Crisis Transmission in the Global Banking Network

Galina Hale*
Federal Reserve Bank of San Francisco

Tümer Kapan
Fannie Mae

Camelia Minoiu
International Monetary Fund

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Abstract

In the wake of the global financial crisis much attention has been devoted to the role of complexity of bank linkages in the transmission of shocks. We shed light on this issue using a rich dataset on international syndicated bank lending matched with bank financial information. To study how financial crises spread through the global banking network, we distinguish among channels such as banks' direct exposures to crisis countries, indirect exposures through informational linkages, and banks' location in the network. We perform the analysis in a large panel of over 2,000 banks from 73 countries spanning the 1997-2010 period. We find that direct exposures to crisis countries through current and past lending hinder bank performance. We also find that a bank's position in the global banking network affects its performance during crises in its home country. Our results underscore the importance of bank linkages for the spread of financial crises internationally.

JEL classification: F34, F36

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*galina.b.hale@sf.frb.org, corresponding author. We thank Stijn Claessens, Era Dabla-Norris, Graciela Kaminsky, and participants at the World Bank Conference "Networks and connectivity tools: A new understanding for practical international economics" (Washington, DC, May 2013) for useful comments. We are grateful to Elliot Marks and Keith Miao for excellent research assistance at different stages of this project. The views expressed in this paper are those of the authors and do not represent those of the Federal Reserve System, Fannie Mae, IMF, or their policies. All errors are our own.

1 Introduction

In the wake of the global financial crisis much attention has been devoted to the role of complexity of bank linkages in the transmission of financial sector shocks. Policy-makers argue that this complexity has grown significantly in recent times and has contributed to the severity of the global financial crisis (Dudley, 2012; Haldane, 2009; Tumpel-Gugerell, 2009). There is also a growing academic literature that emphasizes the role of financial sector complexity in deepening financial crises (Caballero & Simsek, 2009, 2013). We contribute to this literature by analyzing the transmission of financial crises through the global network of bank linkages. Our empirical approach, based on rich data on relationships across banks worldwide, allows us to examine the role of several channels of crisis transmission. Specifically, we distinguish between direct exposures to financial institutions in crisis countries, indirect channels such as informational linkages, and banks' location in the financial network. We find evidence for the presence of all these channels in the data.

The 2008-2009 crisis brought to the fore the challenges faced by economic agents, especially financial institutions, of operating in a complex macroeconomic environment. Following the bankruptcy of Lehman Brothers – a medium-sized yet highly interconnected institution – financial markets shut down, triggering a severe credit crunch and a protracted recession. In the wake of the crisis there have been new efforts to strengthen regulation, in particular for those banks that are so interconnected that their failure may pose systemic risk. To better understand the consequences of interconnectedness we identify specific channels through which banking crises are transmitted internationally. We seek to determine whether direct exposure to institutions in a crisis country, direct informational linkages with these institutions, indirect connections with them, and the position of banks in the global banking network explain banks' performance during crises.

To study the transmission of financial crises we map international financial linkages by constructing a global banking network using loan-level data on bank-to-bank syndicated loans from

Dealogic's Loan Analytics.[1] Specifically, we construct two versions of the bank-level global banking network (GBN). These networks are made of exposures ("edges") among banks ("nodes") that are built through syndicated loans extended by banks to banks. The first network – the "exposure" GBN (EGBN) – is a directed network based on syndicated loans outstanding at a given point in time. Edges in this network refer to the actual exposure of banks vis-à-vis one another in this market. The EGBN thus refers only to *current* connections. The second network – the "relationship" GBN (RGBN) – is a directed network in which loan origination establishes relationships that never expire.[2] The RGBN is based on *current and past* connections. We interpret edges in this network as capturing information flows and learning among banks based on their entire history of financial transactions, as in Hale (2012). The RGBN can also be thought of as a proxy for more complete bank-to-bank exposures that are otherwise difficult to observe. For both networks we construct measures of direct and indirect linkages among banks as well as indicators of banks' global connectivity profile.

A crucial step in our analysis is to link information on syndicated lending with banks' financial data, which we are first to accomplish in a systematic fashion.[3] We then empirically study the effect of a lending bank's connectedness in the GBN on its performance during crises abroad. We define banking crises as systemic country-wide banking crises and study specifically the effects of crises in countries to which banks are directly or indirectly exposed. We also examine whether a lending bank's location in the EGBN and RGBN – its global connectivity profile – is important in

[1] Participation of financial institutions in the international syndicated market is significant. During 1980-2012, financial institutions borrowed on average almost one fifth of the total syndicated loan volume; among these, banks accounted for about 5 percent of the total volume. Loan issuance to banks reached USD 400 billion at the peak of the market in 2007, representing almost 10 percent of global issuance. Banks appear as borrowers in 7 percent of syndicated loan deals.

[2] In this we differ from two recent papers that also use syndicated loan data to construct banking networks (Cai et al., 2012; Bos et al., 2013). In these studies the link arises when banks arrange a loan together, while we define a link as a loan exposure from any lender in the syndicate to the borrower. It follows that our network includes many more banks and the interpretation of bank linkages is also different.

[3] Giannetti & Leaven (2012) and De Haas & Van Horen (2013) also conduct this match, but only for 256 banks and 117 banks, respectively, as opposed to over 2,000 banks that we match for our sample.

explaining its performance during crises the bank's home country and abroad.

To construct our dataset, we combine exposure and connectivity measures from the two GBNs with bank balance sheet data from Bankscope. Using this rich bank-level panel dataset spanning the 1997-2010 period, we are able to test whether direct and indirect exposures to crisis countries through the EGBN and the RGBN as well as bank's connectivity profile play a role in explaining bank performance. For the baseline regressions, our measure of bank performance is return on assets. In all benchmarks specifications we control for country fixed effects, year fixed effects, and bank characteristics. Thus, our identification comes from differences in network characteristics across banks in a given country and within banks over time.[4]

In theory, higher financial interconnectedness carries both benefits and risks. More interconnectedness improves risk sharing, but can also facilitate contagion when shocks occur. A large body of work following the seminal study of Allen & Gale (2000) investigates the link between the pattern of relationships connecting economic agents on the one hand, and the response of the network as a whole to shocks on the other. Due to the complex nature of network topologies, much of this literature has relied on simulations (see Upper (2011) for a review) and has focused only on the negative side of the coin — financial contagion.[5] Our contribution is to be among the first to study the channels of crisis transmission through the the GBN using observational data rather than simulations, while also identifying factors, such as a bank's position in the network, that may affect bank performance during crises. Moreover, since our approach is fully agnostic *a priori* with respect to the effects of network connectivity on bank performance, we are able to identify both the costs and benefits of bank linkages during normal and crisis times.

Some of our results are consistent with findings from previous studies. Like Greenwood et al.

[4]Most of our results also survive when we control for bank fixed effects, indicating that identification largely hinges on within-bank variation.

[5]See, for example, Battiston et al. (2012); Castiglionesi & Navarro (2011); Chan-Lau et al. (2009); Cocco et al. (2009); Craig & von Peter (2010); Delli Gatti et al. (2010); Elliot et al. (2012); Garratt et al. (2011); Giannetti & Leaven (2012); Haldane (2009); Haldane & May (2011); Imai & Takarabe (2011); Kalemli-Ozcan et al. (2013); May & Arinaminpathy (2010); Mirchev et al. (2010); Nier et al. (2007); Sachs (2010) and von Peter (2007).

(2012), we find that larger direct exposures to banks in crisis countries through syndicated lending have a negative impact on banks' returns during crises. In addition, we find that informational linkages that arise from past loans that are no longer outstanding have a similar effect. One interpretation of this result is that informational linkages created by past financial contracts lead to other types of business relationships among banks. These linkages may thus capture bank-to-bank exposures through lines of business other than syndicated loans. This is important because the available data do not allow us to observe banks' total exposures to one another.

Overall, our results suggest that global banking linkages act as a conduit for the spread of financial crises, with banks that are exposed to banking systems in crisis posting lower returns. However, we find that these crises do not spread very far. On the one hand, the effects of direct exposures on bank performance are small in magnitude, which means that direct exposures by themselves are unlikely to generate losses large enough to produce cascades of systemic crises. On the other hand, we find that indirect exposures to banks in crisis countries do not hinder bank performance. These results suggest that the spread of banking crises may be limited to direct linkages.

We also find that banks' position in the global banking network has an effect on their performance during home-country crises but not during crises in other countries. In particular, banks that serve as "key intermediaries" between the center of the network and their regional banking systems play the role of local insurers: they collect rents during normal times but perform worse that other banks when their home countries experience a crisis. Moreover, being *at* the center of the network has very different consequences from being *close to* that center: banks that are central in the network appear to be safer — they have lower returns during normal times, but do better during crises. By contrast, banks that are close to the network's center benefit from this position during normal times, but fare worse than other banks during periods of financial stress.

Our study contributes to a large literature on contagion in financial markets, especially network contagion (see Allen et al. (2009), for a survey). In the recent literature there is no consensus regarding the effects of connectivity on macroeconomic performance during crises. Lee et al. (2011) examine the global trade network as a conduit for financial crises, and show that the connectivity of individual countries helps 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, and there are nonlinear effects. Caballero et al. (2009) show that countries with banks that are more central in the global banking network of syndicated lending, such as France and Germany, had better stock market performance during 2007-2008 than countries with more peripheral banks, such as Iceland, Ireland, and Greece. Our findings add to this literature by focusing on the banking system and using the most granular data available to shed light on the role of financial linkages in the spread of systemic banking crises internationally.

The remainder of the paper is organized as follows. In Section 2 we present a simple mechanism for banking contagion. In Section 3 we describe our empirical approach and our data. In Section 4 we present our results. Section 5 concludes.

2 Contagion Mechanism

Suppose bank performance can be measured by Y, and the exposure of bank i to bank j by $E_{ij}\delta^{(s)}$, where E is either a binary indicator of the existence of exposure, or a measure of its intensity and $\delta^{(s)}$ is the decay factor that depends on the number of steps s between banks i and j in the network. Denote as C_i a binary indicator for whether there is a crisis in the country of bank i. We will omit time subscript t to avoid excessive clutter. A simple contagion mechanism in the banking network can be written as a spacial recursive equation

$$Y_i = \alpha_i + \beta\, C_i + \gamma \sum_j Y_j E_{ij} \delta^{(s)}, \tag{1}$$

where α_i reflects all other factors affecting the performance of bank i.

The above equation can be expanded infinitely to obtain an expression for the effects of exposure of bank i to crises in other countries:

$$Y_i = \alpha_i + \beta\, C_i + \bar{\alpha}\gamma \sum_j E_{ij} + \beta\gamma \sum_j C_j E_{ij} + \frac{\bar{\alpha}\gamma^2}{1-\gamma} \sum_j P_{ij} + \frac{\beta\gamma^2}{1-\gamma} \sum_j C_j P_{ij}, \tag{2}$$

where we assume $\delta^{(1)} = 1$ and $\delta^{(s)} = 1/s$ and P_{ij} is network proximity between banks i and j defined as inverse of the (weighted) network distance between banks i and j. We give formal definition of proximity in Section 3.3. $\bar{\alpha}$ is a weighted average of other characteristics that affect performance of banks other than bank i.

Equation (2) shows how the performance of bank i depends on its direct and indirect exposures to banks in countries that are experiencing crisis. This is our benchmark specification for the empirical analysis.

We can expand equation (1) by explicitly allowing bank performance to be affected by its position in the global banking network, which we denote N_i, as follows

$$Y_i = \alpha_i + \beta C_i + \mu N_i + \nu N_i C_i + \gamma \sum_j Y_j E_{ij} \delta^{(s)}, \tag{3}$$

where we allow for different impact of the network position during tranquil and crisis times. This equation, too, can be expanded infinitely with the same set of assumptions and definitions to obtain

$$
\begin{aligned}
Y_i = \alpha_i + \beta C_i + \mu N_i + \nu N_i C_i + \bar{\alpha}\gamma \sum_j E_{ij} + \beta\gamma \sum_j C_j E_{ij} + \mu\gamma \sum_j N_j E_{ij} + \nu\gamma \sum_j N_j C_j E_{ij} \\
+ \frac{\bar{\alpha}\gamma^2}{1-\gamma} \sum_j P_{ij} + \frac{\beta\gamma^2}{1-\gamma} \sum_j C_j P_{ij} + \frac{\mu\gamma^2}{1-\gamma} \sum_j N_j P_{ij} + \frac{\nu\gamma^2}{1-\gamma} \sum_j N_j C_j P_{ij}.
\end{aligned}
\tag{4}
$$

When we estimate the above equation, however, we find that the last terms are insignificant and we can therefore rewrite it in a simplified way, ignoring the last two terms as

$$
\begin{aligned}
Y_i = \alpha_i + \beta C_i + \mu N_i + \nu N_i C_i + \bar{\alpha}\gamma E_{ij} + \beta\gamma \sum_j C_j E_{ij} + \mu\gamma \sum_j N_j E_{ij} + \nu\gamma \sum_j N_j C_j E_{ij} \\
+ \frac{\bar{\alpha}\gamma^2}{1-\gamma} \sum_j P_{ij} + \frac{\beta\gamma^2}{1-\gamma} \sum_j C_j P_{ij} + (o).
\end{aligned}
\tag{5}
$$

This is the equation we bring to the data in the empirical analysis reported below.

3 Empirical Strategy and Data

3.1 Data sources

We use two main data sources in our analysis. The first is Dealogic's Loan Analytics, a proprietary database that reports all the international syndicated bank loans issued since the early 1980s. We use these data starting in the late 1990s as prior coverage was limited and financial data for the banks is only available starting 1997. From this database we extract only loans extended to banks. For each loan we collect information on the name and country of the borrower, the name and country of each syndicate participant, loan amount (expressed in 1982 USD using the US CPI), and loan origination and maturity dates. Loan amounts are divided equally among syndicate participants (see Kapan & Minoiu (2013); Hale (2012); Giannetti & Leaven (2012)). The data allow us to construct, for each year, the RGBN - a network in which links result from loans extended at a given date and never expire. Using loan maturity dates we also construct the EGBN - a network of *current* exposures. An important caveat in constructing the EGBN is that we only observe loans at origination and do not have data on actual drawdowns on credit lines, liquidation, or prepayments. While this is likely to create noise in our exposure estimates, it also helps us avoid some of the endogeneity problems we discuss later on. We end up with some 5,500 banks that are interconnected.

Our data on bank performance measures, return on assets and return on equity, come from Bankscope, a proprietary database distributed by Bureau Van Dijk. Bankscope reports balance sheet information for banks in all countries going back to the late 1990s. We merge the bank interconnectedness data based on Loan Analytics with balance sheet information from Bankscope manually by bank name and country. To ensure consistency of the dataset, we carefully adjust lender names in Loan Analytics to account for name changes, mergers, and acquisitions. (See Appendix A for details of the merging procedure.) The final balanced panel dataset comprises 2,066 banks over the 1997-2010 period.[6]

Data on systemic banking crises is taken from Laeven & Valencia (2012).

3.2 Empirical specifications

We run regressions at the bank level. The main specification links a bank performance measure Y_{iht} (bank i in country h in year t) to systemic banking crises in all countries d ($CRIS_{dt}$) in year t, including $d = h$, through:

- Direct current exposures E^{EGBN}_{ihdt-1} of bank i to banks in country d at the end of period $t-1$ from EGBN. We compute two versions of these variables: based on the dollar amounts used as edge weights in the weighted EGBN; and based on the binary EGBN only measuring the

[6]The regression sample contains fewer banks due to missing information on balance sheet variables.

number of banks in country d to which bank i has outstanding claims in year t.

- Direct past exposures, E_{ihdt-1}^{RGBN} of bank i to banks in country d at the end of period $t-1$ from RGBN. As the RGBN is based on the full history of transactions in the syndicated loan market, and links in the RGBN never expire, these exposures capture informational linkages across banks and can be thought of as broader proxies for business relationships among banks. Direct *past* exposures are computed as the difference between RGBN and EGBN direct exposures.

- Indirect linkages R_{ihdt-1} of bank i to banks in country d at the end of period $t-1$ computed as total network proximities of bank i to all banks in country d in the binary RGBN, excluding direct linkages in the binary RGBN. (See next section for a formal definition of network proximity.)

- Bank i's individual network position measures N_{iht-1} in the binary EGBN and RGBN. These are betweenness centrality, closeness centrality, and proximity to the network center. (See next section for formal definitions of individual network indicators.)

For each bank, we compute direct and indirect linkages to countries that are experiencing systemic banking crises at time t and to countries that are not experiencing crises. We also interact the network position measures with an indicator for banking crisis in the bank's home country.[7] The

[7] We experimented with specifications in which we interacted network position measures with the number of crises in other countries but these did not have any effect on bank performance (results not reported).

most complete specification regressions are estimated at the bank-year level, using OLS, as follows:

$$
\begin{aligned}
Y_{iht} = {} & \alpha_h + \alpha_t + \beta_1 \sum_{d=1}^{D} E_{ihdt-1}^{EGBN} I(Crisis_{dt} = 0) + \beta_2 \sum_{d=1}^{D} E_{ihdt-1}^{EGBN} I(Crisis_{dt} = 1) \\
& + \gamma_1 \sum_{d=1}^{D} E_{ihdt-1}^{RGBN} I(Crisis_{dt} = 0) + \gamma_2 \sum_{d=1}^{D} E_{ihdt-1}^{RGBN} I(Crisis_{dt} = 1) \\
& + \delta_1 \sum_{d=1}^{D} R_{ihdt-1} I(Crisis_{dt} = 0) + \delta_2 \sum_{d=1}^{D} R_{ihdt-1} I(Crisis_{dt} = 1) \\
& + \lambda_1 N_{iht-1} + \lambda_2 N_{iht-1} I(Crisis_{ht} = 1) + \zeta Z_{iht} + \varepsilon_{iht},
\end{aligned} \tag{6}
$$

where Z_{iht} are bank-specific control variables. We compute robust standard errors clustered on bank to deal with residual serial correlation in the errors. While in our baseline specification we include only bank country fixed effects α_h, because we are interested in the effects of differences across banks, we test whether our results hold with bank fixed effects, that is, only using variation arising from changes in banks' connectivity over time. We allow for the impact on bank performance of systemic banking crises to be instantaneous, but exposures and network measures are lagged one period to avoid direct reverse causality.

An important econometric issue facing our specification is endogeneity. In theory, direct exposure measures may suffer from endogeneity because banks may liquidate assets and reduce exposures in response to past or expected future performance-related shocks, leading to a problem of reversed causality. The imperfection of our data, however, plays in our favor. Because we use information on loans from Loan Analytics, we only have data on loan origination, not on loan liquidation, actual drawdown, or prepayment. Thus, the only way in which endogeneity would affect our results is through changes in the pattern of new loan origination, but not through changes in the rest of the loan portfolio. Furthermore, the endogeneity problem is less of a concern when it comes to the network-based relationships R and indicators N because they are determined not only by the actions of each bank i but also by the actions of all the other banks in the network. Finally, lagging the main covariates further reduces the possibility that the results are driven by the acquisitions of soon-to-fail assets.

3.3 Variable definitions

We consider the following outcome variables Y: return on assets (ROA) for the benchmark results and return on equity (ROE) for robustness tests. These variables, as well as our bank-level control variables come from Bankscope. Our control variables include measures of bank leverage (equity/assets), size (log-assets), indicators for the type of entity (controlled subsidiary, global ultimate owner, or other),[8] and bank specialization (commercial banks, bank-holding companies, and other).[9] Our measure of systemic banking crises is at the country-year level and is taken from Laeven & Valencia (2012). We use this measure for the home country of a bank as a variable that captures financial and macroeconomic conditions in that country.

Direct and indirect linkages are based on syndicated loan exposures. Loan Analytics reports, for each loan, the amount extended LE_{ijt} "loan from bank i to bank j extended at time t," and the loan signing and maturity dates. We use this information to construct the networks of current exposures (EGBN) and relationships based on all loans extended up to date (RGBN). For the EGBN we rely on reported maturity dates to compute the amounts of loans outstanding of bank i vis-a-vis bank j at time t, LO_{ijt}, as well as the number of banks in country d to which bank i has outstanding loans at time t, LN_{idt}.

The network measures E^{EGBN}, E^{RGBN}, R, and N are described below.[10] E measures are

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

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

[10] All network measures are computed using the SGL Stata routine developed by Miura (2011).

based on either the weighted or binary networks, while all other measures are based on the binary networks. Since the EGBN and RGBN are directed, we compute network measures based on both assets and liabilities (i.e., lending *and* borrowing relationships). We report only the results for the asset-based measures, since we did not find any statistically significant effects for the liability-based measures.

$E_{ihdt}^{EGBN} = \sum_{j \in d} LO_{ijt}$**:** EGBN-based current exposures computed for each year as the amount of loans outstanding, using maturity dates, from each bank i to all banks $j \in d$. This is not a network measure, but simply the direct (total) exposure in real USD through the syndicated loan market.

$E_{ihdt}^{EGBN01} = LN_{idt}^{EGBN}$**:** binary EGBN-based current exposures computed for each year as the number of banks in country d to which bank i has loans outstanding. This is not a network measure, but simply the direct (total) exposure in terms of the number of connections.

$E_{ihdt}^{RGBN01} = LN_{idt}^{RGBN} - LN_{idt}^{EGBN}$**:** binary RGBN-based past exposures computed for each year as the number of banks in country d to which bank i has extended loans in the past but has no current loans outstanding. This measure captures all past direct linkages in the RGBN between bank i and country d that are not included in E_{ihdt}^{EGBN01}.

$R_{ihdt}^{RGBN} = \sum_{j \in d} 1/D_{ijdt}^{RGBN} - LN_{idt}^{RGBN}$**:** binary RGBN-based indirect network proximities. This measure is computed for each bank as the inverse of network distance D to all other banks in the network.[11] Thus, this measure reflects all indirect connections based on loans extended in the past, including currently outstanding loans. We aggregate bank-level proximities R for each bank-country pair id by summing up proximites of bank i to all banks in country d. To check robustness we also compute average proximities – that is, total proximities R as

[11] We define network distance between two nodes as the length of a shortest path between these two nodes in the binary network. If two nodes are connected directly, the distance is 1. If there is no path connecting the two nodes, the distance is set to a large number exceeding network diameter (the longest distance between connected nodes).

defined above divided by the number of banks in each country d.

The overall connectivity measures N are computed for both the EGBN and RGBN and include: betweenness centrality, closeness centrality, and total proximity to banks with the highest degree of closeness centrality, which we call "network centers." As with exposures, we compute the network statistics separately for both lending and borrowing banks, but we only report the results of the asset-based measures because we did not find any statistically significant effects of liability-based measures.

Betweenness centrality is the number of bank pairs that are only related through a given bank i. Formally, it is defined as the number of bank pairs that do not include bank i, for which the shortest path (or one of the shortest paths) goes through bank i, divided by the total number of bank pairs that do not include bank i in the network. We refer to banks with positive betweenness as "key intermediaries" as they tend to "lie at the crossroads" and link different clusters of banks in the network to each other or the center of the network to peripheral clusters. In the analysis we use an indicator variable for banks with positive betweenness centrality.

Closeness centrality is inversely related to the number of banks that a given bank i has to go through on average to reach all the other banks in the network. Formally, closeness centrality is equal to the inverse of the average network distance from bank i to all other banks in the network. It can be thought of as an average proximity of bank i to all other banks in the network.

The banks with the highest closeness centrality in the binary and weighted networks each year are tagged as "network centers." The third network indicator refers to the proximity of each bank i to the network center. For banks that are themselves network centers we set this variable equal to 1.

3.4 Summary statistics

Summary statistics for all the variables used in the analysis are shown in Table 1. Our sample comprises mainly commercial banks (accounting for 81 percent of all banks), and half of all banks are controlled subsidiaries. Average return on assets in the sample is 0.85 and ranges between -6.59 and 8.05. As shown in Figure 1, both bank profitability and leverage (measured as the ratio of assets to equity) have trended upward during the years preceding the global financial crisis. However, both measures have experienced a sharp correction during the crisis.

The middle portion of Table 1 summarizes our exposure and proximity measures. Direct exposures reflect the dollar amount of current outstanding exposures or the number of counterparties in the syndicated loan market (EGBN) and the number of counterparties each bank has established through past lending activity (RGBN), excluding linkages due to loans outstanding. Each variable is computed as total exposures vis-a-vis crisis and non-crisis countries. The average bank has USD 17 billion in total exposures vis-a-vis non-crisis countries and US 1 billion vis-a-vis crisis countries at any given point in time.[12] The average bank also has current exposures vis-a-vis 4 borrowers and past exposures vis-a-vis 6 borrowers in non-crisis countries. Past exposures to crisis countries are about 10 times smaller. The maximum number of current and past borrowers is 202 and 279 in the EGBN and RGBN, respectively. The distribution of the direct exposure measures is heavily skewed towards zero.[13] Indirect proximities based on past relationships vary between 0 and 1, with higher values indicating a lower distance, in network terms, to banks in crisis and non-crisis countries.

Figure 2 depicts the evolution of the total number of connections in the past relationship and current exposures networks. The RGBN is a cumulative network in which banks are linked through lending relationships underpinning asset exposures that never expire. Thus, the number of links in the RGBN increases throughout the sample period. By contrast, the number of links in the EGBN,

[12] Dollar exposures are expressed in constant 1982 USD.

[13] This is a common property of the edge weight and degree distributions in financial and trade networks, as shown, for instance, in Chinazzi et al. (2013) and Fagiolo et al. (2010).

which reflects current interbank relationships, trends downward during 1997-2003 and since 2008, with a gradual increase from 2004 to 2008. These dynamics are a reflection of the two periods of consolidation of the banking system worldwide – mostly through merger and acquisition activity – as well as a period of rapidly growing banking activity in the 2000s.

The bottom portion of Table 1 summarizes the network statistics used in the analysis. We can see that 3 percent of banks in the RGBN and 9 percent of banks in the EGBN on average play the role of a "key intermediary" in the network (that is, they have positive betweenness).

4 Results

We begin our analysis with a simplified version of equation (1) and focus solely on direct exposures via the EGBN and RGBN. Since our goal is to study how systemic banking crises spread through the GBN, we refine our measures of direct linkages by separating them into exposures to crisis vs. non-crisis countries each year. We then turn to the analysis of the link between individual bank network positions and performance during crises. Our dependent variable for the benchmark set of results is return on assets (ROA). We lag all exposure and network measures by one year, and estimate how these lagged measures affect the impact of contemporaneous crises on bank performance. More specifically, we measure exposure of a bank in time $t-1$ to countries that experience systemic banking crisis in time t.

4.1 Bank-level linkages to crisis countries

Table 2 shows a set of regressions in which the covariates of interest are either current exposures (Panel A) or past exposures (Panel B) from the binary EGBN and RGBN. We find that current and past direct linkages to countries in crisis negatively affect bank performance regardless of specification. The results are not sensitive to including bank country fixed effects, bank-level controls, an indicator for crisis in the bank's own country, or year fixed effects (columns 1-4).[14] As expected, once we control for bank characteristics, exposure to *non-crisis* countries does not affect banks' ROA.

Including bank fixed effects in column (5) of Table 2 allows us to link within-bank changes in financial exposures to bank performance. However, the effect of exposures to crisis countries is smaller in magnitude and statistically insignificant, which suggests that most of the negative effect of direct exposures is driven by cross-sectional rather than within-bank variation. Since we are interested in exploiting differences *across* rather than *within* banks, and since all of our control variables enter these specifications significantly, we use column (4) of Table 2 as our benchmark specification.

We can evaluate the magnitude of the effects in column (4) using an example. The dependent variable, ROA, has mean 0.85 and standard deviation 1.66. Let us compare a bank that is not exposed to crisis countries at all ($E^{EGBN01} = 0$) to a bank that is exposed to 40 banks in crisis countries ($E^{EGBN01} = 40$), as was the case with ING in recent years. Other things being equal, the bank with no exposure will have an ROA that is higher by 0.012*40=0.5 than the bank with heavy exposure. This effect is not negligible but is probably not large enough to cause a systemic banking crisis in the country of the exposed bank. Thus, we conclude that the effects of direct linkages on bank performance identified here are unlikely to generate systemic banking crises in other countries through direct bank linkages alone.

To further understand how financial crises spread through the GBN, we combine several measures of direct exposures from the EGBN and RGBN. The results are presented in Table 3. First, we show that it does not matter whether we measure direct current exposures in USD or in terms of the number of banks in each country to which a given bank lends. Except for the size of the estimated coefficient (which is the result of the scale of the measure itself), the results in columns

[14]For RGBN exposures, controlling for bank characteristics is important to obtain the negative effect of exposures to crisis countries.

(1) and (2) where we use USD and binary direct exposures, are virtually identical.

In column (3) of Table 3 we combine direct exposures to crisis countries in terms of loans outstanding in the year prior to the crisis, and in terms of loans that were extended in the past and are no longer outstanding in the year prior to the crisis. We find that both current and past connections with banks in crisis countries are associated with worse bank performance. This latter finding is quite interesting. While the negative effect of direct exposures is very intuitive, that of past connections to crisis country banks is less obvious. One possibility is that past connections may be correlated with other types of business relations that banks engage in after syndicated loan contracts mature. In this sense, RGBN exposures may capture bank-to-bank exposures through multiple lines of business that go beyond borrowing and lending in the syndicated loan market. We continue to find, as expected, that direct exposures to banks in non-crisis countries do not affect ROA.

In column (4) of Table 3 we add a measure of indirect connections based on all loans issued in the past including those currently outstanding. All our previous results hold up to the inclusion of this new variable. We notice that while indirect linkages to crisis countries do not affect bank performance, a higher network proximity to non-crisis countries is negatively associated with bank performance. We find this result counter-intuitive, but it could be understood as follows. Banks for which this measure is high are those that tend to lend to institutions with many direct connections. It is possible that these well-connected institutions are large and have the market power that allows them to obtain cheap funding from other banks, squeezing these banks' profit margins and lowering their return on assets. When their own loan portfolios are at risk because the borrowers' countries are experiencing crises, they can no longer exercise their market power and benefit from access to cheap funding, thus eliminating the negative impact on the profitability of their creditors – the banks with high indirect proximity.

To summarize, our main findings from Table 3 are two-fold. First, direct financial linkages to banks in crisis countries, captured by current loans outstanding, hurt bank performance. Second, past direct linkages have the same effect, possibly capturing the multitude of business relationships that banks share and are difficult to observe otherwise, but are measured here as past interactions in the syndicated loan market. These findings are consistent with those in Battiston et al. (2012) and Nier et al. (2007) in that they show that higher connectedness leads to higher vulnerability. In addition, it appears that while crises definitely spread through the network, they do not spread very far, as suggested by the fact that bank performance does not worsen due to indirect connections to crisis countries. Theoretically, even without indirect effects, the cascade of systemic crises could be generated through direct linkages if banks that are directly exposed to a crisis countries suffer such losses that their own country's banking system goes into a systemic crisis. The magnitudes of the direct effects that we find, however, are not large enough to create such a cascade of systemic banking crises.

We subject these findings to robustness tests in Table 4. In column (1) we replicate the benchmark specification in column (4) of Table 3. In column (2) we use ROE instead of ROA as our measure of bank performance. The results remain qualitatively the same but the coefficients are less precisely estimated. In column (3) we drop the top and bottom 1 percent of the size distribution of banks and the results hold up. In column (4) we include bank fixed effects and find that while direct current exposures are no longer important in transmitting crises, past connections and indirect linkages still have the same effects. In column (5), instead of computing total indirect proximities to all banks in each country (such that proximity of 1/2 to a country with one bank and proximity of 1/4 to each of the two banks in another country produce the same aggregate proximity measures), we divide this number by the number of banks in each country. This allows us to measure average connection "intensity" in that proximity to the second country now becomes 1/4 and is thus lower than proximity to the first country. Our results are robust to this change in definition. Finally, in column (6) we cluster the standard errors by bank country instead of bank and find that the standard errors are virtually unchanged.

4.2 Bank-level global network connectivity

We build on our previous findings to study the effects on bank performance of individual banks' locations in the GBNs. We continue to control for direct and indirect linkages as in our benchmark specification (column (4) of Table 3) and add our three measures of bank centrality in each of the two networks. We also include interactions between these measures and an indicator for systemic banking crises in the bank's home country.[15] We report the results using the network measures based on the RGBN, since it is a more comprehensive summary of all linkages, but we repeat our analysis for the EGBN as a robustness test.

To describe these connectivity measures more intuitively, betweenness of a node reflects its status as an important intermediary in the network, since it counts the number of shortest paths in the network that pass through it. Thus, banks that connect large clusters to one another or the center of network to peripheral clusters tend to have high betweenness. Since many of the nodes, and all terminal nodes, have betweenness of 0, we analyze the effect of a bank having *positive* betweenness, which we call a "key intermediary." We can think of a key intermediary bank as playing the role of a hub, similar to a major airline hub that connects passengers to flights from one continent to another. In the case of banks, a key intermediary borrows from many banks and in turn lends to many banks. One example is Arab Bank Plc (Jordan), which in 2010 had syndicated loan liabilities vis-a-vis 29 banks, mostly European banking groups, and syndicated loan claims on 16 banks, mostly banks from the Middle East.

High closeness centrality describes banks that have, on average, shorter lending chains incident from them and thus, in a graphical representation of the network, will appear to be in the network's center. A bank with high lending closeness centrality may have many borrowers, or it may have few borrowers which are themselves lending to many banks. Banks with very high closeness centrality

[15]We also investigated the effects of interactions with crises in other countries but found that these do not have significant effects on banks' performance.

tend to be the “usual suspects” – large global banks that are likely “too big to fail.” Banks that have high proximity to the network center are banks that are closely connected, through lending, to these global banks. Such banks are still highly connected but are probably not “too big to fail.” The list of banks with maximum closeness centrality – the network centers – for the 1997-2010 period is provided in Appendix B.

Table 5 presents the results where we analyze how being a key intermediary, being close to all other banks in the network, or being close to the network’s center affects bank’s performance during normal times and during crises. Note first that the effects of direct and indirect exposures from our benchmark regressions hold up in these richer specifications. The only difference is that now the effect of higher direct current exposures to non-crisis countries is positive and statistically significant (columns 1-4). This coefficient estimate has a rather small magnitude, as before, but is now more precisely estimated.

Turning to network measures, we focus on column (4) of Table 5 that includes all global connectivity measures at the same time. We find that being a key intermediary in the RGBN is profitable during tranquil times in the bank’s home country. However, when the bank’s home country experiences a systemic banking crisis, being a key intermediary is costly. As the example above illustrates, many of key intermediaries are banks that connect the center of the network to the smaller banks in the region. This unique position allows them to collect rents during normal times, but if their country is affected by a crisis, they may have a harder time getting their regional customers to repay, while still having to honor their obligations to the more centrally-located banks. In this sense, the key intermediaries act as insurers for the regional banking system – during normal times they collect rents, but provide cheap credit or are unable to collect on their loans when crises hit their region.

This effect, however, does not apply to banks that are central in terms of closeness: they have lower returns during normal times but relatively higher returns when their home countries experience crises. The banks with the highest closeness – those located towards the center of the network – are thus relatively safer than others: while they are less profitable during normal times, they post higher returns during crises. The fact that they are on average closer in a network sense to all the other banks in the network means that they have a more diversified set of borrowers, which lowers their yields in normal times but keeps them safe during periods of financial stress. Some of these banks may also benefit from implicit government guarantees during crises, as they tend to be too big and too connected to fail.[16]

Finally, being *close* to the network center does not have the same effect as being *the center* of the network: banks that are in close proximity to the network center tend to do better during normal times, but worse when there is a crisis in their home markets. This suggests that being close to the most centrally-located banks in the GBN can provide informational, reputational, or other benefits during good times. However, these benefits turn to costs during crises in banks' home countries when their reliance on their network center does not provide the same hedge that equally diversified yet more remote banks may have.

Our results in Table 5 are robust to a number of specifications, presented in Table 6, one of which includes bank fixed effects (column 4). The coefficients are relatively stable when we add bank fixed effects, indicating that changes in a bank's position in the global banking network over time – rather than the cross-sectional variation – helps pin down our results. As before, using ROE instead of ROA increases the standard errors, but does not qualitatively change the results (column 2). Dropping the top and bottom 1 percent observations from the banks' size distribution does not materially affect the results, which suggests that the patterns we have identified are quite general and not driven by a handful of large global banks (column 3). Using average (as opposed to total) indirect exposures to crisis countries leads to statistically insignificant effects for direct EGBN exposures, but the coefficients for direct and indirect RGBN exposures, as well as the effects

[16] Note that our analysis is subject to survival bias. We are not looking at bank failures, but some of the banks for which ROA is low in a given period may fail in subsequent periods.

of connectivity measures, hold up (column 5). Finally, replacing the global connectivity measures based on the past relationship network RGBN with those from the current exposures network EGBN does not change our results (column 6), except that there is less evidence for the benefits of being a key intermediary or close to the network center during normal times.

5 Conclusion

In this paper we take a first step towards better understanding the role of financial system complexity in the transmission of shocks worldwide. In particular, we examine how systemic banking crises spread through the web of bank linkages. To do so, we construct a global banking network based on bank-to-bank transactions in the syndicated loan market. While participation in this market does not fully describe bank exposures to one other, we believe that exposures built through the entire history of loan contracts in this market can serve as a useful proxy for more general business linkages across banks. To refine our analysis, we distinguish between current exposures – based on outstanding syndicated loan claims – and connections resulting from past loans that are no longer outstanding.

A crucial step in our analysis is linking information on syndicated lending with bank balance sheet data, which we are first to accomplish in a systematic fashion. We construct a rich dataset for over 2,000 banks from 73 countries for which we have information on both syndicated loan transactions and balance sheets during 1997-2010. The data allow us to measure the effect of financial linkages on bank performance. We also employ data on the incidence of systemic banking crises to study how crises transmit through the global banking network.

We find, not surprisingly, that outstanding loan exposures to banks in crisis countries tend to hurt banks' performance. More interestingly, we find that connections established through past loans to banks which have no current outstanding commitment play a similar role. We conjecture that past transactions in the syndicated loan market create linkages which may result in other business relations, not limited to syndicated lending, and which we do not observe. Thus, we may think of past relationships as a proxy for more complete bilateral bank exposures. Another interesting finding is that indirect linkages to banks in crisis countries do not affect bank performance.

In terms of bank's general connectivity in the global banking network, we find that there are major differences between banks with different positions in the network. In particular, banks that have high betweenness centrality – key intermediaries – have different performance during crises in their home countries compared to banks that are central in terms of closeness centrality. Intuitively, banks with high closeness centrality are "close," in a network sense, to all the other banks in the network, while key intermediaries connect centrally-located banks in the network to regional peripheral institutions. The former type of banks tend to be safer – with lower returns in normal times but higher returns during crises. By contrast, key intermediaries act as insurers for their regional banking systems, extracting higher returns during normal times, but performing worse during crises. Finally, being close to the network's most centrally-located bank – typically a large and reputable global bank – is quite the opposite from being that bank itself: Banks that are close to network centers benefit from this unique position during normal times, but suffer during crises.

Taken together, our findings provide direct evidence of crisis transmission through the global banking network. However, they also indicate that these crises do not spread very far in the network sense, unless losses through direct exposures generate a cascade of systemic banking crises. The magnitude of our effects, however, are too modest to suggest that direct linkages created by syndicated loan exposures – either past or present – are likely to generate systemic crisis on their own. What seems to matter most for bank performance are a bank's direct exposures to crisis countries as well as its location in the global banking network when a crisis hits its home country.

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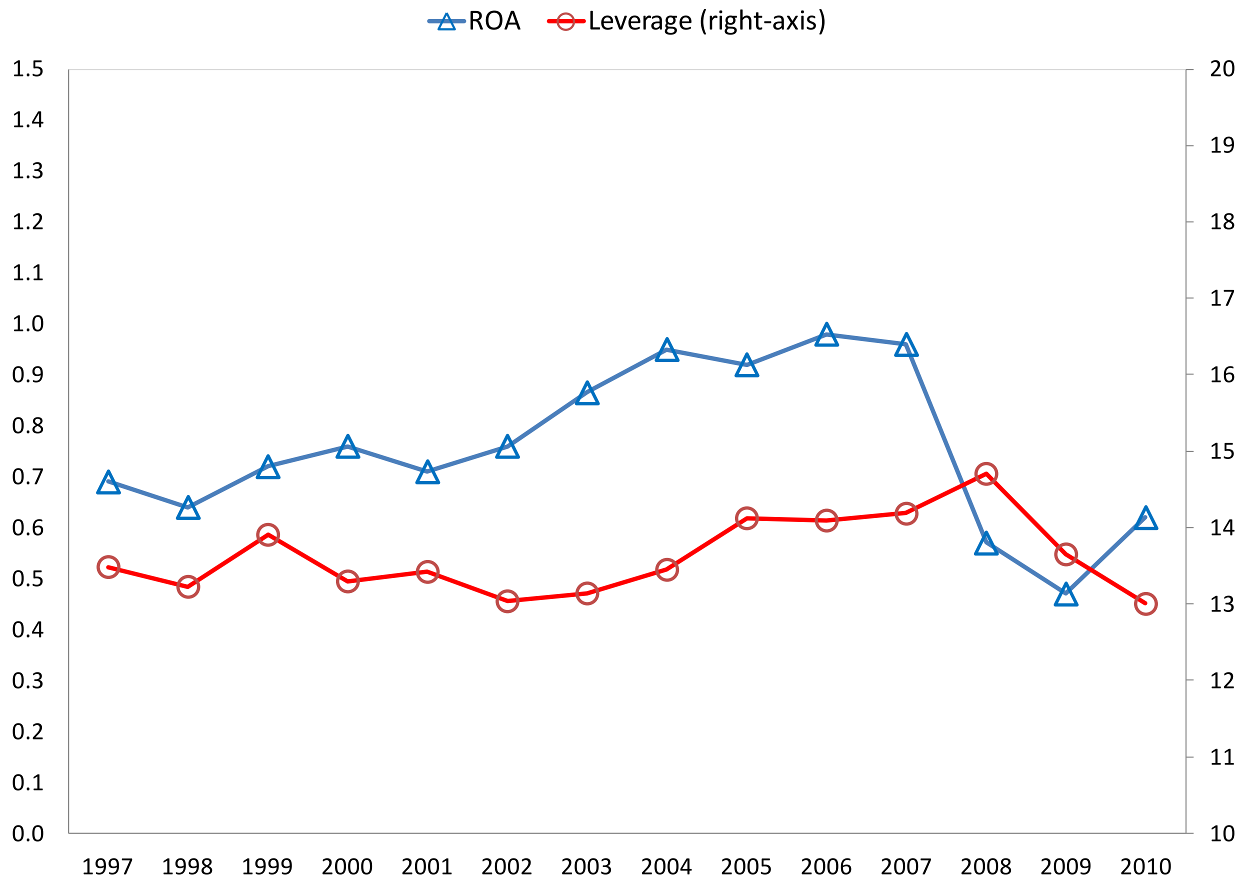
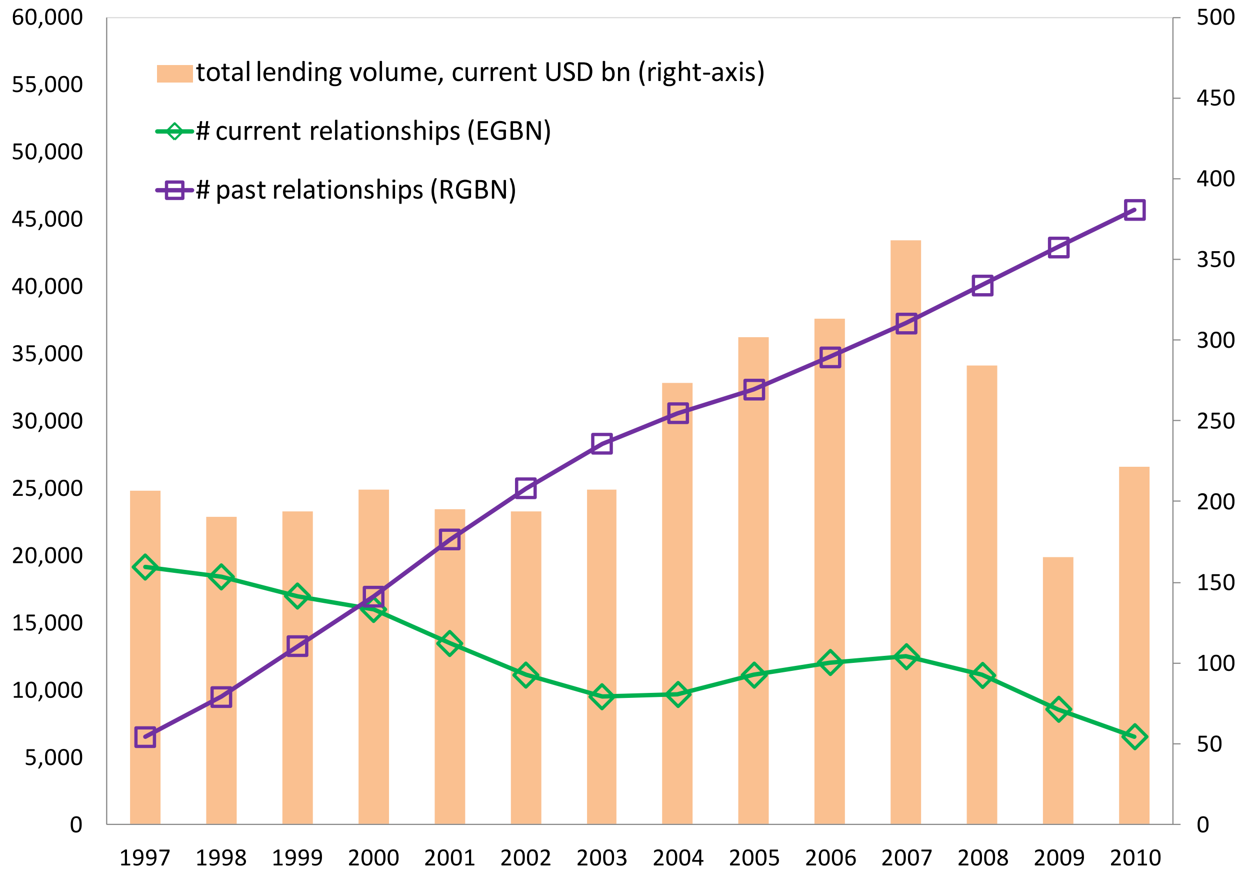
Figure 1: Bank performance and leverage, 1997-2010



Source: Bankscope.

Figure 2: Network connectivity and total bank-to-bank syndicated lending, 1997-2010



Source: Loan Analytics and authors' calculations.

Table 1: Summary statistics

Variable	N	Mean	Median	St. Dev.	Min	Max
Dependent variable						
Return on assets	15,022	0.85	0.72	1.66	-6.59	8.05
Return on equity	15,011	8.50	9.23	16.56	-78.16	54.22
Control variables						
Equity/Assets	15,004	9.58	7.03	10.14	0.32	73.33
Log(assets)	11,600	16.36	16.16	1.69	13.86	20.99
Crisis in home country	14,178	0.22	0.00	0.42	0.00	1.00
Type of entity, *of which:*						
Controlled subsidiary	7,362	0.49	0.00	0.50	0.00	1.00
Global ultimate owner	4,024	0.27	0.00	0.44	0.00	1.00
Other	3,636	0.24	0.00	0.43	0.00	1.00
Specialization, *of which:*						
Commercial bank	12,133	0.81	1.00	0.39	0.00	1.00
Bank holding company	1,341	0.09	0.00	0.29	0.00	1.00
Other	1,548	0.10	0.00	0.30	0.00	1.00
Direct exposures						
Direct current exposure to non-crisis countries (US$)	11,874	0.17	0.00	0.77	0.00	14.96
Direct current exposure to crisis countries (US$)	11,874	0.01	0.00	0.16	0.00	7.21
Direct current exposure to non-crisis countries	11,874	3.96	0.00	12.81	0.00	202.00
Direct current exposure to crisis countries	11,874	0.38	0.00	2.23	0.00	58.00
Direct past exposure to non-crisis countries	11,874	6.04	1.00	17.97	0.00	279.00
Direct past exposure to crisis countries	11,874	0.50	0.00	2.82	0.00	70.00
Indirect exposures						
Indirect proximity to non-crisis countries	11,874	0.03	0.00	0.18	0.00	1.00
Indirect proximity to crisis countries	11,874	0.03	0.00	0.04	0.00	0.13
Indirect proximity to non-crisis countries (average)	11,777	0.37	0.33	0.40	0.00	1.00
Indirect proximity to crisis countries (average)	11,777	0.09	0.00	0.29	0.00	1.00
Network statistics						
Past exposures network (RGBN)						
Key intermediary (betweenness centrality = 1)	11,921	0.03	0.00	0.18	0.00	1.00
Closeness centrality	11,921	0.03	0.00	0.04	0.00	0.13
Closeness to network center	11,921	0.37	0.33	0.40	0.00	1.00
Current exposures network (EGBN)						
Key intermediary (betweenness centrality = 1)	11,921	0.09	0.00	0.29	0.00	1.00
Closeness centrality	11,921	0.05	0.00	0.05	0.00	0.13
Closeness to network center	11,921	0.49	0.50	0.46	0.00	1.00

Notes: Summary statistics are shown for all bank-year observations for which ROA is non-missing. The variables ROA, ROE, equity/assets, and assets are winsorized at the 1st and 99th percentiles. Direct current exposures are expressed in constant (1982) hundreds of USD billions. Sources: Loan Analytics, Bankscope, Laeven and Valencia (2012), and authors' calculations.

Table 2: Effect of current and past *direct* exposures on bank performance

Panel A.	(1)	(2)	(3)	(4)	(5)
L. Direct current exposure to non-crisis countries	-0.003*	0.001	-0.001	-0.000	0.002
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
L. Direct current exposure to crisis countries	-0.019***	-0.014*	-0.016***	-0.012***	-0.004
	(0.006)	(0.007)	(0.004)	(0.004)	(0.005)
Equity/Assets			0.092***	0.092***	0.109***
			(0.013)	(0.014)	(0.017)
Log-assets			0.108***	0.102***	0.376***
			(0.015)	(0.015)	(0.089)
Crisis in home country			-0.827***	-0.772***	-0.744***
			(0.047)	(0.060)	(0.073)
Type of entity FE	no	no	yes	yes	yes
Specialization FE	no	no	yes	yes	yes
Bank FE	no	no	no	no	yes
Bank nationality FE	no	yes	yes	yes	no
Year FE	no	no	no	yes	yes
Observations	11,874	11,874	9,129	9,129	9,129
R-squared	0.002	0.117	0.324	0.334	0.556

Panel B					
L. Direct past exposure to non-crisis countries	-0.003***	-0.000	-0.001	-0.001	0.004*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
L. Direct past exposure to crisis countries	-0.001	0.001	-0.013***	-0.012***	-0.006
	(0.004)	(0.004)	(0.003)	(0.003)	(0.005)
Equity/Assets			0.093***	0.093***	0.109***
			(0.013)	(0.013)	(0.017)
Log-assets			0.108***	0.104***	0.378***
			(0.014)	(0.014)	(0.089)
Crisis in home country			-0.823***	-0.772***	-0.764***
			(0.047)	(0.061)	(0.075)
Type of entity FE	no	no	yes	yes	yes
Specialization FE	no	no	yes	yes	yes
Bank FE	no	no	no	no	yes
Bank nationality FE	no	yes	yes	yes	no
Year FE	no	no	no	yes	yes
Observations	11,874	11,874	9,129	9,129	9,129
R-squared	0.001	0.117	0.324	0.334	0.556

Notes: The dependent variable is ROA. Direct current and past exposures are based on the binary EGBN (Panel A) and binary RGBN (Panel B). Standard errors are clustered on bank. Sources: Loan Analytics, Bankscope, Laeven and Valencia (2012), and authors' calculations.

Table 3: Effect of current and past *direct and indirect* exposures on bank performance - Benchmark

	(1)	(2)	(3)	(4)
L. Direct US$ current exposure to non-crisis countries	0.003			
	(0.019)			
L. Direct US$ current exposure to crisis countries	-0.104***			
	(0.037)			
L. Direct current exposure to non-crisis countries		-0.000	0.000	0.003*
		(0.001)	(0.002)	(0.001)
L. Direct current exposure to crisis countries		-0.012***	-0.009**	-0.009*
		(0.004)	(0.004)	(0.005)
L. Direct past exposure to non-crisis countries			-0.001	-0.001
			(0.001)	(0.001)
L. Direct past exposure to crisis countries			-0.009**	-0.009**
			(0.003)	(0.003)
L. Indirect proximity to non-crisis countries				-0.028**
				(0.011)
L. Indirect proximity to crisis countries				0.033
				(0.038)
Equity/Assets	0.092***	0.092***	0.093***	0.093***
	(0.014)	(0.014)	(0.013)	(0.014)
Log-assets	0.099***	0.102***	0.105***	0.111***
	(0.015)	(0.015)	(0.015)	(0.015)
Crisis in home country	-0.767***	-0.772***	-0.776***	-0.781***
	(0.060)	(0.060)	(0.061)	(0.061)
Type of entity FE	yes	yes	yes	yes
Specialization FE	yes	yes	yes	yes
Bank FE	no	no	no	no
Bank nationality FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Observations	9,129	9,129	9,129	9,129
R-squared	0.333	0.334	0.334	0.335

Notes: The dependent variable is ROA. Direct current US$ exposures are expressed in real USD (hundreds of billions). Direct current exposures are based on the EGBN. Direct past exposures and indirect proximities are based on the RGBN. Standard errors are clustered on bank. Sources: Loan Analytics, Bankscope, Laeven and Valencia (2012), and authors' calculations.

Table 4: Effect of current and past *direct and indirect* exposures on bank performance - Robustness

	(1)	(2)	(3)	(4)	(5)	(6)
	Benchmark	ROE	Drop 1%	Bank FE	Average for indirect	Cluster on country
L. Direct current exposure to non-crisis countri	0.003*	0.008	0.003*	0.001	0.001	0.003*
	(0.001)	(0.022)	(0.001)	(0.002)	(0.001)	(0.002)
L. Direct current exposure to crisis countries	-0.009*	-0.112*	-0.008*	-0.002	-0.008*	-0.009*
	(0.005)	(0.061)	(0.004)	(0.005)	(0.004)	(0.005)
L. Direct past exposure to non-crisis countries	-0.001	0.008	-0.001	0.002	-0.001	-0.001
	(0.001)	(0.014)	(0.001)	(0.002)	(0.001)	(0.002)
L. Direct past exposure to crisis countries	-0.009**	-0.071	-0.010***	-0.009*	-0.009***	-0.009**
	(0.003)	(0.044)	(0.003)	(0.005)	(0.003)	(0.004)
L. Indirect proximity to non-crisis countries	-0.028**	-0.195	-0.028**	-0.029**	-11.249*	-0.028**
	(0.011)	(0.132)	(0.011)	(0.014)	(6.005)	(0.011)
L. Indirect proximity to crisis countries	0.033	0.768	0.035	0.046	12.519	0.033
	(0.038)	(0.496)	(0.040)	(0.047)	(16.188)	(0.049)
Equity/Assets	0.093***	0.315***	0.090***	0.109***	0.091***	0.093***
	(0.014)	(0.086)	(0.014)	(0.017)	(0.014)	(0.006)
Log-assets	0.111***	1.098***	0.112***	0.381***	0.113***	0.111***
	(0.015)	(0.186)	(0.016)	(0.089)	(0.016)	(0.014)
Crisis in home country	-0.781***	-9.998***	-0.815***	-0.764***	-0.810***	-0.781***
	(0.061)	(0.773)	(0.065)	(0.075)	(0.065)	(0.162)
Type of entity FE	yes	yes	yes	yes	yes	yes
Specialization FE	yes	yes	yes	yes	yes	yes
Bank FE	no	no	no	yes	no	no
Bank nationality FE	yes	yes	yes	no	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Observations	9,129	9,128	8,239	9,129	8,322	9,129
R-squared	0.335	0.203	0.328	0.557	0.330	0.335

Notes: The dependent variable is ROA in all columns except column 2 where it is ROE. Direct current exposures are based on the EGBN. Direct past exposures and indirect proximities are based on the RGBN. In column 1 we replicate the benchmark specification from Table 3, column 4. In column 3 we drop the top and bottom 1 percent of the bank size distribution. In column 4 we include bank FEs rather than bank nationality FEs. In column 5 we compute indirect proximities as averages (across the number of banks in each vis-a-vis country) rather than summations. In Column 6 we cluster the standard errors on bank nationality. Standard errors in columns 1-5 are clustered on bank. Sources: Loan Analytics, Bankscope, Laeven and Valencia (2012), and authors' calculations.

Table 5: Effect of network connectivity on bank performance - Benchmark

	(1)	(2)	(3)	(4)
L. Direct current exposure to non-crisis countries	0.003**	0.003*	0.004**	0.003**
	(0.001)	(0.001)	(0.001)	(0.002)
L. Direct current exposure to crisis countries	-0.010**	-0.008*	-0.011**	-0.008*
	(0.005)	(0.004)	(0.005)	(0.005)
L. Direct past exposure to non-crisis countries	-0.001	-0.001	-0.001	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)
L. Direct past exposure to crisis countries	-0.009***	-0.008**	-0.009***	-0.008**
	(0.003)	(0.003)	(0.003)	(0.004)
L. Indirect proximity to non-crisis countries	-0.030***	-0.025**	-0.032***	-0.025**
	(0.011)	(0.011)	(0.011)	(0.011)
L. Indirect proximity to crisis countries	0.034	0.036	0.035	0.036
	(0.040)	(0.039)	(0.040)	(0.039)
L. Key intermediary	0.057			0.149*
	(0.074)			(0.077)
L. Key intermediary * Crisis in home country	-0.286*			-0.538***
	(0.173)			(0.185)
L. Closeness centrality		-0.848**		-1.920***
		(0.391)		(0.649)
L. Closeness centrality * Crisis in home country		1.439*		6.014***
		(0.783)		(1.352)
L. Closeness to network center			0.009	0.142**
			(0.039)	(0.065)
L. Closeness to network center * Crisis in home country			-0.227**	-0.627***
			(0.098)	(0.155)
Equity/Assets	0.091***	0.091***	0.091***	0.091***
	(0.014)	(0.014)	(0.014)	(0.014)
Log-assets	0.116***	0.118***	0.119***	0.118***
	(0.016)	(0.017)	(0.017)	(0.017)
Crisis in home country	-0.803***	-0.849***	-0.738***	-0.724***
	(0.066)	(0.071)	(0.069)	(0.068)
Type of entity FE	yes	yes	yes	yes
Specialization FE	yes	yes	yes	yes
Bank nationality FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Observations	8,342	8,342	8,342	8,342
R-squared	0.331	0.331	0.331	0.335

Notes: The dependent variable is ROA. Direct current exposures are based on the EGBN. Direct past exposures and indirect proximities are based on the RGBN. Standard errors are clustered on bank. See Section 2.3 for definitions of network indicators. Sources: Loan Analytics, Bankscope, Laeven and Valencia (2012), and authors' calculations.

Table 6: Effect of network connectivity on bank performance - Robustness

	(1) Benchmark	(2) ROE	(3) Drop 1%	(4) Bank FE	(5) Average for indirect	(6) EGBN
L. Direct current exposure to non-crisis countries	0.003**	0.003	0.003*	0.000	-0.000	0.003**
	(0.002)	(0.022)	(0.002)	(0.003)	(0.003)	(0.002)
L. Direct current exposure to crisis countries	-0.008*	-0.108*	-0.007	-0.004	-0.001	-0.008*
	(0.005)	(0.059)	(0.004)	(0.006)	(0.006)	(0.004)
L. Direct past exposure to non-crisis countries	-0.002	0.004	-0.001	-0.000	0.000	-0.002
	(0.001)	(0.015)	(0.001)	(0.002)	(0.002)	(0.001)
L. Direct past exposure to crisis countries	-0.008**	-0.070	-0.009***	-0.011**	-0.011**	-0.007**
	(0.004)	(0.046)	(0.003)	(0.005)	(0.005)	(0.003)
L. Indirect proximity to non-crisis countries	-0.025**	-0.172	-0.025**	-0.034*	-14.651**	-0.024**
	(0.011)	(0.132)	(0.011)	(0.018)	(6.810)	(0.011)
L. Indirect proximity to crisis countries	0.036	0.782	0.039	0.028	15.197	0.041
	(0.039)	(0.493)	(0.039)	(0.054)	(21.702)	(0.039)
L. key intermediary	0.149*	1.061	0.145*	0.177**	0.174**	0.069
	(0.077)	(0.878)	(0.078)	(0.078)	(0.078)	(0.075)
L. Key intermediary * Crisis in home country	-0.538***	-2.287	-0.538***	-0.449**	-0.431**	-1.008***
	(0.185)	(2.493)	(0.186)	(0.204)	(0.205)	(0.184)
L. Closeness centrality	-1.920***	-10.509	-1.912***	-1.625**	-1.663**	-1.786**
	(0.649)	(7.936)	(0.649)	(0.757)	(0.755)	(0.800)
L. Closeness centrality * Crisis in home country	6.014***	49.118**	5.968***	6.215***	6.219***	8.211***
	(1.352)	(19.075)	(1.347)	(1.575)	(1.575)	(2.191)
L. Closeness to network center	0.142**	0.993	0.147**	0.087	0.090	0.040
	(0.065)	(0.792)	(0.065)	(0.076)	(0.076)	(0.070)
L. Closeness to network center * Crisis in home country	-0.627***	-5.273**	-0.622***	-0.760***	-0.756***	-0.457**
	(0.155)	(2.096)	(0.154)	(0.177)	(0.177)	(0.233)
Equity/Assets	0.091***	0.319***	0.091***	0.107***	0.107***	0.091***
	(0.014)	(0.091)	(0.014)	(0.018)	(0.018)	(0.014)
Log-assets	0.118***	1.157***	0.115***	0.400***	0.401***	0.117***
	(0.017)	(0.207)	(0.017)	(0.101)	(0.101)	(0.017)
Crisis in home country	-0.724***	-9.541***	-0.725***	-0.648***	-0.653***	-0.919***
	(0.068)	(0.950)	(0.068)	(0.078)	(0.078)	(0.085)
Type of entity FE	yes	yes	yes	yes	yes	yes
Specialization FE	yes	yes	yes	yes	yes	yes
Bank FE	yes	no	no	yes	no	no
Bank nationality FE	yes	yes	yes	no	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Observations	8,342	8,341	8,258	8,342	8,322	8,342
R-squared	0.335	0.202	0.334	0.561	0.561	0.340

Notes: The dependent variable is ROA in all columns except column 2 where it is ROE. Direct current exposures are based on the EGBN. Direct past exposures and indirect proximities are based on the RGBN. In column 1 we replicate the benchmark specification from Table 5, column 4. In column 3 we drop the top and bottom 1 percent of the bank size distribution. In column 4 we include bank FEs rather than bank nationality FEs. In column 5 we compute indirect proximities as averages (across the number of banks in each vis-a-vis country) rather than summations. In Column 6 we cluster the standard errors on bank nationality. Standard errors are clustered on bank.
Sources: Loan Analytics, Bankscope, Laeven and Valencia (2012), and authors' calculations.

Appendix A. Data Construction

To construct our dataset we proceed as follows:

- Step 1. We download from Loan Analytics all syndicated loans to banks signed between January 1990 and December 2010.

  We drop the syndicated loan deals for which the lender is recorded as "unknown" or "undisclosed [Asian, French, German, Japanese] bank". We also drop the loan deals that involve non-bank borrowers. 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 information is correct by comparing banks that appear both as borrowers and lenders. We also retain the loan deals with multiple borrowers (representing less than 1 percent of the sample), for which we impute their nationality only if it cross-checks with information in Bankscope.

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

  - If a bank changed name during 1990-2010, we retain its Bankscope name (as of end-2010) 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.

  The RGBN and EGBN are constructed using the full set of about 5,500 distinct banks that appear as lenders or borrowers in the syndicated lending market during 1990-2010.

- Step 3. After cleaning the bank names, we match all institutions – by bank name and country – with balance sheet data from Bankscope. We use various sources to learn the institutional history of banks and make appropriate matches. These include bank websites, the FDIC website[17] and Bloomberg Businessweek.[18] Subsidiaries that report balance sheet information in Bankscope are treated as distinct entities and are not linked to their parent financials.

The merged sample of banks that participate in the syndicated loan market and report balance sheet information to Bankscope contains about 2,000 distinct banks.

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

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

Appendix B. Network Centers

The table below reports the network centers, i.e., the banks with the highest closeness centrality in the EGBN and RGBN, respectively, during 1997-2010.

Year	Bank	Bank nationality	Bank	Bank nationality
	EGBN		RGBN	
1997	JP Morgan	US	JP Morgan	US
1998	JP Morgan	US	LRP	Germany
1999	BayernLB	Germany	WestLB	Germany
2000	BayernLB	Germany	Citibank	US
2001	BayernLB	Germany	Unicredit	Germany
2002	BayernLB	Germany	HSBC	UK
2003	WestLB	Germany	HSBC	UK
2004	HSBC	UK	HSBC	UK
2005	HSBC	UK	HSBC	UK
2006	Santander	Spain	Santander	Spain
2007	BBVA	Spain	BBVA	Spain
2008	BBVA	Spain	BBVA	Spain
2009	BBVA	Spain	BBVA	Spain
2010	BBVA	Spain	BBVA	Spain

Sources: Loan Analytics and authors' calculations.