Crisis Transmission in the Global Banking Network*

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Abstract

To shed light on the role of international bank connections in the transmission of financial sector shocks, we construct a global network of interbank exposures. We then study the impact of direct and indirect exposures to banks in crisis countries on bank profitability. We perform the analysis in a panel of 1,875 banks from 110 countries spanning the 1997-2012 period. We find that direct (first degree) and indirect (second degree) exposures to crises reduce bank profitability. Furthermore, banks with higher betweenness centrality, which tend to borrow from and lend to large numbers of banks, have lower profitability than other banks, especially when they have many crisis exposures. These results support the notion that interconnected systems are prone to shock transmission and that network position matters for bank performance.

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1 Introduction

In the wake of the global financial crisis much attention has been devoted to the role of interbank connections in the transmission of financial sector shocks. Policymakers argue that the interconnectedness of the global financial system, which has grown significantly in recent years, has contributed to the severity of the crisis (Dudley, 2012; Haldane, 2009). Recent studies emphasize the role of financial sector complexity in generating panics and deepening crises (Caballero & Simsek, 2009, 2013). We contribute to this discussion by analyzing the transmission of financial crises through the global banking network ("GBN"). Specifically, we model interbank exposures among a large number of banks as a network and analyze how banking crises are transmitted through these exposures to impact bank profitability. We examine the distinct effect of direct and indirect exposures to banks in countries that experience a crisis, as well as that of bank's overall network position in the GBN.

Using deal-level data on interbank syndicated loans, we construct a large financial network for each year between 1997 and 2012. This is a standard directed network in which edges represent interbank exposures (stocks of outstanding claims) and the nodes are banks. For each bank in the GBN, we construct measures of direct (first degree) and indirect (second degree) exposures to banks in crisis countries ("crisis exposures"). We then examine the link between these crisis exposures and bank profitability after controlling for the balance sheet characteristics of each bank and those of its direct and indirect counterparties. We find that direct exposures to crises reduce bank profitability. Indirect exposures to crises through crisis banks further reduce it, while indirect exposures to non-crises through crisis banks dampen the negative effect of direct crisis exposures.

We then test whether banks' global position in the GBN, or degree of centrality, affects their performance during crisis and normal times. We focus on a particular type of centrality to identify "key intermediaries" in the network. These are banks that are essential in connecting groups of banks and are defined as banks with positive betweenness centrality. Key intermediaries tend to borrow from global banks that are themselves highly centric and lend to peripheral banks. We find that banks with higher betweenness centrality, who play more of an intermediating role in the network, have lower profitability than other banks, especially when exposed to many banks in crisis countries.

Syndicated loan data, which are available at the deal level, represent a unique source of information about interbank lending and borrowing activities, and can be used to construct interbank exposures on a global scale. The syndicated loan market is an important source of funding for corporations and sovereigns, as well as for financial institutions, especially banks. Total deal volume reached USD 4.3 trillion at the peak in 2007, of which about 10 percent represented lending to banks. Loan syndications allow internationally active banks to diversify their portfolios while respecting individual counterparty exposure limits. Lending to banks allows them to learn about new foreign markets and to build relationships with banks that have local knowledge of those markets. This can be seen as an intermediate step before engaging in direct lending to corporations in new markets, some of which is done through co-syndications with domestic banks. Banks from both advanced economies and emerging markets tap this market to broaden their sources of funds and support balance sheet growth. The largest lenders and borrowers by volume are banks from the US and UK. Syndicated interbank borrowing is a sizeable share of bank liabilities in emerging market countries such as Latvia, Poland, and Turkey.

To construct the GBN we use data on 11,752 interbank syndicated loan deals issued during 1990-2012 by lenders in 117 countries to borrowers in 126 countries for a total of 6,083 distinct banks. We then link banks' exposure data with their financial statement information. We are first to accomplish this for an international sample of more than 2,000 banks.[1] By combining measures of crisis exposure in the GBN with bank balance sheet data, we obtain a bank-level panel dataset spanning the 1997-2012 period. For the baseline regressions, our measure of bank profitability is return on assets (ROA). Given that bank defaults are rare, we focus on bank ROA as an indicator of general financial health. In all regressions we include country-year fixed effects to control for unobservable heterogeneity in bank performance at the country-year level such as changes in the financial regulatory landscape and macroeconomic environment.

An important issue in our analysis of how interbank exposures relate to bank performance is the potential endogeneity of these exposures. Endogeneity can arise in two ways. The first is that banks may react to past or anticipated negative shocks from vis-a-vis banks by reducing their exposures to them. If they were to do so, this would affect our results by attenuating the effect of crisis exposures on bank performance. This kind of endogeneity would therefore work against our finding a link between crisis exposures and bank performance. Second, banks may recognize that being interconnected could be risky and try to form links in way that partly mitigates this risk. The result would be an endogenous network in which the banks have positioned themselves in a way that helps them manage shocks. They could also hedge some of the risk in their interbank

[1] Giannetti & Laeven (2012) and de Haas & van Horen (2013) construct matched samples for 256 banks and 117 banks, respectively.

exposures, for instance by buying credit default swaps (CDS). These mechanisms would also reduce the probability of our finding significant effects of banking crises on bank performance.

It is also important to note that our measure of bank network position, betweenness centrality, could be endogenous if banks sought to alter their position in the GBN in response to profitability shocks. However, since this measure is determined by the collective actions of all banks in the network, each individual bank's ability to significantly influence their global network position through unilateral actions is limited.

Our study is related to two strands of literature. First, we contribute to the study of contagion in financial markets. This literature highlights the role of international banks in transmitting financial sector shocks worldwide.[2] But closer to our analysis is the sub-literature on interconnections among financial institutions modeled as networks (Allen et al., 2009). Contagion can arise when global banks are connected through interbank exposures, as the default of one bank can create difficulties at the banks with claims on it, and these difficulties can propagate through the financial system via chains of interbank claims. Studies of complex networks advance the notion that a denser web of interconnections is both good and bad. Higher network density can be beneficial as it can provide better risk sharing opportunities in the case of small shocks. However, after a certain level, a denser web of connections can also serve as a mechanism of shock propagation and hence facilitate contagion (Acemoglu et al., 2014; Elliott et al., 2014).

Second, our work adds to the literature on the stability of financial networks pioneered by Allen & Gale (2000). Most papers examine the link between network structure and systemic stability by testing the resilience of different financial networks to shocks.[3]. However, due to data limitations, especially at the international level, most studies rely on simulations (see the discussion in Upper (2011)).[4] We contribute by overcoming some of the data limitations and analyzing the transmission of crises through an interbank network using observational data rather than simulations. Our network also differs from domestic interbank networks that have been commonly analyzed as it has global coverage.

[2]See Calomiris & Mason (1997); Kaminsky & Reinhart (2000); Rijckeghem & Weder (2003); Kaminsky et al. (2003) for early contributions, and Kapan & Minoiu (2014); de Haas & van Horen (2013); Cetorelli & Goldberg (2011) for analyses of the global financial crisis. Kalemli-Ozcan et al. (2013) and Kalemli-Ozcan et al. (2013) test for business cycle comovement across countries exposed, which may be accentuated by common shocks such as financial crises.

[3]See, for instance, Glasserman & Young (2015). For reviews of this literature, see Chinazzi & Fagiolo (2013); Summer (2013); Allen & Babus (2009)

[4]See, for example, Battiston et al. (2009); Chan-Lau et al. (2009); Cocco et al. (2009); Craig & von Peter (2014); Gatti et al. (2010); Haldane & May (2011); Imai & Takarabe (2011); May & Arinaminpathy (2009); Nier et al. (2007); Sachs (2014) and von Peter (2007).

Our paper is also related to empirical analyses of networks underpinned by interactions in the syndicated loan market. Cai et al. (2014), Bos et al. (2013), and Godlewski et al. (2012) construct GBNs in which links arise when banks participate in the same lending syndicate. These "co-syndication" networks capture interconnectedness of banks through common asset exposures. Cai et al. (2014) show that global banks that are highly interconnected in the co-syndication network contribute more to systemic risk. Bos et al. (2013) find that syndicated loans arranged by highly centric banks in the same network tend to be made to more opaque borrowers. Our concept of interconnectedness and GBN are different from these studies in that the links in the network arise when banks create exposures to other banks through lending/borrowing as opposed to participating in the same deals. (See Hale (2012) for a similar approach.) Thus, our analysis refers to contractual interconnectedness rather than interconnectedness created through common exposures.

Recent studies examine the effects of interconnectedness on macroeconomic performance during financial crises. Lee et al. (2011) look at the cross-country linkages created through global trade as potential conduits for financial crises, and show that the connectivity of individual countries in the trade network explain the spread of crises above and beyond their macroeconomic fundamentals. Chinazzi et al. (2013) find that countries with high connectivity in the global financial network, defined through cross-country debt and equity investments, experienced a smaller decline in output between 2008 and 2009. Caballero et al. (2009) show that countries with banks that were more centric in the global syndicated loans network had better stock market performance during 2007-2008 than countries with more peripheral banks. Minoiu et al. (2014) and Minoiu & Reyes (2013) show that financial crises are accompanied by a significant loss of network density. Our paper uses the most granular data available to shed light on the role of interbank rather than intercountry financial linkages, which allows us to control for a rich set of confounding factors.

The remainder of the paper is organized as follows. In Section 2 we describe the interbank syndicated loan market and advance some interpretations of the GBN. In Section 3 we present a simple contagion mechanism for our network and the empirical specifications. In Section 4 we describe the data and variables. In Section 5 we present our results and robustness tests, and in Section 6 we conclude.

2 The Global Syndicated Interbank Market

Syndicated loans are an important source of funds for corporations, sovereigns, and banks worldwide. They are extended by financial institutions organized in lending syndicates, and take the form of credit lines and term loans. Syndicated loans are originated by one or more "lead arrangers" or "lead banks" who sell portions of the loan to other lenders. Large loan deals can have tens of participants. The median size of syndicated loans is close to USD 500 million and median maturity is 5 years. Most loans are issued in USD and have floating interest rate based on the LIBOR. Syndicated loans are generally extended to creditworthy borrowers and are held to maturity. However, there is an active secondary market for loans extended to highly leveraged borrowers.

The interbank segment of the syndicated loan market represents about 10 percent of total syndicated loan issuance, both in terms of deal number and volume (Figure 1, Panel A). From the lenders' side, syndicated interbank loan exposures account for 12.5 percent of total cross-border interbank loan exposures (Panel B).[5] During 1997-2012 the largest lenders in this market were the US, UK, Japan, France, and Germany. From the borrower side, syndicated interbank loans represent 33 percent of interbank liabilities, 9.5 percent of total liabilities less deposits, and 4.3 percent of total liabilities.[6] Table 1 lists the top 25 borrowers in terms of importance of this market as a source of funding. We can see that these loans are a more significant source of funding for banks from emerging market countries. The top 5 emerging market borrowers (by volume) are Brazil, India, the Russian Federation, South Korea, and Turkey.

Interbank exposures formed through syndicated lending, while important in their own right, are likely to also capture other types of relationships across banks. The corporate finance literature emphasizes the complex nature of bank-borrower relationships, which often entail interactions in multiple lines of business such as underwriting, advisory contracts, and direct lending. Bharath et al. (2007) show that prior lending relationships are conducive to future lending and underwriting relationships and Chen et al. (2013) find that prior IPO underwriting increases the probability of subsequent lending. Banks often act as both loan underwriters and merger advisors to the same firm, which suggests that lending to a borrower is often associated with additional lucrative services (Allen & Peristiani, 2007). We bring an additional piece of evidence to support this idea by

[5] This estimate is obtained by comparing our syndicated interbank loan exposures, from which we remove undrawn portions of credit lines following the methodology outlined in Cerutti et al. (2014), with total cross-border loan exposures for reporting countries from the Bank of International Settlements (BIS). The remainder is accounted for by single-lender loans and intragroup transfers.

[6] These estimates are for the 2007-2012 period and refer to the sample of banks we matched to Bankscope.

examining the link between prior lending relationships and subsequent co-underwriting interactions in the same market. In Table 2 we regress an indicator for co-syndication (for bank-pairs that are lead banks in at least one loan in any given year) on an indicator for previous lending relationship lagged by one year.[7] We also control in some specifications for lagged co-syndication to allow for persistence in these interactions. The results show a positive and statistically significant association between prior lending/borrowing interactions and the future probability of doing business together, suggesting that the GBN may serve as a proxy for a larger set of banking relationships.

We can also interpret syndicated loan exposures as a proxy for bank exposures to asset classes other than syndicated loans. Cerutti et al. (2014) and Gadanecz & von Kleist (2002) show that syndicated loan exposures and total cross-border banking activity are positively correlated at the country-pair level. To provide evidence on this point at a more granular level, we plot data on bank-level sovereign bond exposures to a large set of countries[8] against syndicated loan exposures (Figure 2). There is an upward sloping relationship between the two types of exposures, which is particularly evident for claims on emerging market economies from Europe (Panel A). Notwithstanding that the relatively small sample of banks for which we have individual positions on these assets, the finding of a positive correlation between syndicated interbank exposures and sovereign bond exposures suggests that our data may be seen as a proxy for bank positions that go beyond large interbank loans.

3 Contagion Mechanism and Empirical Specification

In this section we describe a simple contagion (crisis transmission) mechanism in our interbank network. Assume that bank performance can be measured by Y, and let the exposure of bank i to bank j be denoted by E_{ij}, where E is an indicator for the presence of an exposure.[9] Let C_i denote an indicator for a systemic banking crisis in the country of bank i and X_i denote the vector of bank i's characteristics. Omitting the time subscript for simplicity, a contagion mechanism in the GBN

[7] The results are unchanged if we use longer lags for up to 5 years.

[8] The source of the data is the European Banking Authority 2013 EU-wide transparency exercise as reported by SNL Financial.

[9] We briefly consider the case where E is the dollar value of the exposure in the Results section.

can be written as follows:

$$Y_i = X_i\beta + \lambda C_i + \gamma \sum_j E_{ij} Y_j, \tag{1}$$

Note that the performance of bank i, Y_i, is a function of its own characteristics, X_i and C_i, and the return of the banks to which it is exposed. Equation 1 can be expanded infinitely and simplifies to:

$$\begin{aligned} Y_i = X_i\beta + \lambda C_i + \gamma \sum_j E_{ij_1} X_{j_1}\beta + \gamma \sum_{j_1} E_{ij_1}\lambda C_{j_1} + \gamma^2 \sum_{j_2} E_{ij_1}E_{j_1j_2}X_{j_2}\beta + \gamma^2 \sum_{j_2} E_{ij_1}E_{j_1j_2}\lambda C_{j_2} \\ + ... + \gamma^n \sum_{j_n} E_{ij_1}E_{j_1j_2}...E_{j_{n-1}j_n}X_{j_n}\beta + \gamma^n \sum_{j_n} E_{ij_1}E_{j_1j_2}...E_{j_{n-1}j_n}\lambda C_{j_n}, \end{aligned} \tag{2}$$

where j_1 represents the first degree connections of bank i, j_2 represents the second degree connections of banks $j_{1,}$ etc., and n is the highest degree connection of bank i. Note that the union of the sets of first degree connections of all j_1 banks corresponds to the set of second degree connections of bank i. Note also that the union of the sets of first degree connections of all j_1 banks correspond to the set of second degree connections of bank i. Equation 2 shows how the performance of bank i depends on its direct (first degree) and indirect (second degree) exposures to borrowers in countries that are experiencing a banking crisis. In the empirical implementation of this equation, we keep track of bank i's consecutive connections up to the second degree, and estimate equation 2.

We can expand equation 1 by explicitly allowing bank performance to be affected by the bank's overall network position in the GBN, for instance, the degree to which it plays the role of a key intermediary. We denote this property as N_i and add it as follows:

$$Y_i = X_i\beta + \lambda C_i + \mu N_i + \nu N_i C_i + \gamma \sum_j E_{ij} Y_j, \tag{3}$$

where we allow for a differential impact of the bank's degree of interconnectedness during normal and crisis times. Note that adding the bank's network position is equivalent to adding another dimension to the vector of bank i's characteristics. This equation, too, can be expanded infinitely with the same set of assumptions and definitions to obtain an equation similar to equation 2.

Based on equation 2, a complete empirical specification would link measures of bank performance to bank-specific controls, an indicator for whether the bank is in a country experiencing a systemic banking crisis, the bank's first, second, and higher-degree exposures, the characteristics of all vis-a-vis banks, and its network position. The coefficient γ decays exponentially, drastically reducing the potential impact of higher-degree connections. For this reason, in the implementation of equation 2 we include only first and second degree exposures. (All variables are defined in the next section.)

Adding subscripts for time t and bank nationality h, the most complete specifications are as follows:

$$\begin{aligned} Y_{iht} = \alpha_{ht} + X_{iht}\beta + \lambda C_{iht} + \sum_{j} E_{ij_1t}X_{j_1t}\beta' + \lambda' \sum_{j_1} E_{ij_1t}C_{j_1t} \\ + \sum_{j_2} E_{ij_1t}E_{j_1j_2t}X_{j_2t}\beta' + \lambda' \sum_{j_2} E_{ij_1t}E_{j_1j_2t}C_{j_2t} + \varepsilon_{iht}, \end{aligned} \tag{4}$$

where X_{iht} is a vector of bank controls and C_{iht} is the indicator for systemic banking crisis in bank i's home country. The next terms refer to controls and an indicator for systemic banking crises for the banks vis-a-vis which bank i has first- and second-degree connections. All variables enter the regressions contemporaneously. When we estimate equation 4, we find that the characteristics of vis-a-vis banks yield coefficients that are statistically insignificant in most specifications. For simplicity we do not show the coefficient estimates for these variables in the tables, but report the p-value of an F-test of their joint statistical significance for each regression.

The regressions are estimated using Ordinary Least Squares (OLS), with country-year fixed effects (α_{ht}), and with standard errors that are clustered on bank. Controlling for country-year fixed effects α_{ht} implies that identification comes from the variation in exposures and network position across banks in a given country and within banks over time.

Notice that in the equations above we focus only on the impact on bank performance of exposures vis-a-vis banks. In reality, a bank's profitability is also affected by its exposures to non-bank borrowers such as corporates and sovereigns. To capture these, in the empirical specifications we control for banks' total assets. [10]

[10]Introducing direct non-bank exposures (in dollar terms) in the empirical specifications in addition to total assets

4 Data and Variable Definitions

4.1 Data

We draw on two main data sources. The first is Dealogic's Loan Analytics, a database that reports the universe of syndicated loans issued since the early 1980s.[11] To construct interbank exposures for the 1997-2012 period, we obtain information for 170,274 syndicated loan deals originated between 1990 and 2012. For each loan we observe the identities of the borrower and those of all syndicate participants, the loan amount in USD (which we express at 2005 prices using the US CPI),[12] and loan origination and maturity dates. Using these data we construct, for each year, the GBN, a network of international interbank exposures among 6,083 banks. (Further details on the construction of the GBN are provided in the Data Appendix.)

An important caveat is that we only observe loans at origination and do not have data on drawdowns on credit lines, liquidation, prepayments, side-arrangements made by lenders to reduce these exposures on their balance sheets, or sales of syndicated credits on the secondary market. This likely creates noise in our USD exposure estimates, but it also helps avoid endogeneity problems. In particular, when regressing bank ROA on interbank exposures, a problem of reversed causality can arise if banks liquidate assets and reduce exposures in response to past or expected performance-related shocks. However, since our data refer solely to loan originations, the only way in which endogeneity could operate is through changes in the pattern of new loan origination (not through changes in the rest of the loan portfolio). To address the problem of measurement error in the estimated loan exposures, most of our results use measures of exposure counts (rather than dollar value) from the binary GBN.

We then merge the GBN interconnectedness measures, for each bank-year, with bank balance sheet information from Bankscope. To minimize errors, we inspect all automatic matches and then manually match the remaining banks. To ensure consistency of the dataset, prior to the merge we adjust lender names in Loan Analytics to account for name changes, mergers, and acquisitions over the sample period. (See Data Appendix for details.) The final (unbalanced) panel dataset

leaves the results unchanged.

[11]This implies that our network contains the universe of banks (nodes) that operate in this market during the period of analysis, and does not suffer from econometric problems associated with sampled networks (Chandrasekhar & Lewis, 2011).

[12]For 40 percent of the loan deals we observe individual loan shares by each syndicate participant. For the remainder, we estimate them using a regression-based approach as in Kapan & Minoiu (2014) and de Haas & van Horen (2013). See Data Appendix for more details.

comprises 2,200 banks during the 1997-2012 period, and the regression sample contains 1,875 banks due to missing balance sheet information for some banks. [13]

Data on the incidence of systemic banking crisis dates comes from the Laeven & Valencia (2013) dataset. Systemic banking crises are defined as periods in which the domestic banking system experiences significant stress and receives at least three of the following five policy interventions: public guarantees, liquidity support, asset purchases, public takeovers of financial institutions, and large restructuring costs (Laeven & Valencia, 2012, 2013).

4.2 Variable definitions

Our outcome variable is bank ROA for the benchmark results but we also consider return on equity (ROE), net interest margins (NIM), and respectively the bank z-score as a measure of "distance from default" in additional specifications. The z-score is an indicator of bank riskiness based on book data, and is defined as the sum of the bank's ROA and capital (equity/assets) ratio divided by the standard deviation of ROA. Lower values of the z-score indicate a "riskier" bank.[14] Our control variables are bank capital (equity/assets), size (log-total assets), indicators for the type of bank (controlled subsidiary, global ultimate owner, or other),[15] and bank business model (commercial banks, investment banks, and other).[16]

Direct and indirect exposures, and the global network position variable, betweenness centrality, are defined as follows. Direct exposures represent the number of banks to which bank i has direct exposures at time t. This variable, computed on the binary GBN, is also known as out-degree and reflects a bank's local centrality measured by the number of direct counterparties. In a few specifications we also consider the dollar value of this measure, computed on the weighted GBN, which reflects a bank's local centrality measured by the intensity of its outgoing connections (and is also called out-strength). Indirect, second-degree, exposures are defined as the number of banks to which the banks to which bank i has direct exposures at time t. These are two-step away exposures

[13] Note that our analysis is subject to survival bias, as some of the banks experiencing large losses in a period may fail in later periods. However, survival bias works against us finding results.

[14] Ideally we would like to also examine the impact of crisis exposures on bank stock market returns but this requires constructing the network and performing the analysis at the bank holding company level. Unfortunately, reliable time-series data on the composition and ownership changes of banking groups since 1990 is unavailable.

[15] The "Other" category includes branch locations, independent companies, and single location banks.

[16] The "Commercial banks" category includes cooperative banks, saving banks, real estate and mortgage banks, and other credit institutions. The "Other" category includes bank holding companies, finance companies (credit card, factoring and leasing), investment and trust corporations, securities firms, private banking and asset management companies, and group finance companies.

because they represent the number of counterparties of a bank's first-degree counterparties.

Finally, bank i's global network position at time t refers to betweenness centrality, which is defined as the number of shortest paths between two banks in the GBN that go through bank i divided by the total number of alternative shortest paths. This is a measure of global centrality. In the text we refer to banks with positive betwenness centrality as "key intermediaries" because they are essential connectors between groups of banks, performing the function of borrowing from and lending to large numbers of banks. About 5 percent of the banks in the GBN are key intermediaries.

Summary statistics for all variables are reported in Table 3.

4.3 A preliminary look at the data

Figure 3 depicts network density (defined as the number of observed connections in the network divided by the total number of possible connections) and the number of participating banks during the period of analysis. Network density ranges between a minimum of 0.3 percent in 1998 and a maximum of 0.48 percent in 2007, which is comparable to domestic interbank markets. The Italian interbank market has density of 0.3 percent (Gabrieli, 2011) and the German interbank market has density of 0.7 percent (Alter et al., 2014). Visualizations of the GBN in 2007 and 2010 for the largest 100 banks are provided Figure 4, showing reduced network density after the global financial crisis as many loans were not renewed during the crisis (Cerutti et al., 2014).

In Figure 5 we take a first look at the link between banks' profitability and financial crises, both in general as well as in the countries to which banks have direct interbank exposures. Panel A depicts the inverse relationship between average bank ROA and the number of systemic banking crises that occurred during 1997-2012. As bank profitability achieves a sample minimum in 2009 during the "deepest and most synchronized recession of the postwar period" (Kose et al., 2009), we will test the robustness of our baseline results to excluding this year from the sample. In Panel B we further investigate the ROA-crises link by plotting the entire ROA distribution (pooled across banks and years) against the number of countries to which the banks have crisis exposures. Moving from the left (where we look at banks connected to banks in no-crisis countries) to the right (where we look at banks with no crisis connections), we notice that the entire ROA distribution shifts downwards as median profitability declines, monotonically, with the number of crises (while its dispersion measured by the interquartile range remains relatively stable). Comparing the last two buckets, while median ROA for the 6+ crises-group is comparable to that for the 5-crisis group, the volatility of ROA is larger for the banks exposed to more financial systems in turmoil. In the following section we refine this result by examining the impact not of the number of *banking systems* in crisis, but that of the exact number of *banks* in crisis countries on bank profitability.

5 Results

We begin the regression analysis with a specification similar to equation 4 that links bank ROA to bank characteristics, including an indicator for crisis in home country (for the bank itself and its vis-a-vis banks), and direct and indirect interbank exposures. Then we turn to the performance of key intermediaries.

5.1 Baseline

In Table 4 we report the results of regressions in which the covariates of interest are direct and indirect exposure counts. The effect of home financial crises, as well as that of unobserved macroeconomic factors that may be affecting financial sector profits in any given country-year pair, are subsumed by country-year fixed effects. Column 1 shows that a higher number of direct exposures to crisis banks—banks in countries experiencing systemic banking crises—reduces bank profitability. The coefficient estimates indicate that keeping the total number of connections constant and increasing the number of direct crisis exposures by one reduces ROA by 0.03 percent.[17] For a bank balance sheet that is levered 30 times, which was not uncommon before the global financial crisis, a ROA reduction of 0.03 percent becomes an ROE reduction of 0.9 percent, which is an economically significant effect. For a bank with total assets of USD 1 trillion, an additional crisis connection would translate into a reduction in returns of USD 300 million. It would take an additional 25 crisis exposures, which is the figure for the Bank of Tokyo-Mitsubishi UFJ in 2008, to reduce ROA by half a standard deviation.

In Table 4 columns 2-3 we add indirect (second degree) exposures. We first measure these with the number of crisis and non-crisis exposures of the first-degree banks (column 2). The coefficients on these second order exposure variables are not statistically significant. However, it could be that, conditional on the crisis status of intermediate banks, second degree exposures significantly affect bank returns. To explore this possibility, in column 3 we split the two second-order exposure

[17] In fact, since the coefficient on total number of exposures is statistically insignificantly different from zero, the point estimates suggest that adding one more direct crisis exposure to the existing exposures also reduces ROA by 0.03 percent. In addition, adding a non-crisis exposure does not affect ROA.

variables into four exposure paths: exposures through crisis banks to (i) crisis banks and to (ii) non-crisis banks; and exposures through non-crisis banks to (iii) crisis banks and to (iv) non-crisis banks. The coefficient estimates suggest that on top of the baseline negative effect of direct crisis exposures on ROA (-0.026), there are negative effects stemming from the presence of second-degree crisis exposures. Specifically, an additional indirect exposure through a crisis bank to a *crisis* bank further reduces ROA by 0.006 (about 25 percent of the base effect). By contrast, an additional indirect exposure through a crisis bank to a *non-crisis* bank dampens the negative effect on ROA by 0.003 (11.5 percent of the base effect).

The specifications in the first three columns of Table 4 reflect the contagion mechanism in equation 2, where exposures are measured as counts (number of counterparties). Slightly modifying this mechanism allows us to explore the impact of exposures measured in dollar terms on bank performance. We do so in columns 4-6 where we replace the exposure counts with dollar values while keeping the same control variables.[18] This approach yields negative and statistically significant effects of direct crisis dollar exposures on bank returns, but weaker effects of indirect crisis exposures. As our estimates of exposure magnitudes are likely subject to measurement error, we prefer to use counts. In subsequent analysis, we use the model in column 3 as our baseline specification.

Taken together, these results suggest that direct and indirect crises exposures reduce bank profitability after controlling for banks' own characteristics and those of its first- and second-degree counterparties. Thus, global interbank exposures are a channel of international shock transmission of systemic banking crises, which means that diversification across financial partners can turn into vulnerability when the countries where these partners operate experience financial turmoil. This also points to the importance of country risk. The magnitudes of the estimated impacts may not seem very large, but should be interpreted in the context of the large and highly leveraged bank balance sheets in modern financial systems, where small ROA movements can imply large dollar losses.

5.2 Other measures of bank performance and potential mechanisms

Our baseline findings suggest that exposures to banks in crisis countries reduce bank profitability measured by ROA. Here we examine three additional measures of bank performance: NIM, z-score, and ROE. The results, shown in Table 5, indicate that direct crisis exposures reduce banks' NIM

[18] Technically, replacing exposure counts with dollar values in equation 1 requires computing summations of all the vis-a-vis bank characteristics multiplied by dollar values of exposures. In our modified specification, we left the other control variables unchanged.

and ROE, and increase distance to default as measured by the z-score. The coefficients on direct exposures in columns 1-2 suggest that keeping the total number of connections constant and increasing the number of direct crisis exposures by one reduces NIM by 0.018-0.022 percent. An additional 53 crisis exposures, the maximum number of crisis exposures in our sample (corresponding to the Hong Kong subsidiary of Long-Term Credit Bank of Japan (LTCB) in 1998) would reduce NIM by approximately half a standard deviation. This effect is not economically very large but hints at the presence of possible channels behind our baseline results.

A potential channel through which crisis exposures reduce bank profits, is losses due to borrower defaults. However, the syndicated loan market exhibits lower default rates, especially for bank borrowers, and higher loan recovery rates than other segments of the credit market.[19] Furthermore, borrower distress in this market typically leads to renegotiations that result in an amendment to modify the terms of the loan. At the height of the global financial crisis, the most popular practice was loan renegotiations. Loan restructuring, the most frequent manner in which troubled loans are handled in the syndicated loan market, effectively reduces the cash outlays of the borrower and the present value of the loan for the lender, resulting in lower NIM. Another way in which NIMs can be squeezed for banks with crisis exposures is through larger funding costs. Creditors may demand higher interest on loans to banks that are known to have exposures to borrowers in crisis countries.

Yet another mechanism behind our results could be losses in banks' securities portfolio. Losses would occur if banks placed their syndicated loans in the securities book and marked them to market using secondary market prices. This is more likely to happen for high-yield loans for which there is an active secondary market. To the extent that these loans are designated as "held for trading," marked-to-market losses and gains would affect net income and hence ROA. Unfortunately, we do not have information on the accounting designation of syndicated exposures, so we cannot test for this channel.

In Table 5 columns 3-4 we replace the dependent variable with the bank z-score, a measure of bank solvency derived from accounting information. Lower values of the z-score indicate higher bank instability. Demirguc-Kunt & Huizinga (2010) show that the z-score is negatively correlated with the market-to-book ratio and CDS spreads. The coefficient estimates on direct crisis exposures are negative and statistically significant in column 3 but not in the specification with indirect exposures (column 4). However, in column 4 we can see that indirect exposures through non-crisis banks to

[19] During 2011-2012, loan default rates were 2 percent. Over five years, the default rate for firms rated AAA was 0.38 percent while that for firms rated B was 21.76 percent during 1981-2010. Loan recovery rates have been 71 percent compared to 43.5 percent for unsecured lending during 1989-2009 (Standard & Poor's, 2011).

non-crisis banks have an intuitive positive effect on bank stability.

5.3 Key intermediaries

We build on our baseline specification to study the effects on bank performance of global bank connectivity in the GBN. The connectivity measure refers to betweenness centrality, a concept that we use to define key intermediary banks. These are banks that tend to lie "at the crossroads" by being in the essential position of linking groups of banks in the network to one another, or the more centric banks in the network to peripheral banks. There were 129 banks with positive betweenness centrality in the 2010 GBN, roughly equally split between advanced economies and emerging market countries. Selected key intermediaries in the 2010 GBN are listed in Table 6. For illustration, two of them—Commonwealth Bank of Australia and Arab Bank Plc of Jordan—are shown in Figure 6 along with their direct borrowing and lending relationships. These two key intermediaries borrow from large global banks and lend to many banks in their domestic and regional markets.

In Table 7 we examine the effect of betweenness centrality on bank ROA during crisis and normal times. We control for direct and indirect crisis exposures (as in column 3 of Table 4) and add the betweenness centrality measure, as well as interactions between this variable and an indicator for banking crises in the bank's home country and, respectively, the bank's crisis exposure count. In columns 1-4 we include country and year fixed effects, as well as country-specific trends, which allows us to obtain a coefficient estimate on the systemic banking crisis variable. In columns 5-8 we re-estimate the same specifications with country-year fixed effects to show that the results to our baseline set of controls.

Note first that the effects of direct and indirect crisis exposures from our baseline model remain statistically significant in these richer specifications. The estimates in column 1 indicate that banks with higher betweenness centrality have lower ROA than other banks. From columns 2-4 we see that this effect persists; in addition, holding betweenness centrality constant, more crisis exposures further reduce ROA. A possible mechanism behind this effect is that key intermediaries, by lying on the shortest path between many pairs of banks and hence connecting different parts of the network, are more frequently exposed to crises in different parts of the network. Key intermediaries from emerging markets are likely to experience more frequent crises in their home countries as emerging markets are more susceptible to financial crises and sudden stops. Sudden stops can increase the vulnerability of key intermediaries to funding shortages to the extent that these banks use syndicated loans as a significant source of funding.

5.4 Robustness

We subject our findings to several robustness tests in Table 8. In columns 1-4 we show that the baseline results (from column 3 in Table 4) are not driven by sample banks of a certain size, by running the regressions after dropping each quartile of the size distribution. Columns 5-8 perform four more robustness checks: first, we drop the year 2009 when bank ROA was unusually low compared to the rest of the sample as the global financial crisis unfolded. Then, we keep in the sample only the countries that have at least 5 banks during the sample period (column 6), and further we keep in the sample only the banks that have at least 5 observations during the sample period (column 7). Finally, in column 8 we drop the 18 banking entities of Citigroup, which are very active in the syndicated loan market. Our baseline results, especially for direct crisis exposures, are robust to these sample changes. For indirect exposures, the coefficients are sometimes less precisely estimated than in our baseline regressions.

6 Conclusions

In this paper we analyze the role of bank linkages in the transmission of financial sector shocks across countries. We focus on a specific type of interconnectedness that refers to interbank claims and liabilities created through lending/borrowing activities in the international syndicated loan market. We construct a global banking network for each year between 1997 and 2012 period, covering more than 6,000 banks, from granular information on syndicated loan deals and information on individual lenders, borrowers, loan amounts and maturity profiles. We then link the bank exposures to bank balance sheet information and crisis dates. We obtain a panel dataset comprising 1,875 banks from 110 countries. This unique dataset, which includes direct and indirect interbank exposures, measures of network centrality, and balance sheet data, allows us to estimate the effect of crisis exposures on bank performance.

We find that a larger number of outstanding loan exposures to bank borrowers in countries experiencing systemic banking crises reduce bank profitability, measured by return on assets, return on equity, and net interest margins. Furthermore, more direct crisis exposures are associated with lower bank stability as measured by z-score. Our main coefficient magnitudes on direct and indirect crisis exposures are both statistically and economically meaningful. A possible mechanism for reduced bank returns in the face of crisis exposures stems from loan restructuring, the most prevalent way in which troubled syndicated loans are handled, which lowers the present value of loans for lenders and impacts their net interest margins.

We also assess the link between banks' interconnectedness in the global banking network and profitability by focusing on betweenness centrality, a measure that identifies banks connecting different parts of the network. This concept of centrality allows us to identify key intermediaries in the network—banks with positive betweenness centrality. Key intermediaries tend to borrow from global banks that are very active in the loan syndication market, and lend to banks in domestic and regional markets. We find that key intermediaries, half of which are in emerging market countries, have lower ROA than other banks, and this effect is amplified when they have more crisis exposures. This result suggests that a large pool of creditors and debtors can expose key intermediaries to crises more frequently.

Overall, our results suggest that international financial linkages created through interbank exposures can enable the transmission of shocks across borders. We hope that the proposed contagion mechanism and the supporting empirical evidence documenting crisis transmission through a global banking network contributes to the policy discussion on global financial stability and leads to more research on the costs and benefits of interconnectedness.

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Data Appendix

To construct our dataset we proceed as follows:

- Step 1. We download from Dealogic's Loan Analytics data on 170,274 syndicated loan deals signed between January 1990 and December 2012. To construct the GBN we retain only the 11,752 loans extended by banks to banks.

  We drop the deals for which the lender is recorded as "unknown", "undisclosed syndicate", or "undisclosed investor (unknown)" and the deals that involve multiple borrowers (representing less than 1 percent of the sample). For lender country we use the variable "Lender nationality" as reported in Loan Analytics; for borrower country we use the variable "Deal nationality" after cross-checking that the variable is correct by comparing banks that appear both as borrowers and lenders. Bank borrowers are identified using the general industry group "Finance" and the sub-classifications commercial and savings banks, provincial banks, municipal banks, savings and loans, and investment banks.

- Step 2. Given that some bank names are recorded in Loan Analytics with typos, refer to banks that have changed name over time, or have been acquired by or merged with other banks, we clean up the bank names as follows:

  - If a bank changed name during 1990-2012, we retain its Bankscope name (as of end-2012) throughout the entire sample period;
  - If two or more banks merged during the sample period to form a new bank, they are kept as distinct banks until the year of the merger and cease to exist after the merger; the bank resulting from the merger is kept subsequent to the merger;
  - If a bank was acquired by another bank, it appears as a distinct bank until the year of the acquisition;
  - Lending from multiple branches of the same bank in a foreign country is aggregated;
  - Lending from off-shore branches of a bank is aggregated.

- Step 3. After cleaning the bank names, we match all the banks on a locational basis, by name and country, with balance sheet data from Bankscope. For the banks that are not matched automatically, which we carefully inspect for consistency, we perform matches manually. We use various sources to learn the institutional history of banks and make appropriate matches, including bank websites, the FDIC website[20] and Bloomberg Businessweek.[21] Subsidiaries, branches, and other banking group entities for which there is balance sheet information in Bankscope are treated as distinct entities and are not linked to their parent financials.

The GBN is constructed using the full set of about 6,083 banks that appear as lenders or borrowers in the syndicated loan market during 1990-2012. The merged sample of banks that participate in the loan syndication market and report to Bankscope contains about 2,200 distinct banks. The final regression sample comprises 1,875 banks due to missing data on balance sheet variables.

To construct the GBN we compute interbank exposures using information on the lender, borrower, loan amount, and loan maturity; and treating the loans, for simplicity, as bullet loans

[20] http://www.ffiec.gov/nicpubweb/nicweb/SearchForm.aspx

[21] http://investing.businessweek.com/research/company/overview/overview.asp

(non-amortizing). For about 40 percent of the loan deals there is data on loan amounts contributed by each lender in the syndicate. For the remainder we estimate the individual loan amounts based on a regression model that we estimate on the sample of loans with reported shares over 1990-2012. Specifically, we regress log-shares contributed to each loan deal on the log-loan amount, indicators for original loan currency, number of syndicate participants, indicators for borrower country and industry, indicators for lender role (bookrunner, mandated arranger, arranger, and participant) and lender country, an indicator for prior lending/borrowing relationship, an indicator for the lender and borrower being from the same country, and year-quarter dummies. (The exact specification is reported in the Data Appendix of Kapan & Minoiu (2014).)[22] The regression has an R-squared of 74 percent.

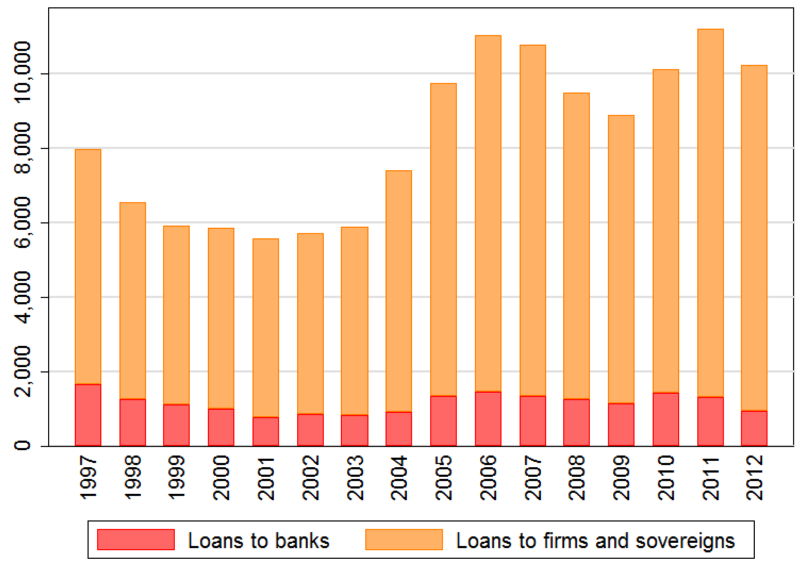
Note that the method for calculating the dollar value of exposures and the imputation of missing loan shares are irrelevant for most of our empirical results, as crisis exposures are computed on the binary GBN as the *number* (rather than the dollar value) of outgoing connections (that is, out-degree). (Dollar values of syndicated interbank exposures are used solely in columns 4-6 of Table 4 and for assessing robustness of our results to controlling for non-bank syndicated exposures.)

[22]http://www.camelia-minoiu.com/basel3paper-appendix.pdf

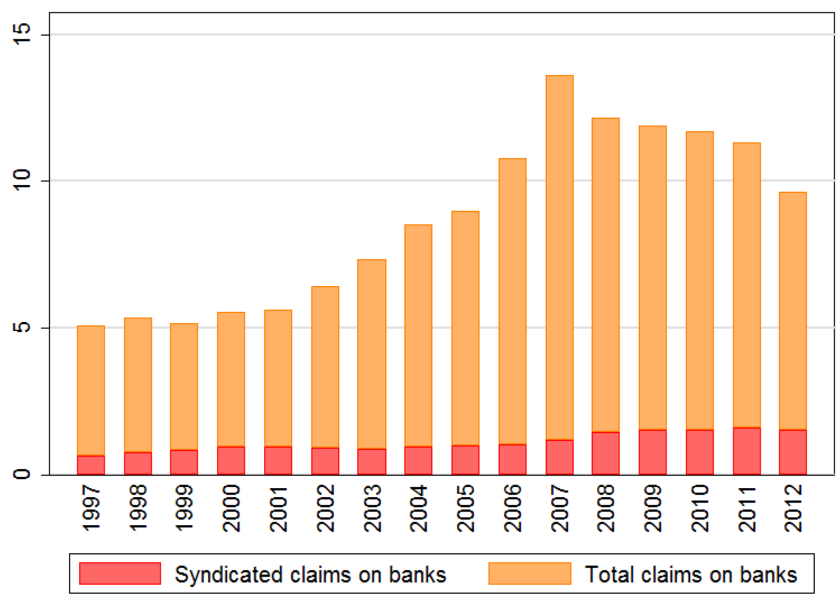
Tables and figures

Figure 1: The syndicated interbank market, 1997-2012

A. Number of loan originations



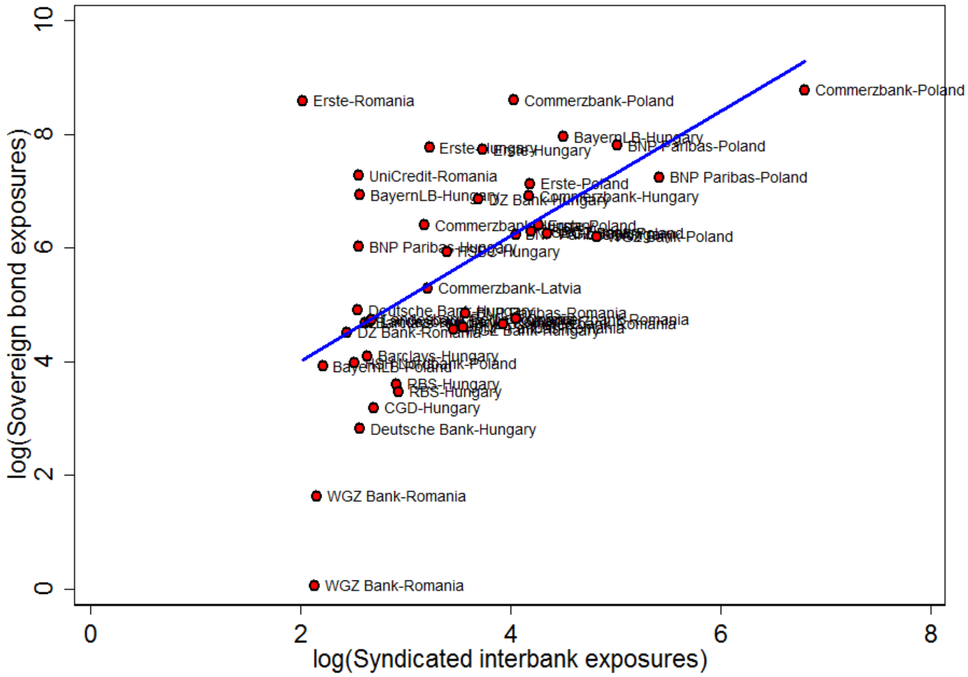
B. Cross-border loan exposures (USD trillion at 2005 prices)



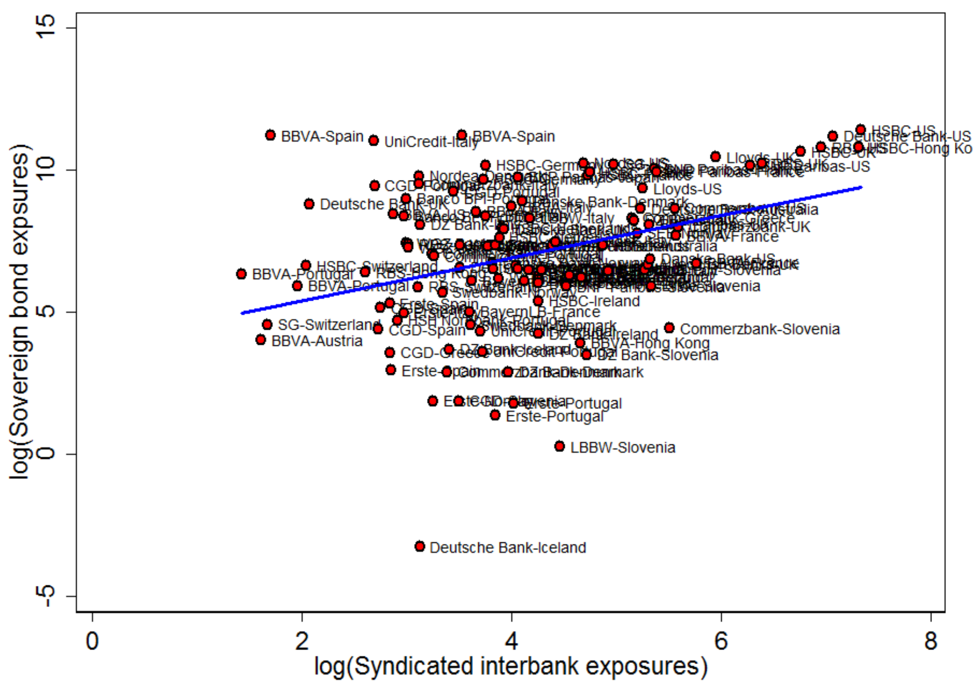
Notes: Panel A shows the number of loans issued to bank vs. other borrowers during 1997-2012. Panel B shows cross-border syndicated loan claims on banks relative to total (BIS) interbank loan claims of 35 banking systems vis-á-vis 197 countries. In Panel B, syndicated interbank claims refer to *on-balance sheet* exposures (drawn credit lines plus term loans) estimated using the methodology described in Cerutti et al. (forthcoming). Source: Authors' calculations using BIS locational banking statistics and Loan Analytics.

Figure 2: Syndicated interbank loan exposure vs. sovereign bond exposures

A. To emerging Europe

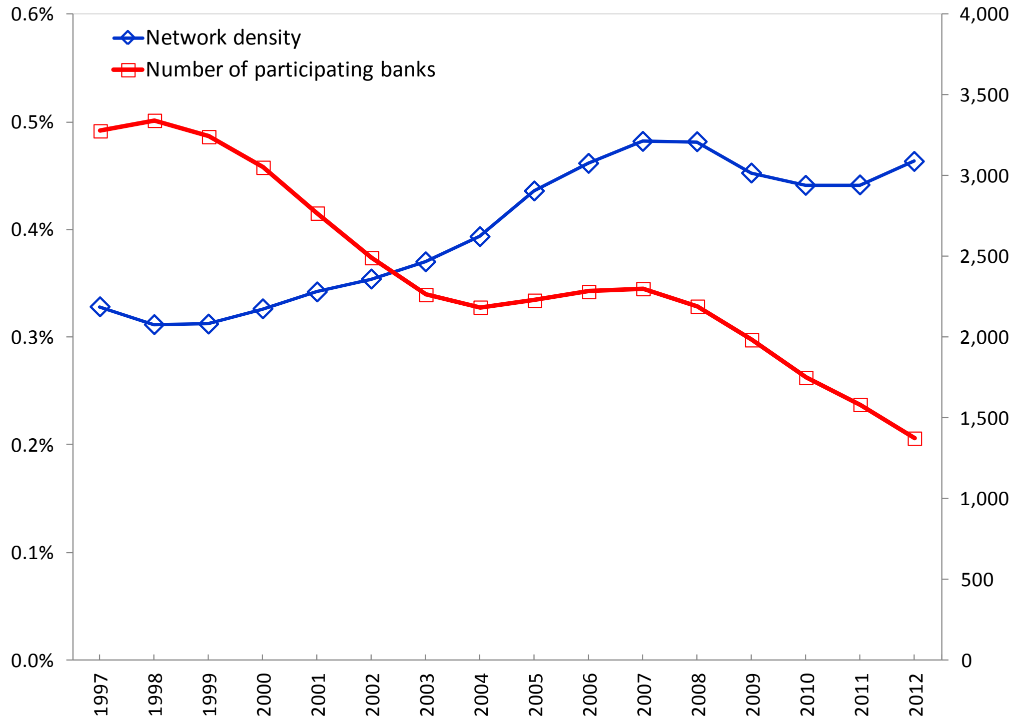


B. To all other countries



Notes: The figure depicts syndicated interbank exposures and sovereign bond exposures for end-2011 and end-2012, pooled, for banks that participated in the European Banking Authority 2013 EU-wide transparency exercise. Marker labels indicate the name of the bank followed by the country vis-a-vis which it has exposures. In Panel A the counterparty countries are from emerging Europe (Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, and Slovakia). The sample is restricted to banks with positive syndicated loan exposures. Source: Authors' calculations based on Loan Analytics and SNL Financial.

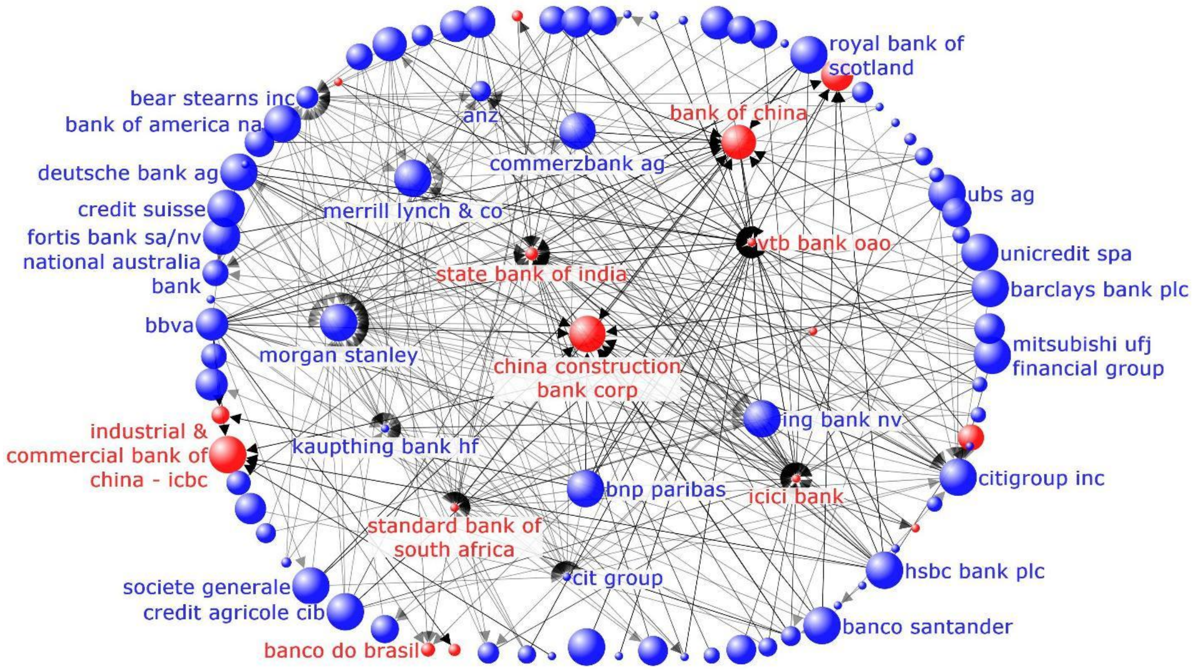
Figure 3: Network connectivity and number of participating banks, 1997-2012



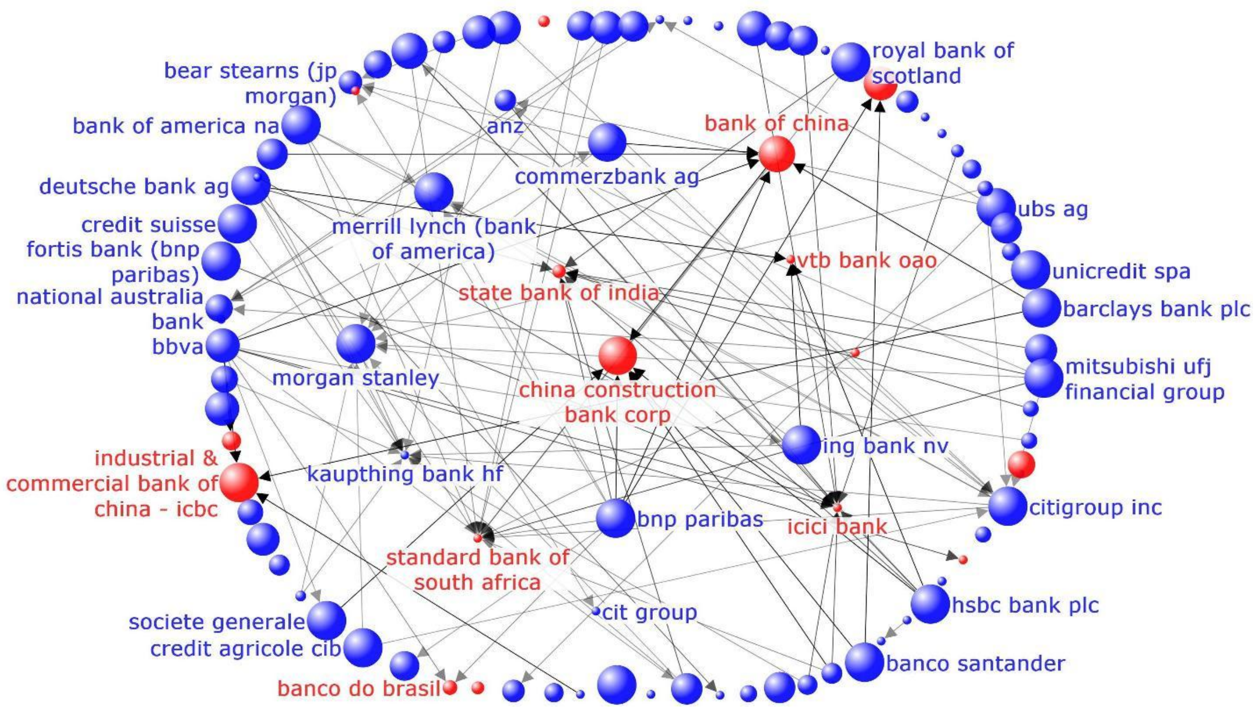
Notes: The chart depicts network density (computed as the number of edges divided by the total number of possible edges in the directed network), and the number of distinct banks (nodes). Source: Authors' calculations based on Loan Analytics.

Figure 4: Global syndicated interbank network

2007



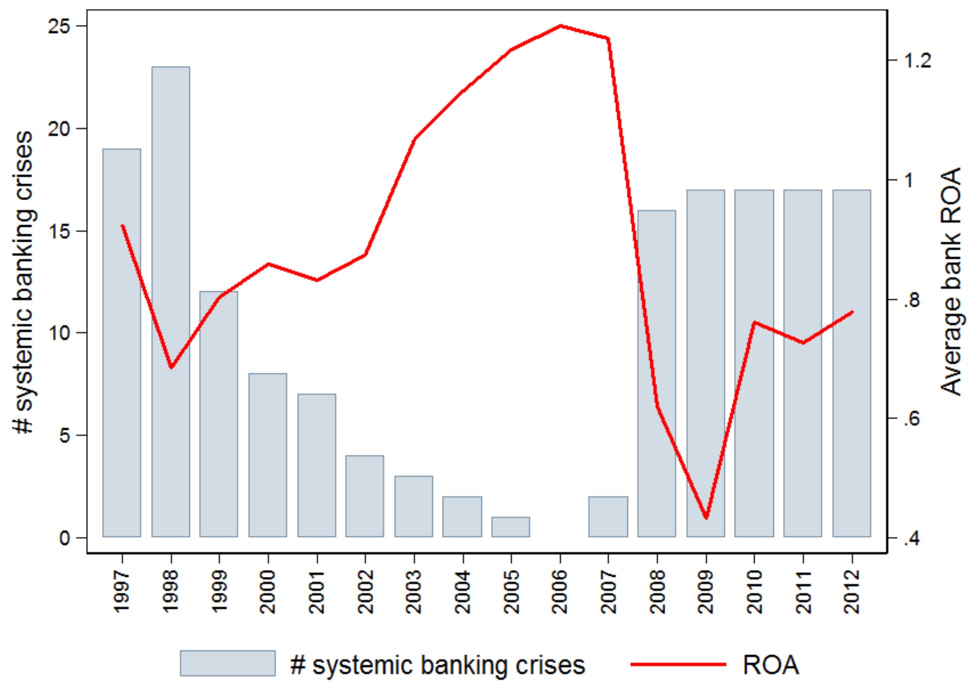
2010



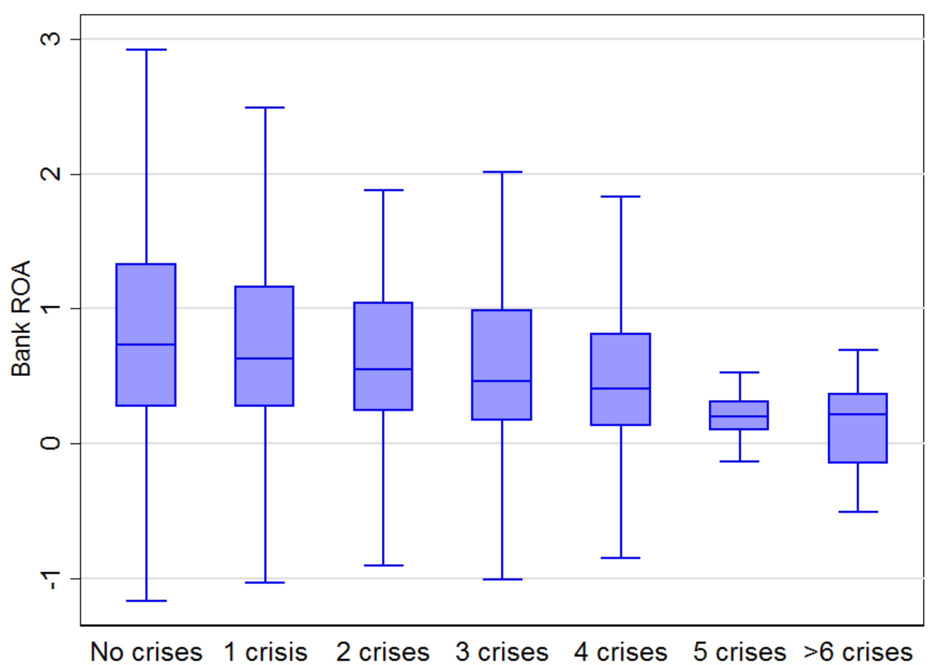
Notes: The figure depicts visualizations of the GBN in 2007 and 2010 for the largest 100 banks by 2007 assets that were lenders, borrowers, or both. Blue nodes are banks in OECD countries and red nodes are banks in non-OECD countries. Edge color is darker for larger exposures. Larger nodes indicate larger banks. The names for selected nodes are shown. The position of the nodes in the network is ad-hoc. Source: Authors' calculations based on Loan Analytics and Bankscope.

Figure 5: Bank performance and systemic banking crises, 1997-2012

A. Bank profitability and number of crises worldwide



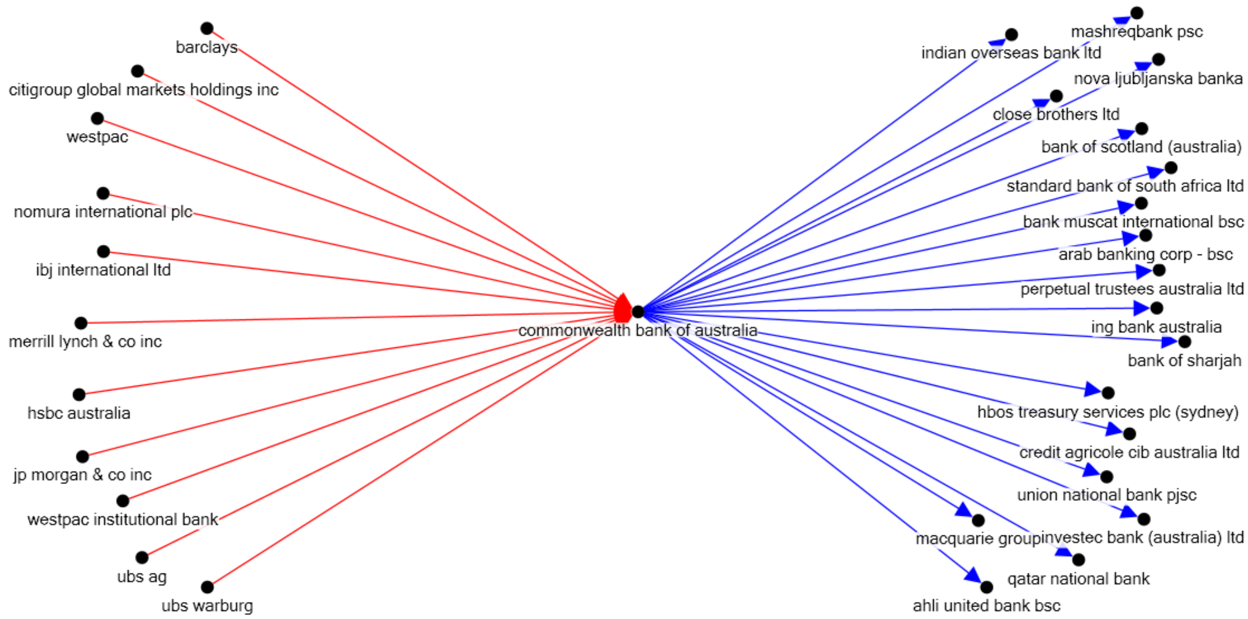
B. Distribution of bank profitability and number of crises in counterparty countries



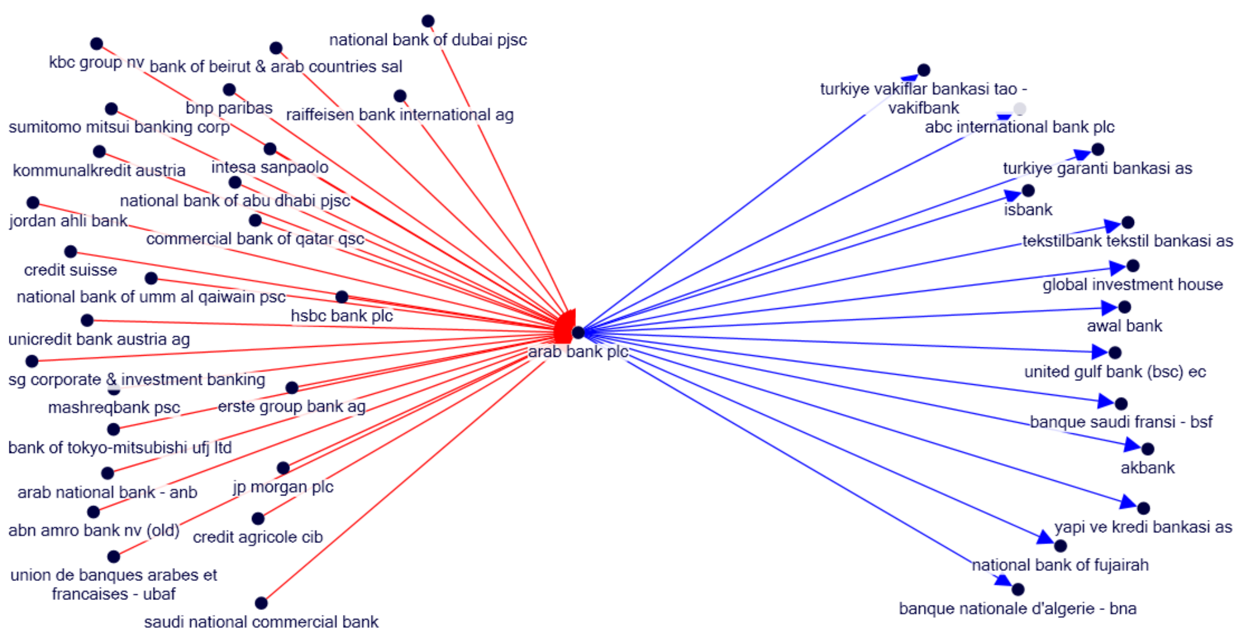
Notes: The bars in Panel B boxplot show the interquartile range of ROA with the median indicated by a horizontal line; the bars extend from the minimum to the maximum value of the ratio. Counterparty countries are the countries vis-à-vis whose banks a bank has direct exposures. Source: Authors' calculations based on Bankscope and Laeven and Valencia (2013).

Figure 6: Examples of key intermediaries

A. Commonwealth Bank of Australia (Australia)



B. Arab Bank PLC (Jordan)



Notes: The figures depict the borrowing and lending relationships of two key intermediaries in the 2010 GBN: Arab Bank Plc (Jordan) and Commonwealth Bank of Australia (Australia). Key intermediaries are defined as banks with positive betweenness centrality. Red edges are incoming (borrowing) relationships; blue edges are outgoing (lending) relationships. For simplicity, 3 banks vis-à-vis which Arab Bank Plc had both interbank claims and liabilities in 2010 are not shown. Source: Authors' calculations based on Loan Analytics.

Table 1: Syndicated interbank loans as a source of funding (%)

A. % of total liabilities				B. % of (total liabilities-deposits)			
Rank	Country	Mean	Median	Rank	Country	Mean	Median
1	Latvia	11.8	12.7	1	Latvia	50.5	56.0
2	Azerbaijan	10.4	10.3	2	Azerbaijan	23.3	23.9
3	Slovenia	10.3	6.7	3	Slovenia	21.8	13.6
4	Kazakhstan	8.6	7.2	4	Turkey	17.7	12.6
5	Bahrain	8.3	7.1	5	Hong Kong, China	14.7	7.6
6	Denmark	7.6	8.3	6	Kazakhstan	14.6	13.1
7	Turkey	7.3	5.3	7	United Arab Emirates	14.4	14.0
8	France	7.0	2.9	8	United Kingdom	13.5	6.4
9	Ukraine	6.8	5.1	9	Denmark	13.1	10.0
10	Norway	6.8	6.0	10	Bulgaria	12.5	10.6
11	United Kingdom	6.2	4.1	11	Bahrain	11.8	8.8
12	Hong Kong, China	6.1	1.9	12	Norway	11.7	11.0
13	Portugal	6.1	7.4	13	Poland	11.4	9.0
14	United Arab Emirates	5.4	4.8	14	Nigeria	9.9	6.8
15	Russian Federation	4.8	3.2	15	Australia	9.8	3.5
16	Australia	4.7	1.4	16	Russian Federation	9.5	6.8
17	Italy	4.7	1.2	17	The Netherlands	9.2	7.8
18	Hungary	3.9	3.7	18	Ukraine	8.9	7.0
19	Bulgaria	3.8	3.6	19	Portugal	8.9	10.7
20	Poland	3.6	3.1	20	Hungary	8.5	7.1
21	The Netherlands	3.5	3.0	21	Romania	8.2	5.3
22	Taiwan	3.5	0.0	22	France	7.0	2.9
23	Romania	3.3	2.8	23	South Africa	6.9	6.0
24	Germany	3.3	0.0	24	Italy	6.4	1.9
25	Brazil	2.8	2.5	25	United States	6.3	2.9
	Top 25 average	6.0			Top 25 average	13.2	
	Full sample average	4.3			Full sample average	9.5	

Notes: The table reports the top 25 countries by share of syndicated interbank liabilities in total liabilities (Panel A) and total liabilities less deposits (Panel B). The full sample average refers to the 39 countries for which there is bank-level data on syndicated loan liabilities and total liabilities for at least 5 banks. The figures refer to the 2007-2012 period. Source: Authors' calculations based on Loan Analytics and Bankscope.

Table 2: Current interbank lending and probability of future co-syndication

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Co-syndication (lag) (ij)	0.292***	0.270***	0.146***		0.341***	0.332***	0.034***	
	(0.001)	(0.001)	(0.001)		(0.003)	(0.003)	(0.003)	
Lending (lag) (ij)	0.095***	0.093***	0.076***	0.095***	0.061***	0.057***	0.032***	0.034***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.006)	(0.009)	(0.009)
Equity/Assets (i)					0.001***	0.001***	0.002***	0.002***
					(0.000)	(0.000)	(0.000)	(0.000)
Equity/Assets (j)					0.001***	0.001***	0.002***	0.002***
					(0.000)	(0.000)	(0.000)	(0.000)
Log-assets (i)					0.024***	0.020***	0.036***	0.037***
					(0.000)	(0.000)	(0.003)	(0.003)
Log-assets (j)					0.025***	0.021***	0.035***	0.036***
					(0.000)	(0.000)	(0.003)	(0.003)
Year FE	no	yes	yes	yes	no	yes	yes	yes
Bank-pair FE	no	no	yes	yes	no	no	yes	yes
Observations	2,489,250	2,489,250	2,489,250	2,489,250	292,958	292,958	292,958	292,958
R-squared	0.082	0.104	0.202	0.185	0.150	0.162	0.368	0.367

Notes: The table shows the results of a linear probability model where the dependent variable is an indicator for co-syndication relationship in at least one loan during 1997-2012. The sample is restricted to lead banks (i.e., bookrunners and mandated arrangers). "Lending" is an indicator for previous lending relationship. The "co-syndication" and "lending" indicators are lagged one year. The specifications are estimated on the sample of bank pairs that co-syndicate at least once during the sample period. Standard errors are clustered on bank pair. # indicates statistical significance at the 15% level, *** at the 1% level, ** at the 5% level, and * at the 1% level. Sources: Authors' calculations based on Loan Analytics, Bankscope, and Laeven and Valencia (2013).

Table 3: Summary statistics

Variable	N	Mean	St. Dev.	Min	Max
DEPENDENT VARIABLES					
Return on assets (ROA)	14,483	0.810	1.556	-6.790	8.840
Return on equity (ROE)	14,480	8.409	16.43	-78.09	53.17
Net interest margins (NIM)	14,350	2.757	2.237	-0.910	15.89
Z-score	13,927	1.798	2.135	-3.600	9.674
CONTROL VARIABLES					
Equity/Assets	14,483	8.751	9.323	0.320	81.51
Assets (USD bn)	14,483	66.55	191.3	0.450	1,290
Log(Assets, USD mn)	14,483	16.31	1.702	13.02	20.98
Business model: Commercial bank	14,483	0.809	0.393	0	1
Business model: Investment bank	14,483	0.0695	0.254	0	1
Business model: Other	14,483	0.122	0.327	0	1
Bank type: Sybsidiary	14,483	0.508	0.500	0	1
Bank type: Global ultimate owner	14,483	0.304	0.460	0	1
Bank type: Other	14,483	0.188	0.391	0	1
Systemic banking crisis	14,483	0.208	0.406	0	1
DIRECT EXPOSURES					
$ exposure to all banks	14,483	0.183	1.704	0	78.59
$ exposure to crisis banks	14,483	0.00987	0.103	0	3.832
# exposures to all banks	14,483	4.324	13.81	0	190
# exposure to crisis banks	14,483	0.251	1.551	0	40
INDIRECT EXPOSURES					
$ exposures through crisis banks to crisis banks	14,483	0.0391	0.628	0	51.35
$ exposures through crisis banks to non-crisis banks	14,483	0.0538	0.627	0	32.69
$ exposures through non-crisis banks to crisis banks	14,483	0.0165	0.162	0	12.53
$ exposures through non-crisis banks to non-crisis banks	14,483	0.218	1.145	0	76.61
# exposures through crisis banks to crisis banks	14,483	1.004	8.885	0	417
# exposures through crisis banks to non-crisis banks	14,483	2.132	20.32	0	936
# exposures through non-crisis banks to crisis banks	14,483	1.168	6.070	0	136
# exposures through non-crisis banks to non-crisis banks	14,483	11.79	45.43	0	842
GLOBAL NETWORK POSITION					
Betweenness centrality *100	14,483	0.00594	0.0594	0	2.465

Notes: Summary statistics are based on the regression sample. The z-score is defined as the sum of the bank's ROA and its capital (equity/assets) ratio divided by the standard deviation of its ROA; and is computed based on a 4-year rolling window. All the bank balance sheet variables are winsorized at the 1st and 99th percentiles of their respective distributions. $ exposures are expressed in $ billion at 2005 prices. Sources: Authors' calculations based on Loan Analytics, Bankscope, and Laeven and Valencia (2013).

Table 4: Effect of crisis exposures on bank performance - Baseline

	(1)	(2)	(3)	(4)	(5)	(6)
		# exposures			$ exposures	
Equity/Assets	0.055***	0.055***	0.055***	0.055***	0.055***	0.055***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Log-assets	0.069***	0.069***	0.069***	0.069***	0.069***	0.069***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Business model: Commercial bank	0.150*	0.150*	0.147*	0.149*	0.149*	0.147*
	(0.080)	(0.080)	(0.080)	(0.080)	(0.081)	(0.080)
Business model: Investment bank	0.166	0.165	0.162	0.168	0.167	0.165
	(0.148)	(0.148)	(0.148)	(0.148)	(0.148)	(0.148)
Bank type: Subsidiary	0.152***	0.152***	0.153***	0.151***	0.151***	0.151***
	(0.057)	(0.057)	(0.057)	(0.057)	(0.058)	(0.058)
Bank type: Global ultimate owner	0.231***	0.231***	0.231***	0.231***	0.231***	0.230***
	(0.051)	(0.051)	(0.051)	(0.051)	(0.052)	(0.051)
DIRECT EXPOSURES						
Exposures to all banks	-0.002	-0.002	-0.001	0.001	0.000	0.000
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Exposures to crisis banks	-0.030***	-0.031***	-0.026***	-0.212**	-0.217***	-0.245***
	(0.009)	(0.010)	(0.010)	(0.086)	(0.082)	(0.087)
INDIRECT EXPOSURES						
Exposures to all banks		-0.000			0.009	
		(0.001)			(0.009)	
Exposures to crisis banks		0.001			-0.008	
		(0.002)			(0.023)	
Exposures through crisis banks to crisis banks			-0.006**			-0.039
			(0.003)			(0.026)
Exposures through crisis banks to non-crisis banks			0.003**			0.068*
			(0.001)			(0.038)
Exposures through non-crisis banks to crisis banks			0.003			0.054
			(0.002)			(0.089)
Exposures through non-crisis banks to non-crisis banks			-0.001			0.006
			(0.001)			(0.008)
Country-year FE	yes	yes	yes	yes	yes	yes
p-value test that characteristics of vis-à-vis banks do not matter	0.199	0.305	0.289	0.140	0.261	0.374
Observations	14,483	14,483	14,483	14,483	14,483	14,483
R-squared	0.441	0.441	0.441	0.440	0.441	0.441

Notes: The dependent variable is bank ROA. A constant term and characteristics for one-step and two-steps away vis-a-vis banks are included in all specifications, but the coefficients are not shown. Standard errors are clustered on bank. # indicates statistical significance at the 15% level, *** at the 1% level, ** at the 5% level, and * at the 1% level. Sources: Authors' calculations based on Loan Analytics, Bankscope, and Laeven and Valencia (2013).

Table 5: Effect of crisis exposures on bank performance - Other measures

	(1)	(2)	(3)	(4)	(5)	(6)
	Return on equity		Net interest margins		Z-score	
Equity/Assets	0.071	0.071	0.019***	0.019***	0.019**	0.020**
	(0.045)	(0.045)	(0.004)	(0.004)	(0.008)	(0.008)
Log-assets	0.805***	0.806***	-0.090***	-0.090***	0.084**	0.086***
	(0.149)	(0.149)	(0.023)	(0.023)	(0.033)	(0.033)
Business model: Commercial bank	1.438*	1.417*	0.226	0.223	0.328	0.337
	(0.777)	(0.777)	(0.145)	(0.145)	(0.207)	(0.207)
Business model: Investment bank	1.450	1.414	-0.689***	-0.692***	-0.365	-0.357
	(1.210)	(1.210)	(0.206)	(0.206)	(0.236)	(0.237)
Bank type: Subsidiary	1.634**	1.626**	0.073	0.074	-0.135	-0.139
	(0.640)	(0.640)	(0.090)	(0.091)	(0.147)	(0.146)
Bank type: Global ultimate owner	2.629***	2.614***	0.042	0.041	0.152	0.151
	(0.607)	(0.607)	(0.092)	(0.092)	(0.158)	(0.158)
DIRECT EXPOSURES						
# exposures to all banks	0.038	0.036	-0.002	-0.001	0.004	0.001
	(0.043)	(0.043)	(0.002)	(0.003)	(0.005)	(0.005)
# exposures to crisis banks	-0.324**	-0.200*	-0.022**	-0.018*	-0.041*	-0.034
	(0.126)	(0.122)	(0.009)	(0.010)	(0.023)	(0.025)
INDIRECT EXPOSURES						
# exposures through crisis banks to crisis banks		-0.094*		-0.004*		0.001
		(0.049)		(0.002)		(0.005)
# exposures through crisis banks to non-crisis banks		0.034#		0.001		-0.002
		(0.023)		(0.001)		(0.003)
# exposures through non-crisis banks to crisis banks		0.008		0.002		0.002
		(0.033)		(0.002)		(0.006)
# exposures through non-crisis banks to non-crisis banks		0.001		-0.001		0.004**
		(0.008)		(0.001)		(0.002)
Country-year FE	yes	yes	yes	yes	yes	yes
p-value test that characteristics of vis-à-vis banks do not matter	0.161	0.123	0.266	0.566	0.184	0.177
Observations	14,480	14,480	14,350	14,350	13,927	13,927
R-squared	0.345	0.346	0.631	0.631	0.324	0.326

Notes: The dependent variable is bank ROE (columns 1-2), NIM (columns 3-4), and z-score (columns 5-6). A constant term and characteristics for one-step and two-steps away vis-a-vis banks are included in all specifications, but the coefficients are not shown. Standard errors are clustered on bank. # indicates statistical significance at the 15% level, *** at the 1% level, ** at the 5% level, and * at the 1% level. Sources: Authors' calculations based on Loan Analytics, Bankscope, and Laeven and Valencia (2013).

Table 6: Examples of key intermediaries

Rank	Country	# banks	Selected examples
A. Advanced economies			
1	US	9	Bank of NY Mellon Corp, Citibank NA, HSBC Bank USA, Morgan Stanley, Citigroup Inc
2	Australia	6	National Australia Bank, ANZ, WestPac, Macquerie Bank Ltd, Commonwealth Bank of Australia
3	Hong Kong (SAR)	6	Bank of East Asia, Hongkong & Shanghai Banking Corp, ICBC (Asia), Standard Chartered Bank (Hong Kong)
4	Japan	5	Daiwa Securities Capital Markets, Nomura Holdings, Mizuho Trust & Banking, Sumitomo Trust & Banking, Mizuho Securities
5	UK	5	Nomura International, Standard Bank, ABC International Bank, Leeds Building Society, Standard Chartered Bank
B. Emerging market economies			
1	China	7	Bank of China, Agricultural Bank of China, ICBC, China Development Bank, China Construction Bank
2	Turkey	6	Akbank, Garanti, Turk Economi Bankasi, Vakiflar Bankasi, Yapi ve Credi Bankasi
3	Russian Federation	5	VTB Bank, Sberbank, Alfa Bank, Bank of Moskow, Bank Uralsib
4	India	4	Axis Bank, ICICI Bank, Bank of Baroda, State Bank of India
5	Brazil	2	Itau Unibanco, Banco do Brasil

Notes: This table lists the top advanced economies and emerging market countries with key intermediaries in the 2010 GBN. Key intermediaries are banks with positive betweenness centrality. Sources: Authors' calculations based on Loan Analytics.

Table 7: Effect of crisis exposures and global network position on bank performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Equity/Assets	0.057***	0.057***	0.057***	0.057***	0.055***	0.055***	0.055***	0.055***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Log-assets	0.071***	0.071***	0.071***	0.071***	0.070***	0.070***	0.070***	0.070***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Business model: Commercial bank	0.181**	0.180**	0.181**	0.180**	0.149*	0.149*	0.150*	0.150*
	(0.077)	(0.077)	(0.077)	(0.077)	(0.080)	(0.080)	(0.080)	(0.080)
Business model: Investment bank	0.178	0.179	0.177	0.177	0.163	0.163	0.162	0.162
	(0.142)	(0.142)	(0.142)	(0.142)	(0.148)	(0.148)	(0.148)	(0.148)
Bank type: Subsidiary	0.123**	0.123**	0.125**	0.125**	0.156***	0.156***	0.157***	0.157***
	(0.056)	(0.056)	(0.056)	(0.056)	(0.057)	(0.057)	(0.057)	(0.057)
Bank type: Global ultimate owner	0.210***	0.210***	0.211***	0.212***	0.232***	0.232***	0.233***	0.233***
	(0.050)	(0.050)	(0.050)	(0.050)	(0.051)	(0.051)	(0.051)	(0.051)
Systemic banking crisis (home)	-0.497***	-0.493***	-0.500***	-0.495***				
	(0.091)	(0.091)	(0.091)	(0.091)				
DIRECT EXPOSURES								
# exposures to all banks	-0.002	-0.002	-0.002	-0.002	-0.000	-0.000	-0.000	-0.000
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
# exposures to crisis banks	-0.023**	-0.024**	-0.018*	-0.018*	-0.024***	-0.024**	-0.020**	-0.020**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)	(0.010)
INDIRECT EXPOSURES								
# exposures through crisis banks to crisis banks	-0.005*	-0.005*	-0.006*	-0.006**	-0.006**	-0.006**	-0.007**	-0.007**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
# exposures through crisis banks to non-crisis banks	0.002*	0.002*	0.002*	0.002**	0.002**	0.002**	0.003**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
# exposures through non-crisis banks to crisis banks	-0.000	0.000	-0.000	0.000	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
# exposures through non-crisis banks to non-crisis banks	-0.000	-0.000	-0.000	-0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
NETWORK POSITION								
Betweenness centrality	-0.559***	-0.447***	-0.465**	-0.335**	-0.366**	-0.405**	-0.291*	-0.325*
	(0.195)	(0.160)	(0.193)	(0.148)	(0.171)	(0.181)	(0.163)	(0.171)
Betweenness centrality * Systemic banking crisis (home)		-1.064		-1.176		0.435		0.355
		(0.793)		(0.794)		(0.449)		(0.440)
Betweenness centrality * # exposures to crisis banks			-0.152**	-0.162***			-0.115**	-0.112**
			(0.062)	(0.062)			(0.055)	(0.055)
Country FE	yes	yes	yes	yes	no	no	no	no
Year FE	yes	yes	yes	yes	no	no	no	no
Country-specific trends	yes	yes	yes	yes	no	no	no	no
Country-year FE	no	no	no	no	yes	yes	yes	yes
p-value test that characteristics of vis-à-vis banks do not matter	0.123	0.132	0.121	0.133	0.232	0.239	0.240	0.246
Observations	14,483	14,483	14,483	14,483	14,483	14,483	14,483	14,483
R-squared	0.321	0.321	0.321	0.321	0.442	0.442	0.442	0.442

Notes: The dependent variable is bank ROA. A constant term and characteristics for one-step and two-steps away vis-à-vis banks are included in all specifications, but the coefficients are not shown. Standard errors are clustered on bank. # indicates statistical significance at the 15% level, *** at the 1% level, ** at the 5% level, and * at the 1% level. Sources: Authors' calculations based on Loan Analytics, Bankscope, and Laeven and Valencia (2013).

Table 8: Effect of crisis exposures on bank performance - Robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sequentially drop quartiles of the bank size distribution				Drop 2009	Keep countries > 5 banks	Keep banks > 5 years	Drop Citigroup
	Bottom quartile	Second quartile	Third quartile	Top quartile				
Equity/Assets	0.063***	0.052***	0.054***	0.058***	0.054***	0.055***	0.056***	0.055***
	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)
Log-assets	0.048***	0.060***	0.060***	0.144***	0.061***	0.070***	0.063***	0.070***
	(0.013)	(0.013)	(0.013)	(0.027)	(0.013)	(0.012)	(0.014)	(0.012)
Business model: Commercial bank	0.073	0.143	0.140	0.241**	0.105	0.146*	0.129	0.140*
	(0.067)	(0.088)	(0.086)	(0.113)	(0.083)	(0.080)	(0.086)	(0.081)
Business model: Investment bank	0.101	0.071	0.133	0.395**	0.137	0.160	0.114	0.180
	(0.146)	(0.144)	(0.157)	(0.199)	(0.152)	(0.147)	(0.164)	(0.153)
Bank type: Subsidiary	0.136***	0.148**	0.176***	0.138**	0.160***	0.157***	0.160**	0.162***
	(0.050)	(0.064)	(0.066)	(0.070)	(0.057)	(0.057)	(0.065)	(0.057)
Bank type: Global ultimate owner	0.178***	0.257***	0.237***	0.228***	0.222***	0.226***	0.212***	0.238***
	(0.048)	(0.057)	(0.062)	(0.062)	(0.051)	(0.051)	(0.057)	(0.051)
DIRECT EXPOSURES								
# exposures to all banks	0.001	-0.001	0.000	-0.005	-0.000	-0.000	-0.002	-0.000
	(0.002)	(0.004)	(0.005)	(0.015)	(0.005)	(0.004)	(0.004)	(0.004)
# exposures to crisis banks	-0.012*	-0.024**	-0.028***	-0.026	-0.025**	-0.025***	-0.021**	-0.026**
	(0.007)	(0.010)	(0.010)	(0.024)	(0.010)	(0.009)	(0.010)	(0.010)
INDIRECT EXPOSURES								
# exposures through crisis banks to crisis banks	-0.003	-0.006**	-0.005*	-0.013***	-0.006**	-0.006**	-0.005*	-0.006**
	(0.002)	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
# exposures through crisis banks to non-crisis banks	0.001	0.003**	0.002	0.010	0.003**	0.002**	0.002*	0.003**
	(0.001)	(0.001)	(0.001)	(0.006)	(0.001)	(0.001)	(0.001)	(0.001)
# exposures through non-crisis banks to crisis banks	0.002	0.002	0.001	0.000	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.007)	(0.002)	(0.002)	(0.002)	(0.002)
# exposures through non-crisis banks to non-crisis banks	-0.000	0.000	0.000	0.001	-0.000	0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Country-year FE	yes	yes	yes	yes	yes	yes	yes	yes
p-value test that characteristics of vis-à-vis banks do not matter	0.278	0.189	0.509	0.0158	0.152	0.126	0.168	0.131
Observations	10,814	10,822	10,853	10,960	13,248	14,189	12,766	14,336
R-squared	0.496	0.454	0.457	0.449	0.443	0.431	0.454	0.444

Notes: The dependent variable is bank ROA. In columns 1-4 we sequentially drop each of the four quartiles of the size distribution of banks. In column 5 we drop data for the year 2009. In column 6 we keep countries with at least 5 banks in any given year. In column 7 we keep banks that are present at least 5 consecutive years in the dataset. In column 8 we drop the 18 bank entities of Citigroup from the dataset. A constant term and characteristics for one-step and two-steps away vis-a-vis banks are included in all specifications, but the coefficients are not shown. Standard errors are clustered on bank. # indicates statistical significance at the 15% level, *** at the 1% level, ** at the 5% level, and * at the 1% level. Sources: Authors' calculations based on Loan Analytics, Bankscope, and Laeven and Valencia (2013).