUTATION TEST RESULTS FOR LOAN CHARACTERISTICS IN LOW- AND FULL-DOCUMENTATION LOANS

	Interest rate	Loan-to-value ratio	Debt-to-income ratio	Prepayment penalty	Actual prepayments	CLTV ratio
Panel A: Low-documentation loan characteristics						
Pooled FICO $\geq$ 620 (β)	0.02	0.54	0.42	−0.016	−0.0004	0.05
t-stat	0.32	1.40	1.25	1.23	0.44	0.73
Permutation test p-value	.90	.46	.32	.55	.84	.96
Panel B: Full-documentation loan characteristics						
Pooled FICO $\geq$ 600 (β)	0.39	−0.26	0.68	0.008	−0.0009	0.17
t-stat	1.63	1.91	1.83	0.73	1.51	0.39
Permutation test p-value	.20	.07	.11	.45	.35	.62

Notes. This table reports the estimates of the regressions on loan characteristics across the credit threshold of 620 for low-documentation loans and credit threshold of 600 for full-documentation loans. We pool the loans across all years and remove year effects to account for vintage effects. We use specifications similar to Appendix I.A for estimation. Permutation tests, which allow for a discontinuity at every point in the FICO distribution, confirm that these jumps are *not* significantly larger than those found elsewhere in the distribution. We report p-values from these tests in the table.

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Assessing financial contagion in the interbank market: Maximum entropy versus observed interbank lending patterns

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ASSESSING FINANCIAL CONTAGION IN THE INTERBANK MARKET: MAXIMUM ENTROPY VERSUS OBSERVED INTERBANK LENDING PATTERNS

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Abstract

Interbank markets allow banks to cope with specific liquidity shocks. At the same time, they may be a channel allowing a bank default to spread to other banks. This paper analyzes how contagion propagates within the Italian interbank market using a unique data set including actual bilateral exposures. Since information on bilateral exposures was not available in most previous studies, they assumed that banks spread their lending as evenly as possible among all the other banks by maximizing the entropy of interbank linkages. Based on the data available on actual bilateral exposures for all Italian banks, the results obtained by assuming the maximum entropy are compared with those reflecting the observed structure of interbank claims. The comparison indicates that, in line with the thesis prevailing in the literature, the maximum entropy method tends to underestimate the extent of contagion. However, this does not hold in general. Under certain circumstances, depending on the structure of the interbank linkages, the recovery rates of interbank exposures and banks' capitalization, the maximum entropy approach overestimates the scope for contagion.

Keywords: interbank market, financial contagion, systemic risk, maximum entropy.
JEL classification: G21, G28.

Contents

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1. Introduction[1]

Systemic risk has always played a prominent role in the economic policy debate. A widely shared view is that the banking system is an important chain in the propagation of shocks to the entire economy.[2] Early theoretical works concerning systemic risk in the banking sector have focused on depositor runs triggered by self-fulfilling expectations (Diamond and Dybvig, 1983) or by signals regarding bank solvency (Chari and Jagannathan, 1988 and Jacklin and Bhattacharya, 1988). More recently, attention has been paid to financial contagion in the interbank market (Rochet and Tirole, 1996). While the interbank market may allow banks to cope with specific liquidity shocks (Bhattacharya and Gale, 1987), interbank relationships may represent a channel for contagion: the economic distress of an insolvent bank may propagate to other banks through interbank linkages.[3] Recent theoretical works (Allen and Gale, 2000; Freixas, Parigi and Rochet, 2000) have also highlighted that the propagation of shocks within the interbank market is dependent on the exact pattern of banks' financial linkages.

Many contributions have sought to measure the vulnerability of the interbank market to financial contagion.[4] However, these works suffer from two main data limitations. First, detailed data on banks' bilateral exposures are generally not available. In order to circumvent this problem, two approaches have been adopted: a) the severity of financial contagion in the interbank market has been measured by focusing on a specific segment of

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[2] De Bandt and Hartmann (2000) and Kaufman (1994) provide a detailed discussion on the definition of systemic risk.

[3] A different channel for contagion through the interbank market could be related to signals or self-fulfilling expectations triggering interbank deposits withdrawals.

[4] See Upper (2007) and *Appendix A* for details of the literature on financial contagion.

the market for which actual bilateral exposures were available; in particular, Furfine (2003) has investigated contagion in the Federal Reserve's large-value transfer system (Fedwire) which, however, represents a small fraction of U.S. total interbank exposures (according to Furfine himself, approximately 14 per cent); b) other contributions have taken into account the whole interbank market. However, since detailed information on banks' bilateral exposures is not available, these works have had to assume a specific pattern for them. In particular, it is possible to distinguish between two different cases: *i*) interbank bilateral exposures are obtained on the basis of aggregated interbank assets and liabilities by maximising the entropy[5] of the matrix of bilateral claims (e.g. Upper and Worms, 2004) or *ii*) when information about large bilateral exposures is available, the entropy maximisation method is applied only to those elements of the matrix of bilateral exposures that are not known (Blavarg and Nimander, 2002; Wells, 2004; Degryse and Nguyen, 2007; van Lelyveld and Liedorp, 2006). The main limitation of this approach is that it assumes a market structure which might be quite different from the actual one. Indeed, the maximisation of the entropy rules out lending relationships in the interbank market[6] since it assumes that each bank lends to all the other banks in the market.

A second data limitation concerns the structure of the banking system. The existing literature has typically overlooked the fact that banks are often affiliated with a conglomerate, even if this may, quite obviously, affect the resilience of the banking system to systemic shocks.

In this paper, financial contagion in the interbank market is investigated using a unique data set including detailed information on each actual bilateral exposure for all the Italian banks. Thus, the analysis deals with all kinds of interbank financial linkages, besides derivatives and shares, for every Italian bank and for each bank-to-bank relationship. According to the previous literature, the paper uses simulation techniques to measure the severity of financial contagion.

[5] See Appendix B for details.

[6] Cocco et al. (2003) find evidence supporting the existence of lending relationships in the interbank market for overnight funds.

The paper contributes to the literature in two main respects. Firstly, it provides a measure of the vulnerability to financial contagion of the Italian interbank market,[7] thus enriching the evidence so far available for most of the industrialised countries. However, the analysis differs from those made for other countries as it is based on actual bilateral exposures instead of maximum entropy exposures. Furthermore, by taking into account the affiliation of banks with a conglomerate, it provides evidence on the link between financial conglomeration and banking system stability. The paper shows that even if the Italian interbank market is conducive to financial contagion it hardly triggers a systemic crisis. Banks conglomeration tends to improve the resilience of the banking system to shocks. However, in some cases, since conglomeration induces a strong interdependency among affiliated banks, the extent of contagion may be even wider if banks' affiliation is taken into account than when it is ignored.

Secondly, it shows that the measure of financial contagion depends on the pattern of interbank linkages. To this end, the paper applies the maximum entropy method, it re-runs the simulation exercises and then compares them with the results based on actual bilateral exposures. The comparison indicates that, in line with the thesis prevailing in the literature, the maximum entropy method leads to an undervaluation of the extent of contagion. However, this does not hold in general. Under certain circumstances, depending on the structure of the interbank linkages, the recovery rates of interbank exposures and banks' capitalisation, the maximum entropy approach implies an overvaluation of the scope for contagion.

These results have two consequences. On the empirical level, it indicates that in some circumstances, depending on the structure of the interbank market, the maximum entropy approach may not be very reliable in assessing the severity of financial contagion. Furthermore, since it does not provide a lower bound to contagion vulnerability, it may not be reliable either for assessing whether the interbank market is conducive to contagion or not. On the theoretical level, following Allen and Gale's (2000) taxonomy, the comparison between maximum entropy and observed exposures may be interpreted as a comparison

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[7] The paper by Angelini et al. (1996) has also analysed the risk of contagion in the Italian interbank market, although the work takes into account only the netting system segment.

between complete and incomplete markets. In this respect, the results obtained in this paper show that complete markets are not always less conducive to contagion than other markets, as Allen and Gale (2000) stated.

The remainder of the paper is organised as follows. The next section describes the methodology and data. The third section deals with the vulnerability to financial contagion of the Italian interbank market. Section 4 investigates how the maximum entropy method affects the severity of financial contagion by comparing, for the Italian case, the results obtained on the basis of the maximum entropy matrix of bilateral exposures with those obtained using the observed matrix. The final section concludes and summarises the main findings.

2. Data and methodology

2.1 Data

Data on gross bilateral interbank exposures are obtained from the Bank of Italy supervisory reports database. Since January 1989 all Italian banks, including their foreign branches, submit to the Bank Italy their end-of-month bilateral exposures to all other banks, foreign intermediaries included. Data refer to all kinds of interbank assets except shares. The database allows for a distinction between different claims (CDs, current accounts, repos, other loans, subordinated and unsubordinated bonds) classified according to their maturity (up to 18 months, over 18 months), currency of denomination and counterpart nationality (Italy vs. rest of the world).

At the end of 2003, interbank exposures accounted for a substantial share of the total assets of Italian banks. The total amount of loans to banks and of securities issued by banks held by the Italian banking system was equal to 24 per cent of total assets at the end of 2003; it was 37 per cent for the banks in the euro area as a whole. More importantly, from the perspective of financial contagion, interbank exposures were over 3 times the total amount of capital and reserves in Italy, 6 times that in the euro area. If one considers only the domestic segment of the market, interbank assets were 18 per cent of total assets in Italy and 21 per cent in the euro area. The interbank asset-to-capital ratio was respectively 2.4 and 3.5 for the Italian banking system and the euro area banks.

2.2 The contagion mechanism

All banks raising funds in the interbank market are allowed to fail one at a time. The losses suffered by banks lending to the failed bank are then computed. If the amount of the losses is greater than lenders' tier-1 capital (i.e. capital and reserves) then lenders default. The simulation is then iterated by verifying if banks that fail after the first iteration make other banks fail as well. At each iteration banks that failed in the previous one are dropped from the set of banks which may be affected by contagion. The simulation continues until at least one bank default occurs.

More formally, let B be the set of banks and x_{ij} denote the funds that bank $j \in B$ borrows from bank $i \in B$, where $x_{ij} \geq 0 \;\; \forall (i,j) \in B \times B$ and $x_{ii} = 0 \, \forall i \in B$, by $c_i > 0$ the initial capital endowment of bank i , and by $\alpha \in [0,1]$ the rate of loss (i.e. the incidence of losses due to contagion out of the interbank exposure). Finally, let $z \in B$ denote the first bank that defaults because of some idiosyncratic shock, and define $D_z^n \subseteq B$ and $S_z^n \subseteq B$ as the set of banks, respectively, defaulted and surviving at the *n*-th step of the contagion path initiated by bank *z* , as follows:

(1) $$D_z^n = \left\{ k \in B : c_{k,z}^n \leq 0 \,\middle|\, c_{k,z}^{n-1} > 0 \right\} \qquad S_z^n = \left\{ k \in B : c_{k,z}^n > 0 \right\}, \qquad \forall n \geq 1$$

where $c_{k,z}^n$, which is the capital of bank *k* at the *n*-th step of contagion initiated by bank *z,* is equal to:

(2) $$c_{k,z}^n = c_{k,z}^{n-1} - \alpha \sum_{j \in D_z^{n-1}} x_{kj} \,, \quad \forall n \geq 1 \text{ and } \forall k \neq z$$

The contagion path is then the following:

Failed banks | **Surviving banks**

$$D_z^0 = \{ z \} \qquad S_z^0 = \{ k \in B \setminus \{z\} \}$$

$$D_z^1 = \left\{ k \in S_z^0 : c_{k,z}^1 = (c_k - \alpha x_{kz}) \le 0 \right\} \qquad S_z^1 = \left\{ k \in S_z^0 : c_{k,z}^1 = (c_k - \alpha x_{kz}) > 0 \right\}$$

$$D_z^2 = \left\{ k \in S_z^1 : c_{k,z}^2 = \left(c_{k,z}^1 - \alpha \sum_{j \in D_z^1} x_{kj} \right) \le 0 \right\} \qquad S_z^2 = \left\{ k \in S_z^1 : c_{k,z}^2 = \left(c_{k,z}^1 - \alpha \sum_{j \in D_z^1} x_{kj} \right) > 0 \right\}$$

...

$$D_z^n = \left\{ k \in S_z^{n-1} : c_{k,z}^n = \left(c_{k,z}^{n-1} - \alpha \sum_{j \in D_z^{n-1}} x_{kj} \right) \le 0 \right\} \qquad S_z^n = \left\{ k \in S_z^{n-1} : c_{k,z}^n = \left(c_{k,z}^{n-1} - \alpha \sum_{j \in D_z^{n-1}} x_{kj} \right) > 0 \right\}$$

...

$$D_z^N = \{\varnothing\} \qquad S_z^N = \left\{ k \in S_z^{N-1} : c_{k,z}^N = \left(c_{k,z}^{N-1} - \alpha \sum_{j \in D_z^{N-1}} x_{kj} \right) > 0 \right\}$$

and the process stops after N iterations when no default occurs.

Before commenting on some shortcomings of the contagion mechanism it is useful to emphasise two characteristics of the process. First, default condition (1) refers to interbank gross exposures instead of net ones. The main reason for this is that bilateral netting is not feasible because when banks fail, their liabilities are pooled and satisfied according to seniority. Moreover, this kind of procedure usually lasts many years. Second, simulations are run on unconsolidated interbank bilateral exposures. An alternative contagion mechanism could be based on consolidated exposures. However, consolidating interbank exposures would amount to assuming that, in the case in which a bank affiliated with a group fails, internal exposures (i.e., interbank exposures among banks affiliated to the same parent company) are senior to the others. On the other hand, one can define an alternative contagion mechanism such that banks affiliated to a group may be bailed out by their parent company if the consolidated tier-1 capital is larger than the losses suffered from contagion (see Section 3.2 below).

The contagion mechanism described above suffers from some drawbacks. In particular:

i) loss rates are constant across banks and through different stages of financial contagion propagation and they are also not dependent on loan contract covenants;

ii) the analysis focuses on contagion only among banks operating in Italy;

iii) the contagion mechanism concentrates on a specific channel for contagion ignoring any other source which could interact with the propagation of contagion within the interbank market;[8]

iv) banks are not allowed to issue shares in order to compensate for the losses they suffer from the failure of some interbank market counterpart;

v) creditor runs are ruled out.

As far as loss rates are concerned (*i*), bank failures are rarely observed and therefore it is difficult to estimate a loss rate for interbank exposures.[9] For this reason, this paper follows the approach adopted by previous works (e.g. Furfine, 2003; Upper and Worms, 2004) of measuring the risk of contagion at different loss rates between 0 and 1. It is also assumed that the loss rate does not depend on the banks involved. While this assumption is not quite realistic, it is not easy to endogenise loss rates. The risk could be that of introducing even increasingly unrealistic parameters in simulations.

The analysis focuses on contagion among banks operating in Italy (*ii*) because otherwise it would be not possible to analyze all “second-round” effects. Actually, as far as external interbank exposures are concerned, interbank linkages among foreign banks are not known. This implies that is not possible to verify whether, say, the failure of a foreign bank (bank *i*) triggers indirectly the failure of a bank operating in Italy (bank *k*) by causing first the failure of another foreign bank (bank *j*) that has borrowed money from the first (bank *i*).

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[8] For example, exposures from the payment and settlement system may provide alternative channels for contagion. Furthermore, loans to non-banks may amplify the effect of a bank failure by causing liquidity shortages and the insolvency for some borrowers which in turn may make the banking system suffer other loan losses.

[9] Some authors have tried to estimate the loss rates for the U.S. banking system. However, their estimates are very different: James (1991) has found a loss rate of 40 per cent while Kaufman’s (1994) estimate is 5 per cent.

The analysis of a more comprehensive contagion mechanism (*iii*) would certainly add to the realism of the analysis. On the other hand, by making the contagion process more complex it might be more difficult to isolate the contribution of each channel for contagion.

Some of the shortcomings mentioned above would be solved if more detailed information were available (*i*-*iii*). On the other hand, others (*iv*-*v*) seem to be more difficult to tackle with as they would require a theoretical foundation that, to the best of my knowledge, is not yet available.

All the drawbacks of the analysis mentioned above may affect the measure of the severity of contagion in a specific interbank market. However, they do not affect the comparison between the results based on the maximum entropy matrix of bilateral exposures and those based on actual bilateral exposures as they are obtained by the same contagion mechanism.

3. Is the Italian interbank market vulnerable to financial contagion?

The aim of this section is to assess whether the Italian interbank market is vulnerable to financial contagion. The analysis is divided into two parts. The first one (subsection 3.1), following the literature on financial contagion in the interbank market, addresses the issue of financial contagion by assuming that banks cannot react to a shock by, for example, raising capital to compensate for the losses suffered from the failure of their interbank counterparts. In the second part (subsection 3.2), parent banks are allowed to recapitalise their affiliates by redistributing capital resources within the conglomerate.

3.1 The benchmark analysis

Table 1 reports simulation results referring to December 2003.[10] Different measures of financial contagion propagation have been computed *i*) the number of banks whose default causes at least one bank failure by contagion (*contagious banks*), *ii*) the number of banks that fail by contagion and their total assets as a percentage of the Italian banking system's

[10] It is worth noting that results are not affected by an end-of-year effect. Simulations for other months of 2003 (March, June and September) have produced similar results.

total assets (*banks failing by contagion*), and *iii*) the number and the total assets, as a percentage of the Italian banking system's total assets, of banks that never fail independently of the bank failing by some idiosyncratic shock (*contagion-proof banks*).

Overall, the evidence indicates that financial contagion may occur in the Italian banking system. This result does not hold in general but depends on the bank that fails at the initial stage. In fact, Table 1 shows that, even for high loss rates, only a limited number of banks are contagious: the number of contagious banks ranges from 16 to 67, depending on the loss rate, out of 789 Italian banks operating at the end of 2003. It is also worth noting that contagious banks are not necessarily large ones. Some small bank may be contagious, particularly for high loss rates. On the other hand, even if the loss rate is equal to one, not all large banks (22 at the end of 2003) are able to make other banks fail.

Since many banks are not contagious, the propagation of contagion is fairly limited on average, both in terms of the number of banks failed and their share of the banking system's total assets.

Furthermore, as far as contagion-proof banks are concerned (i.e. banks which, for a given loss rate and independently of the bank that initiates the contagion process, never fail) the results indicate that a large part of the banking system is immune to contagion. Even in the worst case (i.e. when the loss rate is equal to 1) banks immune to contagion represent a considerable share of the banking system (529 out of 789 banks; about 60 per cent of the banking system's total assets).

All in all, these results suggest that, even if contagion may occur in the Italian interbank market, there is little scope for financial contagion in Italy. However, one may be interested in other characteristics of the distribution of contagion other than mean values. Following previous works on financial contagion, the maximum impact of financial contagion (*worst scenario*) has also been reported in Table 1. This is the result of the failure of the bank that produces the maximum contagion impact. While such an event is unlikely it makes sense to consider it in an analysis whose aim is to quantify risks and their consequences. In this case, the number of banks failing by contagion ranges from 4 to 116 and is greater than 50 for a loss rate greater or equal to 0.7; the share of total assets of banks failing by contagion ranges from 0.5 to 15.9 per cent and is greater than 10 per cent for a loss rate greater than or equal to 0.7.

Table 1

Severity of financial contagion

(December 2003)

Loss rate	Banks failing by contagion										Contagion-proof banks (2)			Contagious banks (3)		
	Total assets (as a percentage of banking system total assets)					Number of banks					Total assets (as a percentage of banking system total assets)	Number of banks		Total assets (as a percentage of banking system total assets)	Number of banks	
	Worst scenario		*Mean values*		*Std.dev.* (all banks)	*Worst scenario*		*Mean values*		*Std.dev.* (all banks)			*of which: large banks* (1)			*of which: large banks* (1)
	All banks	*Large banks* (1)	*All banks*	*Large banks* (1)		*All banks*	*Large banks* (1)	*All banks*	*Large banks* (1)							
0.1	0.466	0.203	0.004	0.000	0.036	4	1	0.029	0.001	0.219	98.6	755	21	25.2	16	5
0.2	3.467	3.467	0.013	0.007	0.149	4	2	0.056	0.006	0.314	91.9	743	18	41.5	28	12
0.3	7.422	7.339	0.028	0.018	0.326	7	3	0.107	0.010	0.606	84.9	721	17	49.2	35	14
0.4	7.870	7.339	0.037	0.019	0.363	12	3	0.159	0.011	0.890	80.1	694	16	54.3	39	16
0.5	7.906	7.339	0.054	0.031	0.485	21	3	0.243	0.017	1.435	77.5	674	15	58.9	45	17
0.6	7.906	7.339	0.072	0.039	0.544	28	3	0.341	0.022	2.025	73.8	655	14	60.1	51	17
0.7	8.280	7.339	0.092	0.052	0.645	53	4	0.486	0.038	3.286	72.0	623	13	60.2	52	17
0.8	15.207	11.136	0.115	0.068	0.917	79	6	0.621	0.044	4.784	64.5	589	11	60.5	55	17
0.9	15.637	11.136	0.138	0.078	1.029	98	6	0.823	0.050	6.190	59.7	552	10	62.2	57	18
1.0	15.878	11.136	0.154	0.087	1.086	116	6	0.983	0.054	7.314	59.4	529	10	63.5	67	18

(1) Large banks are defined as banks whose total assets are at least equal to 20 billion euro. (2) Banks which are never affected by contagion. (3) Banks which make at least one bank fail.

The effects of contagion are highly concentrated. Up to a loss rate equal to 0.7, financial contagion affects mainly large banks. Only if loss rates exceed that threshold do small banks account for a significant share of the overall extent of contagion. Large banks generally play a substantial role in the contagion mechanism, not only as banks initiating the process (i.e. contagious banks) but also as banks affected by contagion. Among large banks (22 at the end of 2003), most of them are contagious for a loss rate greater than 0.1.

Large banks are relatively less important in the propagation of contagion: for a loss rate lower than 0.9, most of them are immune to contagion. Only in the worst scenario do they account for a large share of the impact of contagion when it is measured in terms of total assets.

Overall these results suggest that for loss rates up to 0.7 the spreading of contagion is very limited. For loss rates greater than 0.7, financial contagion becomes significant, although it seems unable to trigger a systemic crisis.

3.2 The effect of bail-outs within conglomerates

The results obtained in Section 3.1 are based on the hypothesis that banks cannot react to any shock by, for example, raising capital to compensate for the losses suffered from the failure of their interbank counterparts. While this assumption may be quite suitable for stand-alone banks, it seems less appropriate for banks affiliated with a conglomerate. Indeed, it seems quite reasonable to assume that parent companies may recapitalise affiliated banks that would otherwise fail by, at least, redistributing capital resources among subsidiaries. On one hand, this would improve the resilience of the banking system to financial contagion since contagion losses are shared among all banks belonging to a group. On the other, banks that are not financially linked (directly or indirectly) to the bank that fails in the first step may suffer from losses due to financial contagion if other affiliates are financially linked to the bank which triggers the contagion process.

In this section we analyse how results change if we assume that banks can be bailed out by other banks belonging to the same conglomerate. Simulations are still based on unconsolidated interbank exposures and run in the same way as before except for assuming a slightly different default condition. In particular, that condition now refers to the consolidated capital as it is assumed that losses are now shared among banks affiliated with a certain conglomerate. [11]

Let C_s denote the set of banks affiliated with conglomerate *s* and k_s the capital of conglomerate *s*. Let bank $z \in B$ default. The capital of conglomerate *s* at the *n*-th contagion path initiated by bank *z* is equal to

(3) $$k_{s,z}^{n} = k_{s,z}^{n-1} - \alpha \sum_{i \in C_s, j \in D_z^{n-1}} x_{ij} , \quad \forall n \geq 1$$

and

(4) $$D_z^{n} = \left\{ i \in C_s : k_{s,z}^{n} \leq 0 \,\middle|\, k_{s,z}^{n-1} > 0 \right\} \quad , \forall n \geq 1$$

It is worth highlighting some important differences with respect to previous simulations: the default of bank *z* affects the solvency of bank $i \in C_s$ not only because of the losses bank *i* faces in lending money to bank *z* , but also because of the losses all other banks affiliated with conglomerate *s* suffer in lending to bank *z*. In fact, all the losses suffered by the banks affiliated with a conglomerate *s* affect the consolidated capital k_s. This bears out the hypothesis that, at each stage of the contagion process, banks can be bailed out by other banks affiliated with the same conglomerate if the consolidated capital is greater than the overall amount of the losses.

When conglomerates are considered another issue arises. As there may be close interdependencies among banks affiliated with a conglomerate, apart from those related to financial interlinkages, it could be that a shock that hits one bank will hit all banks of the same conglomerate. Thus, in this section, the impact of financial contagion is computed under two different hypotheses that *i*) the initial shock that makes banks fail at the first stage is bank-specific (one bank fails), or that *ii*) it is conglomerate-specific (i.e. one conglomerate as a whole fails).

[11] For stand-alone banks previous conditions hold.

Table 2 shows the results of simulations obtained for bank-specific shocks. The comparison with the results based on individual capital (Table 1) indicates that the effect of contagion is on average smaller if bail-outs within conglomerates are allowed. This reflects the fact that some relatively small banks can be bailed out by their parent company. Thus, one might conclude that banking conglomerates may lower the impact of financial contagion.

However, this result does not hold in general. In some cases, the severity of contagion may be even greater. The results for the *worst scenario* indicate that, under the hypothesis of bail-outs within conglomerates, financial contagion, for loss rates ranging from 0.4 to 0.7, is significantly more dangerous in terms of total assets affected than in the benchmark case. Similarly, the total assets of contagion-proof banks account for a smaller share of the banking system's total assets if loss rates are above 0.3 than in the benchmark case. This means that in the latter case, the impact of contagion tends to be more concentrated than in the former.

On the contrary, the maximum impact measured in terms of the number of banks failed by contagion is almost always less than the impact computed when bail-outs are not allowed. The same holds for contagious banks.

This evidence reflects the fact that conglomerate bail-outs have two opposing effects on the severity of contagion: on one hand, they imply a strengthening of subsidiaries' capital position, on the other, they add another channel for contagion as banks in a conglomerate suffer not only from the losses due to their interbank linkages but also from the losses due to all the other conglomerate affiliates' interbank exposures. The first effect is relatively greater for small banks, which may be more easily bailed-out by the conglomerate they are affiliated with. This explains why the number of failed banks tends to be lower, even in the worst scenario than in the case in which bail-outs are not allowed. On the contrary, this effect is limited in terms of the total assets affected by contagion as banks that may be bailed out are typically small.

All in all, the severity of contagion when bail-outs are allowed may be even greater compared with the benchmark case.

Table 2

Conglomerates and severity of financial contagion: bank-specific shocks

(*December 2003*)

Loss rate	Banks failing by contagion										Contagion-proof banks (2)			Contagious banks (3)		
	Total assets (as a percentage of banking system total assets)					Number of banks					Total assets (as a percentage of banking system total assets)	Number of banks	*of which: large banks* (1)	Total assets (as a percentage of banking system total assets)	Number of Banks	*of which: large banks* (1)
	Worst scenario		*Mean values*		Std.dev. (all banks)	*Worst scenario*		*Mean values*		Std.dev. (all banks)						
	All banks	*Large banks*	*All banks*	*Large banks*		*All banks*	*Large banks*	*All banks*	*Large banks*							
0.1	0.466	0.000	0.003	0.000	0.035	4	0	0.022	0.000	0.203	98.2	760	22	19.7	11	4
0.2	0.466	0.000	0.004	0.000	0.036	4	0	0.024	0.000	0.210	98.2	759	22	23.0	13	5
0.3	0.475	0.000	0.004	0.000	0.036	5	0	0.042	0.000	0.317	98.1	749	22	31.0	18	8
0.4	12.767	11.830	0.049	0.037	0.698	19	5	0.145	0.019	1.236	78.1	712	14	35.9	23	10
0.5	12.767	11.830	0.063	0.046	0.762	19	5	0.199	0.023	1.486	67.5	682	11	41.0	26	11
0.6	12.786	11.830	0.075	0.055	0.817	20	5	0.243	0.027	1.689	67.4	670	11	47.7	31	13
0.7	12.786	11.830	0.079	0.055	0.834	28	5	0.301	0.027	2.086	65.4	643	11	47.7	31	13
0.8	12.786	11.830	0.099	0.069	0.924	43	5	0.381	0.034	2.553	50.8	599	6	48.6	35	13
0.9	12.786	11.830	0.106	0.069	0.937	58	5	0.469	0.034	3.117	49.0	566	6	53.9	41	15
1.0	12.827	11.830	0.110	0.069	0.947	73	5	0.538	0.034	3.637	46.4	534	6	56.2	49	15

(1) Large banks are defined as banks whose total assets are at least equal to 20 billion euro. (2) Banks which are never affected by contagion. (3) Banks which make at least one bank fail.

On the other hand, given that the number of banks involved in the contagion process, both contagious and contagion-affected banks, is smaller it could be easier to manage a systemic crisis in this case.

Apart from bail-outs, bank conglomerates may damage the resilience of the interbank market to financial contagion as they also raise the interdependence among banks. Table 3 shows that, if at the first stage of simulations a conglomerate as a whole fails instead of a single bank, the impact of contagion is greater.

4. Maximum entropy versus observed interbank lending patterns

This section compares the results obtained in the previous section with those that would be obtained if the matrix of bilateral exposures were not known and, by following previous contributions, the maximum entropy method (ME) were adopted.[12] This comparison is important in two respects. Firstly, it sheds some light on the reliability of the ME approach for assessing whether the interbank market is vulnerable to financial contagion. Secondly, as the ME matrix represents, according to Allen and Gale's (2000) taxonomy, a *complete* market, the comparison between the results obtained using the actual matrix of bilateral exposures and those based on the ME matrix may provide some evidence in support of the hypothesis that the pattern of interbank linkages affects the severity of financial contagion.

Section 4.1, after briefly recalling the main results of Allen and Gale's (2000) model, shows, in contrast, that complete markets are not necessarily less conducive to contagion than incomplete markets. To do this, some simple numerical examples are considered. Section 4.2 applies the same approach to the Italian interbank market. The results support the analysis of Section 4.1 indicating that in the Italian case the ME method may in certain overrate the vulnerability to contagion.

[12] See *Appendix B* for details.

Table 3

Conglomerates and the severity of financial contagion: conglomerate-specific shocks

(*December 2003*)

Loss rate	Banks Failing by Contagion										Contagion-proof banks (2)			Contagious Conglomerates (3)		
	Total assets (as a percentage of banking system total assets)					Number of banks					Total assets (as a percentage of banking system total assets)	Number of banks		Total assets (as a percentage of banking system total assets)	Number of conglomerates	
	Worst scenario		*Mean values*		*Std.dev.* (all banks)	*Worst scenario*		*Mean values*		*Std.dev.* (all banks)			*of which: large banks* (1)			*of which: large conglomerates* (4)
	All banks	*Large banks (1)*	*All banks*	*Large banks (1)*		*All banks*	*Large banks (1)*	*All banks*	*Large banks (1)*							
0.1	0.720	0.000	0.006	0.000	0.050	6	0	0.038	0.000	0.351	97.4	755	22	38.1	11	5
0.2	12.703	11.830	0.042	0.033	0.630	14	5	0.083	0.014	0.808	74.6	732	14	61.1	14	7
0.3	12.751	11.830	0.048	0.036	0.647	17	5	0.122	0.020	1.046	70.5	710	11	65.7	17	8
0.4	12.767	11.830	0.085	0.060	0.837	19	5	0.191	0.031	1.401	49.2	675	5	68.9	19	9
0.5	12.767	11.830	0.092	0.060	0.847	19	5	0.251	0.031	1.698	44.5	644	5	71.2	21	9
0.6	12.786	11.830	0.096	0.060	0.852	20	5	0.291	0.031	1.834	42.7	627	5	72.4	23	9
0.7	12.786	11.830	0.099	0.060	0.862	28	5	0.354	0.031	2.212	41.1	598	5	72.8	24	9
0.8	12.786	11.830	0.122	0.077	1.010	43	5	0.442	0.032	2.929	29.2	559	4	73.1	26	9
0.9	12.786	11.830	0.126	0.077	1.024	58	5	0.522	0.032	3.522	28.4	530	4	77.4	29	10
1.0	12.827	11.830	0.127	0.077	1.030	73	5	0.574	0.032	4.050	28.0	508	4	78.3	34	10

(1) Large banks are defined as banks whose total assets are at least equal to 20 billion euro. (2) Banks which are never affected by contagion. (3) Banks which make at least one bank fail. (4) Conglomerates including at least one large bank.

4.1 Interbank lending patterns and the theory of financial contagion

Recent theoretical contributions (Allen and Gale, 2000; Freixas, Parigi and Rochet, 2000) have highlighted that the propagation of shocks within the interbank market is dependent on the exact pattern of banks' financial linkages. Allen and Gale (2000) identify two key structural characteristics of the market which affect financial contagion: market *completeness* and market *interconnectedness*. A market is *complete* if each bank lends to all the others. On the other hand, a market is *perfectly interconnected* if each bank is financially linked to all the others, regardless of the kind of linkage, which may be both direct (i.e. each bank lends to all the others) and indirect (the link that a bank could indirectly establish with another if a third one is linked to both of them).

Those authors point out that the more *complete* the market the less severe is the financial contagion and the more *interconnected* the market the more severe is the contagion. Thus, there is a trade-off in terms of the propagation of contagion between *completeness* and *interconnectedness*. These two concepts are strictly linked. A *complete* market is a specific case of a *perfectly interconnected* market where banks are financially linked to all the others only by direct exposures. Otherwise, *incomplete* markets may be differently *interconnected*: they may be both perfectly or partially *interconnected* depending on the pattern of financial linkages. In general, markets that are *incomplete* and not perfectly *interconnected* may differ both in terms of *completeness* and *interconnectedness*.

The comparison between ME and observed interbank patterns may be interpreted as the comparison between complete and incomplete markets with the notable qualification that Allen and Gale's (2000) model does not allow for bank heterogeneity. On the contrary, the ME method assumes that banks spread their lending as evenly as possible, consistently with their aggregate interbank assets and liabilities which may, in turn, differ considerable among banks.

Let us ignore for a while the issue of bank heterogeneity, which will be dealt with later. According to Allen and Gale's (2000) taxonomy, the comparison between actual and ME bilateral exposures may lead to the following cases,

(a) the (actual) market is complete,
(b) the (actual) market is incomplete but perfectly interconnected, and
(c) the (actual) market is incomplete but not perfectly connected.

In the first case, the ME matrix of bilateral exposures and the observed ones coincide. Thus, the measure of the impact of financial contagion is not affected by the ME hypothesis. On the other hand, if the market is incomplete but perfectly interconnected (case b), ME leads to an undervaluation of financial contagion. To show this consider Figure1, which represents the ME matrix of bilateral exposures under the assumption that, for each bank, total interbank liabilities and total interbank assets are equal.

This assumption is needed only to simplify the maximisation of the entropy. It does not imply any loss of generality as contagion is based on gross exposures. Let us assume also that bank capital is equal to k and that a bank fails if losses exceed its capital and reserves. Thus, if bank A fails due to a specific shock[13] it is easy to verify that there is no contagion unless the loss rate is greater than 0.5 (i.e. losses are greater than k). In that case, all banks fail by contagion (Table 4).

We now compare these results with those obtained for case *b*) (Figure 2).[14] It is easy to verify that all banks in the market fail if the market is incomplete and perfectly connected unless the loss rate is lower than 0.2 (1/6 to be precise). This confirms that, if the actual market is incomplete but perfectly connected, the maximum entropy method tends to underrate the extent of contagion (in this specific case when the loss rate ranges from 0.2 to 0.5).

This is due to a typical effect of risk diversification. In fact, while complete markets and incomplete but perfectly connected markets do not differ in terms of the number of banks potentially affected by contagion (as a shock may propagate from each bank to all the others in both cases), complete markets allow banks to better diversify credit risk than incomplete ones, given that each bank lends directly to all the other banks instead of holding the financial assets issued by a limited number of counterparts.

[13] In the absence of bank heterogeneity the identity of the bank that fails due to some idiosyncratic shock is not relevant.

[14] This corresponds to the incomplete market structure depicted in Allen and Gale's (2000) Figure 1.

Figure 1

A complete market
(maximum entropy)

	Bank A	*Bank B*	*Bank C*	*Bank D*	**Total assets**
Bank A	0	2k	2k	2k	**6k**
Bank B	2k	0	2k	2k	**6k**
Bank C	2k	2k	0	2k	**6k**
Bank D	2k	2k	2k	0	**6k**
Total liabilities	**6k**	**6k**	**6k**	**6k**	**24k**

Table 4

Financial contagion: complete versus incomplete markets
(number of banks failing by contagion)

Loss Rate	*Symmetric case*			*Asymmetric case*	
	Complete markets (fig.1)	**Incomplete but perfectly connected market** (fig. 2)	**Incomplete and disconnected market** (fig. 3)	**Complete markets** (fig.4)	**Incomplete and disconnected market** (fig. 4)
0.1	0	0	0	0	0
0.2	0	3	1	0	1
0.3	0	3	1	0	1
0.4	0	3	1	3	1
0.5	0	3	1	3	1
0.6	3	3	1	3	1
0.7	3	3	1	3	1
0.8	3	3	1	3	1
0.9	3	3	1	3	1
1.0	3	3	1	3	1

Figure 2

An incomplete but perfectly connected market

	Bank A	*Bank B*	*Bank C*	*Bank D*	**Total assets**
Bank A	0	6k	0	0	**6k**
Bank B	0	0	6k	0	**6k**
Bank C	0	0	0	6k	**6k**
Bank D	6k	0	0	0	**6k**
Total liabilities	**6k**	**6k**	**6k**	**6k**	**24k**

Consider now case c) as depicted in Figure3.[15] In this case it is straightforward to verify that the maximum entropy method does not affect the measure of contagion if loss rates are lower than 0.2 (1/6); it underrates the scope for contagion if loss rates range from 0.2 to 0.5 and it overrates it for loss rates greater than 0.5.

The reason why, in spite of lower market concentration, complete markets may , *ceteris paribus*, be even less resilient to financial contagion than incomplete ones is that, if the size of the interbank market is sufficiently large with respect to bank capital, there could be limited scope for risk diversification, especially for large loss rates, from spreading interbank exposures over a great number of counterparts. It is easy to verify that if the total amount of interbank assets held by each bank were less than $3k$, complete markets would be totally immune to contagion, thus representing, in line with Allen and Gale (2000), the most resilient market structure. For larger interbank markets, the sole effect of diversification is that market interconnectedness rises, favouring the propagation of contagion.

In general, for N homogenous banks the interbank assets-to-capital ratio has to be at least equal to $(N – 1)$ to make the failure of a bank propagate within the market. However, actual interbank markets are not so large. On the other hand, according to the evidence provided by those authors who have resorted to the maximum entropy method, even complete markets are vulnerable to financial contagion. The reason for this result is that,

[15] This corresponds to the disconnected incomplete market structure depicted in Allen and Gale’s (2000) Figure 3. This market is made of two totally disconnected segments: to one of them belong bank A and B, to the other bank C and D.

although markets are assumed to be complete, the ME does not rule out bank heterogeneity and, as shown below, the condition for contagion propagation then becomes less stringent.

Figure 3

An incomplete and disconnected market

	Bank A	*Bank B*	*Bank C*	*Bank D*	**Total assets**
Bank A	0	6k	0	0	**6k**
Bank B	6k	0	0	0	**6k**
Bank C	0	0	0	6k	**6k**
Bank D	0	0	6k	0	**6k**
Total liabilities	**6k**	**6k**	**6k**	**6k**	**24k**

To show how the resilience of the market may deteriorate when bank heterogeneity is allowed, let us consider the interbank market depicted in Figure 4, which is equal to the one represented in Figure 3 apart from the fact that banks differ in terms of interbank asset-to-capital ratio. In this case, the identity of the bank that fails due to some idiosyncratic shock is not irrelevant any more. The maximum impact of financial contagion is obtained when bank *A* defaults (i.e. the bank that is better capitalised than the others). For a loss rate greater than 0.1 the failure of bank *A* makes only bank *B* fail by contagion according to the observed matrix (panel a).

On the other hand, bank *A* makes all other banks fail unless the loss rate is lower than 0.3. Thus, the two matrices produce the same result up to a loss rate equal to 0.2, the maximum entropy method underrates the severity of contagion for loss rates ranging from 0.1 to 0.3 and overrates the extent of contagion if the loss rate is greater than 0.3. This means that, by allowing for some heterogeneity in banks' capitalisation, the maximum impact of financial contagion tends to be overstated for lower loss rates than in the case in which banks are homogenous (loss rates greater than 0.5). It may be also verified that in this case, even if each bank held an amount of interbank assets lower than $3k$, complete markets would not be immune to contagion as they were in the symmetric case (Figure 1).

Figure 4

Bank Heterogeneity

a) *observed matrix of bilateral exposures*

An incomplete and disconnected market

	Bank A	*Bank B*	*Bank C*	*Bank D*	**Total assets**
Bank A	0	6k	0	0	**6k**
Bank B	6k	0	0	0	**6k**
Bank C	0	0	0	6k	**6k**
Bank D	0	0	6k	0	**6k**
Total liabilities	**6k**	**6k**	**6k**	**6k**	**24k**
Capital and reserves	**2k**	**2/3k**	**2/3k**	**2/3k**	**4k**

b) *ME matrix of bilateral exposures*

A complete market
(maximum entropy)

	Bank A	*Bank B*	*Bank C*	*Bank D*	**Total assets**
Bank A	0	2k	2k	2k	**6k**
Bank B	2k	0	2k	2k	**6k**
Bank C	2k	2k	0	2k	**6k**
Bank D	2k	2k	2k	0	**6k**
Total liabilities	**6k**	**6k**	**6k**	**6k**	**24k**
Capital and reserves	**2k**	**2/3k**	**2/3k**	**2/3k**	**4k**

The main conclusion of this section is that, apart from the cases in which the actual market is complete or is incomplete and perfectly connected, ME may involve, for high loss rates, an overstatement of the severity of financial contagion. This may also happen more easily when banks are heterogeneous.[16]

This possible effect seems to be quite realistic as there are at least three reasons why actual interbank markets are, in general, incomplete and to some extent disconnected. First, the existence of informational asymmetries or, in general, transaction costs may prevent

[16] This result is in line with Iori, Jafarey and Padilla (2006).

banks from fully exploiting their capacity to diversify interbank counterparts. Second, for banks that are affiliated with conglomerates the multiple money centre structure seems to be suitable to exploit economies of scale in liquidity management. Finally, in many countries banks differ in size considerably and therefore the assumption that the interbank market is made of homogenous banks seems unrealistic.

4.2 The Italian case

Some characteristics of the Italian interbank market suggest that it is far from being a complete market and that the adoption of the ME method may therefore significantly affect the assessment of financial contagion. Indeed, the Italian interbank market fits quite well in the multiple money centre structure described in Freixas, Parigi and Rochet (2000), in which some banks trade with a bank (the money centre) while they do not trade with each other: at the end of 2003, more than two thirds of interbank claims were traded among banks belonging to the same group. As far as interconnectedness is concerned, banks were on average financially linked, both directly and indirectly through other banks, to one half of the total number of counterparts.[17]

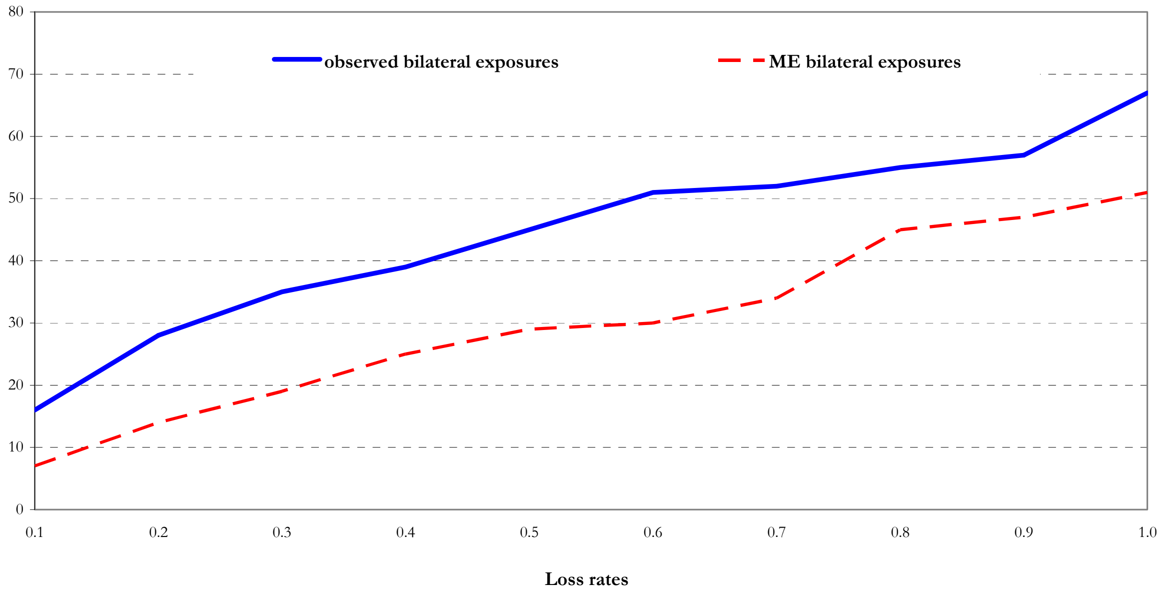
The comparison of the severity of financial contagion in the Italian interbank market by using, alternatively, the maximum entropy (ME) matrix and the observed matrix of bilateral exposures (Figures 5-9) confirms that ME may provide a quite different measure of financial contagion.

Figure 5 supports the hypothesis that complete markets are more resilient to contagion than incomplete ones, at least in terms of contagious banks. In this case, one can argue that a smaller number of banks have to be monitored in order to avoid the propagation of contagion within the banking system if the market were complete.

Figures 6 and 7 indicate that the ME method leads, on average, to an undervaluation of the severity of financial contagion, both in terms of the number of banks and of the total assets affected by contagion, if the loss rate is not above 0.8 and 0.9, respectively. Similarly, according to Figures 8 and 9, ME underrates the maximum impact of financial contagion, measured by the maximum number of banks failed and the maximum share of the banking system's total assets affected by contagion, for loss rates not greater than 0.7.

Figure 5

Number of contagious banks
(December 2003)



To sum up, the evidence suggests that in most cases ME tends to underrate the impact of financial contagion. On the contrary, for high loss rates ME may imply an overvaluation of the severity of contagion.

A further complication is that the lowest loss rate at which ME overvaluates the severity of financial contagion depends on the characteristics of the market. As shown in Section 4.1, that critical value may also be quite low. From the previous discussion it may also be argued that the lowest loss rate at which ME underrates the extent of contagion is negatively related to the asymmetry among market participants in terms of the amount of bilateral exposures and to the size and the disconnectedness of the interbank market. In other words, when the interbank market is made up of a few big players raising funds from many relatively small counterparts, interbank exposures account for a large share of banks' capital and the market

[17] The computation of a measure of interconnectedness for the Italian interbank market refers only to those financial linkages such that contagion is at least possible (i.e. such that for a loss rate equal to 1, interbank exposures exceed bank capital).

Figure 6

Banks failing by contagion
Number of banks affected by contagion - mean values
(December 2003)

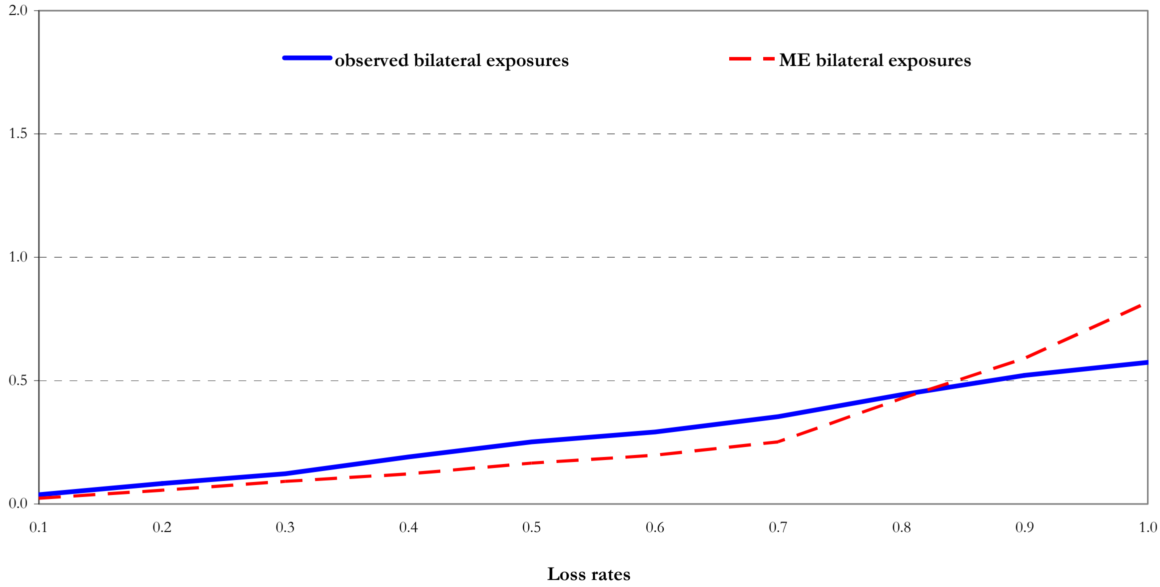


Figure 7

Banks failing by contagion
Percentage of banking system total assets affected by contagion - mean values
(December 2003)

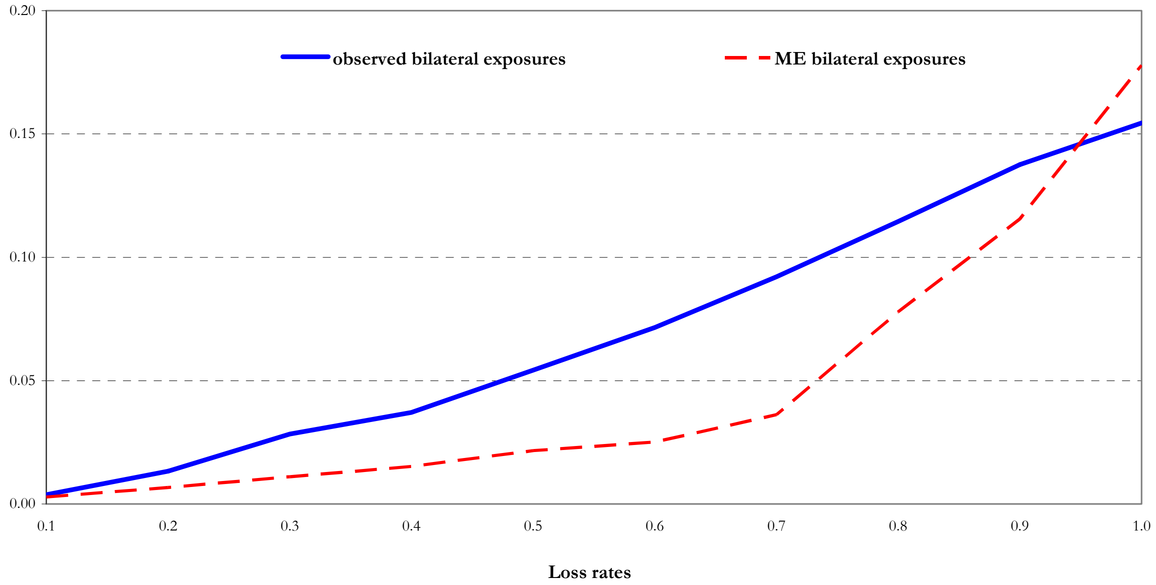


Figure 8

Banks failing by contagion
Number of banks affected by contagion - worst scenario
(December 2003)

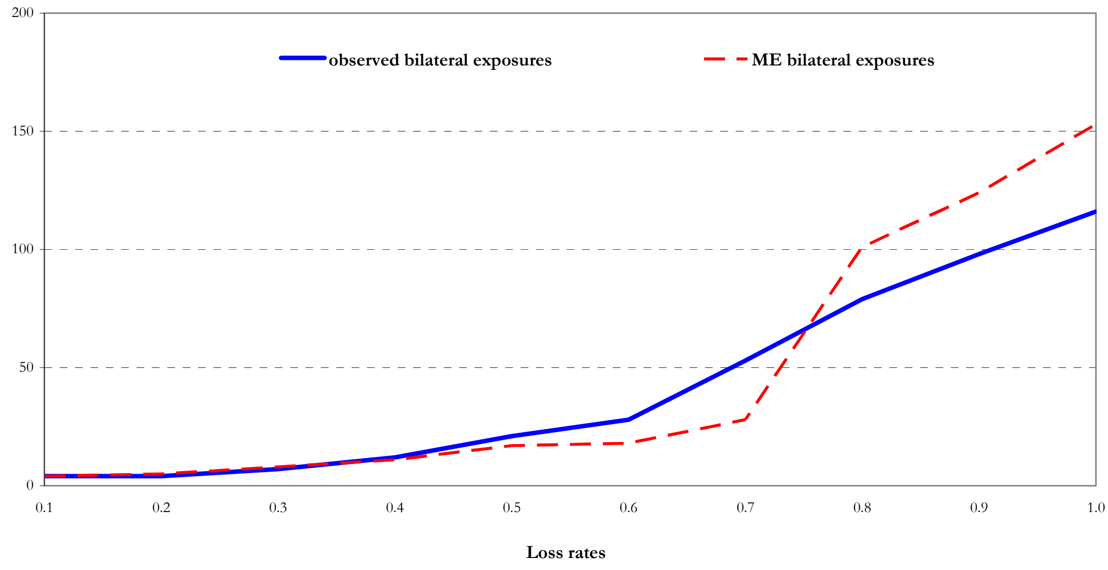
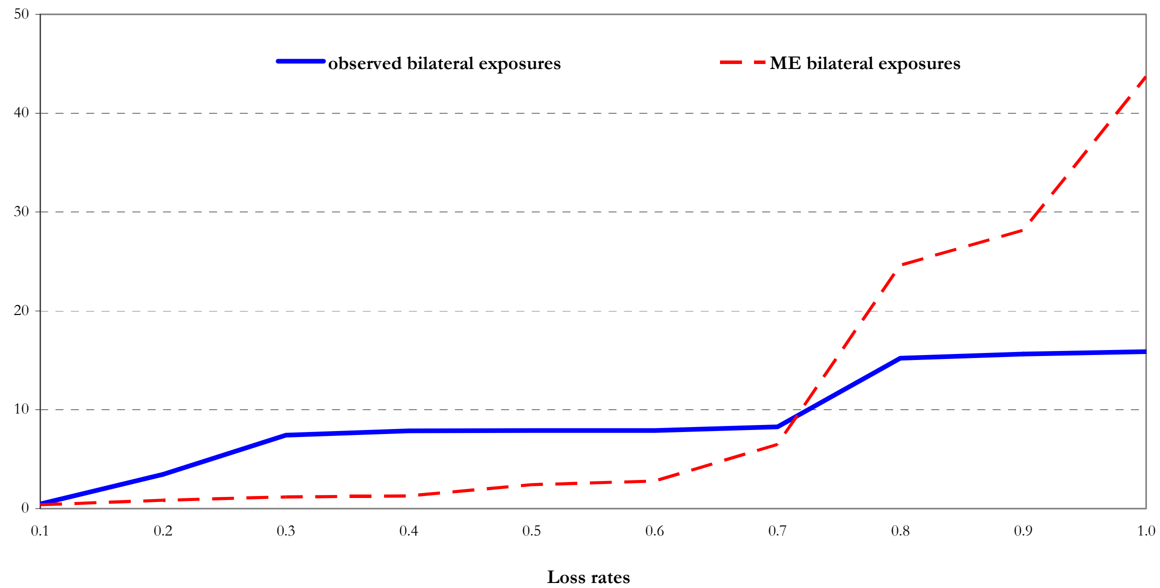


Figure 9

Banks failing by contagion
Percentage of banking system total assets affected by contagion - worst scenario
(December 2003)



is highly segmented, ME may then be of little help in assessing the severity of financial contagion as it would overstate the impact of financial contagion even for low loss rates. As a consequence, in that situation the ME approach might not be very reliable even for assessing whether a danger of financial contagion exists or not.

The comparison between the ME and actual measures of financial contagion has been done by the Wilcoxon signed-rank test (Table 5). In particular, this test compares, for each bank *i* and a given loss rate, the severity of contagion triggered by its default (Ω_i), computed on the base of the actual matrix of bilateral exposures, with the severity of contagion triggered by the same bank *i*, calculated on the base of the ME matrix (Ω_i^{ME}). The null hypothesis is that the median of the differences ($\Omega_i - \Omega_i^{ME}$) is zero. Table 5 reports the results for both the distribution of the number of banks failing by contagion and the distribution of the total assets affected by contagion. The results indicate that the ME method tends to provide a measure of the severity of contagion that is statistically different from the one obtained on the base of actual bilateral exposures.

Table 5

A test for the equality of ME and observed financial contagion distributions (1)
(*December 2003*)

	Loss rate									
	0.1	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1.0**
	Total assets affected by contagion									
	All banks									
Wilcoxon signed-rank test	1.517	2.516	3.061	2.932	3.250	4.638	4.150	2.946	2.514	3.312
p-value	*0.1292*	*0.0119*	*0.0022*	*0.0034*	*0.0012*	*0.0000*	*0.0000*	*0.0032*	*0.0119*	*0.0009*
	Contagious banks									
Wilcoxon signed-rank test	2.535	3.462	3.735	3.850	4.193	5.530	5.237	4.692	3.945	4.366
p-value	*0.0112*	*0.0005*	*0.0002*	*0.0001*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
	Number of banks affected by contagion									
	All banks									
Wilcoxon signed-rank test	1.775	1.678	2.123	2.263	2.912	3.343	3.346	2.251	2.311	3.234
p-value	*0.0760*	*0.0934*	*0.0337*	*0.0236*	*0.0036*	*0.0008*	*0.0008*	*0.0244*	*0.0209*	*0.0012*
	Contagious banks									
Wilcoxon signed-rank test	2.856	2.170	2.740	3.244	3.664	4.284	4.635	4.280	4.176	4.788
p-value	*0.0043*	*0.0300*	*0.0061*	*0.0012*	*0.0002*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*

(1) Distributions refers to a measure of the propagation of financial contagion in the interbank market computed for each bank failing by an idiosyncratic shock.

5. Conclusion

This paper has investigated whether interbank linkages may be conducive to financial contagion. The contribution to the existing literature is twofold. Firstly, it enriches the evidence so far available on financial contagion by providing the first comprehensive analysis for the Italian interbank market. To this end, unlike previous contributions, which are based on ME bilateral exposures, the paper is based on a unique data set of actual bilateral exposures. It has also taken into account the effect of banking conglomerates in terms of banking system stability. This aspect has been ignored by previous works. Secondly, the paper compares the results obtained by using ME bilateral exposures with those obtained on the base of actual bilateral exposures. This allows us to show how the ME method widely used in the literature may affect the analysis of financial contagion.

The main result is that: the Italian interbank market is conducive to financial contagion. However, even for high loss rates, the default of banks raising funds in the interbank market hardly triggers a systemic crisis. Only in some extreme cases does the severity of financial contagion seem considerable. Simulations also indicate that, by allowing conglomerates to recapitalise their affiliates which otherwise would fail, the resilience to financial contagion of the banking system tends to improve. However, in some cases the fact that losses are shared among banks affiliated to a conglomerate, adding another channel for contagion means that banking stability may even worsen.

The paper also indicates that the maximum entropy procedure, widely adopted in previous contributions, may overvalue the severity of contagion. This contrasts with the common view that complete markets are more resilient to financial contagion. In some circumstances, depending on the size of the interbank market, the presence of large players, and the loss rate, complete markets may be even more conducive to contagion than incomplete ones. In that case, the benefits from diversifying the interbank exposures are more than counterbalanced by the costs due the fact that each bank establishes a large number of financial linkages, thus making a domino effect viable.

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Appendix A

The empirical investigation on financial contagion

Reference	Country	Institutions	Type of Data	Period	Type of Shock
Angelini, Maresca and Russo (1996)	Italy	288 banks	Bilateral end-of-day net balances	January 1992	idiosyncratic shock
Bech, Madsen and Natorp (2002)	Denmark	Danish banks	Interbank multilateral netting system, daily data	Dec. 21st 2001 - Jan. 25th 2002	idiosyncratic shock
Blavarg and Nimander (2002)	Sweden	Four largest swedish banks	15 largest bilateral interbank exposures	September 1999 - September 2001	idiosyncratic shock
Degryse and Nguyen (2007)	Belgium	Belgian banks	Estimated bilateral interbank exposures (RAS algorithm), large bilateral exposures (December 2003), quarterly data	1993-2002	idiosyncratic shock
Elsinger, Lehar and Summer (2006)	Austria	Austrian banks	Estimated bilateral interbank exposures (RAS algorithm)	September 2001	macroeconomic shock
Furfine (2003)	United States	Fedwire participants (719 commercial banks)	Federal funds bilateral exposures (daily data)	February 1998 - March 1998	idiosyncratic shock
Sheldon and Maurer (1998)	Switzerland	Swiss banks	Estimated bilateral interbank exposures (RAS algorithm), overnight interbank loans	1987-95	idiosyncratic shock
Upper and Worms (2004)	Germany	German banks and foreign bank branches operating in Germany	Estimated bilateral interbank exposures (RAS algorithm)	December 1998	idiosyncratic shock
Van Lelyveld and Liedorp (2006)	Netherlands	Dutch banks and foreign subsidiaries and branches	Estimated bilateral interbank exposures (RAS algorithm), large bilateral exposures, ad hoc survey	December 2002	idiosyncratic shock
Wells (2004)	United Kingdom	UK banks	24 largest individual exposures and estimated bilateral interbank exposures (RAS algorithm)	December 2000	idiosyncratic shock

Appendix B

The maximum entropy methodology for obtaining interbank bilateral exposures

The interbank linkages may be represented by the following $N \times N$ matrix

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1N} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ x_{i1} & \dots & x_{ij} & \cdots & x_{iN} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ x_{N1} & \cdots & x_{Nj} & \cdots & x_{NN} \end{bmatrix}$$

where $a_i = \sum_{j=1}^{N} x_{ij}$, $l_j = \sum_{i=1}^{N} x_{ij}$ are, respectively, the total amount of money bank *i* lends to other banks and bank *j* raises from other banks. In the absence of any assumption about the distribution of bilateral exposures, the matrix *X* cannot be identified as $N^2 - 2N$ unknowns have to be estimated.

The common approach is to assume that banks maximise the dispersion of their interbank exposures. Following an appropriate normalisation this implies that bilateral exposures are given by a simple solution: $x_{ij}^* = a_i l_j$. However, this solution would imply that for banks that are both lender and borrower in the market they lend to themselves. In order to rule out this outcome it is necessary to assume that $x_{ij}^* = 0, \forall i = j$.

The problem is then to estimate bilateral exposures such that the matrix $\hat{X}$ obtained by the maximisation becomes as close as possible to matrix X^*. This is generally obtained by minimising the cross-entropy between the two matrices:

$$\min_{\hat{x}_{ij}} \sum_{i=1}^{N} \sum_{j=1}^{N} \ln\left(\frac{\hat{x}_{ij}}{x_{ij}^*}\right)$$

$$s.t.$$

$$\sum_{i=1}^{N} \hat{x}_{ij} = a_i \qquad \sum_{j=1}^{N} \hat{x}_{ij} = l_j \qquad \hat{x}_{ij} \geq 0 \quad \forall i \neq j \qquad \hat{x}_{ij} = 0 \quad \forall i = j$$

This problem has been solved numerically using the RAS algorithm.[18]

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[18] See Censor and Zenos (1997) for details.

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Cross-Border Banking and the International Transmission of Financial Distress during the Crisis of 2007-2008*

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Abstract

We study the effect of financial distress in foreign parent banks on local SME financing in 14 central and eastern European countries during the early stages of the 2007-2008 financial crisis. We use survey data on $9,360$ applicant and non-applicant firms that enable us to disentangle effects driven by shocks to the banking system from recession-driven demand shocks that may vary across lenders. We find strong evidence that new bank lending tightened in the relatively early stages of the crises caused by the following types of bank financial distress: 1) low equity ratio; 2) low Tier 1 capital ratio; and 3) losses on financial assets. We also find that the size of the transmission of such shocks to Main Street increases with the degree of foreign bank presence. The observed decline in credit is greater among riskier firms and firms with fewer tangible assets.

JEL classification: E44, E51, F34, G21
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1 Introduction

The increasing integration of the European banking industry offers the prospect of important gains in terms of efficiency and diversification, but it also creates potential risks. One such risk is associated with the possibility that a shock to a cross-border bank's capital will result in a reduction in lending to firms and consumers in an economic environment that is uncorrelated with the origins of that shock. Given the size and penetration of a number of west European and U.S. banks in central and eastern Europe, their financial distress associated with the meltdown of subprime mortgages and securitized products in 2007 and 2008 and the run on banks by short-term creditors, counterparties, and borrowers concerned about the liquidity and solvency of the banking sector[1], may have led to such a realization.[2] The goal of this paper is to put this hypothesis to the test.

We investigate one key mechanism through which foreign financial distress may have been transmitted to local economic conditions, namely the supply of credit to small and medium enterprises. SMEs dominate the corporate landscape in central and eastern Europe, comprising up to 99% of all firms. Moreover, because of their opacity SMEs may be particularly vulnerable to contractions in the supply of credit. With this high dependency on the SME sector and with immature capital markets, banks are by far the main provider of funds for capital investment and expansion. An important feature of the central and eastern European banking market is its ownership structure. In particular, foreign ownership in the banking sector has grown so dramatically in the recent decade, that by 2008 foreign banks controlled around 80% of the assets in the region's banking industry.[3] The serious financial distress of pan-European banks like Erste, KBC, and Societe Gen-

[1]See Brunnermeier (2009), Gorton (2009), and Ivashina and Scharfstein (2009) for a timeline of the 2007-2008 global financial crisis. See Table 1 for developments concerning the financial sector in the countries covered by this paper.

[2]Signs of the negative effects of the global financial crisis on business firms in emerging Europe through the channel of bank lending were seen as early as the Fall of 2007. For instance, in October, the EBRD's chief economist Erik Berglof warned that "the crisis in the West will be a serious one which will last for some time and this means it will definitely have an impact on our countries [...] due to the difficulties and higher costs associated with obtaining credit" (EBRD (2007)). The euro zone Bank Lending Survey indicated that euro zone banks started tightening lending standards in Q3:2007 (ECB (2008)).

[3]For summaries of the literature on the motivations for foreign entry into banking markets and the relative performance/behavior of foreign versus domestic banks (including behavior in credit markets) see Degryse, Havrylchyrk, Jurzyk, and Kozak (2010) and Berger, DeYoung, Genay, and Udell (2000).

erale since 2007 stemming from economic circumstances unrelated to their operation in central and eastern Europe provides a natural experiment to study the channels through which the effects of the financial crisis that started in the U.S. spread through out the global economy.

Our key data come from a survey of a large group of SMEs in emerging Europe administered in April 2005 and April 2008. The data allow us to directly observe firms whose loan application was turned down over the course of the previous year, or which were discouraged from applying for bank credit by high rates and unfavorable collateral requirements. While we do not observe the bank which granted/denied the loan, we observe the extent of the operations of all banks present in the firm's city of incorporation. By using balance sheet data on the parent banks, foreign or domestic, we construct an index of financial distress at the level of each locality in 14 countries in the region, which we then map into data on loan rejection rates. The final data consist of $9,360$ firms in $1,803$ localities served by a total of 141 banks over the 2005-2008 period. The majority of localities, however, are served by just a handful of banks, with the degree of foreign ownership of those varying by both country and locality. This allows us to answer two important questions: 1) did banks transmit their financial distress by shrinking loans to business customers issued by their branches and subsidiaries in the early stages of the 2007–2008 crisis?, and 2) did foreign banks transmit to the corporate sector a larger share of their respective financial troubles than domestic banks?

The classic problem with identifying a credit crunch is that firms' demand shifts during a credit crunch following the deterioration of firms' balance sheets. This would not be an issue if we were studying the cross-border transmission of financial distress into an economic area insulated from that distress through all other channels but the bank lending channel. As the sub-prime mortgage crisis was associated since its very beginning with the expectations of a global recession, the measured effect of bank loan supply shocks will likely be contaminated by demand shifts. Some studies that identify demand use the decline in loan applications across differentially affected lenders to argue that there haven't been variations in the decrease in demand across lenders. One problem with that identification approach may be limited data availability on loan applications. However, even when one observes the universe of loan applications, applicant firms could be a systematically truncated sub-sample of all firms: some firms do not apply because they do not need credit, while others do not apply because they are discouraged. Not accounting for discouraged firms results in a poor proxy for credit constraints, especially in the region of central and eastern Europe, where recent studies (Brown, Ongena, Popov, and Yesin (2010)) have shown that the share of firms discouraged from applying is up to twice as large as the share of firms which applied and had their loan application rejected. Then it could well be that for banks negatively affected by the crisis, it is the financially healthy borrowers that are selecting themselves out of the application process (firms that do well during a recession), while for other banks, it is the weak firms that do so, discouraged by news of a contraction in lending. Thus, at different types of banks, non-applicant firms may have systematically different reasons for selecting themselves out of the application process, confounding identification and making it difficult to separate the bank lending from the balance sheet channel.

We overcome this obstacle by employing observable survey information on firms that choose to select themselves out of the bank credit application process, be it because they were discouraged, or because they do not need credit. Thus we are able to account not just for the decrease in firms' demand, but also for the *composition* of firms that account for the decrease in demand. While there is already extensive evidence on the real effects of this financial crisis[4], our paper is the only one we know of which simultaneously 1) studies the international transmission of financial distress, 2) accounts for the changes in the level and composition of loan demand, and 3) is able to construct a proxy for credit constraint based on discouragement as well as on actual rejection. As such, our paper adds to a very scarce literature employing data on the selection process involved in the granting of business loans.[5]

This paper confirms the hypothesis that the contraction of banks' balance sheets caused by losses on financial assets and the deterioration of their equity positions was transmitted cross-border to central and eastern Europe in the relatively early stages of the 2007-2008 crisis. In particular, we find a higher probability of firms' being credit constrained in localities served by

[4]De Haas and van Horen (2009), Huang (2009), Ivashina and Scharfstein (2009), Jimenes, Ongena, Peydro, and Saurina (2009), Puri, Rochol, and Steffen (2009), and Santos (2009) all provide evidence on the credit crunch associated with the 2007-2008 financial crisis.

[5]The very few studies known to us that do so are Cerqueiro (2009), Chakravarty and Yilmazer (2009), and Ongena and Popov (2009).

foreign banks whose parents had 1) a low ratio of equity to total assets, 2) a low Tier 1 capital ratio, and 3) high losses on financial assets, including ABSs and MBSs. The result is strongest and most consistent for equity capital and for Tier 1 capital. The key results hold both when we assume equal access of each firm to all banks present in the firm's locality, or when we weigh access by the branch penetration of each bank. For example, we find that in foreign-dominated markets, a two-standard deviation deterioration in the respective proxy for financial distress results in a between 8% and 13% higher probability of rejection faced by an identical firm. We find that the probability of banks' shrinking their portfolio in response to financial distress, especially low Tier 1 capital ratios, the measure of financial distress that is most consistently associated with credit rationing, increases with the magnitude of foreign bank ownership. Finally, we find that financial distress is transmitted differently across firms and industries, in that firms that are high-risk and firms with fewer tangible assets suffer the most.

Our paper relates to a number of studies that have aimed at identifying the transmission of shocks from banks' balance sheets to lending activity in various economic circumstances. The bank lending channel has been studied extensively (e.g., Kashyap and Stein (2000)), and banks have been found to rely heavily on the use of internal capital markets in order to dampen domestic liquidity shocks (e.g., Stein (1997); Houston, James, and Marcus (1997)). The U.S. credit crunch in 1990-92 spawned a large literature that investigated its causes and its effects (e.g., Bernanke and Lown (1991); Berger and Udell (1994); Peek and Rosengren (1995); Wagster (1996); Hancock and Wilcox (1998)). Banking crises and liquidity shocks elsewhere in the world similarly generated considerable academic attention (e.g., Woo (1999); Kang and Stulz (2000); Hayashi and Prescott (2002); Khwaja and Mian (2008); Paravisini (2008)). Peek and Rosengren (1997) were one of the first to identify the international transmission of financial shocks when they investigated how the collapse of asset prices in Japan during the early 1990s affected the operations of Japanese bank subsidiaries abroad. In particular, they show that the decline in the parents' risk-based capital ratio translated into a significant decline in total loans by the U.S. subsidiaries. Chava and Purnanandam (2009) and Schnabl (2009) use the exogenous shock provided by the Russian crisis of 1998 to study the effect on lending to U.S. and Peruvian borrowers, respectively. Cetorelli and

Goldberg (2008) show that the existence of internal capital markets with foreign bank affiliates contributes to an international propagation of domestic liquidity shocks to lending by affiliated banks abroad. In the context of the financial crisis of 2007-2008, Ivashina and Scharfstein (2010) document that new loans to large borrowers declined by 79% by the end of 2008 relative to the peak of the credit boom (Q2:2007). They analyze the effect that the failure of Lehman Brothers had on the syndicated loan market to identify the reduction in new lending. Jimenez, Ongena, Peydro, and Saurina (2010) use the universe of bank loans by Spanish banks to identify separately the bank lending channel and the balance sheet channel, and find that they dampen each other: more liquid firms are less vulnerable to the contraction of bank lending, and if banks have ample liquidity, the balance sheet channel partially shuts down. Finally, Puri, Rocholl, and Steffen (2010) test the effect of deteriorating balance sheets of German banks hit by the crisis on lending to domestic retail customers. Our paper contributes to this emerging literature by presenting evidence for a cross-border transmission by foreign banks in a large cross-country setting, as well as by incorporating information on discouraged firms in the empirical proxy for credit constraint.

The paper proceeds as follows. Section 2 presents the data. Section 3 describes the empirical methodology and the identification strategy. Section 4 presents the empirical results. Section 5 concludes with the main findings of the paper.

2 Data

The data for our analysis come from three main sources. The core firm level data come from the 2008 version of the Business Environment and Enterprise Performance Survey (BEEPS), administered jointly by the World Bank and the European Bank for Reconstruction and Development. The survey was carried out between March 10th and April 20th 2008 among $12,010$ firms from 27 countries in central and eastern Europe and the former Soviet Union. The survey response rate was 36.9%. Surveyees who declined to participate or were unavailable for interviews accounted for 38.3% of the original target group. Firms that were ineligible due to the necessity to fulfill industry quotas and firm size quotas accounted for the remainder. We narrowed that sample down to the countries that were most relevant in terms of foreign bank penetration. We complement this data with analogical information on 11,399 firms operating in the same countries and localities, derived from the 2005 version of the survey. We reduce the initial sample of 27 countries to a sample of 14 countries for which foreign bank ownership is sufficiently relevant over the period in question. The final sample thus consists of 9,360 firms, observed either in 2005 or in 2008, in the following countries: Albania, Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Macedonia, Montenegro, Poland, Romania, Slovakia, and Slovenia.

The main purpose of the survey is to obtain information from firms about their experience with financial and legal constraints, as well as government corruption. In addition, however, BEEPS also included questions about firm ownership structure, sector of operation, industry structure, export activities, use of external auditing services, subsidies received from central and local governments, etc. Respondent firms come from 6 different sectors: construction; manufacturing (11 sub-sectors); transport; wholesale and retail; IT; and hotels and restaurants. The number of firms covered is roughly proportional to the number of firms in the country, ranging from 260 in Albania to 1,592 in Poland. The survey tried to achieve representativeness in terms of the size of firms it surveyed: between three quarters and nine tenths of the firms surveyed are "small" (less than 100 workers) and only around 5% of the firms surveyed are "large" (more than 500 workers).[6] The survey also aimed to achieve representativeness in terms of private vs. public firms, firms with access to foreign product markets, firms which receive government subsidies, etc. Table 2 provides the summary statistics on the number of firms and their size, ownership, and market characteristics by country. Appendix 1 explains the construction of all firm-level (as well as industry- and country-level) variables in the data.

For the purpose of estimating the effect of the financial crisis on business lending, we focus on the information on credit constraints faced by the firms in the past fiscal year. Question K16 asks: "Did the establishment apply for any loans or lines of credit in fiscal year 2007?"[7] For firms that answered

[6] See http://www.ebrd.com/country/sector/econo/surveys/beeps.htm for further detailed reports on the representativeness of the survey.

[7] Fiscal year 2007 refers to the calender year 2007. However, for tax purposes, in the countries in the sample firms can choose to extend it to March 31, 2008, which is precisely why the Survey was administered in March-April 2008. Given that signs of a credit crunch started emerging right after August 9, 2007, the data gives us at least two and at most three quarters of credit crunch effects potentially experienced by firms.

"No" to K16, Question K17 subsequently asks: "What was the main reason the establishment did not apply for any line of credit or loan in fiscal year 2007?". For firms that answered "Yes" to K16, Question K18a subsequently asks: "In fiscal year 2007, did this establishment apply for any new loans or new credit lines that were rejected?". Firms that answered "No need for a loan" to K17 were classified as firms that do not desire bank credit. Firms that answered "Yes" to K18a or "Interest rates are not favorable", "Collateral requirements are too high", "Size of loan and maturity are insufficient", or "Did not think it would be approved" to K17 were classified as constrained. The latter classification is in line with the unofficial definition by the US Federal Reserve of a credit crunch, i.e., a simultaneous increase in the price and decrease in the availability of credit.[8] This strategy of grouping firms that were turned down and firms that were discouraged from applying is also employed in Cox and Jappelli (1993) and in Duca and Rosenthal (1993), who find that rejected and discouraged borrowers are almost identical on observables, and is fairly standard in studies that rely on detailed questionnaires. Also, it is crucial given our empirical strategy to separate the firms that did not apply for credit because they didn't need it from those that did not apply because they were discouraged. Table 3 presents a summary by country of the shares of firms in need of bank loans and of constrained firms. As the data suggest, while fewer firms needed credit in fiscal year 2007 than in fiscal year 2004 (57% vs. 69%), a larger portion of the firms that needed credit were constrained (37% vs. 33%).

In addition to the information described above, BEEPS contains information on the locality of the operation of each firm. A total of $1,803$ localities are present in the data, for an average of 5.2 firms per locality. That geographic information was then matched with data on bank presence coming from the central banks of the 14 countries involved in the study.[9] Pursuing a trade-off between representativeness and manageability, we narrowed our focus to the banks that comprise at least 85% of the banking sector assets in each country. This gives us a range of between 4 banks in Estonia and 9 banks in Bulgaria. Given this criterion, it was determined that the localities in

[8]The origin can be traced to Bernanke and Lown (1991) who define a credit crunch as a "[...] significant leftward shift in the supply curve for loans, holding constant both the safe real interest rate and the quality of potential borrowers".

[9]The matching was made possible after an extensive research of the web pages of all banks involved. In quite a few cases, information was only available in the respective national language.

the sample were served by a total of 141 banks. Out of those, 26 are domestic banks, and 115 are branches or subsidiaries of 23 foreign banks. There is considerable variation in foreign bank penetration in the sample: in 2008, foreign ownership of banking sector assets ranges from 22.8% in Slovenia to 98.9% in Estonia. Finally, we performed an extensive internet search to determine which of these banks were present in which locality in the sample, and how many branches each had in each locality in which it was present. This allows us to determine not just which bank is present where, but also its market share at the unit of observation of the locality (city).

Next, we used Bankscope to extract balance sheet information on those 141 bank. We collected data from 2005 to 2008 in order to evaluate how the condition of the banks' balance sheets is associated with a potential reduction in credit. We chose our potential explanatory variables in the context of the main issues surrounding the financial crisis of 2007-2008. The bursting of the housing bubble forced banks to write down several hundred billion dollars in bad loans caused by mortgage delinquencies. At the same time, the stock market capitalization of the major banks declined by more than twice that amount. The total loss in financial assets globally is estimated in the trillions of dollars. Central banks around the world pumped hundreds of billions of dollars in short-term liquidity, alongside reducing discount rates at an unprecedented speed, in order to prop up illiquid and likely insolvent banks (Brunnermeier (2009)).

Hence, we focused primarily on banks' capital ratios (Tier 1 and total), equity capital, and gains/loss on financial assets. In the case of foreign ownership, we focused on the financial position of the parent bank in order to study, for example, how the investment allocation of UniCredit Group into MBSs and the loss of capital associated with this allocation affects business lending by international branches and subsidiaries of UniCredit. Table 4 summarizes the main variables of interest which were used in the final empirical tests. There are apparent cross-country differences - for example, in 2008 Latvian banks had a somewhat low average Tier 1 capital ratio (6.55), close to the 4% regulatory requirement, owing to the relative undercapitalization of their parent foreign banks, while Polish banks had an average Tier 1 capital ratio of 9.39, mostly due to the fact that the largest bank in Poland is the well-capitalized domestic bank PKO Bank Polski. Also, the banks present in Macedonia incurred almost no losses on financial assets in 2007-08, while in 2008 the parents of the banks present in the Czech Republic had an average ratio of gains on financial assets to total assets of -0.12. In general, banks were making on average gains on financial assets in 2005 and losses on financial assets in 2008.

Appendix 2 illustrates the degree of foreign bank penetration in each country in the sample. Clearly, a group of 23 west European and U.S. banks controls the vast majority of assets in the region. These are Erste Group, Hypo Group, Reiffeisen, and Volksbank (Austria), Dexia and KBC (Belgium), Danske Pank (Denmark), Nordea Bank (Finland), Societe Generale (France), Bayerische Landesbank and Commerzbank (Germany), Alpha Bank, EFG Eurobank, Emporiki Bank, National Bank of Greece, and Piraeus Bank (Greece), AIB (Ireland), Intessa San Paolo and UniCredit Group (Italy), ING Bank (Netherlands), Swedbank and Skandinaviska Enskilda Bank (Sweden), and Citibank (U.S.). There is also substantial regional variation in the degree of penetration: for example, the Greek banks operate mostly in south-eastern Europe, the Scandinavian banks in the Baltic countries, and the Austrian banks in central Europe. In addition, there is one domestic "global" bank, the Hungarian OTP, as well as cross-border penetration by, for example, Parex Group - Latvia and Snoras Bank - Lithuania.

3 Empirical methodology and identification

3.1 Main empirical model

We want to estimate the international transmission of financial distress. We hypothesize that banks with a foreign owner are more likely to do so than domestic banks. For example, if bank-firm relationships are particularly strong and important, banks may be reluctant to reduce credit to their long-time domestic customers and shift more of the shock to overseas markets (Peek and Rosengren (1997)).

We first exclude all localities with zero presence by foreign banks in 2008 or 2005 (about 0.4% of the sample). Next, we use the 2008 cross-section data on bank balance sheets, firm characteristics, and credit constraints to check for a "credit crunch" by estimating the following basic model:

$$Y_{ijkl} = \beta_1 \cdot X_{ijkl} + \beta_2 \cdot Finance_{jk} + \beta_3 \cdot D_k + \beta_4 \cdot D_l + \varepsilon_{ijkl} \tag{1}$$

where Y_{ijkl} is a dummy variable equal to 1 if firm i in city j in country k in industry l is credit constrained in fiscal year 2007; X_{ijkl} is a matrix of firm characteristics; $Finance_{jk}$ is the index of bank health in city j in country k; D_k is a matrix of country dummies; D_l is a matrix of industry dummies; and ε_{ijkl} is an idiosyncratic error term. The firm-level co-variates control for observable firm-level heterogeneity. The two sets of dummy variables control for any unobserved market and industry variation. Essentially, they eliminate the contamination of the estimates by sectoral and macroeconomic circumstances, like growth opportunities, common to all firms in the same industry, or taxes, common to all firms in a particular country.

Next, we pool the 2005 and 2008 samples in order to be able to conduct a proper pre-post analysis using the full sample of firms that were observed either in 2007/2008 (the beginning of the financial crisis) or in 2004/2005 (the peak of the credit cycle). We estimate two different models on the pooled data. First, we estimate the model

$$Y_{ijkt} = \beta_1 \cdot X_{ijkt} + \beta_2 \cdot Post \cdot Finance_{jkt} + \beta_3 \cdot Post + \beta_4 \cdot Finance + \beta_5 \cdot D_k + \varepsilon_{ijkt} \tag{2}$$

In this model, we are able to capture the effect of financial distress after the crisis started relative to identical financial distress before the crisis started. We do not include year dummies, as the level effect over time is captured by the variable $Post$, a dummy equal to 1 if the year is 2008. We exclude the industry dummies because industries are classified differently in the two surveys.[10]

Because the above model pools the data for all localities, including such present only in 2005 or only in 2008, we also estimate a model which allows us to compare variations in rejection rates over time of "affected" vs. "non-affected" localities. In particular, we estimate the standard difference-in-difference model

[10]BEEPS 2005 uses a SIC 1-digit classification, while BEEPS 2008 uses a SIC 2-digit classification dominated by manufacturing.

$$Y_{ijkt} = \beta_1 \cdot X_{ijkt} + \beta_2 \cdot Non-Affected \cdot Post + \beta_3 \cdot Non-Affected + \beta_4 \cdot Post + \beta_5 \cdot D_k + \varepsilon_{ijkt} \quad (3)$$

where $Affected$ is a dummy variable equal to 1 if the respective finance variable decreased by at least 1 standard deviation between 2005 and 2008. Consequently, $Non-Affected$ is a dummy variable equal to 1 if the respective finance variable decreased by less than 1 standard deviation between 2005 and 2008.

The main parameter of interest in all three models is β_2, which measures the cross-section effect of financial distress (Models 1), the cross-section effect of financial distress in 2008 relative to 2005 (Model 2), and the effect of a change in financial distress (Model 3) of the banks in each locality on credit access by firms in that locality. As lower values of $Finance$ are associated with bigger bank distress, we expect the sign of β_2 to be negative in all models. We construct our bank distress index by aggregating balance sheet information from Bankscope after determining which banks were present in that locality, and the original ownership of each bank in that locality. The underlying assumption in the absence of a direct match of each loan to the lending bank and of each rejection to the rejecting bank is that if firms were granted/denied credit, then it was most likely the result of interaction with banks in the firms' locality of incorporation. We use two different weighting criteria in constructing the index, namely, giving equal weight to each bank in that particular locality, or weighting each bank's financial position by the number of branches it has in the locality.

Here is an example to clarify the above procedure. There are 4 banks in Estonia that hold close to 100% of the banking assets in the country: Swedbank, SEB, Sampo Pank, and Nordea. They are subsidiaries of Swedbank - Sweden, SEB - Sweden, Danske Pank - Denmark, and Nordea - Finland. In 2008, the 4 parent banks had Tier 1 capital ratios of 8.4, 8.4, 6.9, and 12, respectively. Consider the city Lihula in which only Swedbank has branches. We assign Lihula a Tier 1 capital ratio of 8.4, and then we match the index of financial distress in Lihula with all firms present in that city. Consider alternatively the city of Kuresaare, in which Swedbank, SEB, and Nordea are present.

They have 2, 1, and 1 branches in that city, respectively. Consequently, in the main analysis, where we assign equal probability of each firm in that city doing business with each bank present in that city, we assign a Tier 1 capital ratio of $9.6 = \frac{1}{3} \cdot 8.4 + \frac{1}{3} \cdot 8.4 + \frac{1}{3} \cdot 12$, which is then matched to all firms located in Kuresaare. And in the exercises where we weigh the probability of each firm doing business with each bank present in Kuresaare by the number of that bank's branches in that locality, we assign a Tier 1 capital ratio of 9.3 ($\frac{1}{2} \cdot 8.4 + \frac{1}{4} \cdot 8.4 + \frac{1}{4} \cdot 12$).

This procedure gives us considerable variation of our main financial variables of interest within each country, due to the fact that not all banks present in a country are present in each city, and whenever they are, not to the same extent. For example, in the 2008 sample of firms, there are 1,215 localities in the 14 countries in the sample, characterized by 262 unique values of city-specific Tier 1 capital, when data on all banks in a locality are counted equally, and by 732 unique values of city-specific Tier 1 capital when data on all banks is branch-weighted. Consequently, there is little reason to worry that the country fixed effects in the regressions capture the same variation as locality-specific financial stress.

Next, we want to estimate how credit constraints vary with the degree of foreign bank presence. We estimate the following difference-in-differences specifications:

$$\begin{aligned} Y_{ijkl} = \; & \beta_1 \cdot X_{ijkl} + \beta_2 \cdot Finance_{jk} \cdot Foreign_{jk} + \beta_3 \cdot Finance_{jk} + \beta_4 \cdot Foreign_{jk} + \\ & + \beta_5 \cdot D_k + \beta_6 \cdot D_l + \varepsilon_{ijkl} \end{aligned} \tag{4}$$

$$\begin{aligned} Y_{ijkt} = \; & \beta_1 \cdot X_{ijkt} + \beta_2 \cdot Post \cdot Finance_{jkt} \cdot Foreign_{jkt} + \beta_3 \cdot Post + \beta_4 \cdot Finance + \\ & + \beta_5 \cdot Foreign_{jkt} + \beta_6 \cdot D_k + \varepsilon_{ijkt} \end{aligned} \tag{5}$$

$$\begin{aligned} Y_{ijkt} = \; & \beta_1 \cdot X_{ijkt} + \beta_2 \cdot Non-Affected \cdot Post \cdot Foreign_{jkt} + \beta_3 \cdot Post + \\ & + \beta_4 \cdot Non-Affected + \beta_5 \cdot Foreign_{jkt} + \beta_6 \cdot D_k + \varepsilon_{ijkt} \end{aligned} \tag{6}$$

where $Foreign_{jk}$ is an indicator equal to 1 if city j in country k is in the top half of the distribution of foreign bank ownership. The primary control group here is all firms incorporated in locations with little foreign bank penetration. Now β_2 measures whether for the same degree of financial distress, foreign banks translate more of it into loan application rejections than domestic banks. Consistent with our hypothesis, we expect the sign of β_2 to be negative.

While in our specifications so far we are capable of estimating the effect of financial distress net of industry-wide and country-wide recession developments that are common to all firms in the respective industry (country), they don't allow us to test whether financial distress differentially affects firms, and our estimates are prone to contamination by location-specific unobservables. Regarding the first point, it is generally predicted that riskier firms and firms with fewer tangible assets are more likely to be shut out of credit markets (see, for example, Berger, Ofek, and Swary (1996), Beck, Demirgüç-Kunt, and Maksimovic (2005), and Brown, Jappelli, and Pagano (2009)). Regarding the second one, macroeconomic circumstances like unemployment usually vary at the city level, and so our specification so far will be contaminated by this variation. To address both points, we employ one final specification on the 2008 cross-section:

$$Y_{ijkl} = \beta_1 \cdot X_{ijkl} + \beta_2 \cdot Finance_{jk} \cdot Z_l + \beta_3 \cdot D_l + \beta_4 \cdot D_{jk} + \varepsilon_{ijkl} \tag{7}$$

Now the location dummies in D_{jk} absorb the effect of locality-specific unobservables. The interaction term containing the industry-level benchmark for asset tangibility in Z_l allows us to measure whether the potential effect of the credit crunch is indeed strongest for those firms which theory predicts are most vulnerable to credit market shutdowns (firms with risky profit prospects, and firms with little collaterizable assets, for instance).

Finally, we need to emphasize that throughout the paper, it is implicitly assumed that the effect of bank financial distress is localized and realized predominately by firms headquartered in the locality in which the bank has operations. All our empirical specifications presume that firms borrow from banks located near their address of incorporation, which is identical to the approach in, for example, Gormley (2009). In general this is expected to hold as banks tend to derive market power ex ante from geographical proximity (e.g., Degryse and Ongena (2005)). Lending support to that conjecture, empirical work regarding lending relationships in different countries has demonstrated that the average distance between SMEs and banks is usually very small. For example, Petersen and Rajan (2002) find that the median distance between a firm and its main bank over the 1973-1993 period was only four miles.

3.2 Isolating demand shocks

It is a common challenge of studies that analyze the association between financial distress and bank lending to isolate supply shocks satisfactorily. Namely, it is likely that not only does loan demand weaken for all firms in periods when bank capital declines, but the composition of firms that demand credit during recessions changes. The solutions to this problem vary in the literature. For example, Peek and Rosengren (1997) bypass this issue by claiming that the identification problem is rather weak in the case of the international transmission of financial shocks into a recession-free environment. However, the financial crisis of 2007-2008 was followed by one of the deepest global recessions in postwar history, and this recession was already being predicted as soon as the extent of the sub-prime mortgage meltdown became apparent in late summer 2007. Hence, as we observe the firms in our sample in late 2007 and early 2008, it is conceivable that they were already behaving in a way consistent with a global recession environment. Puri, Rocholl, and Steffen (2010) and Jimenez, Ongena, Peydro, and Saurina (2010) incorporate data on loan applications to account for the explicit weakening of the firm balance sheet channel. However, this strategy does not account for the changing composition across business lenders of firms that demand bank credit as these studies do not observe firms which select themselves out of the loan application process due to 1) weak own demand for loans, or to 2) being discouraged by the deteriorating lending environment. Failure to account for this changing composition will result in a bias in the estimation of the true extent of the transmission of financial distress.

As we explained in Section 2, we eliminate the contamination of the estimates induced by 2) by incorporating data on discouraged firms in the measure of credit constraint. As for 1), we eliminate the effect of the balance sheet channel by incorporating observable information on firms which did not apply for bank credit in fiscal year 2007 because they did not need it (see Section 2 for the exact definition). We apply Heckman's (1979) selection procedure to eliminate the bias arising from the left-truncation of the sample in that sense. Thus, credit constraint is only observable when a firm actually applies for a loan, and the firm only does so if it needs one, or if it is not discouraged. Let the dummy variable Q equal 1 if the firm desires positive bank credit and 0 otherwise. The value of Q is in turn determined by the latent variable:

$$q = \zeta \cdot Z_{ijkl} + \varepsilon_{ijkl} \tag{8}$$

where Z_{ijkl} contains firm and location variables that may effect the firm's fixed costs and convenience associated with using bank credit. The variable $Q = 1$ if $q > 0$ and $Q = 0$ otherwise. The error ε_{ijkl} is normally distributed with mean 0 and variance σ^2. Models (1)-(7) are then updated by adding the term $\sigma\frac{\phi(q)}{\Phi(q)}$ to the RHS, where $\frac{\phi(q)}{\Phi(q)}$ is the inverse of Mill's ratio (Heckman (1979)). Identification rests on the exclusion restriction which requires that q has been estimated on a set of variables that is larger by at least one variable then the set of variables in models (1)-(7), respectively.

4 Empirical results

4.1 Bank credit application

Before considering our main empirical model, we first consider the bank credit application tests that we use for our Heckman selection correction. Table 5 presents the results from the first stage probit regression. The probability of needing bank credit is generally higher for firms in more financially distressed localities, and when financial distress is measured as high losses on financial assets, the effect is also significant. Not accounting for this selection would thus bias the estimates of the transmission of financial distress towards zero.

In terms of firm-level co-variates, the need for bank credit increases in the size of the firm. One potential explanation is that small firms face higher application costs (Brown, Ongena, Popov, and Yesin (2010)). Also, in a beginning-of-a-recession environment it might be that small firms are better equipped to finance investment with cash flows than - potentially - more highly leveraged large firms. In addition, some of the size effects may be picked by ownership and structural characteristics, as sole proprietorships and public companies have a higher demand for loans. The probability of desiring credit is higher for exporters potentially due to their faster expansion, and for audited firms, which might simply imply that firms choose to be audited (i.e., they are willing to pay for transparency) when they plan to apply for bank credit.[11] It may also be the case that audited firms have access to financial statement lending which may be a cheaper lending technology.

In terms of the exclusion restriction, the variables "Competition" and "Subsidized" are included in this demand model, but excluded from the rest of the exercises. The rationale for using these particular variables as instruments for demand is the following. Firms in more competitive environments will likely have a higher demand for external credit due to lower profit margins, but it is unlikely that credit decisions will be correlated with product market competition. Analogically, having applied for state subsidies is likely a signal for external financial need. These considerations make both variables good firm demand shifters. Both variables are very positively correlated with the demand for loans, and the effect is statisticically significant at the 1% level. The F-statistics from a first-stage regression of loan demand on the two variables (unreported) is 20.77, satisfying the validity test.

4.2 International transmission of financial distress

4.2.1 Nonparametric difference-in-differences estimates

Table 6 gives a simple non-parametric illustration of the validity of our empirical strategy. We separate the data on geographic and financial dimensions. Specifically, we average the data on rejection rates across localities for the 2005 vs. the 2008 samples, and also for affected vs. non-affected localities. In determining which localities are affected, we use Tier 1 capital and define "affected" as localities where the average Tier 1 capital ratio of banks present in that locality decreased by at least one standard deviation between 2005 and 2008. The table implies that credit constraints vary over time, given different degrees of financial distress. In particular, average

[11] The results are broadly consistent with Ongena and Popov (2009) who apply a double selection technique to the BEEPS 2005 sample.

rejection rates for non-affected localities didn't change much between 2005 and 2008: they went from 31.9% to 33.2%, and this increase is not statistically significant. In comparison, in affected localities rejection rates went up to 40.2% in 2008, from 33.5% in 2005, with this increase being significant at the 1% level. Looking at the same development from another angle, while rejection rates were similar for all banks in 2005, in 2008 they were much higher in localities where banks experienced a large drop in capital in the meantime. This result is the first (albeit arguably imperfect) piece of evidence that foreign banks reacted to their respective financial troubles by shrinking their loan portfolios.

4.2.2 Cross-section results

Table 7 reports the estimates of the effect of parent banks' financial distress on credit constraints faced by local firms for all firms present in BEEPS 2008. We report the results of the model in equation (1) alongside the results from the Heckman selection-corrected version in order to contrast the two approaches. The three main explanatory variables of interest are: the ratio of equity over total assets; the Tier 1 capital ratio; and the gain on financial assets over total assets. We first report the results from the model in which each bank is given equal weight in each locality where the bank is present (Panel A). As expected, all else equal, small firms and sole proprietorships are more credit constrained, potentially indicating lower ability to tap alternative capital markets; audited firms are less constrained, implying gains from the reduction of informational opacity; and firms that export part of their production are less constrained, potentially signalling the willingness of banks to lend to firms with higher growth prospects. The variables of interest have a generally insignificant impact on the probability of firms being constrained in the credit market, with the sign of Tier 1 capital going in the expected direction.

When we apply the second weighting criterion in Panel B, namely, weighting the probability of the firm doing business with each particular bank by the number of branches the bank has in that locality, we find a large and significant impact of a low bank Tier 1 capital ratio on rejection rates. The magnitude of the effect is also economically meaningful: a 2-standard deviation decrease in the average Tier 1 capital ratio for banks in a particular locality increases the probability of identical firms in this locality being credit constrained by about 8%.

In both panels, the sign of the inverse of Mill's ratio is generally negative, implying that unobservables which increase the probability of needing bank credit, also decrease the probability of being constrained in credit markets.

Finally, recall that by looking at fiscal year 2007, we are capturing only the initial stages of the crisis up to March 31, 2008. In addition to that, our results are contaminated by months of pre-crisis experience before August 2007. In that sense, if there is bias in our estimates, it only goes against finding any transmission of crisis-related financial distress. The large and statistically significant effect of low Tier 1 capital on rejection rates could thus only be a lower bound of the true effect.

4.2.3 Transmission of shocks over time

We next repeat the empirical tests on the sample of firms that are present either in the 2008 and the 2005 BEEPS, employing the Heckman selection-corrected version of model (2). This allows us to account for the changing composition of firms that select themselves out of the application process, going from the peak to the trough of the credit cycle. In other words, the information on whether firms do not apply for credit because they don't need it, or because they are discouraged, and how that changes over time, is used to eliminate the potential contamination of our estimates by the correlation between credit needs and bank financial health. In addition, we can compare the effect of being financial distressed in 2008 vs. having financial problems in 2005.

These results are reported in Table 8, Panel A.[12] In this specification, we find again that Tier 1 capital affects rejection rates, regardless of whether we weight each bank's presence in a locality equally or by number of branches. The interpretation of the coefficient on the branch-weighted Tier 1 capital is that for the sample average degree of financial stress, an identical firm had a 9% higher chance of being constrained in fiscal year 2007 than in fiscal year 2004, and this probability increases with the level of distress. Importantly, we confirm that not accounting for selection introduces downward bias. The sign of the inverse of Mill's ratio is again generally negative, and

[12]In all tables to follow, only coefficients of interest are reported for brevity.

this time significantly so, implying that firms which did not apply for a loan would have faced a higher probability of being rejected.

In panel B of Table 8, we report the results from Model (3) where we only look at localities for which at least 1 firm is present both in 2005 and in 2008. Now instead of the level of distress, we look at the change in financial health over time. We define affected localities as ones in which average financial health (measured by our three financial variables of interest) declined by at least one standard deviation between fiscal 2005 and 2008.

In this specification, we find that equity capital matters for the transmission of shocks. For example, consider our measure of average equity capital constructed by weighting information on each bank present in a locality equally. We find that in localities where equity capital declined by at least one standard deviation between 2005 and 2008, the probability of a firm being rejected increased by 13% more than for an identical firm in a locality where equity capital did not decline as much. We find similar results for the branch-weighted measure of equity capital.

4.3 Robustness

4.3.1 The degree of foreign ownership

An important question that arises given the evidence so far is, does the magnitude of the transmission of financial shocks depend on the degree of foreign bank ownership. For example, given our empirical design, it could be that the results are driven by lower levels of foreign bank ownership, while there is no cross-border transmission of financial shocks in localities dominated completely by foreign banks. Table 9 reports the estimates from the difference-in-differences models (4)-(6) which allow us to estimate the transmission of financial distress by foreign bank presence. We find that our results are indeed driven by substantial foreign bank presence. With one exception, whenever significant, the interaction effect of interest implies that in localities with larger foreign bank presence, banks responded to shocks to their balance sheets by shrinking their portfolio more than banks in localities with lower foreign bank presence. This is most pronounced in the case of the banks' response to loss on financial assets, where the effect is consistently large and significant across model specifications. We also record the same direction of this effect in the case of a decline in equity capital, albeit it is significant in one case only.

4.3.2 EU countries vs. non-EU countries

Another point to address is the heterogeneity of the sample. In particular, 10 out of the 14 countries in our sample are EU member states. The cross-border transmission of shocks in these countries is likely to have been affected by the regulatory architecture of the EU. For example, it is conceivable that banks in EU member countries have been less motivated to withhold new lending due to the anticipated cushion provided by EU-wide deposit insurance, or by recapitalization and bail-out programs agreed to in a co-ordinated fashion at the level of the EU. Conversely, foreign banks in EU non-member states may have anticipated that local governments would act outside of any co-operative agreements, mostly in the interest of domestic bank champions, and may have as a result had the motivation to withdraw from the market for new loans more forcefully. If this is the case, then our results may be mostly driven by the non-EU countries in our sample.

In Table 10, we test this hypothesis by performing our main empirical exercises on our sample after excluding the 4 countries that are not in the EU (namely, Albania, Croatia, Macedonia, and Montenegro). Taken as a whole, these new estimates strongly negate the hypothesis that our results are driven by the rapid decline in new lending by EU banks in non-EU countries. On the contrary, if anything our results are strengthened by the exclusion of the non-EU countries. For example, in the case of both Tier 1 capital and equity capital, we find that higher financial distress is associated with higher rejection rates across all three empirical specifications. The magnitude of the transmission effect also increases slightly after focusing on EU countries only.

4.3.3 Which firms are affected by the transmission of shocks?

Next, we ask which firms are most affected from the transmission of financial distress. There are clear arguments in the literature on which firms and industries should be most affected by credit rationing. Firm risk and the tangibility of the firm's assets, for example, are expected to play an important role in explaining differences in credit availability across firms. High-risk firms tend to suffer more from credit rationing, especially when foreign bank lending is involved (Berger, Klapper, and Udell (2001)). Regarding asset tangibility, Berger, Ofek, and Swary (1996) show that firms with less tangible assets are more likely to lose access to credit when banks reprice risk. The rationale is that lenders rely more on collateral when making lending decision rather than investing in costly screening technologies, and this problem will tend to be exacerbated in an environment where risk is suddenly priced higher.

We proceed by collecting data on mature U.S. firms and using it to construct industry benchmarks for riskiness and asset tangibility. The rationale for doing so goes back to Rajan and Zingales (1998) who argued that the actual capital structure of small firms is a function of financial constraints, while the capital structure of large mature firms is more representative of the cross-industry variations in the scale of projects, gestation period, the ratio of hard vs. soft information, the ratio of tangible vs. intangible assets, follow-up investments, etc. In addition, doing so for large U.S. firms makes sure that what is taken as a "natural" industry feature is not contaminated by shallow financial markets.

Following Rajan and Zingales's (1998) original approach, we proceed by taking all Compustat firms between 1990 and 2000. We first exclude all firms that are young in the sense that they have gone public only recently (in the last 10 years) to make sure that we are not capturing the excessive appetite for funds exhibited during the early life of a public firm. For each firm, we sum across all years its ratio of research and development expenses over sales. We take the median industry value of that ratio and this value constitutes our industry benchmark for "R&D intensity". This is both a measure of risk and of asset tangibility: firms with a lot of R&D investment will simultaneously have riskier returns due to more uncertain profits, and less collaterizeable assets. Second, we sum across all years each firm's ratio of total physical capital used in production over the number of employees. The industry median value of that variable constitutes our industry benchmark for "Capital intensity", which again captures partially risk and partially asset tangibility. For each of the two benchmarks, we have an 18-industry variation.

Table 11 reports the estimates of equation (7) where each measure of financial distress has been interacted with a dummy variable equal to 1 if the firm's sector of operation is in the top 50% of the distribution of "R&D intensity", or alternatively in the bottom 50% of "Capital intensity".

In both cases, a dummy value of 1 implies higher risk and lower asset tangibility. We only focus on financial distress as measured by low Tier 1 capital ratios, as this is the one measure that is most consistently associated with higher loan rejection rates in the analysis so far. Importantly, this specification gives us interaction at the city and industry level, and thus we can include city dummies in the regression. The direct effect of financial distress is now fully absorbed by the city dummies, along with any unobservable variation in macroeconomic conditions at the location level. The effect on rejection rates of the sector-wide variation in growth opportunities is absorbed by the industry dummies, as before. The interpretation of the coefficient on the interaction term is in terms of a relative effect: a negative sign would imply that an increase in banking distress would increase credit constraints relatively more for riskier firms and for firms with fewer collaterizeable assets.

The results confirm the intuition: firms tend to suffer more from the transmission of financial distress when they have riskier growth prospects, or when they do not have enough assets to pledge as collateral. Numerically, the same branch-weighted Tier 1 capital ratio is associated with a 12.5% higher probability of loan rejection for firms in industries with high R&D intensity; and with a 20.4% higher probability of loan rejection for firms in industries with low per-worker capital.

4.3.4 Issues of measurement, geography, and monetary policy

Finally, we address issues of measurement, geography, and monetary policy. First, recall that our estimation method relies on constructing locality-specific average measures of bank distress, and then match all firms incorporated in a particular locality to this locality's measure of financial distress. One natural objection is that the more banks there are in this locality, the poorer the measure of financial distress will capture actual firm experience. Another is that many firms which can afford it could be doing business with banks outside of their locality of incorporation, in a hunt for better credit conditions. Finally, monetary policy and especially access to the same pool of central bank liquidity could play a role in explaining our findings.

We address these issues in Table 12. In order to alleviate the first two concerns, we would ideally restrict our sample to the localities where we could match firms and banks better, and to those firms for which the cost of applying for credit far from their locality of incorporation is too high given the expected gain in loan terms (Degryse and Ongena (2005)). To address the former, we could look at localities with one bank only. As there is an insufficient amount of those, we look at the localities where there are at most two banks (first column of Table 12). This procedure does not eliminate the significance of our results, so we conclude that they are not driven by mismeasuring true financial distress. We also exclude all non-small firms in the sample (that is, firms with more than 100 employees). Small firms are the ones that are likely to find it most costly to do business with banks located far from their city of incorporation. The second column of Table 12 confirms that our main results survive this procedure. We also do the most stringent test, namely, focusing on small firms in localities with at most two banks (third column of Table 12). While there are only 76 such firms, our results still stand and are significant at the 5%.

Finally, we ask if our results are not contaminated by the fact that banks operating in euro zone member countries may behave differently than banks in non-euro zone countries, due to the fact that domestic banks also have access to the same pool of central bank liquidity, and so could be behaving in a similar fashion. Then, what we denote as cross-border transmission of distress would be indistinguishable from local behavior. In the fourth column of Table 12, we interact our measure of financial distress with a dummy equal to 1 if the country is in the euro zone (Slovakia and Slovenia), or has its currency pegged to the euro (Bulgaria, Estonia, Latvia, and Lithuania). We find that while the cross-border transmission of shocks is higher for euro countries, it is not statistically so.

4.4 Discussion of results

It is important to reconcile our findings with, for example, Cetorelli and Goldberg (2009) and Navaretti, Calzolari, Possolo, and Levi (2010), who find that total outstanding loans by foreign affiliates in central and eastern Europe did not decrease in the early stages of the crisis. Given that these papers look at total loans outstanding, while we look at new bank credit, our evidence does not necessarily contradict these other results. The two sets of findings can be reconciled by the simple difference between stocks and flows: a decline in new loans does not necessarily imply a decline in total loans outstanding, if the unused portion of credit lines and overdraft facilities are utilized. The evidence suggests that this occurred in the early stages of the crisis in the U.S., as argued by Cohen-Cole, Duygan-Bump, Fillat, and Garriga (2008) in response to Chari, Christiano, and Kehoe (2008): while new bank credit declined dramatically after the collapse of Lehman Brothers, total credit outstanding remained almost flat as firms started drawing extensively on their existing credit lines.

Second, it could in principle be argued that our empirical methodology is deficient in one important way. Our identification strategy rests on estimating the transmission of shocks by foreign banks to small firms while accounting for changes in the level and composition of firm credit demand. In theory, however, our estimates could be contaminated by simultaneity if foreign bank entry was endogenous to the business characteristics of the localities in our sample. For example, if more risk-loving banks established branches in localities populated by risk-loving firms which ended up weak and discouraged from borrowing when the crisis started, our estimates of the transmission of shocks would be inflated. However, in practice the dominant form of entry of foreign banks in central and eastern Europe throughout the 1990s and 2000s has been the subsidiary form: foreign banks bought existing banking networks of largely predetermined size and outreach (EBRD Transition report 2008). Thus, if foreign banks were chasing particular customers, they did not just open a branch in a certain locality, but in fact had to buy a whole branching network. In our view, this fact largely eliminates any simultaneity concerns which could in theory be biasing our results.

Finally our results offer important insights into the role of foreign banks in emerging markets. In general, the effect of foreign banks on business lending in the literature is ambiguous. A large literature has found that foreign bank presence is associated with higher access to loans (Clarke, Cull, and Peria (2006)), higher firm-level sales (Giannetti and Ongena (2009)), and lower loan rates and higher firm leverage (Ongena and Popov (2009)). On the other hand, Berger, Klapper, and Udell (2001), Mian (2006), and Gormley (2009) show that foreign banks tend to finance only larger, established, and more profitable firms. Such evidence is mostly derived from experience during "good times". Our paper complements that picture by providing evidence that foreign banks tend to shrink their loan portfolio following a capital crunch, pointing to a certain trade-off between efficiency and stability.

Managerial issues might be important here given the managerial challenges associated with cross border banking (e.g., Berger, DeYoung, Genay, and Udell (2000)). Managerial focus on solving problems at the headquarters level in the home country could reduce the ability of the parent bank to monitor lending activities in its foreign facilities. Given the organizational frictions associated with lending a la Stein (2002), this reduced monitoring ability could have a disproportional effect on the contraction of credit by foreign banks. Perhaps our results on foreign bank behavior are also related to the more general finding in the literature that lending tends to be pro-cyclical (e.g., Borio, Furfine, and Lowe (2001), Dell'Ariccia, Igan, and Laeven (2008), Pannetta et al. (2009)). Our finding that riskier borrowers are more affected might even suggest a link to the institutional memory explanations of pro-cyclical lending behavior (e.g., Berger and Udell (2004)) where eroded lending expertise is more problematic at foreign banks.

5 Conclusion

The financial crisis of 2007-2008, which started with the meltdown of sub-prime mortgages and securitized products and which has been characterized by severe losses and depletion of bank capital, has spurred unprecedented government recapitalization programs and liquidity injections by central banks. Since the inception of the crisis, it was feared that this depletion of capital may result in a severe credit crunch, especially to the corporate sector in countries populated by the hardest hit banks. Because the European economy is heavily bank-dependent and SMEs - usually the most vulnerable to a credit crunch due to their opacity - comprise up to 99% of the corporate sector, it was feared that European firms would be particularly heavily hit, despite the fact that the causal factors of the credit crunch originated elsewhere.

In this paper, we use data on $9,360$ SMEs to investigate empirically the international transmission of financial distress, from the loss in value of financial assets to the balance sheets of big European and U.S. banks to business lending in their foreign markets - specifically, central and eastern Europe. Several very recent studies have documented a credit crunch associated with weakened capital positions, however, ours is the first one to simultaneously 1) demonstrate the cross-border dimensions of this phenomenon, and 2) eliminate the contamination of the lending channel by selection bias resulting from the changing composition of firms' demand for credit during recessions and by the failure to account for discouragement in the proxy for credit constraint.

We find that different types of financial distress at foreign (mostly western European) parent banks are associated with a significant impact on business lending to central and eastern European firms. While we do not observe an actual match between a bank and a firm, we match firms and banks by the locality of their respective operation. We find that as early as late 2007/early 2008, firms reported higher credit constraints in localities dominated by branches or subsidiaries of foreign-owned banks which in 2008 had low equity capital, low Tier 1 capital ratios, and had recorded severe losses on financial assets. The magnitude of this effect increases in the degree of foreign bank presence. Our results are not driven by the experience in non-EU countries where in theory banks could have been quicker to withdraw from the market due to the lack of local regulatory and policy cushions. We also find that high-risk firms and firms with fewer tangible assets were differentially more affected by this capital crunch. These results hold when we eliminate the effect of demand shifts in response to weakening firm balance sheets, as well as the bias resulting from the systematic selection of firms out of the application process. Our evidence implies that all else equal, firms in countries where major portions of the banking market were held by relatively undercapitalized foreign banks were 1) more credit constrained than identical firms in countries served by better capitalized foreign banks, and 2) more credit constrained than identical firms in countries where major portions of the banking market were held by equally undercapitalized domestic banks. This is direct evidence of the global transmission of financial distress in the relatively early stages of the 2007-2008 financial crisis, in a way unrelated to the demand for loans in local markets.

The financial crisis of 2007-2008 has finally laid to rest the idea that the effect of large financial shocks can be confined locally. We have shown how the collapse of housing values in the U.S. has affected the financing conditions of, for example, Slovak firms through the deteriorating capital positions of Austrian, Belgian, and Italian banks operating in Slovakia through their subsidiaries.

While the credit crunch only started in the third quarter of 2007, banks kept tightening credit standards until as late as the fourth quarter of 2009[13], and most likely after that. Thus, despite the coordinated actions of various national and supranational authorities, which kept the global financial system from collapsing after the fall of Lehman Brothers in September 2008, it is likely that the losses that the financial system endured have induced, and will continue to induce, a much larger impact on the real sector than the one estimated in this paper. The true extent of the credit crunch will only become clear with the availability of new, more comprehensive data.

[13] See ECB (2009) for details.

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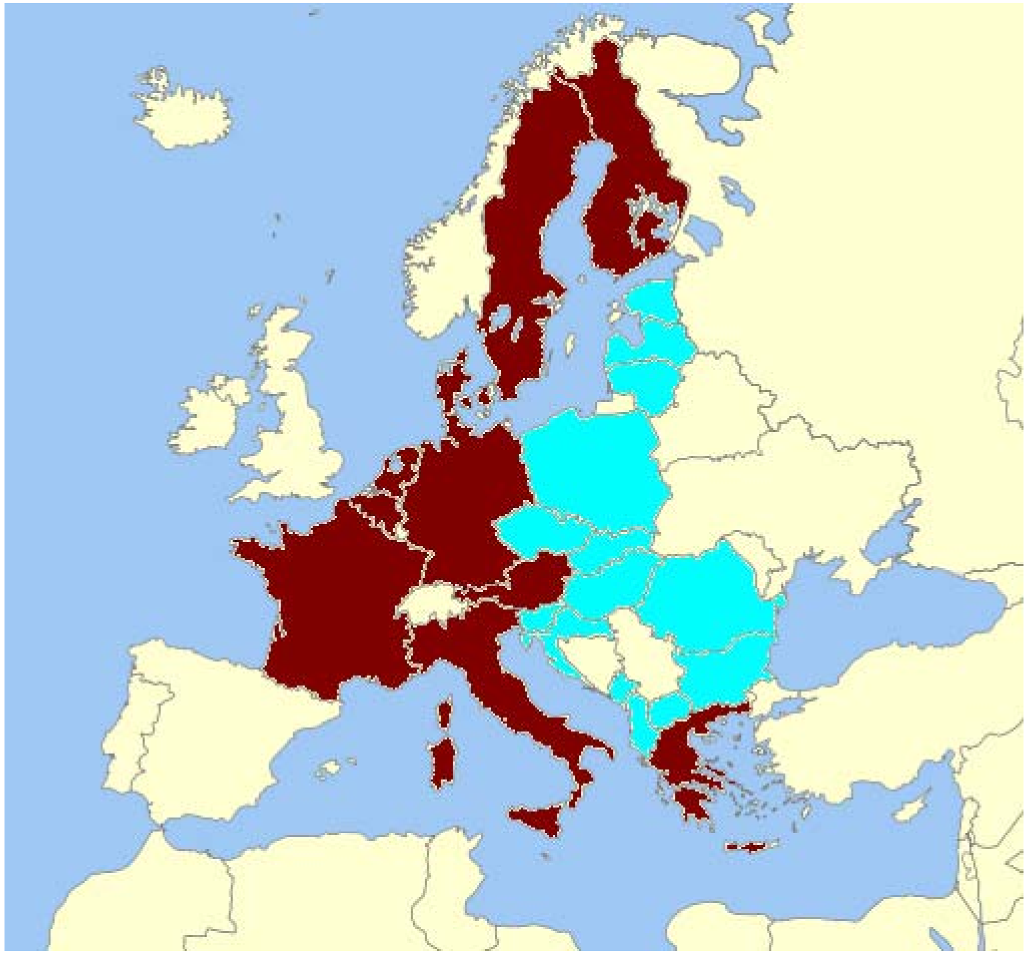
Figure 1. Origin and target countries in the data



The map shows the cross-border dimension of the underlying data. Countries in dark color (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Netherlands, and Sweden) are those in which the parent banks in the dataset are incorporated. Countries in light color (Albania, Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Macedonia, Montenegro, Poland, Romania, Slovakia, and Slovenia) are those where the firms in the dataset are incorporated.

Table 1.
Timeline of events during the 2007-2008 crisis concerning banks and countries in the data

Timeline	Country	Event
Aug. 2007 – Aug. 2008	Germany	Bayerische LandesBank is one of three LandesBanken to receive capital injections, credit lines, and asset-backed securities loss guarantees.
Sept. 2008	France	The government recapitalizes Dexia.
	U.S.	Emergency Economic Stabilization Act, containing a commitment for up to 700 bln. USD to purchase bad assets from banks.
	Italy	The parliament approves a law granting the government the possibility to recapitalize distressed banks.
	Netherlands	The government announces that public funds can be used for bank recapitalization, of which 20 bln. EUR are immediately available.
Oct. 2008	France	The Government approves 320 bln. EUR to provide loans to banks and other financial firms, including a 40 billion euro recapitalization plan.
	Sweden	The government announces that it will guarantee up to 1.5 trillion SEK in new debt issues, and a 15 billion SEK stabilization fund.
	Germany	The government announces a 400 billion EUR plan to guarantee bank financing, including a 70 billion EUR recapitalization fund.
	US	The Treasury subscribes 20 bln. USD preferred shares at Citigroup and ring-fences its troubled assets worth up to 300 billion USD.
Nov. 2008	Italy	The government approves a law to inject capital into sound banks.
	Germany	Bayerische LandesBank receives 7 billion EUR of capital from the Bavarian state.
Dec. 2008	Germany	The Finance ministry provides Bayerische LandesBank with 15 billion EUR .
	Germany	The Finance ministry provides Commerzbank with a 8.2 billion EUR loan, and buys 1.8 trillion EUR worth of equity.
Jan. 2009	France	The government implements a second round of bank recapitalization for 10.5 billion EUR.
	Netherlands	The Dutch government provides a back-up facility to back up the risks of ING’s securitized mortgage portfolio worth 35.1 billion EUR.

Table 2.
Summary statistics: Firm characteristics

Country	# firms	Small firm	Big firm	Public company	Private company	Sole proprietorship	Privatized	Exporter	Audited	Subsidized	Competition
Albania	260	0.90	0.03	0.01	0.19	0.74	0.06	0.31	0.74	0.04	0.74
Bulgaria	609	0.84	0.03	0.05	0.38	0.51	0.12	0.24	0.42	0.06	0.62
Croatia	372	0.79	0.05	0.06	0.41	0.44	0.23	0.36	0.47	0.18	0.79
Czech Republic	670	0.79	0.04	0.04	0.48	0.41	0.08	0.35	0.43	0.16	0.82
Estonia	557	0.79	0.03	0.13	0.55	0.27	0.11	0.34	0.80	0.14	0.77
Hungary	992	0.80	0.04	0.01	0.32	0.63	0.12	0.36	0.74	0.22	0.88
Latvia	529	0.73	0.04	0.01	0.56	0.36	0.13	0.31	0.68	0.12	0.79
Lithuania	544	0.77	0.02	0.02	0.68	0.24	0.16	0.37	0.40	0.15	0.78
Macedonia	611	0.81	0.03	0.05	0.48	0.32	0.16	0.39	0.54	0.04	0.84
Montenegro	151	0.86	0.01	0.04	0.25	0.71	0.12	0.15	0.48	0.04	0.69
Poland	1,592	0.83	0.02	0.05	0.12	0.78	0.09	0.26	0.37	0.13	0.84
Romania	1,247	0.73	0.04	0.04	0.73	0.17	0.13	0.20	0.37	0.09	0.71
Slovakia	610	0.74	0.05	0.06	0.29	0.54	0.11	0.34	0.55	0.13	0.79
Slovenia	616	0.74	0.05	0.08	0.50	0.29	0.21	0.56	0.43	0.22	0.79
Total	9,360	0.79	0.03	0.05	0.42	0.46	0.12	0.32	0.51	0.13	0.79

Note: The table presents statistics on the number of firms and the share of firms by size, ownership, privatization history, access to foreign product markets, access to international auditing, subsidies from central and local governments, and degree of competition, by country. See Appendix 1 for exact definitions. Source: BEEPS (2008 and 2005).

Table 3.
Summary statistics: Credit demand and access

	BEEPS 2008		BEEPS 2005	
Country	Need loan	Constrained	Need loan	Constrained
Albania	0.29	0.47	0.68	0.30
Bulgaria	0.58	0.52	0.65	0.36
Croatia	0.59	0.42	0.78	0.14
Czech Republic	0.53	0.32	0.56	0.41
Estonia	0.54	0.27	0.60	0.23
Hungary	0.41	0.31	0.78	0.28
Latvia	0.59	0.48	0.70	0.27
Lithuania	0.60	0.23	0.71	0.30
Macedonia	0.59	0.50	0.68	0.56
Montenegro	0.78	0.48	---	---
Poland	0.53	0.41	0.68	0.45
Romania	0.61	0.33	0.72	0.32
Slovakia	0.53	0.40	0.62	0.21
Slovenia	0.64	0.15	0.72	0.12
Total	0.57	0.37	0.69	0.33

Note: The table presents statistics on the share of firms who declare bank loans desirable, and the share of firms out of those that need a loan that have been formally rejected or did not apply because they found access to finance too difficult, by country. The data are for the fiscal year 2007 (until March 31, 2008) and for fiscal year 2004 (until March 31, 2005). See Appendix 1 for exact definitions. Source: BEEPS (2008 and 2005).

Table 4.
Bank ownership balance sheet data

	2005	2008	2005	2008	2005	2008	2005	2008
Country	% foreign owned bank assets		Equity/assets		Tier 1 capital ratio		Gain on financial assets	
Albania	0.92	0.94	0.065	0.053	8.39	7.88	0.016	-0.067
Bulgaria	0.75	0.82	0.069	0.064	10.10	8.89	0.049	-0.044
Croatia	0.91	0.90	0.067	0.061	7.33	7.59	0.039	-0.027
Czech Republic	0.82	0.86	0.041	0.042	7.74	8.29	0.120	-0.117
Estonia	0.99	0.99	0.047	0.038	8.88	8.71	0.051	-0.029
Hungary	0.83	0.64	0.068	0.065	8.89	8.51	0.021	-0.081
Latvia	0.58	0.64	0.076	0.049	7.98	6.55	-0.004	-0.057
Lithuania	0.92	0.92	0.058	0.054	8.14	8.19	0.041	-0.035
Macedonia	0.51	0.86	0.076	0.071	10.37	8.60	0.052	-0.012
Montenegro	0.88	0.79	0.144	0.094	16.91	9.45	0.197	-0.030
Poland	0.74	0.76	0.082	0.081	10.32	9.39	0.015	-0.041
Romania	0.59	0.87	0.059	0.053	8.31	7.81	0.075	-0.049
Slovakia	0.97	0.99	0.058	0.055	7.93	8.12	0.018	-0.083
Slovenia	0.23	0.29	0.058	0.050	8.83	8.81	0.063	-0.158

Note: The table reports summary statistics on the share of the domestic banking system owned by branches and subsidiaries of foreign banks, of the average ratio of equity financing to total bank assets, of the average Tier 1 capital ratio, and of average gains on financial assets by the parent of the banks operating in each country, by country. The data are averaged for 2005 and 2008, respectively. See Appendix 1 for exact definitions. Source: EBRD Transition Report (2008) and Bankscope (2005 and 2008).

Table 5.
Probability of desiring bank credit

	Finance = Equity/assets		Finance = Tier 1 capital ratio		Finance = Gains on fin assets	
	Equally-weighted	Branch-weighted	Equally-weighted	Branch-weighted	Equally-weighted	Branch-weighted
Finance	-0.027	-0.022	-0.029	-0.003	-0.011	-0.003
	(0.020)	(0.020)	(0.025)	(0.025)	(0.005)**	(0.004)
Small firm	-0.147	-0.147	-0.149	-0.149	-0.145	-0.145
	(0.046)***	(0.046)***	(0.047)***	(0.046)***	(0.046)***	(0.046)***
Big firm	0.100	0.099	0.102	0.099	0.087	0.088
	(0.095)	(0.095)	(0.096)	(0.096)	(0.096)	(0.096)
Public company	-0.047	-0.045	-0.045	-0.045	-0.057	-0.053
	(0.091)	(0.081)	(0.081)	(0.081)	(0.082)	(0.082)
Sole proprietorship	0.165	0.167	0.168	0.167	0.159	0.160
	(0.038)***	(0.038)***	(0.038)***	(0.039)***	(0.038)***	(0.039)***
Privatized	0.113	0.113	0.115	0.114	0.122	0.121
	(0.052)**	(0.052)**	(0.052)**	(0.052)**	(0.053)**	(0.053)**
Exporter	0.191	0.191	0.191	0.190	0.187	0.189
	(0.036)***	(0.036)***	(0.036)***	(0.036)***	(0.036)***	(0.036)***
Audited	0.113	0.112	0.111	0.111	0.107	0.108
	(0.035)***	(0.035)***	(0.035)***	(0.035)***	(0.036)***	(0.036)***
Competition	0.176	0.176	0.176	0.176	0.174	0.175
	(0.039)***	(0.039)***	(0.038)***	(0.038)***	(0.039)***	(0.039)***
Subsidized	0.313	0.315	0.313	0.313	0.314	0.316
	(0.050)***	(0.050)***	(0.050)***	(0.050)***	(0.050)***	(0.050)***
Country fixed effects	Yes					
Year fixed effects	Yes					
Observations	7,004	7,004	7,002	7,002	6,948	4,948
Pseudo R-squared	0.04	0.04	0.04	0.04	0.04	0.04

Note: The dependent variable is a dummy variable equal to 1 if the firm desires bank credit. 'Finance' is one of the three financial variables from Table 4. Each finance variable is locality-specific and is constructed by weighting equally (Columns labelled "Equally-weighted") or by number of branches (Columns labelled "Branch-weighted") the respective financial variable for each parent bank which has at least one branch or subsidiary in that locality. 'Small firm' is a dummy equal to 1 if the firm has from 2 to 49 employees. 'Big firm' is a dummy equal to 1 if the firm has more than 250 employees. 'Public company' is a dummy equal to 1 if the firm is a shareholder company, or its shares traded in the stock market. 'Sole proprietorship' is a dummy equal to 1 if the firms is a sole proprietorship. 'Privatized' is a dummy equal to 1 if the firm is a former state-owned company. 'Exporter' is a dummy equal to 1 if the firm exports to non-local markets. 'Audited' is a dummy equal to 1 if the firm employs external auditing services. 'Competition' is a dummy equal to 1 if the firm faces fairly, very, or extremely strong competition. 'Subsidized' is a dummy equal to 1 if the firm has received in the last 3 years subsidies from central or local government. Omitted category in firm size is 'Medium firm'. Omitted category in firm ownership is 'Private company'. Only localities with non-zero foreign bank presence included. All regressions include country and year fixed effects. White (1980) robust standard errors are reported in parentheses, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. See Appendix 1 for exact definitions. Source: BEEPS (2005 and 2008) and Bankscope (2005 and 2008).

Table 6.
Affected vs. non-affected banks: Rejection rates pre- vs. post-

	2005	2008	Difference
Affected localities	0.335	0.402	-0.067***
Non-affected localities	0.319	0.332	-0.013
Difference	0.016	0.070***	-0.054***

Note: The table reports a difference-in-differences estimate from a Mann-Whitney two-sided test. ‘Affected’ are localities where the average Tier 1 capital ratio of all banks present decreased by at least 1 standard deviation between fiscal year 2004 and fiscal year 2007. The statistical significance of the difference-in-differences estimate can be found next to the difference, where *** indicates significance at the 1% level. Only localities with non-zero foreign bank presence included. Source: BEEPS (2005 and 2008) and Bankscope (2005 and 2008).

Table 7.
Probability of being constrained (2008 sample)

Panel A. Equally weighted bank data for each locality

	Finance = Equity/assets		Finance = Tier 1 capital		Finance = Gains on fin assets	
Finance	0.030	0.021	-0.05	-0.059	0.012	0.009
	(0.035)	(0.035)	(0.066)	(0.066)	(0.011)	(0.011)
Small firm	0.349	0.343	0.349	0.346	0.35	0.33
	(0.082)***	(0.092)***	(0.082)***	(0.093)***	(0.083)***	(0.093)***
Big firm	-0.073	-0.074	-0.062	-0.065	-0.106	-0.105
	(0.188)	(0.190)	(0.188)	(0.190)	(0.192)	(0.194)
Public company	0.404	0.405	0.408	0.411	0.391	0.386
	(0.141)***	(0.142)***	(0.140)***	(0.142)***	(0.142)***	(0.144)***
Sole proprietorship	0.162	0.172	0.16	0.168	0.157	0.177
	(0.082)**	(0.088)*	(0.082)*	(0.089)*	(0.082)*	(0.089)**
Privatized	-0.063	-0.047	-0.07	-0.056	-0.068	-0.043
	(0.097)	(0.102)	(0.097)	(0.102)	(0.098)	(0.104)
Exporter	-0.225	-0.216	-0.223	-0.218	-0.218	-0.196
	(0.075)***	(0.088)**	(0.075)***	(0.088)**	(0.076)***	(0.088)**
Audited	-0.264	-0.239	-0.263	-0.24	-0.265	-0.233
	(0.069)***	(0.073)***	(0.069)***	(0.073)***	(0.070)***	(0.074)***
Inverse Mill's ratio		-0.045		-0.032		-0.088
		(0.141)		(0.140)		(0.144)
Country fixed effects			Yes			
Industry fixed effects			Yes			
Observations	1,951	1,926	1,950	1,925	1,924	1,899
Pseudo R-squared	0.09	0.09	0.09	0.09	0.09	0.09

Note: The dependent variable is a dummy variable equal to 1 if the firm is credit constrained. ‘Finance’ is one of the three financial variables from Table 4. Each finance variable is locality-specific and is constructed by weighting equally the respective financial variable for each parent bank which has at least one branch or subsidiary in that locality. ‘Small firm’ is a dummy equal to 1 if the firm has from 2 to 49 employees. ‘Big firm’ is a dummy equal to 1 if the firm has more than 250 employees. ‘Public company’ is a dummy equal to 1 if the firm is a shareholder company, or its shares traded in the stock market. ‘Sole proprietorship’ is a dummy equal to 1 if the firms is a sole proprietorship. ‘Privatized’ is a dummy equal to 1 if the firm is a former state-owned company. ‘Exporter’ is a dummy equal to 1 if the firm exports to non-local markets. ‘Audited’ is a dummy equal to 1 if the firm employs external auditing services. ‘Inverse Mill’s ratio’ is the inverse of Mill's ratio from the probit model in Table 5 for each respective financial variable. Omitted category in firm size is ‘Medium firm’. Omitted category in firm ownership is ‘Private company’. Omitted categories from the probit equation in Table 5 are ‘Competition’ and ‘Subsidized’. The analysis is performed on all firms present in the 2008 survey. Only localities with non-zero foreign bank presence included. All regressions include country and industry fixed effects. White (1980) robust standard errors are reported in parentheses, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. See Appendix 1 for exact definitions. Source: BEEPS (2008) and Bankscope (2008).

Table 7.
Probability of being constrained (2008 sample)

Panel B. Branch-weighted bank data for each locality

	Finance = Equity/assets		Finance = Tier 1 capital		Finance = Gains on fin assets	
Finance	-0.041	-0.047	-0.188	-0.189	0.012	0.01
	(0.035)	(0.035)	(0.065)***	(0.066)***	(0.010)	(0.010)
Small firm	0.346	0.343	0.347	0.343	0.349	0.338
	(0.082)***	(0.092)***	(0.082)***	(0.093)***	(0.083)***	(0.093)***
Big firm	-0.071	-0.076	-0.051	-0.055	-0.107	-0.108
	(0.187)	(0.189)	(0.187)	(0.189)	(0.192)	(0.194)
Public company	0.411	0.414	0.415	0.417	0.392	0.39
	(0.140)***	(0.142)***	(0.141)***	(0.142)***	(0.142)***	(0.143)***
Sole proprietorship	0.163	0.172	0.165	0.174	0.16	0.174
	(0.082)**	(0.089)*	(0.082)**	(0.089)*	(0.082)*	(0.089)*
Privatized	-0.067	-0.052	-0.07	-0.055	-0.066	-0.046
	(0.097)	(0.102)	(0.097)	(0.102)	(0.098)	(0.103)
Exporter	-0.225	-0.22	-0.218	-0.213	-0.218	-0.204
	(0.075)***	(0.088)**	(0.075)***	(0.088)**	(0.076)***	(0.088)**
Audited	-0.266	-0.243	-0.266	-0.242	-0.264	-0.236
	(0.069)***	(0.073)***	(0.069)***	(0.073)***	(0.070)***	(0.074)***
Inverse Mill's ratio		-0.032		-0.033		-0.062
		(0.141)		(0.141)		(0.143)
Country fixed effects			Yes			
Industry fixed effects			Yes			
Observations	1,951	1,926	1,950	1,925	1,924	1,899
Pseudo R-squared	0.09	0.09	0.09	0.09	0.09	0.09

Note: The dependent variable is a dummy variable equal to 1 if the firm is credit constrained. ‘Finance’ is one of the three financial variables from Table 4. Each finance variable is locality-specific and is constructed by weighting by number of branches the respective financial variable for each parent bank which has at least one branch or subsidiary in that locality. ‘Small firm’ is a dummy equal to 1 if the firm has from 2 to 49 employees. ‘Big firm’ is a dummy equal to 1 if the firm has more than 250 employees. ‘Public company’ is a dummy equal to 1 if the firm is a shareholder company, or its shares traded in the stock market. ‘Sole proprietorship’ is a dummy equal to 1 if the firms is a sole proprietorship. ‘Privatized’ is a dummy equal to 1 if the firm is a former state-owned company. ‘Exporter’ is a dummy equal to 1 if the firm exports to non-local markets. ‘Audited’ is a dummy equal to 1 if the firm employs external auditing services. ‘Inverse Mill’s ratio’ is the inverse of Mill's ratio from the probit model in Table 5 for each respective financial variable. Omitted category in firm size is ‘Medium firm’. Omitted category in firm ownership is ‘Private company’. Omitted categories from the probit equation in Table 5 are ‘Competition’ and ‘Subsidized’. The analysis is performed on all firms present in the 2008 survey. Only localities with non-zero foreign bank presence included. All regressions include country and industry fixed effects. White (1980) robust standard errors are reported in parentheses, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. See Appendix 1 for exact definitions. Source: BEEPS (2008) and Bankscope (2008).

Table 8.
Probability of being constrained, 2005 and 2008 samples

Panel A. Difference-in-differences 1

	Finance = Equity/assets		Finance = Tier 1 capital		Finance = Gains on fin assets	
	Equally-weighted	Branch-weighted	Equally-weighted	Branch-weighted	Equally-weighted	Branch-weighted
Post × Finance	0.088	-0.044	-0.118	-0.243	-0.015	-0.018
	(0.064)	(0.032)	(0.063)*	(0.049)***	(0.016)	(0.015)
Finance	-0.076	-0.025	0.008	0.086	0.015	0.015
	(0.054)	(0.034)	(0.039)	(0.036)**	(0.014)	(0.011)
Post	-0.377	0.282	1.039	2.115	0.074	0.074
	(0.549)	(0.210)	(0.548)*	(0.425)***	(0.111)	(0.095)
Inverse Mill's ratio	-0.309	-0.304	-0.294	-0.300	-0.331	-0.321
	(0.078)***	(0.076)***	(0.077)***	(0.077)***	(0.776)***	(0.076)***
Country fixed effects			Yes			
Observations	4,338	4,338	4,337	4,337	4,309	4,309
Pseudo R-squared	0.11	0.10	0.10	0.10	0.10	0.10

Panel B. Difference-in-differences 2

	Finance = Equity/assets		Finance = Tier 1 capital		Finance = Gains on fin assets	
	Equally-weighted	Branch-weighted	Equally-weighted	Branch-weighted	Equally-weighted	Branch-weighted
Post × Non-Affected	-0.391	-0.225	0.045	0.031	0.586	-0.094
	(0.126)***	(0.098)**	(0.103)	(0.100)	(0.584)	(0.398)
Non-Affected	0.163	0.190	0.062	-0.063	-0.865	-0.518
	(0.105)	(0.081)**	(0.103)	(0.086)	(0.347)**	(0.208)**
Post	0.152	0.183	0.047	0.043	0.044	0.055
	(0.075)**	(0.087)**	(0.082)	(0.090)	(0.073)	(0.073)
Inverse Mill's ratio	-0.313	-0.320	-0.329	-0.334	-0.346	-0.337
	(0.083)***	(0.083)***	(0.085)***	(0.085)***	(0.083)***	(0.084)***
Country fixed effects			Yes			
Observations	3,656	3,656	3,655	3,655	3,640	3,640
Pseudo R-squared	0.11	0.11	0.11	0.11	0.11	0.11

Note: The dependent variable is a dummy variable equal to 1 if the firm is credit constrained. 'Finance' is one of the three financial variables from Table 4. Each finance variable is locality-specific and is constructed by weighting equally (Columns labelled "Equally-weighted") or by number of branches (Columns labelled "Branch-weighted") the respective financial variable for each parent bank which has at least one branch or subsidiary in that locality. 'Post' is a dummy variable equal to 1 if the observation is in 2008, and to 0 if it is in 2005. 'Non-Affected' is a dummy variable equal to 1 if the respective finance variable declined by less than 1 standard deviation between 2005 and 2008. 'Inverse Mill's ratio' is the inverse of Mill's ratio from the probit model in Table 5 for each respective financial variable. The regressions also include the rest of the independent variables from Table 7. Omitted categories from the probit equation in Table 5 are 'Competition' and 'Subsidized'. The analysis is performed on all firms present either in the 2005 or in the 2008 survey (Panel A), and on all firms present in localities which appeared both in the 2005 and the 2008 survey (Panel B). Only localities with non-zero foreign bank presence included. All regressions include country and year fixed effects (Panel A) and country fixed effects (Panel B). White (1980) robust standard errors are reported in parentheses, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. See Appendix 1 for exact definitions. Source: BEEPS (2005 and 2008) and Bankscope (2005 and 2008).

Table 9.
Probability of being constrained, by degree of foreign ownership

Panel A. 2008 sample

	Finance = Equity/assets		Finance = Tier 1 capital		Finance = Gains on fin assets	
	Equally-weighted	Branch-weighted	Equally-weighted	Branch-weighted	Equally-weighted	Branch-weighted
Finance × Foreign	-0.159	-0.062	0.097	0.310	-0.034	-0.029
	(0.068)***	(0.055)	(0.158)	(0.137)**	(0.019)*	(0.020)
Country fixed effects			Yes			
Industry fixed effects			Yes			
Observations	1,926	1,926	1,925	1,925	1,899	1,899
Pseudo R-squared	0.09	0.09	0.09	0.10	0.09	0.09

Panel B. 2005 and 2008 samples, difference-in-differences 1

	Finance = Equity/assets		Finance = Tier 1 capital		Finance = Gains on fin assets	
	Equally-weighted	Branch-weighted	Equally-weighted	Branch-weighted	Equally-weighted	Branch-weighted
Post × Finance	-0.006	-0.004	0.001	0.002	-0.026	-0.025
× Foreign	(0.016)	(0.015)	(0.011)	(0.011)	(0.012)**	(0.013)*
Country fixed effects			Yes			
Observations	4,288	4,288	4,287	4,287	4,259	4,259
Pseudo R-squared	0.10	0.10	0.10	0.10	0.10	0.10

Panel C. 2005 and 2008 samples, difference-in-differences 2

	Finance = Equity/assets		Finance = Tier 1 capital		Finance = Gains on fin assets	
	Equally-weighted	Branch-weighted	Equally-weighted	Branch-weighted	Equally-weighted	Branch-weighted
Post × Non-Affected	-0.013	0.116	0.257	0.130	-0.521	-0.490
× Foreign	(0.405)	(0.108)	(0.232)	(0.119)	(0.281)*	(0.182)***
Country fixed effects			Yes			
Observations	3,606	3,606	3,605	3,605	3,587	3,587
Pseudo R-squared	0.11	0.11	0.11	0.11	0.11	0.11

Note: The dependent variable is a dummy variable equal to 1 if the firm is credit constrained. 'Finance' is one of the three financial variables from Table 4. Each finance variable is locality-specific and is constructed by weighting equally (Columns labelled "Equally-weighted") or by number of branches (Columns labelled "Branch-weighted") the respective financial variable for each parent bank which has at least one branch or subsidiary in that locality. 'Post' is a dummy variable equal to 1 if the observation is in 2008, and to 0 if it is in 2005. 'Non-Affected' is a dummy variable equal to 1 if the respective finance variable declined by less than 1 standard deviation between 2005 and 2008. 'Foreign' is a dummy variable equal to 1 if the locality is in the top half of the distribution of foreign ownership. The regressions also include the rest of the independent variables from Table 7, including the inverse of Mill's ratio. Omitted categories from the probit equation in Table 5 are 'Competition' and 'Subsidized'. The analysis is performed on all firms present in the 2008 survey (Panel A), on all firms present either in the 2005 or the 2008 survey (Panel A), and on all firms present in localities which appeared both in the 2005 and the 2008 survey (Panel B). Only localities with non-zero foreign bank presence included. All regressions include country and industry fixed effects (Panel A), country and year fixed effects (Panel B), and country fixed effects (Panel C). White (1980) robust standard errors are reported in parentheses, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. See Appendix 1 for exact definitions. Source: BEEPS (2005 and 2008) and Bankscope (2005 and 2008).

Table 10.
Probability of being constrained: EU countries

Panel A. 2008 sample

	Finance = Equity/assets		Finance = Tier 1 capital		Finance = Gains on fin assets	
	Equally-weighted	Branch-weighted	Equally-weighted	Branch-weighted	Equally-weighted	Branch-weighted
Finance	0.021	-0.078	-0.062	-0.218	0.007	0.010
	(0.040)	(0.043)*	(0.071)	(0.078)***	(0.012)	(0.011)
Country fixed effects			Yes			
Industry fixed effects			Yes			
Observations	1,587	1,587	1,586	1,586	1,565	1,565
Pseudo R-squared	0.09	0.09	0.09	0.10	0.10	0.10

Panel B. 2005 and 2008 samples, difference-in-differences 1

	Finance = Equity/assets		Finance = Tier 1 capital		Finance = Gains on fin assets	
	Equally-weighted	Branch-weighted	Equally-weighted	Branch-weighted	Equally-weighted	Branch-weighted
Post $\times$ Finance	0.064	-0.056	-0.061	-0.225	-0.017	-0.028
	(0.069)	(0.033)*	(0.066)	(0.053)***	(0.019)	(0.016)*
Country fixed effects			Yes			
Observations	3,658	3,658	3,657	3,657	3,634	3,634
Pseudo R-squared	0.10	0.10	0.10	0.10	0.10	0.10

Panel C. 2005 and 2008 samples, difference-in-differences 2

	Finance = Equity/assets		Finance = Tier 1 capital		Finance = Gains on fin assets	
	Equally-weighted	Branch-weighted	Equally-weighted	Branch-weighted	Equally-weighted	Branch-weighted
Post$\times$Non-Affected	-0.409	-0.162	-0.108	-0.152	0.691	0.105
	(0.130)***	(0.097)*	(0.111)	(0.089)*	(0.615)	(0.430)
Country fixed effects			Yes			
Observations	3,072	3,072	3,071	3,071	3,056	3,056
Pseudo R-squared	0.11	0.11	0.11	0.11	0.11	0.11

Note: The dependent variable is a dummy variable equal to 1 if the firm is credit constrained. 'Finance' is one of the three financial variables from Table 4. The sample excludes firms from non-EU countries (Albania, Croatia, Macedonia, and Montenegro). Each finance variable is locality-specific and is constructed by weighting equally (Columns labelled "Equally-weighted") or by number of branches (Columns labelled "Branch-weighted") the respective financial variable for each parent bank which has at least one branch or subsidiary in that locality. 'Post' is a dummy variable equal to 1 if the observation is in 2008, and to 0 if it is in 2005. 'Non-Affected' is a dummy variable equal to 1 if the respective finance variable declined by less than 1 standard deviation between 2005 and 2008. The regressions also include the rest of the independent variables from Table 7, including the inverse of Mill's ratio. Omitted categories from the probit equation in Table 5 are 'Competition' and 'Subsidized'. The analysis is performed on all firms present in the 2008 survey (Panel A), on all firms present either in the 2005 or the 2008 survey (Panel A), and on all firms present in localities which appeared both in the 2005 and the 2008 survey (Panel B). Only localities with non-zero foreign bank presence included. All regressions include country and industry fixed effects (Panel A), country and year fixed effects (Panel B), and country fixed effects (Panel C). White (1980) robust standard errors are reported in parentheses, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. See Appendix 1 for exact definitions. Source: BEEPS (2005 and 2008) and Bankscope (2005 and 2008).

Table 11.
Probability of being constrained: Differential effects

	Equally-weighted	Branch-weighted	Equally-weighted	Branch-weighted
Tier 1 capital × Asset tangibility 1	-0.359	-0.325		
	(0.217)*	(0.137)**		
Tier 1 capital × Asset tangibility 2			-0.673	-0.527
			(0.170)***	(0.119)***
City fixed effects		Yes		
Industry fixed effects		Yes		
Observations	1,210	1,210	1,210	1,210
Pseudo R-squared	0.16	0.16	0.16	0.16

Note: The dependent variable is a dummy variable equal to 1 if the firm is credit constrained. 'Tier 1 capital' is the ratio of Tier 1 capital to total assets. It is locality-specific and is constructed by weighting equally (Columns labelled "Equally-weighted") or by number of branches (Columns labelled "Branch-weighted") the Tier 1 capital ratio for each parent bank which has at least one branch or subsidiary in that locality. 'Asset tangibility 1' is a dummy equal to 1 if the industry is in the top 50% of the distribution of industry medians of the ratio of research and development expenses to sales for mature Compustat firms over the period 1990-2000. 'Asset tangibility 2' is a dummy equal to 1 if the industry is in the bottom 50% of the distribution of industry medians of capital usage per worker with external funds for mature Compustat firms over the period 1990-2000. The regressions also include the rest of the independent variables from Table 7, including the inverse of Mill's ratio. Omitted categories from the probit equation in Table 5 are 'Competition' and 'Subsidized'. The analysis is performed on all firms present in the BEEPS 2008 survey. Only localities with non-zero foreign bank presence included. All regressions include city and industry fixed effects. White (1980) robust standard errors are reported in parentheses, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. See Appendix 1 for exact definitions. Source: BEEPS (2008) and Bankscope (2008).

Table 12. Probability of being constrained: Geography issues

	2008 sample			
	<3 banks	small firms only	<3 banks and small firms only	euro
Tier 1 capital	-0.321	-0.209	-0.746	
	(0.172)*	(0.079)***	(0.277)***	
Tier 1 capital * euro				-0.196
				(0.138)
Country fixed effects		Yes		
Industry fixed effects		Yes		
Observations	103	1,358	63	1,925
Pseudo R-squared	0.29	0.07	0.36	0.09

Note: The dependent variable is a dummy variable equal to 1 if the firm is credit constrained. 'Tier 1 capital' is the ratio of Tier 1 capital to total assets. It is locality-specific and is constructed by weighting by number of branches the Tier 1 capital ratio for each parent bank which has at least one branch or subsidiary in that locality. The sample is restricted to localities with a maximum of 2 banks (Columns labelled "<3 banks"), to the sub-sample of small firms only (Columns labelled "small firms"), and to the sub-sample of small firms in localities with a maximum of 2 banks (Columns labelled "<3 banks and small firms"). 'euro' is a dummy equal to 1 if the country is in the euro zone or has its currency pegged to the euro (Bulgaria, Estonia, Latvia, Lithuania, Slovakia, Slovenia). The regressions also include the rest of the independent variables from Table 6. The analysis is performed on firms present in the 2008 and 2005 BEEPS surveys. Only localities with non-zero foreign bank presence included. All regressions include country and industry fixed effects. White (1980) robust standard errors are reported in parentheses, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. See Appendix 1 for exact definitions. Source: BEEPS (2008) and Bankscope (2008).

Appendix 1. Variables – definitions and sources

Variable Name	Definition	Source
	Firm characteristics	
Small firm	Dummy=1 if firm has less than 99 employees	BEEPS 2005 & 2008
Medium firm	Dummy=1 if the firm has between 100 and 499 employees	BEEPS 2005 & 2008
Big firm	Dummy=1 if firm has more than 500 employees	BEEPS 2005 & 2008
Public company	Dummy=1 if firm is a shareholder company / shares traded in the stock market	BEEPS 2005 & 2008
Private company	Dummy=1 if firm is a shareholder company / shares traded privately if at all	BEEPS 2005 & 2008
Sole proprietorship	Dummy=1 if firm is a sole proprietorship	BEEPS 2005 & 2008
Privatized	Dummy=1 if the firm went from state to private ownership in the past	BEEPS 2005 & 2008
Subsidized	Dummy=1 if the firm has received state subsidized in the past year	BEEPS 2005 & 2008
Exporter	Dummy=1 if firm's production is at least partially exported	BEEPS 2005 & 2008
Competition	Dummy=1 if pressure from competitors is "fairly" or "very" severe	BEEPS 2005 & 2008
Audited	Dummy=1 if the firm has its financial accounts externally audited	BEEPS 2005 & 2008
	Credit demand and credit access	
Need loan	Dummy=1 if the firm doesn't need a loan because it has sufficient capital	BEEPS 2005 & 2008
Constrained	Dummy=1 if the firm was refused a loan or didn't apply for one because of adverse loan conditions	BEEPS 2005 & 2008
	Industry benchmarks	
R&D intensity	Median proportion of the ratio of research and development expenses to sales for mature Compustat firms over the period 1990-2000	Compustat
Capital intensity	Median proportion of capital usage per worker for mature Compustat firms over the period 1990-2000	Compustat

	Bank-level variables	
% foreign owned bank assets	Share of banking sector assets owned by branches or subsidiaries of foreign banks	EBRD Transition report 2008
Foreign	Dummy=1 if the locality is in the top half of the distribution of foreign bank ownership.	Bankscope 2005 & 2008
Equity/assets	Ratio of total equity to total assets	Bankscope 2005 & 2008
Tier 1 capital	Ratio of Tier 1 capital to total risk-weighted assets	Bankscope 2005 & 2008
Gain on financial assets	Gain on financial assets held by the bank	Bankscope 2005 & 2008

Appendix 2. Domestic and parent banks in the sample

Country	Bank	Parent bank and country of incorporation
Albania	Alpha Bank	Alpha Bank - Greece
	Raiffeisen	Raiffeisen - Austira
	Banka Kombetare Trektare	domestic
	Tirana Bank	Pireus Bank - Greece
	Intessa San Paolo Bank Albania	Intessa San Paolo - Italy
	National Bank of Greece	National Bank of Greece
	Emporiki	Emporiki Bank - Greece
	Banka Credins	domestic
Bulgaria	Alpha bank	Alpha Bank - Greece
	Unicredit Bulbank	UniCredit Group - Italy
	DSK	OTP - Hungary
	First Investment Bank	domestic
	PostBank	EFG Eurobank - Greece
	Expressbank	Societe Generale - France
	United Bulgarian Bank	National Bank of Greece
	Reiffeisen	Raiffeisen - Austira
	Piraeus	Piraeus Bank - Greece
Croatia	Zagrebaska Bank	UniCredit Group - Italy
	Privredna Bank Zagreb	Intessa San Paolo - Italy
	Erste & Steiermarkische Bank	Erste Group - Austria
	Raiffeisen Bank	Raiffeisen - Austria
	Societe Generale - Splitska Banka	Societe Generale - France
	Hypo Alde Adria Bank	Hypo Group - Austria
	OTP Banka Hrvatska	OTP - Hungary
	Slavonska Banka	domestic
	Hrvatska Postanska Banka	domestic
Czech Republic	Ceska Sporitelna	Erste Group - Austria
	CSOB	KBC - Belgium
	Komercni Banka	Societe Generale - France
	UniCredit Bank CR	UniCredit Group - Italy
	Citibank	Citibank - US
	Ceskomoravska zarucni a rozvojova banka	domestic
	GE Money Bank	GE Money - US
	Hypotecni Banka	KBC - Belgium
	Raiffeisenbank	Raiffeisen - Austira
Estonia	Swedbank Estonia	Swedbank - Sweden
	SEB	Skandinavska Enskilda Banken - Sweden
	Sampo Pank	Danske Pank - Denmark
	Nordea	Nordea Bank - Finland
Hungary	OTP Bank	domestic
	K&H Commercial and Credit Bank	KBC - Belgium
	MKB Bank	Bayerische Landesbank - Germany
	CIB Bank	Intessa San Paolo - Italy
	Raiffeisen Bank	Raiffeisen - Austira
	Erste Bank Hungary	Erste Group - Austria
	KDB Bank	KDB Seoul - Korea
	UniCredit Bank Hungary	UniCredit Group - Italy
Latvia	Parex	domestic
	Hansabank	Swedbank - Sweden

	Latvijas Krajbanka	Snoras Bank - Lithuania
	SMP Bank	domestic
	Rietumu Banka	domestic
	Trasta Komercbanka	domestic
Lithuania	SEB	Skandinavska Enskilda Banken - Sweden
	Sampo Pank	Danske Pank - Denmark
	Nordea	Nordea Bank - Finland
	Snoras Bank	domestic
	Ukio Bankas	domestic
	Hansabankas	Swedbank - Sweden
	Parex Bankas	Parex Group - Latvia
Macedonia	Alpha Bank	Alpha Bank - Greece
	Stopanska Banka	National Bank of Greece
	Komercijalna Banka	domestic
	NLB Tutunska Banka	NLB - Slovenia
	Ohridska Banka	Societe Generale - France
	Pro Credit Bank	Pro Credit Group
Montenegro	AtlasMont Bank	domestic
	Crnogorska Komercijalna Banka	OTP - Hungary
	Hypo-Alpe-Adria Bank	Hypo Group - Austria
	Komercijalna Banka ad Budva	domestic
	NLB Montenegro Banka	NLB - Slovenia
	Prva Banka Crne Gore	domestic
	Invest Banka Montenegro	domestic
	Podgoricka Banka SG	Societe Generale - France
	Opportunity Bank	domestic
Poland	PKO Bank	domestic
	Bank Pekao	UniCredit Group - Italy
	Bank BPH	UniCredit Group - Italy
	Bank Zachodni WBK	AIB - Ireland
	ING Bank Slaski	ING Bank - Netherlands
	Bank Pocztowy	domestic
	Kredyt Bank	KBC - Belgium
	mBank	Commerzbank - Germany
	Getin Bank	domestic
Romania	BCR	Erste Group - Austria
	BRD Group Societe General	Societe Generale - France
	Volksbank Romania	Volksbank - Austria
	Raiffeisen Bank	Raiffeisen - Austira
	Alpha Bank Romania	Alpha Bank - Greece
	UniCredit Tiriac Bank	UniCredit Group - Italy
	Banca Transilvania	domestic
	Bancpost	EFG Eurobank - Greece
	CEC Bank	domestic
Slovakia	Vseobecna Uverova banka	Intessa San Paolo - Italy
	Slovenska Sporitelna	Erste Group - Austria
	Tatra Banka	Raiffeisen - Austira
	OTP Banka Slovensko	OTP - Hungary
	Dexia Banka Slovensko	Dexia - Belgium
	UniCredit Bank Slovakia	UniCredit Group - Italy
	Volksbank Slovensko	Volksbank - Austria
	CSOB Slovakia	KBC - Belgium

Slovenia	Nova Ljubljanska Banka	KBC - Belgium
	Nova Kreditna Banka Maribor	domestic
	Abanka	domestic
	SKB	Societe Generale - France
	UniCredit	UniCredit Group - Italy
	Banka Koper	Intessa San Paolo - Italy
	Banka Celje	domestic
	Reiffeisen Krekova banka	Raiffeisen - Austira

Appendix 3. Bank data coverage

Country	Ratio assets of the banks in the data set to total assets of the country's banking sector
Albania	0.982
Bulgaria	0.857
Croatia	0.887
Czech Republic	0.913
Estonia	0.956
Hungary	0.948
Latvia	0.851
Lithuania	0.896
Macedonia	0.877
Montenegro	0.862
Poland	0.859
Romania	0.904
Slovakia	0.925
Slovenia	0.862

Source: Bankscope (2008).

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Why do banks securitize their assets?
Bank-level evidence from over one hundred countries

by

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Abstract

In the last decade, the use of credit risk transfer (CRT) techniques by banks has increased spectacularly, raising fundamental questions on its benefits for banks and the financial system at large. We investigate the causes and consequences of securitizations using a large data set of banks from over 100 world countries, controlling for bank specific characteristics as well as country features that might affect banks' decisions. Our results show that banks are more likely to securitize their assets when they face lower direct and indirect costs (e.g., administrative expenses or the loss implied in the sale of opaque assets in an imperfect information environment) and when they face binding capital requirements. More interestingly, we find evidence that banks securitized their assets to contain credit risk, reduce the exposure to liquidity shocks and improve their capital ratios. These results are confirmed using different estimation techniques, and running a number of robustness checks. The ex-post effects of securitizations are consistent with the determinants. In the years after the securitization, banks reduce their riskiness and improve their capital ratios. The crisis has made well clear that some banks have eventually used far too aggressively the possibilities offered by the new techniques for removing the risks from their balance sheets. But, if properly used, these techniques can indeed have positive effects.

JEL-classification: G21, G32
keywords: Credit risk transfer, securitization, financial derivatives

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Introduction

In the last decade, the use of securitization techniques by banks has increased spectacularly, pulled by progress in screening and monitoring technologies and financial engineering techniques. According to the Security Industry and Financial Markets Association, between 1997 and 2008 the outstanding value of ABSs increased by more than 500 per cent, from US$ 404 billion to 2,671 billion (2,472 at the end of 2007). Although the financial crisis has caused a near collapse of securitization markets, commentators and policymakers concur that credit risk transfer (CRT) remains a fundamental tool for banks' activity.

While the removal of credit risk from banks' balance sheets is not a new phenomenon,[1] the most recent wave of securitizations differs from previous ones for the widespread use of sophisticated techniques, which permit to transfer credit risk of a much wider set of assets than in the past, ranging from small, opaque mortgages to credit card receivables.

The availability of these new techniques has raised fundamental questions on the impact of CRT on banks' performance and financial conditions. On the one hand, in the boom years before the financial crisis some commentators suggested that a new banking paradigm had emerged, in which intermediaries are better able to manage credit risk by redistributing loans to outside investors.[2] To quote an authoritative one, in October 2004 Alan Greenspan stated that "these transactions represent a new paradigm of active credit management and are a major explanation of the banking system's strength during the most recent period of stress".[3] Indeed, from a theoretical point of view, the rationale for hedging credit risk is well understood. Diamond (1984) shows that banks should hedge all risks for which they have no comparative advantage, a set that likely includes, for example, such loans as credit card receivables. De Marzo (2005) shows that by pooling large sets of loans and tranching them into securities with different risk it is possible to contain the lemon discount required by investors on the sale of informationally opaque bank assets.

On the other hand, the subprime crisis turned many analysts and policymakers skeptical about the advantages of CRT, emphasizing the potential risks in terms of banks' leverage and transparency. As Chairman Bernanke recently said "the boom in subprime mortgage lending was only a part of a much broader boom characterized by an underpricing of risk, excessive leverage, and the creation of complex and opaque financial instruments that proved fragile

[1] A securitization wave had already taken place in the U.S. in the 1980s, when the ratio of loan sales to total assets rose from 1.6 to 9.0 per cent (Berger and Udell, 1993).

[2] In fact, this labeling of a "new paradigm" is itself not entirely new: Pennacchi (1988) suggested that "The leading banks in loan-selling operations now view themselves more as originators and distributors of loans rather than as institutions holding loans as assets", and Berger and Udell (1993) wrote that "It has been argued that the essence of banking may have changed during the 1980s with the explosive growth of securitization".

[3] Speech given at the American Banking Association Annual Convention, New York, October 5, 2004.

under stress".[4] On a similar line, ECB's President Trichet said that "as the turmoil has since shown, there was a tendency to overestimate the true degree of risk spreading and diversification, especially in credit markets".[5]

As it is clear from this debate, for both research and policy reasons it is of paramount importance to understand the effects of CRT on banks' performance, in order to avoid throwing the baby out with the bath water. A number of crucial questions need to be addressed: what are the costs and benefits of CRT? Do banks securitize their loans to reduce risk and diversify their lending portfolio or do they merely use CRT techniques to increase leverage, exploiting asymmetric information on the quality of the loans that are sold to outside investors? While a number of papers have tried to answer these questions, empirical analyses of the motivations of CRT and its effects on banks' performance has not reached firm conclusions. In this paper we try to fill this gap in the literature by investigating the causes and consequences of CRT.

The extant analyses of why banks transfer credit risk are affected by two weaknesses. First, previous papers have estimated contemporaneous correlations between bank characteristics and the use of CRT (see for example Bannier and Hänsel, 2007). Clearly, this makes it impossible to distinguish the motives that induce banks to use CRT from the effects of CRT on bank's performance. In order to address this problem we review the competing theories of why banks use CRT. Each theory yields a list of factors that are likely to affect the decision to transfer credit risk (*ex ante* analysis, based on the characteristics of the banks before using CRT for the first time) as well as the possible consequences of CRT (*ex post* evidence, based of the performance of those same banks after using CRT). Thus, by analyzing separately ex ante determinants and ex post consequences, we are able to reject some of the competing theories.

Second, previous studies have focused on specific aspects of the effects of securitizations. This may hinder a deep understanding of the motives why banks securitize their assets. For example, a common finding of the literature is that *before* the securitization banks are riskier than average (because they have high risk provisions or charge-offs). This might reflect the fact that banks use CRT instruments to rebalance their loan portfolio in order to achieve a given (lower) level of risk. However, an alternative interpretation is that the securitizing banks are riskier than average because they deliberately follow a high-risk/high-return strategy. The policy implications of these two alternative views are very different, but without a *comprehensive* analysis of the characteristics of the securitizing banks (such as their profitability or their risk profile *after* the securitization) it would be impossible to discriminate among them. In order to overcome these problems, we examine the evolution of a wide range of balance sheet indicators of the banks that decide to securitize their assets.

[4] Speech given at the UC Berkely/UCLA Symposium: The Mortgage Meltdown, the Economy, and Public Policy, Berkley, California, October 31, 2008.
[5] Speach given at the Coface Country Risk Conference 2009, Carrousel du Louvre, Paris, 19 January 2009.

Only some banks use CRT. For example, according to the Bankscope and Dealogic databases, less than 10 percent of the banks with more than US$ 1 billion in total assets originated ABSs, mortgage backed securities (MBSs), collateralized loan obligations (CLOs) or collateralized debt obligations (CDOs) in the period 1992-2007. Even among the 1,031 largest banks (those included in the first decile by size), only one fourth were active in CRT.[6] The fact that some intermediaries use CRT, while others do not, suggests that bank-specific characteristics affect the decision to transfer credit risk; for example, only large banks might afford the (potentially large) fixed costs of organizing complex securitization deals. Hence, in order to investigate the causes and effects of CRT we analyze a large microeconomic data set. Our data set has two important attributes. First, it includes balance sheet data and other information for over 10,000 banks for sixteen years (from 1992 to 2007). Second, it includes detailed information on the banks that in our sample period used CRT techniques. These features allow us to analyze the bank-level motives of the decision to transfer credit risk, and its consequences

The vast majority of the empirical analyses focus on individual countries (mainly the U.S.), thus making it impossible to examine whether the use of CRT techniques reflects country-specific characteristics. Unlike previous papers, we do not concentrate on any single country, but analyze banks from both developed and developing countries. We supplement our bank-level data set with country-specific indicators, such as the degree of development of the credit and equity market or characteristics of the supervisory system. This permits us to examine how the characteristics of the domestic financial system affect banks' use of CRT.

While a wide range of additional instruments can be used to transfer credit risk – from syndicated loans to securitization and credit derivatives – previous analyses suggest that banks tend to use them as complements (Hirtle, 2007; Minton *et al.*, 2008; Cebenoyan and Strahan, 2004). Therefore in our empirical analysis we take the use of securitization techniques such as ABSs, MBSs, CLOs and CDOs as a signal that the bank uses CRT techniques in general.

Our results show that there are multiple causes why banks use CRT techniques. Large banks are more likely to securitize their assets, as they can spread the fixed costs of the deals (e.g., administrative expenses) over a larger base. More interestingly, securitizations are mainly used to contain risks, by reducing credit risk, controlling the exposure to liquidity shocks and improving the capital ratios. According to our ex-post evidence, securitizing banks succeeded in removing risks from their balance sheets and in increasing their capital ratios.

The rest of the paper is organized as follows. Sections I and II describe the hypotheses under scrutiny and relate them to the available empirical evidence. Section III describes the data used in the empirical analysis and presents some descriptive statistics. Section IV and V present the results of the econometric analyses, respectively of the ex-ante characteristics of

[6] Minton *et al.* (2008) show that among the top 395 US banks in 2005, only 5,8 per cent were active in the CDS market. The number of banks that use more traditional ways of transferring credit risk (such as credit syndicates) is also small (Sufi, 2007).

banks that make use of securitizations techniques and of the ex-post effects of securitization. Section VI discusses the empirical results setting them within a unifying framework and concludes.

I. Hypotheses and related research

A bank will transfer part of its credit risk if the ex-ante risk adjusted benefits (e.g., in terms of risk reduction, lower interest expenses or availability of the resources needed to exploit new investment opportunities) exceed the fixed and variable costs of the operation. In this section we review the potential costs and benefits of CRT, highlighting testable implications on both the ex-ante characteristic of the securitizing banks and the ex-post effects of the operations.

A. The costs of securitization

A1. The fixed costs hypothesis

Securitizations involve substantial one-off costs. These include consultancy and organizational costs related to the bundling and tranching of loan portfolios, payments to the agencies responsible for assigning a rating to the different tranches, underwriting fees, and legal expenses. According to Davidson *et al.* (2003), for example, the upfront costs of a typical securitization can easily exceed US$ 1 million, mainly from legal fees and from those due for structuring and arranging the operation. Many of these costs are relatively fixed, and so they bear more heavily on small banks, which should therefore be less likely to use CRT techniques.

A2. The lemon discount hypothesis

Because banks have private information on the quality of their loan portfolio, outside investors will require a lemon discount on the price of the assets that are sold (Gorton and Pennacchi, 1995). The securitized assets are therefore likely to be underpriced relative to the book value of the loans.

According to this hypothesis, banks that pay a lower lemon discount should be more likely to securitize their assets. The discount is likely lower if (i) the bank can credibly certify the quality of the assets it is selling (Focarelli *et al.*, 2008); (ii) private information is less relevant because the loans are less opaque or more standardized; (iii) the loss given default is lower, for example because the loans are collateralized. Thus, banks that in previous years had a lower level of charge-offs and problem loans – which are likely to enjoy a higher reputation and hence can credibly advocate a superior ability in screening and monitoring borrowers – will be more likely to securitize their assets. The probability to use CRT techniques should also be higher for banks with a larger proportion of credit card receivables, automobile loans and mortgages, which are less subject to asymmetric information (because of their high degree of standardization) and have lower loss given default (because of their high degree of collateralization). Listed banks might also pay a lower lemon discount, since their balance sheets are typically under close scrutiny by external analysts.

A3. The cost of funding hypothesis

A securitizing bank may have an incentive to retain a significant share of credit risk, in order to signal the quality of the assets (Pennacchi, 1988; Gorton and Pennacchi, 1995). However, *de facto* for many investors information on the risk retained may be difficult and costly to obtain, leading to imprecise estimates of the bank's overall credit risk. As the subprime mortgage crisis has made clear, uncertainty on the true degree of risk of bank assets can lead to severe funding problems. These problems are likely to be more pronounced for banks with a larger share of short term liabilities and wholesale liabilities, which are subject to frequent rollover on markets that tend to be highly sensitive to issuers' conditions.

Hence, under this hypothesis, the probability to use CRT techniques should be negatively correlated with the share of (i) short term liabilities and (ii) interbank liabilities (as a more intense use of these instruments would imply higher transparency costs for the securitizing bank).

Ex-post, the lower transparency of the bank's assets due to the securitization should increase the cost of these funding sources, thus inducing the securitizing banks to reduce their weight over total liabilities.

A4. The regulatory costs hypothesis

Differences in supervisory and regulatory regimes are likely to influence the costs and benefits that banks face in securitizing their loans.[7]

While specific information on the regulatory treatment of securitizations are not available for a sufficiently wide set of countries, this hypothesis can still be tested using a set of proxies of the stringency of each country's regulatory framework, such as the type and number of bank supervisory authorities, the presence of regulations or guidelines on portfolio concentration and the degree of disclosure of off-balance sheet activities (Barth *et al.*, 2004).

B. The benefits of securitization

B1. The liquidity hypothesis

The possibility to securitize part of its loan portfolio gives a bank an additional funding channel to be used in case of liquidity problems.[8] This opportunity will be more valuable to intermediaries characterized by a larger share of illiquid assets. Banks with a larger share of

[7] For example, in Italy banks retaining the equity tranche of a securitization are required to put aside the same amount of capital as if they had retained the whole loan portfolio; this has contributed to contain the overall volume of securitization by Italian banks.

[8] Clearly, this is likely to work in the event of idiosyncratic shocks, not in the case of a systemic shock that, as in the recent crisis, dries the interbank markets and the markets for securitizations.

loans should therefore be more likely to securitize their assets. Moreover, if the securitizing banks are indeed concerned about the potential effects of a liquidity shock, then they should hold a higher share of liquid assets than their competitors (in spite of the high opportunity cost of assets).

Banks with more demand deposits as a proportion of total liabilities are usually thought to be highly vulnerable to liquidity shocks (see Diamond and Dybvig, 1983). Banks with more deposits should therefore be more likely to securitize their assets. However, the radical changes that invested banking activities in the last decades and the diffusion of deposit insurance schemes have made traditional bank runs nearly obsolete (Brunnermeier (2008)), producing instead other sources of liquidity shocks. During the financial crisis it was banks and money funds that took a run on some core financial institutions (Uhlig (2009)) and traditional retail deposits proved to be in most cases a highly stable source of funding, actually reducing banks' exposure to liquidity shocks. The sign of the correlation between the probability to securitize and the share of demand deposits is therefore ambiguous.

Ex post, the possibility to raise funds through securitization markets should induce banks to increase the proportion of assets represented by illiquid loans and reduce the buffer of liquid assets.

B2. The risk-removal hypothesis

Banks could securitize their loans in order to rebalance their credit portfolio and achieve a different combination of risk and return.

Banks that want to remove undesired risk from their balance sheets can securitize their riskiest loans and invest the proceeds in low-risk assets. This opportunity should be especially appealing to banks that are riskier than average and that, in case of default, would experience large losses, for example because they have a higher franchise value (see Gorton and Souleles, 2006 and Jiangli *et al.*, 2007).

Under the risk-removal hypothesis, banks that have a lower Z-score or a larger share of problem loans (two common proxies of the probability of default)[9] and that have a higher profitability (a proxy for the franchise value) should therefore be more likely to securitize. Ex-post, default risk should decrease.

B3. The risk-taking hypothesis

Benveniste and Berger (1986) suggest that securitizations could instead aim at increasing risk, if banks securitize low-risk credit and grant new loans to riskier borrowers. If this is the case, securitizations should be mainly used by less risky banks: with a higher Z-score or a lower share of problem loans.

[9] In the banking literature, the Z-score is commonly defined as the number of standard deviations that a bank's ROA has to drop below its expected value before equity is depleted (Laeven and Levine, 2009), and therefore is a negative function of the risk of default (i.e, banks with a higher Z-score are less likely to default).

Berger and Udell (1993) argue that banks have stronger incentives to take on risk when they have a high probability of default, in order to exploit the fact that the cost of deposit insurance does not fully reflect or is independent of their risk attitude. Under this additional hypothesis riskier banks should be more likely to securitize their assets in countries with a deposit insurance scheme, in order to increase their overall risk. We test this hypothesis by interacting our proxy of default risk with an index of the degree of moral hazard that depends on the specific characteristics of each country's deposit insurance guarantee scheme (Demirgüç-Kunt and Detragiache, 2002; see below).

Clearly, under the risk-taking hypothesis the ex-post effects of securitizations should be to increase risk, the opposite of what is suggested by the risk-removal hypothesis.[10]

B4. The capital ratio hypothesis

Banks with a capital/asset ratio close to the binding minimum requirements may use securitizations to improve their capital ratios or, in alternative, to exploit the additional margin to take on new lending opportunities. They should therefore be more likely to securitize their loans.

The evolution of the balance sheet of the securitizing banks after the securitization should help discriminate between these two alternative hypotheses. If the reason of the securitization is to exploit profitable lending opportunities, after the operation loans should increase (and the capital-ratio decrease) more than for the non-securitizing banks. If instead the bank's objective is to improve its ratios, then the capital to asset ratios should increase and loans should increase in line or even less than in the control sample. Clearly, intermediate outcomes are also possible, with a bank augmenting its loans and simultaneously increasing its capital ratios, although to a smaller extent than it would have been possible with zero loan growth.

B5. The diversification hypothesis

Asset securitization allows banks to reduce their exposure to specific sectors or geographic areas, thus diversifying their loan portfolio. This mechanism has been studied explicitly in the theoretical literature. Pennacchi (1998), for example, argues that standard incentive-efficient bank contracts give the bank a disproportionate share of a loan credit risk with respect to what would be optimal from the point of view of optimal risk management, but that such excessive credit risk taking can be diversified away through loan sales (see also Morrison, 2005).

[10] This implication is shared by another strand of literature, focusing on the possibility to use securitizations in order to separate investors with different risk attitudes. Benveniste and Berger (1987) and James (1988) show that letting banks issue senior debt claims to more risk averse investors, while leaving less risk averse depositors with claims on the residual loan portfolio, it is possible to reduce the overall costs of funding. In this setting, banks will securitize relatively safe assets, with the consequence of increasing the overall risk of their loan portfolio. The same conclusion that banks securitize their safest assets is reached by Greenbaum and Thakor (1987) in a setting in which a pooling equilibrium is in any case prevented, because borrowers can signal their quality by acquiring an insurance on their probability of default, for example acquiring letters of credit.

If securitization is driven by the diversification motive, banks with more concentrated loan portfolios should be more likely to securitize. To the extent that the size of commercial and industrial loans is on average larger than that of consumer and mortgage loans, banks with a lower share of consumer loans and especially of mortgages should be more likely to use securitization techniques.[11]

The diversification hypothesis would imply that after the securitization banks reduce the concentration of the loan portfolio (measured by a reduction in the share of C&I loans) and possibly credit risk (measured for example by the Z-score or loan loss provisions).

II. Previous evidence

One of the issues that have been more widely analyzed in the previous literature is the relationship between CRT and bank risk. Results are controversial, as they differ according to the country and time period analyzed. Some authors find a positive relationship between bank risk and the use of CRT techniques: the securitizing banks are characterized by high risk provisions (see Bannier and Hänsel, (2007), who examine European banks), high charge-offs (see Pais (2005) on UK and Irish banks) and a high share of non-performing assets (Casu *et al.*, 2009). Similarly, Cebenoyan and Strahan (2004) find that US banks active in the loan sales market operate at higher leverage and hold on average more risky C&I loans and real estate loans. However, other papers find that banks that are more likely to securitize have *lower* leverage (see Gorton and Souleles (2006) and Minton *et al*. (2004), who analyze U.S. banks). Berger and Udell (1993) find a positive and significant relationship between the risk of U.S. banks and securitizations with implicit or explicit recourse (i.e., that do not entirely remove the credit risk from the bank's balance sheet), but no relationship for securitizations with no recourse. A possible explanation of this result is that riskier banks use securitizations with recourse to conceal their actual credit risk.

Other studies have measured risk with the bank's funding costs, again obtaining controversial results. Jiangli and Pritsker (2008) and Jiangli *et al.* (2007) find that US bank holding companies using securitization techniques pay on average lower spreads on uninsured time deposits. This might signal that customers require a lower risk premium to securitizers, or that they can afford to offer low return deposits because they have a larger set of funding sources. In contrast with this result, Gorton and Souleles (2006) find that financial companies with worse bond ratings are more likely to securitize.

Focusing on liquidity risk, a number of papers[12] provide evidence that banks with less liquid assets are more likely to use CRT techniques. Furthermore, Loutskina and Strahan (2009) find

[11] Clearly, this prediction contrasts with the lemon discount effect, suggesting that more standardized and transparent loans are more likely to be securitized. Which effect prevails is therefore an empirical issue.
[12] See Cebenoyan and Strahan (2004), Bannier and Hänsel (2007), Jiangli *et al.* (2007), Minton *et al.* (2008) and Affinito and Tagliaferri (2009).

that an increase in balance sheet liquidity augments the probability that a bank grant loans that are difficult to sell or securitize more than that it grants more liquid loans.

A second aspect analyzed in the literature is the relationship between securitization and regulatory capital. In this case results are less ambiguous, and seem to suggest that securitizations are mainly used by banks with lower capital ratios. For example, Calomiris and Mason (2004) find that banks securitize credit card receivables in order to set capital ratios at levels consistent with market standards.[13]

The possibility to securitize affects banks' lending policies. Goderis *et al.* (2006) and Hirtle (2007) find that banks using CRT techniques increase loan supply. Moreover, Loutskina (2005) shows that banks with a loan portfolio that can be more easily securitized have lending policies that are less sensitive to monetary shocks.

Finally, a few studies examine the characteristics of the loans that are sold, and how the proceedings are used. Mian and Sufi (2008), Keys *et al.* (2008) and Dell'Ariccia *et al.* (2008), provide evidence that in the last decade U.S. banks securitized low-quality mortgage loans. On a related ground, Purnanandam (2008) finds that US banks making larger use of CRT techniques before the 2007 subprime crisis had significantly higher mortgage charge-offs after the crisis, likely an indication that securitizations were associated to lending to customers with high default risk. Interestingly, markets seem to anticipate that banks may be less concerned about the quality of the loans that they will eventually securitize, as suggested by the fact that the announcement of a new bank loan has a less positive effect on the borrower's stock price when the lender is active in the CRT market (see Marsh (2006)).[14]

From this review[15] it appears that previous studies have focused on specific aspects of the effects of securitization, but failed to perform a comprehensive analysis of the overall impact of CRT on banks' performance. To overcome this problem, in the following sections we use a large sample of banks from over one hundred different countries and examine the evolution of a wide range of balance sheet indicators of those banks that decide to securitize their assets. We estimate two separate empirical models, one for the ex-ante characteristics of the securitizing banks and the other for the ex-post effects of the deals.

[13] See also Pais (2005), Bannier and Hänsel (2007), Jiangli *et al.* (2007) and Jiangli and Pritsker (2008)). Minton *et al.* (2008) find similar results for US banks that use credit default swaps (CDS) to buy protection.

[14] We are aware of only two studies of the ex-post effects of securitizations. Michalak and Uhde (2009) find for a sample of European banks that securitization has a negative impact on financial soundness as measured by the Z-score; on the contrary, Casu *et al.* (2009) find no evidence of significant causal effects of securitization on the performance of U.S. banks.

[15] Our review does not consider papers that analyze how markets react to the announcement of securitization. See for example Thomas (2001), Pais (2005) and Hänsel and Krahnen (2007) show that CDO issuance raises the originators' systematic risk, measured by its stock market beta, the more so for financially weaker institutions.

III. Data and summary statistics

The sample of banks that securitized their assets has been constructed from two commercial databases, Dealogic and Bankscope. The first has been used to collect information on banks that originated issues of asset backed securities (ABSs), mortgage backed securities (MBSs), collateralized loan obligations (CLOs) or collateralized debt obligations (CDOs). The information contained in Dealogic reports all types of securitizations performed by banks, including the operations realized indirectly, by initially transferring the loans to a Special Purpose Vehicle (SPV).

Our second source, Bankscope, reports bank balance sheet information for a large number of credit institutions around the world. In absence of a common identification code across the two databases, we painstakingly merged them using as a reference the name of the bank and the country of residence. Each couple so obtained has been hand checked.

Because Bankscope's coverage of small banks across countries is not uniform, we restricted our analysis to banks with at least one billion US$ of total assets at the beginning of our sample period. Moreover, in order to remove potential outliers, we trimmed our data at the 1st and 99th percentile of all variables used in the empirical analysis. We end up with an unbalanced panel of 12,830 banks of 140 countries from 1991 to 2007. Of these, only 696 securitized their assets at least once during our sample period. Unfortunately, not all banks report balance sheet information continuously. In particular, information on charge-offs, loan loss reserves and capital are missing for a large number of credit institutions.

Data on the characteristics of each country's banking and financial sector and on the regulatory framework are from the World Bank database, respectively the updated versions of Beck *et al.* (2000) and Barth *et al.* (2004). Original data on deposit insurance are from Demirgüç-Kunt *et al.* (2005); in particular, the index of moral hazard of each country's deposit guarantee scheme is built as the first principal component of the dummies for no coinsurance, foreign currency deposits covered, interbank deposits covered, type of funding, source of funding, management and membership.

Table 1 presents summary statistics for our entire sample, distinguishing between banks that used CRT techniques and banks that did not. The average size of the banks in our sample is US$ 33.7 billion. The size distribution is strongly skewed to the left, as confirmed by the fact that the median value is of only 3.6 billion. Securitizing banks are much larger than others, with average assets of 118.4 billion and a median of 26.1 billion. They differ from the control group also along other dimensions. Banks active in CRT have on average a lower return on assets (0.80 versus 0.91) in spite of their higher risk (net charge-offs are 0.38 percent of total assets, as against 0.29 per cent for the control group), smaller loan loss reserves as a ratio of net charge-offs (13.7 versus 19.7) and a lower Z-score[16] (0.37 versus 0.52). Moreover, they are less capitalized (1.7 per cent of excess capital versus 4.6) and less liquid (14.6 as opposed to 16.4). Finally, they have a slightly lower share of demand deposits over total liabilities and equity (0.18 versus 0.19) and a smaller share of mortgages over total loans (0.47 versus 0.52). Comparing other sample statistics, it turns out that the patterns found for the mean are confirmed also by the medians.

These differences between characteristics of securitizing banks and other credit institutions might be related to the decision to transfer credit risk. However, sample statistics are not informative on the causal link between bank characteristics and the use of CRT techniques, as they could simply reflect spurious correlations (driven for example by differences in the size or country distribution between the securitizing banks and the control group). For all these reasons, we estimate a multivariate empirical model.

IV. Ex-ante characteristics of securitizing banks

A. Baseline specification

In the following, we will present the results of the econometric analysis on the ex-ante characteristics of banks that make use for the first time of securitization techniques in which our hypotheses are tested within a unified regression framework.

Since our focus is on the ex-ante characteristics of banks deciding to start using securitization techniques, we use a duration model to estimate the probability that at each point in time a bank begins to securitize its assets issuing either an ABS, an MBS, a CLO or a CDO. The general specification that we adopt is that of a survival-time data model by the method of proportional hazards regression first proposed by Cox (1972):

$$\lambda(t_i) = e^{-\beta' x_{it}} \lambda_0(t_i) \qquad (1)$$

where λ_0 is the 'baseline' hazard and X_{ijt-1} is the set of explanatory variables affecting the hazard rate, which includes characteristics of bank *i* of country *j* at time *t*-1, characteristics of country *j* at time *t*-1. Estimates are conducted stratifying by year, bank specialization and balance sheet consolidation. As already mentioned, we examine the factors that lead banks to securitize for the first time and therefore, after the event, the securitizing banks are dropped from the sample.

[16] Assuming that profits follow a normal distribution, a Z-score defined as Z = (ROA+CAR)/σ(ROA) – where ROA are return on assets, σ(ROA) their standard deviation and CAR the capital-asset ratio – measures the number of standard deviations that a bank's ROA has to drop below its expected value before equity is depleted (i.e., that *Prob.*(-ROA<CAR); see, Laeven and Levine (2008)). Having yearly data, we calculate the sample variance over the previous five years and run some robustness checks using variance calculated over three years.

In our analysis we pool together banks from different countries, with different norms and market standards. These differences could influence banks' behavior and the decision to transfer credit risk. For example, Calomiris and Mason (2004) find that U.S. banks securitize their loans in order to bring their capital ratios in line with the standards that are considered as adequate in their specific market of activity.[17] To address the potential heterogeneities that might stem from international differences in market standards, we express all bank-specific variables in deviation from the respective time and country medians. Notice that this choice imposes a very demanding control on our data.[18]

We estimate the empirical model using as controls the non-securitizing banks. Since information on some bank characteristics that are likely to affect the probability that they securitize is not available for the entire sample, we present different specifications trading off the number of regressors with the sample size (in all regressions we report robust standard errors corrected for clustering at the country level).

Panel 1 of Table 2 presents the results of our first specification, estimated on an unbalanced panel of 50,062 observations, including 6,582 banks from 108 countries over 15 years, with 296 instances of first time securitizations.[19] Banks that are more likely to securitize are larger (the coefficient of size is positive and statistically significant). This is consistent with the fixed costs hypothesis, suggesting that the legal and administrative costs of organizing the securitization deals are indeed non negligible. The securitizing banks are also characterized by a larger share of loans over total assets than their competitors: consistent with the liquidity hypothesis, this suggests that these banks decide to securitize their assets in order to increase the overall liquidity of their portfolio. The negative and significant coefficient of the share of deposits over total liabilities provides instead support to the cost of funding hypothesis, as banks with more short term deposits may be more vulnerable to the negative effects of the opacity that is associated to securitization.

In Panel 2 we report the results of a richer specification that includes a larger set of explanatory variables but with a smaller sample (3,268 banks from 73 countries, with 108 instances of securitization).[20] The results confirm those of Panel 1: even for this smaller sample, securitizing banks are larger than average, have a larger share of loans over total assets and a lower proportion of deposits over total liabilities. The positive and significant coefficient of liquid assets provides additional evidence in favor of the liquidity hypothesis.

[17] Due to the influence of banks' analysts on market dynamics, market standards likely influence banks' behavior also in many other important dimensions. For example, the opinions of analysts on what are to be considered adequate standards for banks operating in a given market are likely to influence banks' choice of the liquidity ratio, the overall risk of the loan portfolio, the maturity mismatch, etc..

[18] We replicate our regressions by: a) using banks level variables and stratifying also by country; and b) adding back the country- and time-specific medians to all bank characteristics. The main results are unchanged.

[19] The smaller number of securitizations with respect to what reported in the descriptive statistics depends on: a) the fact that only the first instance of securitization is used in the estimation; b) the trimming of extreme value observations; c) the unavailability of information on the ratio of deposits over total liabilities and the share of loans over total assets for some banks.

[20] Noticeably, the share of securitizing banks remains broadly constant at about 4 per cent.

Panel 2 also shows that the securitizing banks have a larger share of net charge-offs over total assets. This result is consistent with the risk-removal hypothesis, suggesting that riskier banks sell their loans in order to reduce the overall risk of the credit portfolio. The positive and statistically significant coefficient of the returns on equity – implying that banks with a higher franchise value, proxied by profitability, are more likely to securitize their loans – provides further support to the risk-removal hypothesis. At the same time, the higher-than-average value of net charge-offs is at odds with the predictions of the lemon discount hypothesis, as the securitizing banks do not seem to have any particular advantage in certifying the quality of their loan portfolio, and hence are unlikely to face lower securitization costs.

In Panel 3 we report the results of an even richer specification, with a sample of 2,000 banks from 58 countries between 1997 and 2007, with 79 instances of securitization. Consistent with the capital ratio hypothesis, less capitalized banks are more likely to securitize their assets, as shown by the negative and significant coefficient of the total capital ratio. These institutions have strong incentives to use securitizations in order to improve their regulatory capital ratios. Moreover, the negative sign of the Z-score provide further support to the risk-removal hypothesis, although the coefficient is not statistically significant.

The story that has emerged so far is in line with conventional wisdom. Overall, our results suggest that securitizations are mainly used by large and profitable banks willing to contain risk in different ways: by reducing credit risk, containing the exposure to liquidity shocks and improving the capital ratio. In the next section we challenge our results by performing a number of robustness check and including in our analysis country-specific controls.

B. Robustness checks

Large vs. small banks. One potential problem with our results is that some intermediaries – in particular, small banks – sell their mortgages, typically without recourse, to larger banks that eventually securitize them. Unfortunately, these operations are not registered in our data set, and hence in these cases we cannot identify the banks that originated and initially sold the loans. This could affect our results, because the performance of these banks would be affected by operations that however are not recorded in the left-hand side of equation (1).

In order to address this issue we replicate our main regression by considering only the largest banks, that are unlikely to sell their loans to third parties, but instead securitize them directly or indirectly (via an SPV). Table 3, Panel 1, reports the results obtained by estimating the empirical model presented in Table 2 for the 739 large banks included in the first three deciles of the size distribution. In this sample the incidence of securitizations is about 9 per cent, more than double that of the entire sample. Reassuringly, the results are statistically much starker than those obtained from the entire sample, and confirm all our previous findings. [21]

[21] In the residual set of 1,454 smaller banks there are only 10 instances of securitization.[22] In the residual set of 566 banks that are not retail oriented there are only 16 instances of securitization.

Commercial vs. investment banks. The previous analyses includes different types of banks, from retail to investment/wholesale banks. This could induce confounding effects, as the composition of the risks and the sources of funding faced by these two types of banks differ substantially. For example, credit risk is likely to be much more relevant for retail banks, while liquidity risks tend to be prominent for wholesale-oriented banks. To address this potential issue, in Panel 2 of Table 3 we report the results of estimating our model for a sample of 1,434 retail-oriented intermediaries, including commercial, saving and cooperative banks. The results are similar to those obtained for the entire sample, although the coefficient of the share of loans over total assets is not significantly different from zero, weakening only in part the support for the liquidity hypothesis. Liquidity factors are instead relevant for the sub-sample of investment/wholesale banks (results unreported),[22] while the risk-related variables are less significant.

Other bank characteristics. In addition to the characteristics included in our baseline specification, we have (i) checked that other bank features might influence the probability that they securitize their assets, (ii) used alternative measures of riskiness, opaqueness and profitability, and (iii) checked for possible non-linear effects.

Panel A of Table 4 shows that banks with a larger share of problem loans are less likely to securitize, consistent with the lemon discount hypothesis. Reassuringly, while the inclusion of this additional control variable further reduces our sample to less than 9,000 observations, the signs of all other regressors remain unchanged, although their significance in some cases changes. Interestingly, the effect of the Z-score is in this case strongly significant. In Panel B we introduce a term interacting the Z-score with a dummy for larger banks (as before, we include banks in the first three deciles of the sample distribution). We find that the effect of higher riskiness is statistically significant especially for this class of intermediaries. Finally, Panel C shows that substituting returns on equity with returns on assets as a measure of the franchise value does not change our results.

In a number of unreported regressions we check the potential effect of a large number of additional bank characteristics, but none turned out to be statistically significant.[23] In particular, the share of mortgages over total loans has a negative and insignificant effect, most likely because securitizations are relevant also for banks that are less active in the house market, but have a larger share of other types of standardized loans, such as credit card receivables and consumer loans (for which we have no information). Banks that have a higher share of fee-based income are also no more likely to securitize their assets than other banks, neither are relevant characteristic the incidence of funding with money market instruments or the fact that a bank is listed. Finally, we find no evidence that the degree of diversification of banking activities, measured by the two indices proposed by Laeven and Levine (2007), has a significant effect.

[22] In the residual set of 566 banks that are not retail oriented there are only 16 instances of securitization.
[23] These and all other unreported results are available from the authors upon request.

Cross-country differences. As already mentioned, in order to control for country-specific factors that could determine confounding effects on our results, the bank-specific variables included in our regressions are expressed in deviation from the respective country- and time-specific median. However, even this tight control might not be sufficient to take into account country-specific factors. In order to address this issue, we conduct a number of checks.

First, we replicate our baseline regression by controlling for the main characteristics of the financial system of each country. We start by examining the hypothesis that banks securitize their assets in order to supply additional long term securities to long-term investors willing to acquire exposure to credit risk. We then include in our regression the lagged value of total assets of institutional investors as a share of GDP. The coefficient of this variable is positive and statistically significant, confirming the importance of these investors as potential buyers in the securitization market (in unreported regressions, we also check that the sheer effect of life and non-life insurance development is not significant). We then include a time-varying measure of specialization of each country's financial market (the ratio of bank private credit to its sum with the value of outstanding private bonds and equities in each year). If banks securitize in reaction to the competition in their traditional lending activities coming from arm's length financing, those countries where financial markets are relatively more developed than credit markets should have a higher incidence of securitization. In addition, in countries with more developed financial markets it should be easier for banks to find acquirers for their asset backed securities. We therefore expect a negative coefficient. However, contrary to our expectation, we find no significant effect (Table 5, Panel A). Similar results are obtained abstracting from business-cycle fluctuations and considering country averages over our sample period.[24] .

Second, we consider the impact of general economic conditions. The sale of banks' securitized assets is likely to be easier when the economy is buoyant, since this is associated with a lower risk of default. Panel C confirms this hypothesis, showing that lagged real GDP growth has a positive and statistically significant effect.[25]

We then analyze the effect of different regulatory regimes. Most of these measures are time invariant, due to data availability and to the typically low variability of countries' regulatory frameworks, limiting the possibilities to uncover statistically significant effects. To any extent, Panel D shows that securitizations are significantly less likely in countries where commercial bank supervisory agencies are more powerful, because they have right to meet with auditors, force a bank to change its internal organizational structure, and oblige it to provision against potential losses (Caprio *et al.*, 2007). In addition, we checked whether the

[24] In unreported regressions, available from the authors upon request, we also found that securitizations are more frequent in less developed financial systems (i.e., those with a lower ratio of private credit and stock market capitalization over GDP).

[25] Optimistic expectations and a stronger appetite for risk are typically associated also with stock market appreciations. We checked whether securitizations are a positive function of the growth in stock market capitalization over GDP, but found no significant effect.

probability that a bank securitizes its assets depends on other institutional characteristics, such as (1) the degree of moral hazard induced by the deposit insurance guarantee scheme, also interacted with our measures of bank's risk attitude, (2) the presence of one or more supervisory authorities responsible for bank supervision, (3) the presence of a unique authority responsible of supervision of all financial companies, (4) the quality and effectiveness of governance in the country (Kaufmann *et al.*, 2009). None of these variable is statistically significant.

Finally, since innovative behaviors in financial markets typically spread rapidly, for example because banks and other operators learn from their peers, in Panel E we include the number of other banks in each country that contemporaneously securitized for the first time their assets, excluding the bank under scrutiny. As expected, this effect is positive and highly significant, confirming the potential for herd effects or common omitted factors at the country level.

Reassuringly, the inclusion of country characteristics leaves the results of the baseline specification substantially unchanged, although the statistically significance of some coefficients is sometime affected, especially when the sample size is reduced.

Further robustness checks. Finally, Table 6 present the results obtained using different estimation techniques. Panel A estimates a Cox hazard model stratifying also on country, and expressing bank-specific variables in levels instead of deviations from the respective time and country medians. Panel B estimates instead a logistic model, removing after the event the observations of banks that securitized. Finally, the coefficient estimates reported in Panel C are the same as in the baseline specification, but the standard errors are clustered at the bank rather than at the country level. In all cases, the size and the magnitude of the coefficients are in line with those of the baseline specification, although statistical significance is in some specifications different. In unreported regressions we also check that our results are robust to the inclusion of the time and country medians of bank characteristics.

V. Ex-post effects of securitization

Finding what are the ex-ante characteristics of banks making use of securitization techniques is only half of the story. The following question is on the ex-post effects of this operations on banks' balance sheet characteristics and behavior.

To estimate these effects we specify a difference in difference model around the event of the first securitization. Following Focarelli and Panetta (2004), we adopt the following a flexible specification that allows us to distinguish the instantaneous impact of securitizations on bank balance sheets from the longer time effects:

$$R_{it} = \alpha + \gamma_1 DU_{it} + \gamma_2 DU_{it-1} \ldots \gamma_i DU_{it-i} + \delta_1 X_{it} + \delta_2 d_i + \delta_3 d_t + \varepsilon_{it} \qquad (2)$$

where R_{it} is any measure of the characteristics of bank i at time t, DU_{it-i} is a dummy variable that takes the value of 1 if bank i securitized its assets at time $t-i$, X_{it-1} is a set of bank specific characteristics at time $t-1$ (typically total assets), d_i is a bank specific fixed effect, d_t is a time dummy, and ε_{it} is a random error. In this model, non-securitizing banks are used as controls for the behavior of securitizers.

In line with the hypothesis put forward in Section I, we have analyzed the effects of securitizations on: the ratio of demand deposits to total liabilities, the share of loans over total assets, the ratio of net charge-offs to total assets, the Z-score, the share of problem loans on total loans, the ratio of loan loss reserves to total assets, the rate of growth of loans and the capital ratio.

Table 7 presents the results. Since securitizations are unlikely to exhaust their effects on bank balance sheets immediately after they are completed, we measure the effect on the entire transition period, defined as the year of the securitization and the two following years. In unreported regressions we verified the hypothesis that the effect of securitization is constant during the entire transition period. We do so by estimating separately the three dummies for the same year, first year and second year effect after the securitization, and test the linear restrictions of imposing the equality of the coefficients. The values of the F-tests, reported in Table 7, confirm that in all our specifications these restrictions cannot be rejected at very high levels of confidence. The only exception is the effect of securitizations on the Z-score, that only becomes significant starting form the second year. In this case we consider a shorter transition period of just two years.

In addition to the effects during the transition period, we also analyze the longer run effects, including a dummy for the years after the second, defined as “completion period”. Our aim is in particular to verify if banks change their behavior after they have overcome the explicit and implicit barriers for acceding the securitization market, seeing it as a straightforward option, even if they do not use it every year.

Panel 1 shows that securitizations have not any ex-post effect on the ratio of deposits to total liabilities in the transition period, neither in the completion period. The potential negative effect on the cost of funding of the opacity of securitizations, that we found to impact significantly on the ex-ante probability that a bank securitizes, is balanced by the positive liquidity effect coming from the additional option to use securitizations as a funding source, making the overall ex-post effect insignificant.

Panel 2 shows that first time securitizers reduce in the short run their share of loans to total assets, although the coefficient is only statistically significant at the 10 per cent level. Indeed, since we found that securitizing banks have a higher share of loans to assets than non-securitizers, this result might be due not to the securitization itself, but rather to a process of asset reallocation away from risky loans. In the following, we will analyze this hypothesis more thoroughly.

Panels 3-6 provide clear evidence that securitizations affect the level bank risk and a number of choices related to this. Consistent with the risk-removal hypothesis, Panel 3 shows that securitizing banks experience a significant reduction in the ratio of net charge-offs to total assets, both in the transition and in the completion period. Panel 4 shows that they also have an increase in their Z-score, in this case starting from the second year after the operation took place, consistent with the risk-removal and the diversification hypotheses. However, securitizations do not reduce the ratio of problem loans to total loans (Panel 5), although they affects bank's choice on the level of loan loss reserves, that see a significant decline in both the transition and the completion periods (Panel 6).

Finally, first time securitizers have an ex-post higher absolute rate of growth of loans (Panel 7) and, consistent with the capital ratio hypothesis, higher capital ratios, the more so during the completion period (Panel 8).

These results further reinforce the findings of the ex-ante analysis, supporting in particular the view that banks used securitization techniques to remove risks from their balance sheets and to increase their capital ratios.

A problem with our results is that they could suffer from a potential endogeneity bias, if intermediaries with specific characteristics self-selected into the pool of securitizers. Indeed, our previous specification already controlled very robustly for the effects of bank specific features with the inclusion of bank fixed effects, but this could be insufficient if the relevant determinants were time varying. To account for this possibility, we follow Heckman's (1979) two-step procedure and control for the potential self-selection bias created by banks' choice to securitize their asset by modeling it formally into the econometric estimation. The first step involves a probit estimation of the probability that a bank is a first time securitizer. Trading off the richness of our previous specifications of the ex-ante determinants of securitizations with the opportunity of retaining a large number of observations for the ex-post analysis, we choose to include as explanatory variables only the logarithm of the total assets, the number of other securitizers in the same country and in the same year, specialization, country and time dummies. In the second step, the inverse Mill's ratio obtained from the probit estimation is then included among the regressors in model (2).

The results of the augmented model are reported in Table 8. A negative coefficient of the inverse Mill's ratio implies that banks whose characteristics make them more likely to securitize have a lower level of the dependent variable, as it is the case for the ratio of deposits to total liabilities (Panel 1), the ratio of loans to assets (Panel 2) and the rate of growth of loans (Panel 7). The opposite is true for a positive coefficient, as in the case of problem loans (Panel 5), loan loss reserves (Panel 6) and the capital ratio (Panel 8).

The results of the selection model broadly confirm those of the previous estimates. The only exception is the coefficient of the transition period for the ratio of loans to total assets, that controlling for self-selection becomes negative and insignificantly different from zero (Panel

2). The estimated reduction in the share of loans after a securitization is therefore not due to the operation, but to bank characteristics that made the operation itself more likely.

VI. Discussion and conclusions

The recent crisis has put under severe attack the use of credit risk transfer techniques, and their riskiness and opaqueness have been seen as the major causes of the financial turmoil. Banks have been accused of using these instruments carelessly, if not cunningly, to remove risky assets from their balance sheets, increase leverage and boost profits.

In this paper we have analyzed the ex-ante determinants of banks' securitizations and their ex-post effects, using a large sample of intermediaries from over 100 world countries. As it might have been expected, our evidence shows a much more multifaceted, and less negative, scenario. Securitizations are mainly used by large and profitable banks willing to reduce credit risk, contain the exposure to liquidity shocks and improve their capital ratios. Interestingly, the ex-post evidence shows that these goals were initially achieved. In the years following the first securitization, banks experienced a reduction of their overall riskiness and an improvement of their capital ratios.

The crisis has made well clear that some banks have eventually used far too aggressively the possibilities offered by the new techniques for removing the risks from their balance sheets. But, if properly used, these techniques can indeed have positive effects.

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Table 1

Summary statistics

Net charge-offs, loan loss provisions and liquid assets are expressed as percentages of total assets. Securitizers are banks that originated issues of asset backed securities (ABSs), mortgage backed securities (MBSs), collateralized loan obligations (CLOs) or collateralized debt obligations (CDOs). Excess capital is the difference between regulatory capital ratio and the legal requirement in the country; Z-score is defined as (ROA+CAR)/σ(ROA), where ROA are return on assets, σ(ROA) their standard deviation and CAR the capital-asset ratio. The source of data is Bankscope for balance sheet information, Dealogic for bond issues.

Variable	Obs.	Mean	Coeff. of var.	Median	1st percentile	99th percentile
			Panel A: full sample			
Total assets	12,830	33.69	3.63	3.58	0.48	595.17
Liquid / total assets	8,864	16.39	1.03	11.03	0.01	80.62
Returns on assets	10,086	0.91	1.03	0.73	-0.63	4.63
Returns on equity	10,062	10.52	0.79	9.91	-10.85	37.02
Mortgages / total loans	4,095	0.52	0.55	0.52	0.00	1.00
Loans / total assets	9,518	54.44	0.43	58.92	0.18	96.43
Deposits / total liabilities	7,912	0.19	1.01	0.13	0.00	0.94
Money mkt. fund. /tot. liab. and eq.	8,711	12.14	1.94	4.42	0.01	121.28
Net charge-offs / total assets	5,445	0.29	1.64	0.15	-0.11	2.62
Loss reserves / charge-offs	4,726	19.65	2.19	7.38	-42.60	229.26
Z-score	6,410	0.52	1.95	0.34	0.08	3.09
Excess capital	3,631	4.57	3.70	2.47	-11.00	62.28
Dep. and sh. term liab. / tot. ass.	9,185	74.24	0.28	82.20	3.95	95.01
Problem loans / total assets	7,177	0.69	0.50	0.85	0.01	1.00
Problem loans / total loans	5,752	0.77	0.40	0.99	0.02	1.00
Capital / total assets	10,538	0.17	0.96	0.13	0.00	0.85
			Panel B: securitizers			
Total assets	1,248	118.37	2.10	26.06	0.94	1275.06
Liquid / total assets	750	14.56	0.96	11.60	0.00	68.10
Returns on assets	963	0.80	0.99	0.67	-0.42	4.19
Returns on equity	960	11.04	0.70	10.80	-8.62	34.09
Mortgages / total loans	402	0.47	0.59	0.43	0.00	1.00
Loans / total assets	814	57.69	0.39	59.98	0.15	95.41
Deposits / total liabilities	678	0.18	0.96	0.14	0.00	0.92
Money mkt. fund. /tot. liab. and eq.	919	9.43	1.54	4.57	0.01	67.74
Net charge-offs / total assets	590	0.38	1.54	0.21	-0.21	3.12
Loss reserves / charge-offs	488	13.67	2.57	4.93	-46.73	212.82
Z-score	500	0.37	0.50	0.31	0.13	1.26
Excess capital	421	1.63	9.58	0.17	-11.00	17.32
Dep. and sh. term liab. / tot. ass.	780	68.13	0.31	74.27	4.51	93.95
Problem loans / total assets	755	0.73	0.46	0.95	0.00	1.00
Problem loans / total loans	534	0.83	0.35	1.00	0.00	1.00
Capital / total assets	1,006	0.14	0.95	0.11	0.00	0.75

Table 1 (continues)

Variable	Obs.	Mean	Coeff. of var.	Median	1st percentile	99th percentile
			Panel C: non securitizers			
Total assets	11,582	24.56	3.88	3.03	0.46	458.53
Liquid / total assets	8,114	16.56	1.03	11.01	0.01	82.96
Returns on assets	9,123	0.92	1.04	0.74	-0.65	4.71
Returns on equity	9,102	10.47	0.80	9.79	-11.46	37.09
Mortgages / total loans	3,693	0.53	0.54	0.53	0.00	1.00
Loans / total assets	8,704	54.13	0.44	58.81	0.18	96.47
Deposits / total liabilities	7,234	0.19	1.01	0.13	0.00	0.94
Money mkt. fund. /tot. liab. and eq.	7,792	12.46	1.96	4.40	0.01	125.53
Net charge-offs / total assets	4,855	0.28	1.64	0.15	-0.10	2.54
Loss reserves / charge-offs	4,238	20.34	2.15	7.64	-41.05	229.26
Z-score	5,857	0.42	0.60	0.33	0.11	1.42
Excess capital	3,203	4.86	3.43	2.71	-9.41	62.28
Dep. and sh. term liab. / tot. ass.	8,405	74.81	0.28	82.72	3.84	95.05
Problem loans / total assets	6,422	0.68	0.51	0.84	0.01	1.00
Problem loans / total loans	5,218	0.76	0.40	0.98	0.02	1.00
Capital / total assets	9,532	0.17	0.96	0.13	0.00	0.85

Table 2

Determinants of the use of securitization

The event analyzed is the first time a bank was a securitizer (issued either ABSs, MBSs, CLOs or CDOs). The model is estimated using the proportional hazards regression specification proposed by Cox (1972), with stratification by year, balance sheet consolidation type and specialization. All independent variables are lagged one period. All variables are expressed as differences from time and country medians, except in Panel 4. Bank type and balance sheet report consolidation type dummies are included in all specifications. Z-score is defined (ROA+CAR)/σ(ROA), where ROA are return on assets, σ(ROA) their standard deviation and CAR the capital-asset ratio. The source of data is Bankscope for balance sheet information, Dealogic for bond issues. Robust standard errors adjusted for clustering at the country level are reported in italic. The symbol *** indicates a significance level of 1 per cent or less; ** between 1 and 5 per cent; * between 5 and 10 per cent.

Variables	(1)			(2)			(3)		
	Coef. *St.err.*	Sig.	Marg. eff.	Coef. *St.err.*	Sig.	Marg. eff.	Coef. *St.err.*	Sig.	Marg. eff.
Total assets (log)	0.55	***	0,83	0.60	***	1,38	0.62	***	2,38
	0.08			*0.13*			*0.18*		
Loans / total assets	0.01	***	0,02	0.01	**	0,03	0.01		0,04
	0.00			*0.01*			*0.01*		
Demand deposits / liabilities	-0.93	**	-1,40	-1.74	***	-4,02	-2.06	***	-7,88
	0.41			*0.44*			*0.65*		
Liquid / total assets				0.01		0,02	0.03	**	0,11
				0.01			*0.01*		
Net charge offs / total assets				0.49	***	1,14	0.51	***	1,96
				0.15			*0.13*		
Returns on assets				0.04	***	0,08	0.05		0,19
				0.01			*0.01*		
Capital ratio (3 years average)							-0.09	***	-0,32
							0.02		
Z-score (5 years average)							-0.36		-1,38
							0.33		
Observations			50,062			22,052			10,122
No. of securitizers			296			114			85

Table 3

Determinants of the use of securitization: large and retail banks

The event analyzed is the first time a bank was a securitizer (issued either ABSs, MBSs, CLOs or CDOs). The model is estimated using the proportional hazards regression specification proposed by Cox (1972), with stratification by year, consolidation type and specialization. Retail banks are commercial, saving and cooperative banks; large banks are those in the first three deciles of the distribution by size. All independent variables are lagged one period. All variables are expressed as differences from time and country medians. Z-score is defined (ROA+CAR)/σ(ROA), where ROA are return on assets, σ(ROA) their standard deviation and CAR the capital-asset ratio. The source of data is Bankscope for balance sheet information, Dealogic for bond issues. Robust standard errors adjusted for clustering at the country level are reported in italic. The symbol *** indicates a significance level of 1 per cent or less; ** between 1 and 5 per cent; * between 5 and 10 per cent.

Variables	(1) Large banks			(2) Retail banks		
	Coef. *St.err.*	Sig.	Marg. eff.	Coef. *St.err.*	Sig.	Marg. eff.
Total assets (log)	0.66	***	6,90	0.59	***	1,66
	0.23			*0.18*		
Loans / total assets	0.03	***	0,27	0.01		0,03
	0.01			*0.01*		
Demand deposits / liabilities	-2.88	***	-29,97	-1.77	**	-4,93
	0.84			*0.74*		
Liquid / total assets	0.04	**	0,38	0.03	*	0,09
	0.02			0.02		
Net charge offs / total assets	0.48	**	4,94	0.53	***	1,47
	0.22			0.12		
Returns on equity	0.04	***	0,46	0.05	***	0,13
	0.01			*0.01*		
Capital ratio (3 year average)	-0.10	***	-1,02	-0.08	***	-0,23
	0.02			*0.03*		
Z-score (5 year average)	-0.47		-4,91	-0.37		-1,02
	0.33			0.35		
Observations		3,441			6,731	
No. of securitizers		69			69	

Table 4

Determinants of the use of securitization: additional bank controls

The event analyzed is the first time a bank was a securitizer (issued either ABSs, MBSs, CLOs or CDOs). The model is estimated using the proportional hazards regression specification proposed by Cox (1972), with stratification by year, consolidation type and specialization. Retail banks are commercial, saving and cooperative banks; large banks are those in the first three deciles of the distribution by size. All independent variables are lagged one period. All variables are expressed as differences from time and country medians. Z-score is defined (ROA+CAR)/σ(ROA), where ROA are return on assets, σ(ROA) their standard deviation and CAR the capital-asset ratio. The source of data is Bankscope for balance sheet information, Dealogic for bond issues. Robust standard errors adjusted for clustering at the country level are reported in italic. The symbol *** indicates a significance level of 1 per cent or less; ** between 1 and 5 per cent; * between 5 and 10 per cent.

Variables	(1)			(2)			(3)		
	Coef. *St.err.*	Sig.	Marg. eff.	Coef. *St.err.*	Sig.	Marg. eff.	Coef. *St.err.*	Sig.	Marg. eff.
Total assets (log)	0.62	***	2.42	0.70	***	4.55	0.64	***	2.27
	0.18			*0.15*			*0.18*		
Loans / total assets	0.01		.039	0.01		0.04	0.01		0.04
	0.01			*0.01*			*0.01*		
Demand deposits / liabilities	-2.18	***	8.52	-2.47	***	-16.04	-1.88	***	-6.68
	0.60			*0.68*			*0.64*		
Liquid / total assets	0.03	**	.12	0.03	*	0.20	0.03	**	0.10
	0.01			*0.02*			*0.01*		
Net charge offs / total assets	0.51	***	1.98	0.63	***	4.10	0.48	***	1.71
	0.12			*0.21*			*0.10*		
Returns on equity	0.05	***	.20	0.06	***	0.39			
	0.01			*0.01*					
Capital ratio (3 years average)	-0.09	***	-.35	-0.11	***	-0.74	-0.09	***	-0.34
	0.02			*0.04*			*0.02*		
Z-score (5 years average)	0.53		2.09			-5.24	-0.21		-0.75
	0.56						*0.31*		
Z-score (5 years)*large banks	-1.17	*	-4.59						
	0.64								
Problem loans / total loans				-0.81	***	-4.57			
				0.28					
Returns on assets							0.29	*	1.03
							0.16		
Observations		8,880			10,124			10,117	
No. of securitizers		51			76			76	

Table 5

Determinants of the use of securitization: country characteristics

Variables	(1)			(2)			(3)			(4)			(5)		
	Coef. *St.err.*	Sig.	Marg. eff.	Coef. *St.err.*	Sig.	Marg. eff.	Coef. *St.err.*	Sig.	Marg. eff.	Coef. *St.err.*	Sig.	Marg. eff.	Coef. *St.err.*	Sig.	Marg. eff.
Total assets (log)	0.65	***	3,07	0.65	***	3,26	0.64	***	4,23	0.62	***	0,22	0.61	***	2,91
	0.19			*0.20*			*0.17*			*0.20*			*0.18*		
Loans / total assets	0.01		0,04	0.01		0,04	0.01		0,06	0.01		0,00	0.01		0,03
	0.01			*0.01*			*0.01*			*0.01*			*0.01*		
Dem. Dep. / Liab.	-2.04	***	-9,67	-2.33	***	-11,63	-1.79	***	-11,75	-2.28	***	-0,82	-2.30	***	-10,90
	0.50			*0.49*			*0.64*			*0.53*			*0.55*		
Liquid / total assets	0.03	**	0,15	0.03	**	0,16	0.03	*	0,18	0.03	**	0,01	0.03	**	0,13
	0.01			*0.01*			*0.02*			*0.01*			*0.01*		
Net ch. offs / T. ass.	0.57	***	2,69	0.71	***	3,55	0.58	***	3,82	0.57	***	0,21	0.54	***	2,56
	0.12			*0.07*			*0.10*			*0.09*			*0.11*		
Returns on assets	0.05	***	0,22	0.04	***	0,21	0.05	***	0,31	0.05	***	0,02	0.05	***	0,24
	0.01			*0.01*			*0.01*			*0.01*			*0.01*		
Cap. Rat. (3 yrs. av.)	-0.11	***	-0,52	-0.10	***	-0,49	-0.08	***	-0,54	-0.11	***	-0,04	-0.09	***	-0,40
	0.02			*0.01*			*0.02*			*0.02*			*0.02*		
Z-score (5 yrs. av.)	-0.46		-2,16	-0.25		-1,25	-0.37		-2,46	-0.30		-0,11	-0.30		-1,42
	0.31			*0.28*			*0.33*			*0.31*			*0.33*		
Bank cr / T. fin.ass.	0.33		1,57				0.64								
	2.46						*0.17*								
Inst. inv / GDP				0.05	***	0,24									
				0.02											
GDP growth							0.14	***	0,92						
							0.04								
Supervision										-0.20	***	-0,07			
										0.08					
Other securitiziers													37.16	***	175,74
													8.73		
Observations		9,402				9,017			10,022			9,320		10,124	
No. of securitizers		67				64			73			69		76	

Table 6

Determinants of the use of securitization: alternative econometric specifications

The event analyzed is the first time a bank was a securitizer (issued either ABSs, MBSs, CLOs or CDOs). The model is estimated using the proportional hazards regression specification proposed by Cox (1972), with stratification by year, consolidation type and specialization. Retail banks are commercial, saving and cooperative banks; large banks are those in the first three deciles of the distribution by size. All independent variables are lagged one period. All variables are expressed as differences from time and country medians. Z-score is defined (ROA+CAR)/σ(ROA), where ROA are return on assets, σ(ROA) their standard deviation and CAR the capital-asset ratio. The source of data is Bankscope for balance sheet information, Dealogic for bond issues. Robust standard errors adjusted for clustering at the country level are reported in italic. The symbol *** indicates a significance level of 1 per cent or less; ** between 1 and 5 per cent; * between 5 and 10 per cent.

Variables	(1) Stratification by country			(2) Logistic model			(3) Cluster by bank		
	Coef. *St.err.*	Sig.	Marg. eff.	Coef. *St.err.*	Sig.	Marg. eff.	Coef. *St.err.*	Sig.	Marg. eff.
Total assets (log)	0.70	***	29,17	0.56	***	0,44	0.61	***	2,15
	0.17			*0.16*			*0.08*		
Loans / total assets	0.02	**	0,87	0.02	**	0,01	0.01		0,04
	0.01			*0.01*			*0.01*		
Demand deposits / liabilities	-1.92	***	-80,15	-1.55	***	-1,22	-1.97	***	-7,01
	0.66			*0.58*			*0.76*		
Liquid / total assets	0.04	**	1,54	0.03	**	0,02	0.03	***	0,11
	0.01			*0.02*			*0.01*		
Net charge offs / total assets	0.67	***	27,81	0.53	***	0,42	0.50	***	1,79
	0.08			*0.08*			*0.19*		
Returns on assets	0.04	**	1,51	0.04	***	0,03	0.05	***	0,16
	0.02			*0.01*			*0.01*		
Capital ratio (3 years average)	-0.09	***	-3,64	-0.07	*	-0,06	-0.08	***	-0,30
	0.01			*0.04*			*0.03*		
Z-score (5 years average)	-0.41	*	-16,93	-0.46		-0,36	-0.35		-1,24
	0.22			*0.34*			*0.32*		
Observations		10,124			9,954			10,1026	
No. of securitizers		76			76			76	

Table 7

Effects of securitizations on bank balance sheet

The dependent variable is the level of the variable reported in each column of the first row. Transition period is a dummy variable taking the value of one in the year of the first securitization made by the bank (issue either of ABSs, MBSs, CLOs or CDOs) and in the following two years; Completion period takes the value of one from the third year after the first securitization onwards. In the case of the Z-score, the Completion period starts instead from the second year. Total assets are lagged one period. All regressions include bank specific fixed effects. Z-score is defined (ROA+CAR)/σ(ROA), where ROA are return on assets, σ(ROA) their standard deviation and CAR the capital-asset ratio. The source of data is Bankscope for balance sheet information, Dealogic for bond issues. The symbol *** indicates a significance level of 1 per cent or less; ** between 1 and 5 per cent; * between 5 and 10 per cent.

	Dem.dep. / liabilities (1)	Loans / tot. assets (2)	Net ch. offs / tot. assets (3)	Z-score (4)	Prob. loans / total loans (5)	Loan loss res. /tot. assets (6)	Loan growth (7)	Capital ratio (8)
Transition period	0.01	0.92 *	-0.10 ***	-0.00	-0.17	-0.19 ***	0.04 ***	0.35 *
(years 0-2)	*0.01*	*0.37*	*0.02*	*0.02*	*0.45*	*0.05*	*0.01*	*0.17*
Completion period	0.00	-0.01	-0.16 ***	0.13 ***	-0.04	-0.20 **	0.04 *	1.15 ***
(years 3+)	*0.01*	*0.56*	*0.03*	*0.04*	*0.65*	*0.07*	*0.01*	*0.26*
Total assets (log.)	-0.06 ***	1.01 ***	0.00	-0.08 ***	-0.77 ***	-0.03 *	-0.14 ***	-0.80 ***
	0.00	*0.12*	*0.01*	*0.01*	*0.16*	*0.02*	*0.00*	*0.07*
F-test for transition period effect (p-value)	0.92	0.57	0.71	0.26	0.83	0.78	0.43	0.31
Observations	32,724	40,079	20,448	31,198	22,369	27,940	39,617	24,770
Number of securitizers	192	252	128	205	158	210	249	214
R^2	0.059	0.027	0.019	0.018	0.020	0.034	0.115	0.020

Table 8

Effects of securitizations on bank balance sheet

The dependent variable is the level of the variable reported in each column of the first row. Transition period is a dummy variable taking the value of one in the year of the first securitization made by the bank (issue either of ABSs, MBSs, CLOs or CDOs) and in the following two years; Completion period takes the value of one from the third year after the first securitization onwards. In the case of the Z-score, the Completion period starts instead from the second year. The inverse Mill's ratio is obtained from a probit model regression of the probability that a bank is a first time securitizer in a given year, as a function of its total assets, the number of other securitizers in the same country and in the same year, and specialization, country and time dummies. Total assets are lagged one period. All regressions include bank specific fixed effects. Z-score is defined (ROA+CAR)/σ(ROA), where ROA are return on assets, σ(ROA) their standard deviation and CAR the capital-asset ratio. The source of data is Bankscope for balance sheet information, Dealogic for bond issues. The symbol *** indicates a significance level of 1 per cent or less; ** between 1 and 5 per cent; * between 5 and 10 per cent.

	Dem.dep. / liabilities (1)	Loans / tot. assets (2)	Net ch. offs / tot. assets (3)	Z-score (4)	Prob. loans / total loans (5)	Loan loss res. /tot. assets (6)	Loan growth (7)	Capital ratio (8)
Transition period	0.01	-0.06	-0.10 ***	0.00	0.24	-0.16 ***	0.03 **	0.54 **
(years 0-2)	*0.01*	*0.37*	*0.02*	*0.02*	*0.45*	*0.05*	*0.01*	*0.17*
Completion period	0.00	-0.63	-0.15 ***	0.13 ***	0.20	-0.18 **	0.03 *	1.25 ***
(years 3+)	*0.01*	*0.56*	*0.03*	*0.04*	*0.65*	*0.07*	*0.01*	*0.26*
Mill's ratio	-0.02 **	-7.05 ***	0.04	0.03	4.23 ***	0.16 **	-0.07 ***	1.45 ***
	0.01	*0.40*	*0.03*	*0.03*	*0.57*	*0.05*	*0.01*	*0.20*
Total assets (log.)	-0.06 ***	-0.13	0.01	-0.07 ***	-0.07	-0.01	-0.15 ***	-0.56 ***
	0.00	*0.14*	*0.01*	*0.01*	*0.18*	*0.02*	*0.00*	*0.07*
F-test for transition period effect (p-value)	0.93	0.24	0.71	0.28	0.77	0.79	0.32	0.43
Observations	32,724	40,079	20,448	31,198	22,369	27,940	39,617	24,770
Number of securitizers	192	252	128	205	158	210	249	214
R^2	0.059	0.027	0.020	0.017	0.020	0.034	0.115	0.020