

Crisis Transmission in the Global Banking Network*

Galina Hale
Federal Reserve Bank of San Francisco

Tümer Kapan
Fannie Mae

Camelia Minoiu
International Monetary Fund

April 30, 2014

Abstract

To shed light on the role of international bank linkages in the transmission of financial shocks, we construct a global network of interbank exposures. We study the impact of direct and indirect exposures to systemic banking crises in home and foreign countries on bank profitability. We perform the analysis in a panel of over 2,000 banks from 88 countries spanning the 1997-2010 period. We find that, controlling for exposures to non-bank borrowers, larger direct and indirect exposures to bank borrowers in crisis countries reduce bank profitability. We also find that banks that serve as unique connectors or “key intermediaries” in the network have lower profitability during home country crises than other banks.

JEL classification: F34, F36

Keywords: financial networks, syndicated loans, systemic banking crises, contagion

* Author email addresses: galina.b.hale@sf.frb.org; tk2130@columbia.edu; cminoiu@imf.org. We thank Charles Calomiris, Stijn Claessens, Ricardo Correa, Ben Craig, Era Dabla-Norris, Michael Gofman, Mathias Hoffmann, Graciela Kaminsky, Andrew Karolyi, Augustin Landier, José-Luis Peydró, Enrico Sette, and participants at the World Bank Conference “Networks and connectivity tools” (Washington D.C., May 2013), Max-Planck Institute Conference “The Structure of Banking Systems and Financial Stability” (Bonn, Sept 2013), 2nd Annual CIRANO-CIREQ Workshop on Networks in Trade and Finance (Montreal, Nov 2013), SAFE/Bundesbank Conference “Supervising Banks in Complex Financial Systems” (Frankfurt, Nov 2013), Info-metrics Workshop “Information, Instability and Fragility in Networks” (Boulder CO, Nov 2013), PSE/BdF/NYFed/CEPR Workshop “The Economics of Cross-Border Banking” (Paris, Dec 2013), and CEPR/CREI Ninth Annual Workshop on the Macroeconomics of Global Interdependence (Barcelona, April 2014) 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 bank linkages in the transmission of financial sector shocks. Policymakers argue that the complexity of banking connections, which has grown significantly in recent years, has contributed to the severity of the global financial crisis (Dudley, 2012; Haldane, 2009; Tumpel-Gugerell, 2009). The academic literature emphasizes the role of financial sector complexity in generating panics and deepening crises (Caballero & Simsek, 2009, 2013). We contribute to this discussion by analyzing empirically the transmission of systemic banking crises through the global banking network. Our empirical approach, based on modeling the international market for interbank syndicated lending as a network, allows us to examine the role of several channels through which banking crises are transmitted internationally. We seek to determine whether direct exposure to borrowers in countries that experience a crisis, indirect exposures to them, and the interconnectedness of banks in the global banking network explain bank profitability.

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 highly interconnected institution, financial markets shut down, triggering a credit crunch and 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. These efforts have spurred a large literature on the resilience of financial networks to shocks (reviewed, for instance, in Chinazzi & Fagiolo (2013); Summer (2013); Allen & Babus (2009)). However, studies of shock transmission through *empirical* networks remains scarce, mainly due to the data limitations. Our paper aims to fill this gap.

Syndicated loan data provides a unique source of information on interbank exposures on a global scale. Using transaction-level data on syndicated loans, we construct a global banking network and find that it acts as a conduit for the spread of financial crises: larger direct exposures to borrowers,

especially banks, in crisis countries have a negative impact on bank returns. We also find that indirect (higher-degree) exposures to banks in crisis countries reduce bank profitability. We then test whether banks' degree of interconnectedness in the global banking network has an effect on their performance. In doing so, we focus on a particular type of centrality to identify important "intermediaries" in the network. These are banks that act as unique connectors between groups of banks in the network. Key intermediaries tend to connect global banks that are highly centric in the network with peripheral ones. We find that key intermediaries have similar returns to other banks during normal times, but fare significantly worse during periods of financial stress in their home countries. We argue that interbank exposures formed through syndicated lending, while important in their own right, are likely to also capture other types of linkages across banks.¹

To map international financial linkages and study the transmission of crises, we use loan-level data on loan syndications arranged by lenders in 88 countries to borrowers in 141 countries. These linkages refer to exposures created through syndicated lending to financial and non-financial firms, with the former as our main focus. The syndicated loan market is an important source of funding for corporates and sovereigns, but also for financial institutions, especially banks. To illustrate, Turkish banks have recently tapped the international bank loan market to broaden their sources of funds. Their loans have typically been oversubscribed, with many international banks eager to gain exposure to Turkish assets and build relationships with Turkish banks. Total deal volume in the syndicated loan market reached USD 4.3 trillion in 2007, of which about 10 percent represented lending to banks. Major borrowers in this market include banks from the Japan, Hong Kong SAR, Thailand, Turkey, and the UK.

Using data on borrowers and lenders in interbank syndicated loan deals, we construct a bank-level financial network to which we refer as the "exposures global banking network" (EGBN).

¹Corporate finance studies emphasize the complex nature of bank-borrower relationships, which often entail interactions in multiple lines of business such as underwriting and direct lending (Chen et al., 2013; Bharath et al., 2007; Burch et al., 2005).

This is a standard counterparty network: edges represent interbank exposures (i.e., the stock of syndicated loan claims outstanding at a given point in time) and the nodes are banks. The EGBN is a directed network – in constructing loan exposures we focus on lending relationships, and in defining key intermediaries we look at banks that act both as borrowers and lenders. Based on the EGBN we construct measures of direct and indirect linkages among some 5,500 banks as well as bank-level indicators of interconnectedness.

An important 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 for a very large sample of banks.² By combining measures of connectivity in the EGBN with bank financial data, we obtain a rich bank-level panel dataset spanning the 1997-2010 period. We then study the effect of direct and indirect linkages in the EGBN on bank profitability during crisis and tranquil years in the countries to which the banks are exposed. For the baseline regressions, our measure of bank profitability is return on assets (ROA). Crises are defined as systemic country-wide banking crises as in Laeven & Valencia (2012). We also examine whether a bank’s position in the EGBN as a key intermediary is important in explaining profitability during crises in the bank’s home country and abroad.

In theory, higher financial interconnectedness carries both benefits and risks. More interconnectedness improves risk sharing but can also facilitate contagion. A large body of work following the seminal study of Allen & Gale (2000) investigates the link between network topology (the pattern of relationships among economic agents) and the network’s resilience to shocks. Due to the complex nature of real-world network topologies, much of this literature has relied on simulations (see Upper (2011) for a review).³ Our contribution is to study channels of crisis transmission through the EGBN using observational data rather than simulations and to document empirically that network

²Giannetti & Laeven (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 in our sample.

³See, for example, Battiston et al. (2009); Castiglionesi & Navarro (2010); Chan-Lau et al. (2009); Cocco et al. (2009); Craig & von Peter (2010); Gatti et al. (2010); Elliott et al. (2012); Garratt et al. (2011); Haldane & May (2011); Imai & Takarabe (2011); May & Arinaminpathy (2009); Nier et al. (2007); Sachs (2010) and von Peter (2007).

connections and structure are important in the global transmission of financial sector shocks.

Our study contributes to a large literature on contagion in financial markets, especially contractual “knock-on” contagion (see Allen et al. (2009) for a survey). In the recent empirical 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 centric in the global syndicated loans network, 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 banks and using the most granular data available to shed light on the role of financial linkages in the spread of banking crises internationally.

We also contribute to a growing body of work on systemic risk in empirical financial networks constructed from syndicated loan data. Recent studies construct global banking networks in which links arise when banks participate in the same lending syndicate (Bo et al., 2013; Godlewski et al., 2012; Cai et al., 2012). These “co-syndication” networks capture interconnectedness of banks through common asset exposures. Cai et al. (2012) show that global banks that are active underwriters of syndicated loans and are thus highly interconnected in the co-syndication network contribute more to systemic risk. Bo et al. (2013) show that syndicated loans arranged by highly centric banks in the same network tend to be made to more opaque borrowers. Our approach is different from these studies in that links in the EGBN arise when banks create exposures to borrowers through loan syndications. Therefore, ours is a standard network of interbank exposures that captures contractual interconnectedness rather than common exposures. The EGBN also differs

from domestic interbank networks that have been commonly analyzed in the literature in that it has international coverage.

The remainder of the paper is organized as follows. In Section 2 we provide a short description of the interbank syndicated loan market. In Section 3 we present a simple mechanism for contagion in a financial network. Section 4 describes our data and empirical approach. In Section 4 we present our baseline results, a discussion of mechanisms, and robustness tests. Section 5 concludes.

2 A Primer on the Interbank Loan Syndication 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 (loan commitments) and term loans. Syndicated loans are originated by one or more lenders – the so-called “lead arrangers” – 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 the median maturity is around 5 years. Most loans have floating interest rate based on the LIBOR. During 1997-2010 the largest lenders in this market were banks from the US, UK, Germany, Japan, and France. These countries also account for the largest deal volumes to banks. Over the same period, the largest borrowers in the interbank market were banks from the US, UK, Australia, Hong Kong (SAR), and France. Large emerging market borrowers included the Russian Federation, South Korea, Turkey, India, and South Africa.

Focusing on cross-border transactions only, Cerutti et al. (2014) show that syndicated loan exposures represented about one third of total loan claims in 2012.⁴ To estimate the size of the *interbank* segment of this market, we compare cross-border syndicated loan exposures *to banks* with BIS loan exposures *to banks* between 1995 and 2012. We construct three estimates of syndi-

⁴The rest is accounted for by cross-border bilateral loans and internal capital markets transactions.

cated loan exposures (see Figure 1):⁵ (i) an upper bound estimate, which comprises total credit lines and term loans; (ii) an intermediate estimate, which removes undrawn portions of the credit lines; and (iii) a lower bound estimate, which further removes term loans that are more likely to be extended by institutional investors rather than banks. According to these estimates, syndicated loans to banks accounted for between 6.7 and 26.7 percent of total loan claims on banking systems during 1995-2012. The intermediate estimate for the period is 12.5 percent.

3 Contagion Mechanism

In this section we describe a simple contagion 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 $E_{ij}\delta^{(s)}$, where E is either an indicator for the presence of an 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 an indicator for a financial crisis in the country of bank i . Omitting the time subscript for simplicity, a contagion mechanism in the EGBN can be written as a spatial recursive equation as follows:

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

where α_i captures all other factors affecting the performance of bank i . Equation (1) can be expanded infinitely to obtain an expression for the effect of bank i exposure to borrowers in crisis countries:

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

⁵These are obtained using the methodology outlined in Cerutti et al. (2014).

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 “network distance” in the binary EGBN between banks i and j (network distance is the number of steps on the shortest path between the two banks); $\bar{\alpha}$ is a weighted average of other characteristics that affect performance of banks other than i ; and C_j represents an indicator for financial crisis in the country of bank j . Equation (2) thus shows how the performance of bank i depends on its direct and indirect exposures to borrowers in countries that are experiencing a crisis.

We can expand equation (1) by explicitly allowing performance to be affected by the bank’s position in the EGBN – its “global connectivity profile” – which we denote N_i , as follows:

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

where we allow for a differential impact of the bank’s degree of interconnectedness during tranquil and crisis times. This equation, too, can be expanded infinitely with the same set of assumptions and definitions to obtain:

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

When we estimate equation (4), we find that the network characteristics of other banks do not have statistically significant effects and we can therefore simplify this equation to:

$$\begin{aligned} Y_i = & \alpha_i + \beta C_i + \mu N_i + \nu N_i C_i + \bar{\alpha} \gamma \sum_j E_{ij} + \beta \gamma \sum_j C_j E_{ij} \\ & + \frac{\bar{\alpha} \gamma^2}{1-\gamma} \sum_j P_{ij} + \frac{\beta \gamma^2}{1-\gamma} \sum_j C_j P_{ij} + o(\text{other banks' network characteristics}). \end{aligned} \quad (5)$$

In the equations above, we have focused only on the impact on bank performance of exposures vis-a-vis banks (that is, “network” exposures). In reality, however, banks’ performance is also affected by exposures to non-bank borrowers such as corporates and sovereigns (that is, “non-network” exposures). Let the direct exposures of bank i to non-bank borrowers in foreign country k be denoted by D_{ik} .⁶ Furthermore, the impact of crises in foreign countries may interact with the network characteristics of bank i . Adding non-network exposures to our last equation, we obtain:

$$\begin{aligned}
Y_i = & \alpha_i + \beta_1 C_i + \beta_2 \sum_k D_{ik} + \beta_3 \sum_k C_k D_{ik} + \mu N_i + \nu_1 N_i C_i + \nu_2 N_i \sum_k C_k + \bar{\alpha} \gamma \sum_j E_{ij} \\
& + \beta_1 \gamma \sum_j C_j E_{ij} + \frac{\bar{\alpha} \gamma^2}{1 - \gamma} \sum_j P_{ij} + \frac{\beta_1 \gamma^2}{1 - \gamma} \sum_j C_j P_{ij} + o(\text{other banks' network characteristics}).
\end{aligned}
\tag{6}$$

We bring this equation to the data in the empirical analysis.

4 Empirical Strategy and Data

4.1 Data sources

We use two main data sources. The first is Dealogic’s Loan Analytics, a database that reports the universe of international syndicated bank loans issued since the early 1980s.⁷ We obtain information for about 150,000 syndicated loan deals structured in 1,000,000 tranches originated between 1990 and 2010. For each loan we observe the identities of the borrower and all syndicate participants,

⁶Since the effect of *indirect* exposures to non-bank borrowers was not statistically significant in our regressions, we do not include them for simplicity.

⁷This 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).

USD loan amount (which we express at constant prices using the US CPI), and loan origination and maturity dates. We then divide loan amounts equally among syndicate participants (for similar approaches, see Kapan & Minoiu (2013); Hale (2012); Giannetti & Laeven (2012)). Using these data we construct, for each year, the EGBN, a counterparty network of interbank exposures. An important caveat is that we only observe loans at origination and do not have data on actual 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. While this likely creates noise in our exposure estimates, it also helps us avoid endogeneity problems we discuss later on. The EGBN has about 5,500 interconnected banks.

Bank balance sheet data come from Bankscope. We merge the interconnectedness data based on Loan Analytics with balance sheet information from Bankscope manually by bank name and country. To ensure consistency of the dataset, prior to the merge we carefully adjust lender names in Loan Analytics to account for name changes, mergers, and acquisitions. (See Appendix for details.) The final balanced panel dataset comprises 2,066 banks during the 1997-2010 period, although the regression sample contains fewer banks due to missing information on balance sheet variables.⁸

4.2 Empirical specifications and endogeneity

Based on equation (6), our main specification links a bank performance measure Y_{iht} (for bank i in country h in year t) to systemic banking crises in all countries d ($Crisis_{dt}$) in year t , including $d = h$, through direct exposures of bank i to vis-a-vis banks in country d at the end of period $t - 1$ (E_{ihdt-1}), indirect linkages of bank i vis-a-vis banks in country d at the end of period $t - 1$ (P_{ihdt-1}), through direct exposures of bank i to non-bank borrowers in country d (D_{ihdt-1}), as well as bank i 's individual network position N_{iht-1} in the binary EGBN. (These variables are formally defined in the next section.)

⁸Note that our analysis is subject to survival bias, as some of the banks for which ROA is low in a period may fail in subsequent periods. In our setting, survival bias works against us finding results.

For each bank we compute direct and indirect linkages in year $t - 1$ to borrowers in countries that are experiencing systemic banking crises at time t and to countries that are not experiencing crises. We also interact bank's overall network position measure N_{iht-1} with an indicator for banking crises in the bank's home country and the total number of crises outside the bank's home country. The most complete specifications are estimated using Ordinary Least Squares (OLS) as follows:

$$\begin{aligned}
Y_{iht} = & \alpha_h + \alpha_t + \alpha_1 I(Crisis_{ht} = 1) + \lambda Z_{iht} \\
& + \alpha_2 \sum_{d \neq h} D_{ihdt-1} I(Crisis_{dt} = 0) + \alpha_3 \sum_{d \neq h} D_{ihdt-1} I(Crisis_{dt} = 1) \\
& + \beta_1 \sum_{d \neq h} E_{ihdt-1} I(Crisis_{dt} = 0) + \beta_2 \sum_{d \neq h} E_{ihdt-1} I(Crisis_{dt} = 1) \\
& + \gamma_1 \sum_{d \neq h} P_{ihdt-1} I(Crisis_{dt} = 0) + \gamma_2 \sum_{d \neq h} P_{ihdt-1} I(Crisis_{dt} = 1) \\
& + \delta_1 N_{iht-1} + \delta_2 N_{iht-1} I(Crisis_{ht} = 1) + \delta_3 N_{iht-1} \sum_{d \neq h} I(Crisis_{dt} = 1) + \varepsilon_{iht},
\end{aligned} \tag{7}$$

where Z_{iht} are bank-specific control variables. We control for bank nationality fixed effects α_h and year fixed effects α_t , therefore identification comes from variation in connectivity across banks in a given country and within banks over time. We allow for the impact of systemic banking crises on bank performance to be instantaneous, but exposures and network measures are lagged one period to avoid direct reversed causality. In all regressions the standard errors are clustered on bank.

An important econometric issue facing our specification is potential endogeneity. A problem of reversed causality can arise if banks liquidate assets and reduce exposures in response to past or expected performance-related shocks. The nature of our data here plays in our favor. Since our data refer solely to loan origination (not loan liquidation, actual drawdowns, or prepayment), the only way in which endogeneity would affect our results is through changes in the pattern of new loan origination (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 global connectivity indicator N

because it is determined not only by the actions of each bank i but also by the actions of all the other banks in the network. Lagging the main covariates further reduces the possibility that the results are driven by the acquisitions of soon-to-fail assets.

4.3 Variable definitions

We consider the following outcome variables Y : ROA for the benchmark results and ROE for robustness tests. When we explore mechanisms we use loan net charge-off rates (NCO). Our control variables Z include measures of bank leverage (equity/assets), size (log-assets), indicators for the type of entity (controlled subsidiary, global ultimate owner, or other),⁹ and bank specialization (commercial banks, bank-holding companies, and other).¹⁰

Direct and indirect exposures are based on the EGBN. Direct non-network exposures D , direct network exposures E , indirect network exposures P , and the indicator for key intermediaries N are described below. We compute two types of direct exposures based respectively on the weighted and binary EGBN.

D_{ihdt} : Direct dollar exposures of bank i vis-a-vis non-bank borrowers in country d at end-year t .

E_{ihdt} : Direct dollar exposures of bank i vis-a-vis banks in country d at end-year t . The measures D_{ihdt} and E_{ihdt} are computed on the weighted EGBN and are known as out-strength. They reflect a bank’s local centrality measured by the intensity of its outgoing connections.

E_{ihdt}^{01} : Direct exposures representing the number of banks in country d to which bank i has loans outstanding at end-year t . This measure is computed on the binary EGBN and is known

⁹ The “Other” category includes branch locations, independent companies, and single location banks.

¹⁰ 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.

as out-degree. It reflects a bank’s local centrality measured by the number of its outgoing connections.

$P_{ihdt}^{01} = \sum_{j \in d} 1/D_{ijdt} - E_{ihdt}^{01}$: Indirect exposures of bank i vis-a-vis banks in country d at end-year t . This measure is computed for each bank i as the inverse of network distance D to all other banks in the network. Network distance is defined as the length of the shortest path between them in the binary EGBN. 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, which is 10). Note that indirect exposure excludes one-step away (direct) exposure E_{ihdt}^{01} .

N_{iht}^{01} : Bank i ’s individual network position, or global connectivity profile in the binary EGBN at end-year t . This refers to betweenness centrality, which is the number of bank pairs that are only related through a given bank i . Formally, betweenness centrality is defined as the number of shortest paths between two banks in the EGBN that go through bank i divided by the total number of alternative shortest paths. In the analysis we use an indicator variable for banks with positive betweenness centrality, to which we refer as key intermediaries because they are unique connectors between groups of banks in the EGBN.

4.4 Summary statistics

Summary statistics for all the variables used in the analysis are shown in Table 1. Our sample mainly comprises commercial banks (accounting for 78 percent of all banks), and 42 percent of all banks are controlled subsidiaries. Sample ROA is 0.86 on average and ranges between -6.57 and 8.26. As shown in Figure 2, both bank profitability and leverage (measured as the ratio of assets to equity) have trended upward before the global financial crisis and have experienced a sharp correction during the crisis.

The middle portion of Table 1 summarizes our direct non-network exposures, and direct and indirect network exposures. Direct exposures refer to either the dollar amount of outstanding exposures (based on the weighted EGBN) at 2005 prices or the number of counterparties in the syndicated loan market (based on the binary EGBN). The average bank has USD 20.52 billion in total exposures vis-a-vis borrowers in non-crisis countries and US 3.22 billion vis-a-vis borrowers in crisis countries during 1997-2010. Of the USD 21 billion in total exposures to non-crisis countries, almost USD 17 billion are non-network exposures and the remaining 4 billion are network ones. Similarly, of the USD 3 billion worth of syndicated loan exposures vis-a-vis borrowers in crisis countries, USD 2.75 are vis-a-vis non-banks, and USD 500 million are vis-a-vis banks.

Focusing on bank linkages in the binary EGBN, the average creditor bank has network claims vis-a-vis 6 borrowing banks in crisis countries; the maximum out-degree is 240 for crisis countries and 105 for non-crisis countries. The distribution of the direct exposure measures, both weighted and binary, is heavily skewed — a common property of edge weight and degree distributions in empirical financial and trade networks (see Chinazzi et al. (2013) and Fagiolo et al. (2010)). For indirect exposures, a higher value indicates a lower network distance to banks in crisis and non-crisis countries. Finally, we notice that 5 percent of the banks in the EGBN are key intermediaries.

Figure 3 depicts the loan origination volume and the total number of connections in the EGBN over the period of analysis. The total lending volume in the syndicated interbank market peaked at almost USD 400 billion in 2007 before collapsing by almost half by 2009. Network density ranges between 0.02 percent in 1997 and 0.14 percent in 2012, which makes for a relatively sparse network compared with a domestic interbank market. Gabrieli (2011) documents a density of 0.3 percent for the Italian interbank market, while Alter et al. (2014) find a density of 0.7 percent for the German interbank market. A visualization of the EGBN for the largest 100 banks is provided in Figure 4.

4.5 Preliminaries on the drivers of bank ROA

Before presenting our main empirical results, let us establish that bank profitability declines during crises in a bank’s home country, during crises abroad, and that it is correlated with the profitability of a bank’s counterparties.

In Table 2 (Panel A) we report results of panel regressions where bank ROA is regressed on an indicator for systemic banking crisis in the bank’s home country, with and without a comprehensive set of controls (these include bank country and year effects, interactions between the two to control for country-specific trends in bank ROA, and other controls such as bank size and equity-to-assets ratio.) The estimates indicate that bank ROA is lower by between 0.7 and 0.9 for banks in countries experiencing a crisis compared to banks in countries experiencing a tranquil period; this is a non-negligible half a standard deviation of ROA. We control for crises in banks’ home countries in all subsequent regressions.

What happens to bank ROA when there are crises outside the bank’s domestic market? In Panel B we repeat the same regressions but add the “number of crises elsewhere” as a second variable of interest. We find that bank profitability is lower the more crises occur outside the bank’s home country in any given year, which signals the possibility of contagion. In a given year in which 10 foreign countries experience crises, a bank’s ROA falls by a further 0.3-0.4, representing one quarter of a standard deviation. In a severely adverse scenario such as the global financial crisis, a bank that is located in a crisis country will have experienced a total decline in ROA of three quarters of a standard deviation if 10 other countries experience a crisis simultaneously.

Our conjecture is that the effect of “crises elsewhere” presented in Table 2 is at least partly due to interbank exposures created through lending and borrowing operations in the syndicated loan market. To test this conjecture, we estimate the specification presented in equation (1) directly by regressing the ROA of each bank i on the ROAs of all other banks j to which it is directly connected in the EGBN. If these bank linkages transmit shocks, we would expect a positive correlation.

The results of this test are presented in Table 3. As a benchmark, in column 1 we show a regression with just bank i covariates and find that bank size, equity-to-assets ratio, bank type and specialization, as well as an indicator of a systemic banking crisis in bank i 's home country explain 46 percent of the variation in ROA. To this set of variables we add the ROAs of all other banks to which bank i is directly exposed in the EGBN (ROA_j), either with weight 1 (columns 2-3), or weighted by the amount of the dollar exposure (columns 4-5). We find that bank i returns are positively correlated with those of the banks to which it is directly exposed ROA_j and that including this variable explains an additional 5 percent of the variation in ROA. The coefficient on ROA_j is lower when we add year fixed effects (columns 3, 5), which suggest that some of the correlation is driven by unobserved common factors; nonetheless, the (ROA_i, ROA_j) correlation remains positive and statistically significant.

5 Results

Having established that a bank's performance is affected by the performance of the banks to which it is connected in the global banking network, we examine how financial crisis contagion spreads through bank linkages. We begin by estimating a specification similar to equation (7) that links bank performance to *total* direct exposures vis-a-vis borrowers in crisis and non-crisis countries, and then splits these exposures by sector: banks vs. non-banks. Since our goal is to study how systemic banking crises spread through the EGBN, we then separate network exposures into direct and indirect ones. Finally, we turn to the performance of key intermediaries.

5.1 Baseline

Table 4 shows regressions in which the covariates of interest are syndicated loan exposures in USD vis-a-vis all borrowers (columns 1-3) and by sector (columns 4-7). We also examine heterogeneity

in the identified effects for banks with large interbank exposures vs. other banks. To do so, we split the same into some 500 “top” banks with above-median interbank exposures and the remaining “bottom” banks. (The sample correlation between the indicator for above-median interbank exposures and that for above-median total assets is 0.449.) Column 1 shows that direct linkages to borrowers in crisis countries negatively affect bank performance (column 1). This effect is driven by banks with smaller interbank exposures (column 3). An increase in total exposures from 0 to USD 35 billion (the maximum value observed in the sample – for Deutsche Bank in 2007), reduces bank ROA by $0.003 \times 35 = 0.105$. As expected, exposure to borrowers in non-crisis countries does not affect bank ROA.

In columns 4-7 we focus on the impact of network exposures. We find that on their own, interbank exposures reduce ROA when banks are exposed to countries experiencing systemic banking crises. This result holds when we also control for non-bank exposures (column 5). For the top banks, the coefficient on network linkages to crisis countries remains negative and statistically significant, while that on non-network linkages loses statistical significance. For the banks with below-median interbank exposures the coefficient of interest is still negative, but imprecisely estimated; in addition, non-bank exposures to crisis countries hurt ROA of “bottom” banks.

Taken together, these results suggest that despite being smaller in dollar value, interbank exposures to counterparties experiencing systemic banking crises act as a more powerful channel of shock transmission than exposures to other sectors of the economy. This is not surprising as systemic banking crises take a while to transform into recessions, and even when they do, the intensity of the recessions can vary across countries.

In Table 5 we focus on crisis transmission solely through the EGBN. The question we ask is whether the number of connections to banks in crisis countries (out-degree) affects bank profitability once we control for the USD value of exposures (out-strength). To avoid problems of collinearity between out-strength and out-degree, especially for top banks, our control variable is given by *total*

(rather than distinct bank and non-bank) exposures. We add to the specification direct exposures computed from the binary EGBN, representing the number of counterparties in crisis and non-crisis countries. The estimated coefficient on out-degree is negative and statistically significant – both in the full sample and for top banks (columns 1-2). The more direct linkages a bank has to banks in other countries, the worse its performance is when those countries experience a financial crisis.

To evaluate the magnitude of the effect in column (1), we can compare a bank that is *not* exposed to crisis countries to one that is exposed to 40 banks in crisis countries (as was ING in the latter years of our sample). Holding everything constant, the bank with no exposure will have an ROA that is higher by $0.019 \times 40 = 0.76$ than the bank with heavy exposure. Although this effect is less than half a standard deviation of ROA, it is large when we consider the size of losses it implies for a moderately-sized bank (the average bank in our dataset has total assets of USD 100 billion in 2010).

Several considerations should be kept in mind as we interpret these coefficient magnitudes. First, banks may recognize the contagion mechanism and create links to mitigate it, such that they create a network that is stable. This possibility would work against us finding an effect of financial linkages on bank profitability despite the existence of contagion risk. Second, banks do not always retain the originated loans on their balance sheets. Credit lines become on-balance sheet exposures only to the extent that they are drawn. Furthermore, although syndicated credits are typically held to maturity, banks can reduce their exposures after origination through side-deals and sales in the secondary market (see next section for a discussion). Third, banks can hedge their exposures, for instance, by trading credit derivatives. All these factors are likely to reduce the magnitudes of our estimated coefficients.

To further understand how financial crises spread through the EGBN, in columns 4-6 of Table 5 we add to the direct exposure variables a measure of *indirect* connections to banks in crisis and non-crisis countries. The number of counterparties from crisis countries continues to have a negative

effect on bank ROA despite the inclusion of this new variable (column 4). As expected, indirect, higher-degree, linkages to crisis countries also reduce bank performance – the coefficient is negative and statistically significant at the 10 percent level in the full sample, but loses significance for the top banks (column 5). This result suggests that shocks may travel along chains of banks to impact their profitability. Such shocks affect not only the financial performance of a bank’s immediate lenders, but also that of the lenders to that bank, the lenders to the lenders of that bank, etc.

To summarize, there are two main takeaways from the results in Tables 4-5. First, direct financial linkages to banks in crisis countries, captured by outstanding loan claims in USD terms, reduce bank profitability. Controlling for dollar exposures, the number of counterparties in crisis countries also reduce bank ROA, which suggests that diversification across financial partners turns into vulnerability when a large number of these partners are in turmoil. Second, crises spread through the global banking network through indirect linkages as well. Cascades of defaults could be generated through these linkages if banks that are exposed to crises become subject to runs and their home banking systems go into a systemic crisis. The magnitudes of the direct effects that we find are seemingly not very large, but are not trivial either given the size of bank balance sheets in modern financial systems.

5.2 Mechanisms

Our baseline findings suggest that there is crisis transmission through network exposures, in that loan exposures to crises, and hence potential losses, worsens bank performance. What are the mechanisms behind this result? The most obvious channel are losses incurred through borrower defaults, caused, for instance, by borrower bankruptcy. In exploring this channel, it is useful to note that syndicated loans differ from standalone loans in that they are more likely to be extended to relatively safer borrowers (Cerutti et al. (2014)). As a consequence, the loan syndication market exhibits lower default rates (especially for financial institutions) and higher loan recovery rates

than other segments of the credit market.¹¹ Furthermore, defaults in this market typically trigger renegotiation that results in an amendment to extend the maturity of the loan. Outright default can lead the syndicate members to accelerate the loan and force the borrower into bankruptcy, but such instances are rare. At the height of the global financial crisis in 2009, the most popular practice were loan renegotiations.

With these caveat in mind, defaults caused by borrower bankruptcies are a potential mechanism explaining our results. (We are currently examining data on borrower bankruptcy filings to empirically document this mechanism.) To explore this channel, we replace the dependent variable with loan net charge-off rates representing the difference between gross charge-offs and recoveries on delinquent loans, expressed in percentage of total assets. The results, shown in Table 6, show that higher exposures to countries that are *not* experiencing a crisis are associated with *lower* charge-off rates. This evidence, however, is weak as the coefficients on exposures to crisis countries are not statistically significant.¹²

A second potential mechanism are losses that banks may incur in their portfolio of securities. This occurs when banks place their syndicated credits in the securities book and hence mark them to market using secondary market pricing. 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,” realized incomes and gains would affect net income and hence ROA. Aggregate balance sheet data are unfit for a test of this mechanism because variables such as the change in the USD value of trading securities, reported for instance in Bankscope, are contaminated by exchange rate changes. (We are currently gathering data on the secondary market prices of high-yield syndicated

¹¹During 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).

¹²In specifications not reported, we also examined the impact of syndicated loan exposures on non-performing loans and loan-loss reserves, but did not find strong results, likely because of the lack of comparability of these variables across banks and countries due to differences in accounting and reporting rules. Another channel we investigated, but did not find support for with aggregate data, were net interest margins, which may be squeezed when banks are exposed to crises due to higher funding costs.

loans to test this channel.)

One reason why it may turn out difficult to provide robust evidence of mechanisms using data from the loan syndication market may be that our loan exposures capture lines of business that go beyond this market. Such exposures would arise, for instance, from standalone lending and ancillary business such as cash management and advisory services. A high correlation between syndicated loan exposures and other exposures is possible because when banks decide to extend a loan, they not only consider the yield that comes from that loan, but that from the entire loan portfolio to that borrower as well as other sources of revenue from that relationship. Anecdotal evidence suggests that borrowers in the syndicated loan market often use the same underwriters for bond and equity issuances, and may conduct other fee generating business for banks from their lending syndicates (Standard & Poor’s, 2011). This means that loss of income due to crisis risk could be related to banking services other than loan syndications.

5.3 Key intermediaries

We build on our previous findings to also study the effects on bank performance of global bank connectivity in the EGBN. The connectivity measure refers to betweenness centrality, a concept that helps us identify key intermediary banks in the EGBN. Key intermediaries are banks that tend to lie “at the crossroads” by being in unique 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 109 banks with positive betweenness centrality in the 2010 EGBN, roughly equally split between advanced economies and emerging market countries. Selected key intermediaries in the 2010 EGBN are listed, for the top countries, in Table 7. For illustration, two of them – Commonwealth Bank of Australia and Arab Bank Plc of Jordan – are shown in Figure 5 along with their borrowing and lending relationships. As seen from these two cases, key intermediaries tend to borrow from large global banks and lend to banks in domestic and regional markets.

In Table 8 we examine the effect of being a key intermediary on bank ROA during crisis and normal times. We control for direct and indirect linkages (as in column 4 of Table 5) and add an indicator for key intermediaries in the EGBN. We also include interactions between this variable and an indicator for systemic banking crises in the bank's home country as well as the number of systemic banking crises in foreign countries.

Note first that the effects of direct exposures (in particular out-degree) from our benchmark regressions hold up in these richer specifications, although the coefficient estimates on indirect exposures have the expected sign, but are less precisely estimated. The estimates in column 1 indicate that key intermediaries have lower ROA compared to other banks. From columns 2-3 we see that this effect is driven by key intermediaries having significantly lower ROA (by 0.5 percentage points) than other banks *during financial crises at home*. This effect is almost double for banks with below-median interbank exposures, and still negative but statistically insignificant for banks with above-average interbank exposures (columns 4-5). In other words, there is a significant profitability sacrifice associated with being a key intermediary when the domestic market experiences a crisis, especially for banks with below-median interbank exposures, for which the estimated effect is 1 percentage point of ROA (p-value of equality with -1 is 0.814).

A possible mechanism behind this effect are creditors being unwilling to refinance the key intermediary's loans coupled with large drawdowns by its borrowers during banking crises at home. The effect is stronger for banks with below-median interbank exposures, which tend to be smaller banks from emerging market countries. This is not surprising as emerging markets are more susceptible to sudden stops during financial crises. 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. Because of their role in the network, key intermediaries can contribute to the fragility of the overall network (or their regional subnetwork) in the event of sudden stops. The presence of key intermediaries may help explain the regional nature of past systemic banking crises,

especially in emerging market countries.

A natural question that arises is why banks engage in a business that appears to be costly during crises but to bring no benefit in tranquil times. As discussed earlier, and consistent with evidence from the corporate finance literature, it is common for banks to view syndicated lending as a gateway to establishing relationships for present and future ancillary business. Previous studies show that prior lending relationships are conducive to future lending and underwriting relationships (Bharath et al., 2007), while prior IPO underwriting increases the probability of subsequent lending (Chen et al., 2013). We examined the relationship between syndicated loan underwriting and subsequent interactions in the same market, and found that the probability of co-syndicating a loan is higher for bank pairs that have previously established contractual relationships through syndicated lending.¹³ For this reason our network of syndicated loan exposures may be viewed as a proxy for a larger set of banking relationships.

5.4 Robustness

We subject our findings to several robustness tests in Table 9. In columns 1-3 we replicate the specification in column 4 of Table 5. The remaining columns refer to specification 3 in Table 8. For both specifications we perform three checks: (i) using ROE instead of ROA as the measure of bank performance; (ii) double-clustering the standard errors on bank and year (rather than on bank); and (iii) dropping all the banking entities in Citigroup, as they tend to be very active in the syndicated loan market and we want to make sure they are not driving our results. As seen in Table 9, our results are qualitatively robust, although the coefficients are sometimes less precisely estimated than in our baseline regressions. In particular, indirect exposures have a statistically significant coefficient in only 3 of 6 specifications.

¹³These results are work-in-progress and are available upon request.

6 Conclusions

In this paper we aim to better understand the role of bank linkages in the transmission of financial sector shocks worldwide. In particular, we examine how systemic banking crises spread through a counterparty network created by loan contracts in the interbank loan syndication market. We construct the network for the 1997-2010 period from granular information on syndicated loan deals. We then link bank connectivity data from this network – in particular, direct and indirect exposures to borrowers in crisis and non-crisis countries – with bank balance sheet information to obtain a rich panel dataset for more than 2,000 banks from 88 countries. The data allow us to estimate the effect of network and non-network exposures to crises on bank performance.

In a first instance, we link bank performance to syndicated loan exposures vis-a-vis bank and non-bank borrowers, distinguishing between exposures to crisis and non-crisis countries. We find, not surprisingly, that outstanding loan claims on banks in countries that are experiencing a systemic banking crisis reduce bank profitability. We interpret this result as suggesting that international financial linkages created through global interbank exposures can enable the international transmission of shocks. We then distinguish direct from indirect exposures to banks in crisis countries, and find that higher such exposures are associated with lower bank profitability, while higher exposures to banks in non-crisis countries leave bank profitability unchanged.

Then, we assess banks' interconnectedness in the syndicated loan network through the lens of betweenness centrality, a concept that allows us to identify key intermediaries in the network. 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, especially smaller banks from emerging market countries, have markedly lower ROA during financial crises at home. This result suggests that a large and potentially diverse pool of creditors and debtors can make key intermediaries vulnerable to funding shortages and increased demand for liquidity during financial crises at home, squeezing their profitability.

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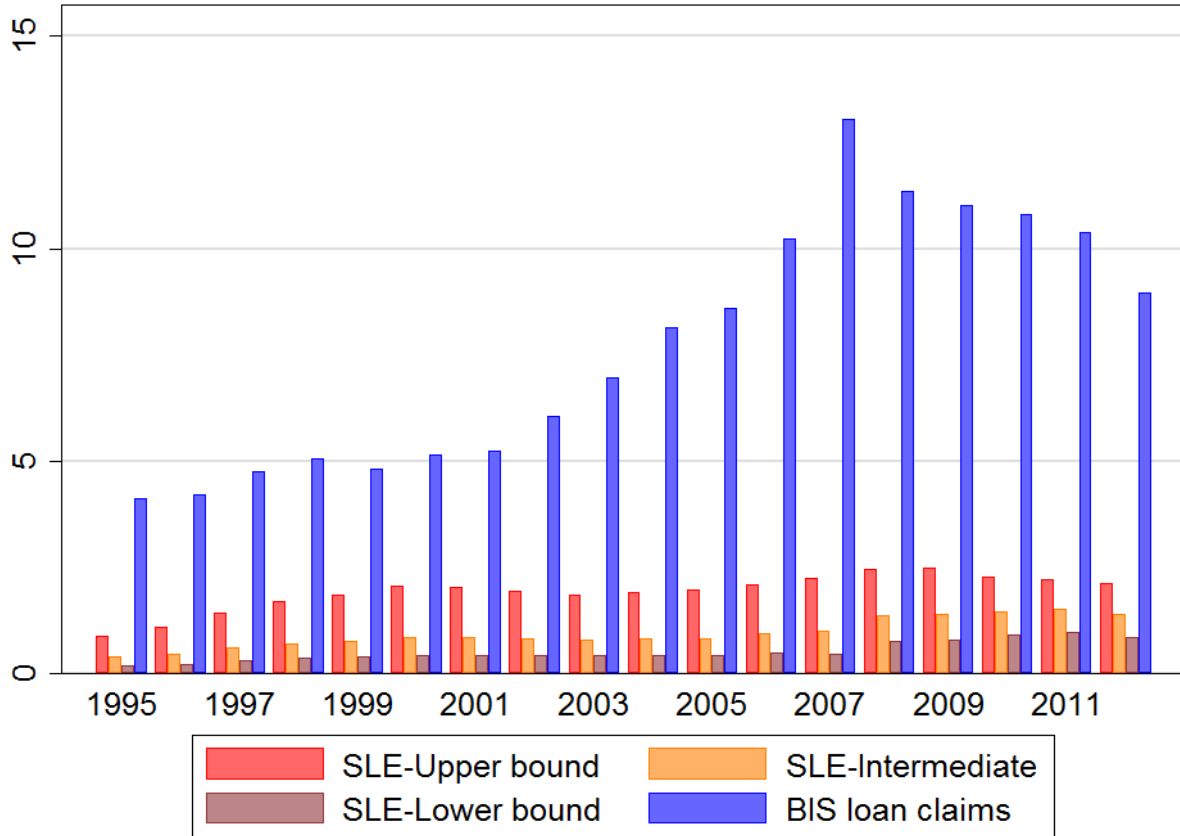
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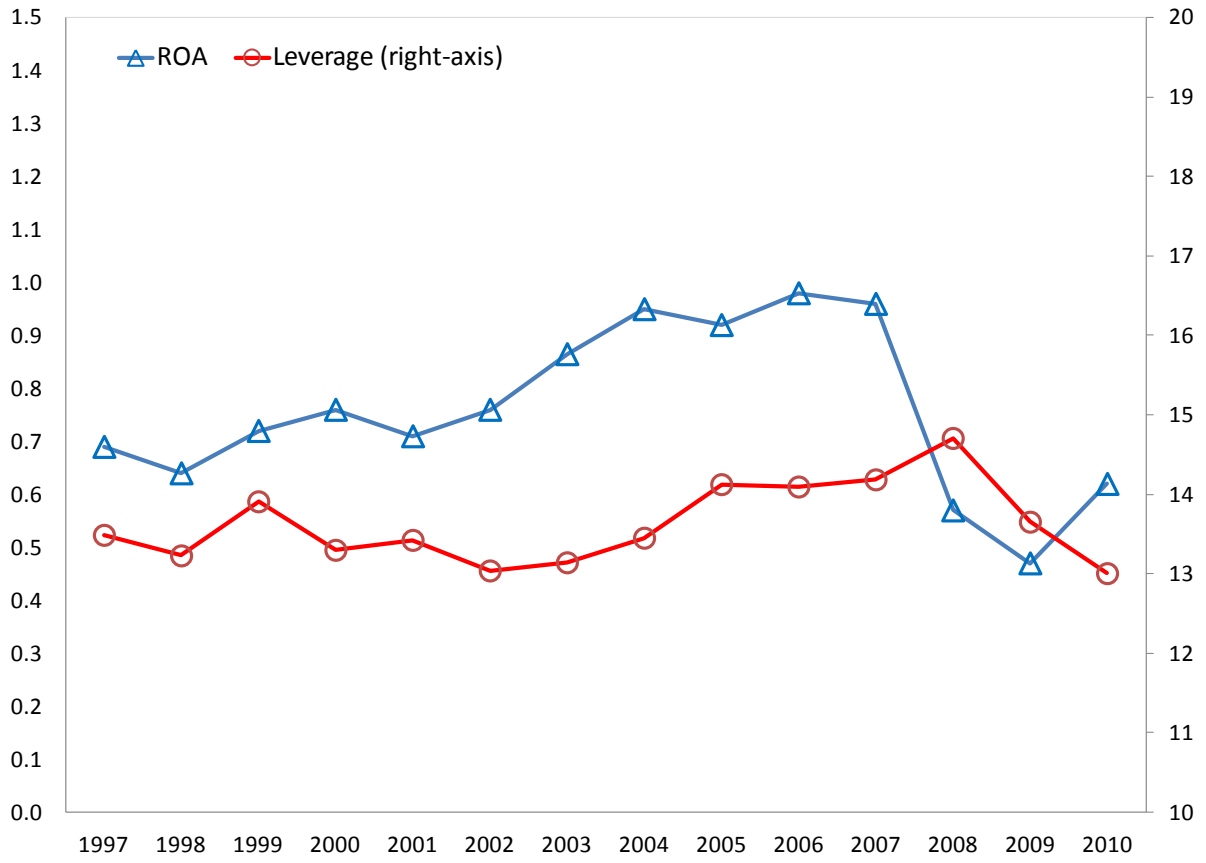
Tables and figures

Figure 1: Syndicated loan exposures vs. BIS loan claims on banks (USD trillion), 1995–2012



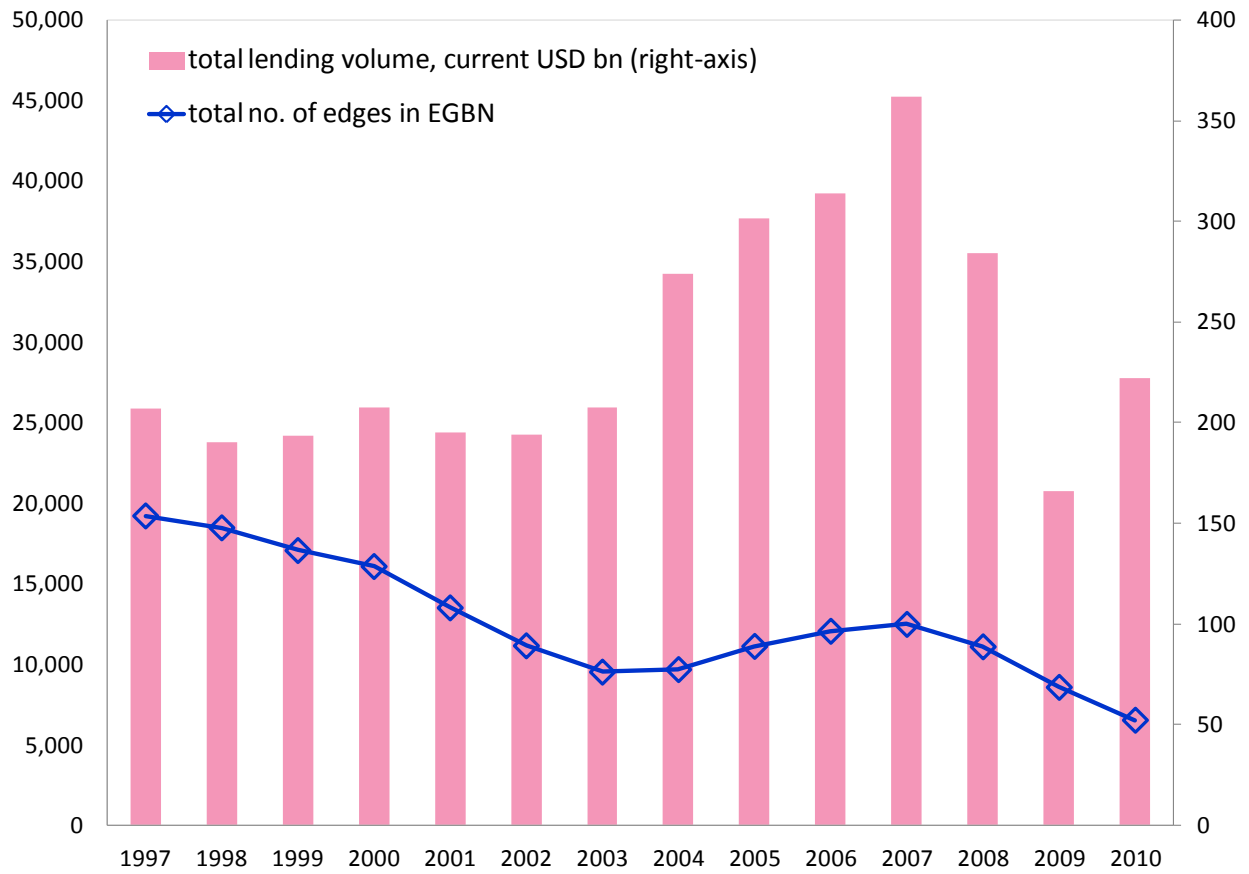
Notes: The figure depicts syndicated loan exposures (SLE) and BIS loan claims by banks in 35 countries vis-à-vis banks in 197 countries during 1995–2012. “SLE-Upper bound” refers to exposures that comprise total credit lines (drawn and undrawn amounts) and term loans. “SLE-Intermediate” refers to on-balance sheet exposures that comprise drawn credit line resources and term loans. To compute on-balance sheet estimates of credit lines, we employ the time-varying credit line usage rates from Cerutti et al. (2014). “SLE-Lower” bound refers to exposures that are further adjusted in that term loans of type other than A are dropped because syndicate participants in such loans are often non-banks. All figures are expressed in USD trillion (at 2005 prices). Source: Authors’ calculations using BIS locational banking statistics and Loan Analytics based on Cerutti et al. (2014).

Figure 2: Bank performance and leverage, 1997-2010



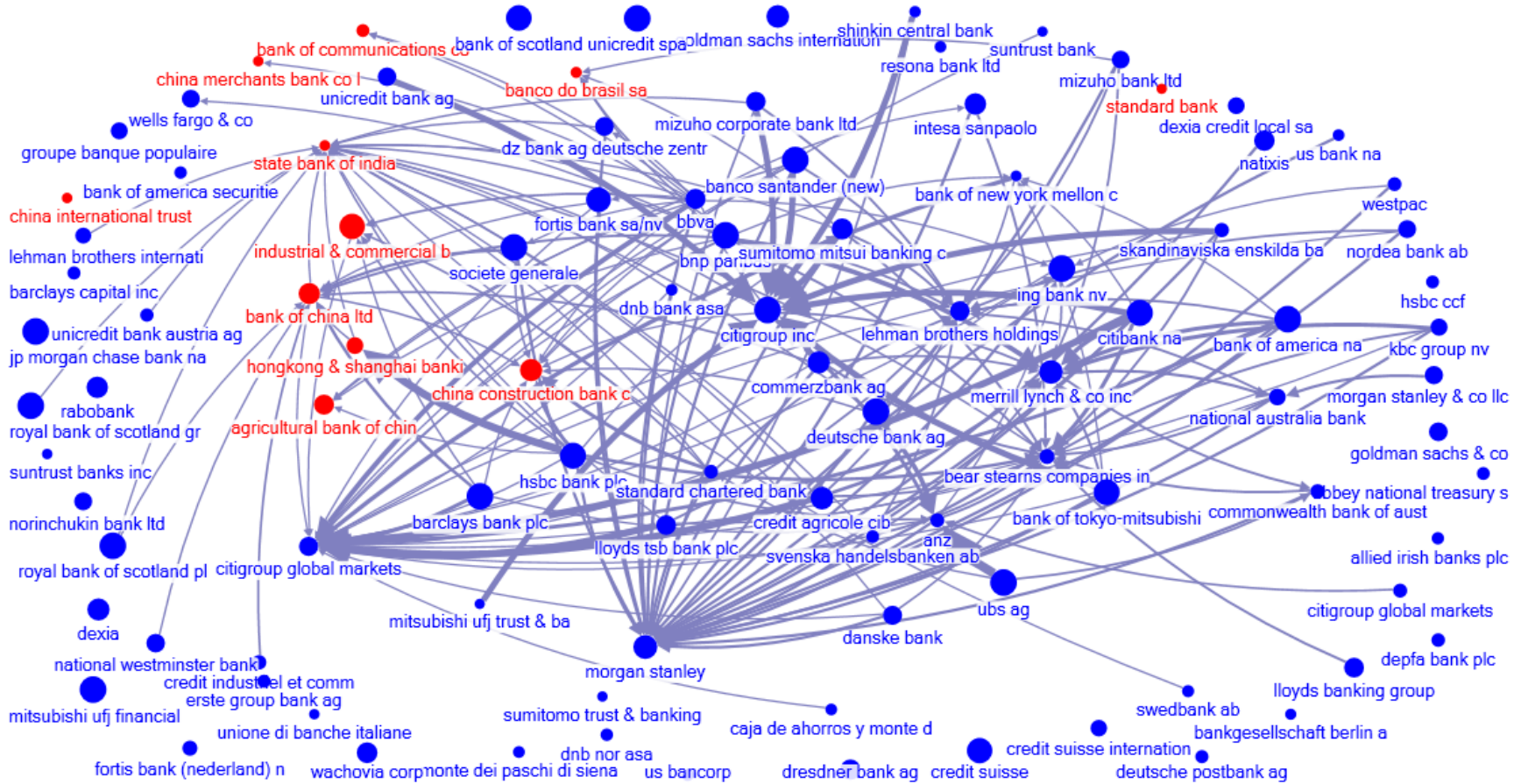
Source: Authors' calculations based on Bankscope.

Figure 3: Network connectivity and total bank-to-bank syndicated lending, 1997-2010



Source: Authors' calculations based on Loan Analytics.

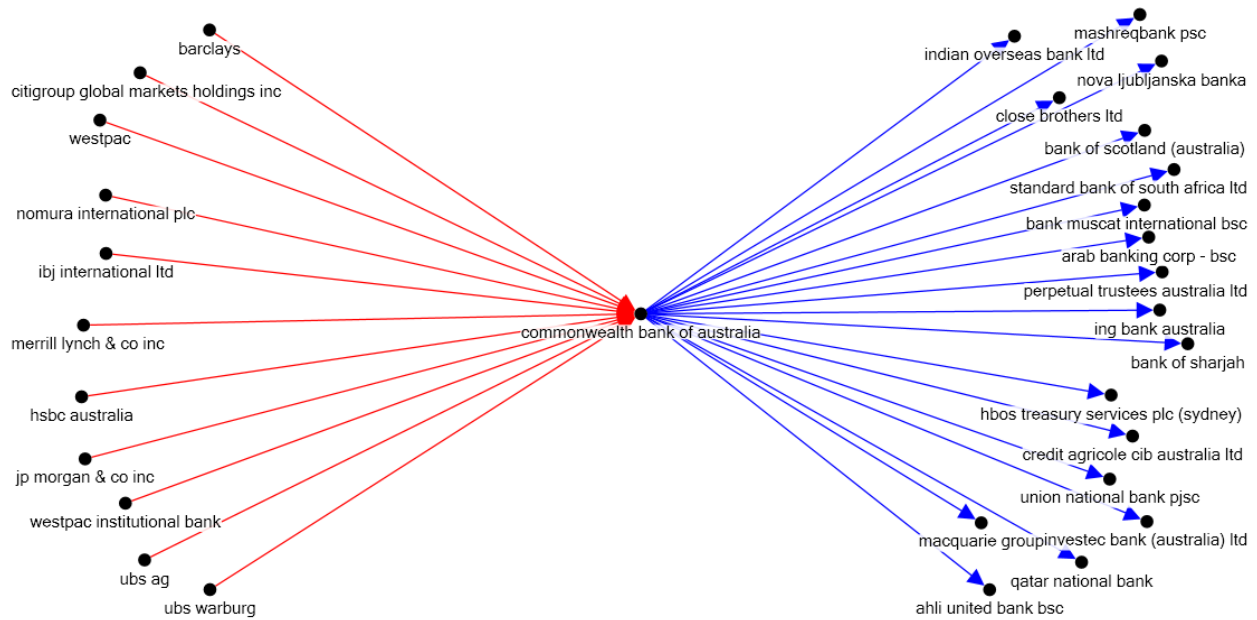
Figure 4: EGBN visualization, 2007



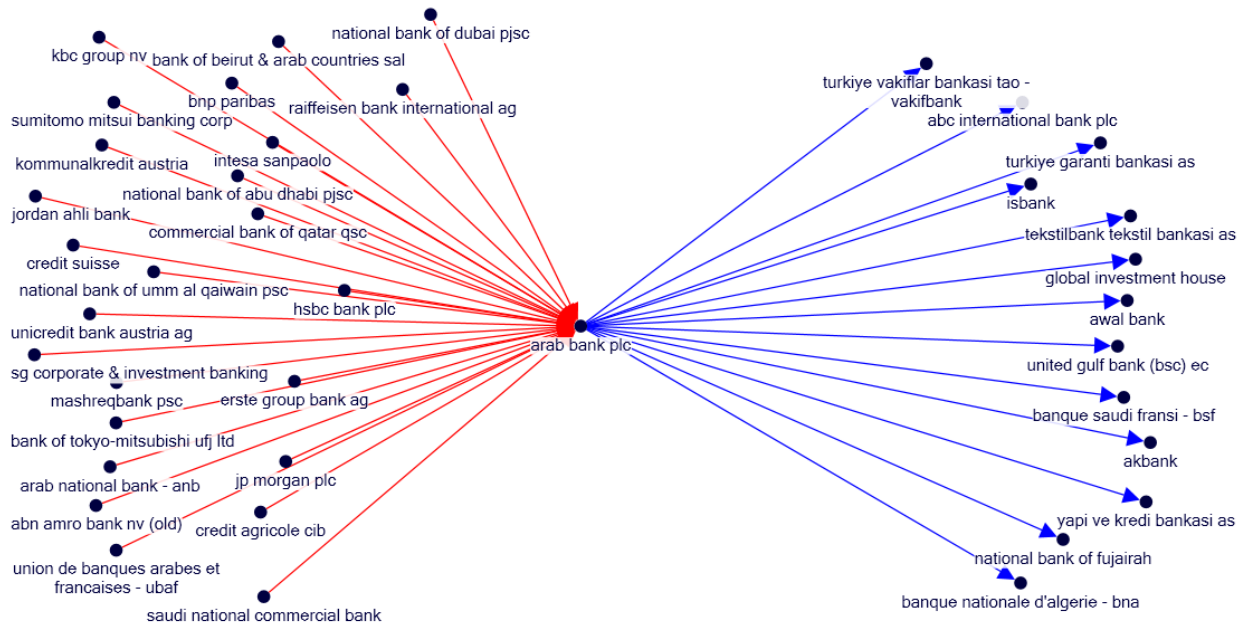
Notes: The figure depicts a visualization of the EGBN in 2007 for the largest 100 banks by assets. Blue nodes are banks in OECD countries and red nodes are banks in non-OECD countries. Edge width is proportional to syndicated loan exposures. Node size is proportional to bank size (total assets). Source: Authors' calculations based on Loan Analytics and Bankscope.

Figure 5: Examples of Key Intermediaries

A. Commonwealth Bank of Australia (Australia)



B. Arab Bank PLC (Jordan)



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

Table 1: Summary statistics

Variable	N	Mean	Median	St. Dev.	Min	Max
Dependent variable						
Return on assets	15,351	0.86	0.73	1.68	-6.57	8.26
Return on equity	15,339	8.51	9.21	16.59	-78.09	55.25
Net charge-off rate	8,197	0.88	0.32	1.76	-2.10	10.66
Control variables						
Equity/Assets	15,534	9.75	7.06	10.53	0.32	74.48
Assets (USD bn)	11,955	71.09	10.73	198.53	1.05	1304.00
Log(Assets, USD mn)	11,955	16.39	16.19	1.69	13.86	20.99
Crisis in home country (Laeven and Valencia 2012)	29,260	0.19	0.00	0.39	0.00	1.00
No. of crises elsewhere (Laeven and Valencia 2012)	29,567	1.60	0.00	2.49	0.00	14.00
Type of entity, <i>of which</i> :						
Controlled subsidiary	12,468	0.42	0.00	0.49	0.00	1.00
Global ultimate owner	6,438	0.21	0.00	0.41	0.00	1.00
Other	11,040	0.37	0.00	0.48	0.00	1.00
Specialization, <i>of which</i> :						
Commercial bank	23,310	0.78	1.00	0.42	0.00	1.00
Bank holding company	2,352	0.08	0.00	0.27	0.00	1.00
Other	4,284	0.14	0.00	0.35	0.00	1.00
Direct and indirect exposures						
Direct US\$ non-crisis exposure (total)	29,946	3.10	0.02	20.52	0.00	670.41
Direct US\$ crisis exposure (total)	29,946	0.18	0.00	3.22	0.00	177.47
Direct US\$ non-crisis exposure (non-banks)	29,946	2.58	0.01	17.01	0.00	563.89
Direct US\$ crisis exposure (non-banks)	29,946	0.15	0.00	2.75	0.00	142.80
Direct US\$ non-crisis exposure (banks)	29,946	0.52	0.00	3.78	0.00	114.94
Direct US\$ crisis exposure (banks)	29,946	0.03	0.00	0.50	0.00	34.67
Direct 0-1 non-crisis exposure (banks)	23,052	3.67	0.00	12.15	0.00	218.00
Direct 0-1 crisis exposure (banks)	23,052	0.46	0.00	2.58	0.00	66.00
Indirect 0-1 non-crisis exposure (banks)	21,926	0.04	0.00	0.10	0.00	2.50
Indirect 0-1 crisis exposure (banks)	21,926	0.00	0.00	0.03	0.00	0.87
Measures of network centrality						
Key intermediary	21,926	0.00	0.00	0.03	0.00	0.87

Notes: Summary statistics are shown for all bank-year observations with non-missing ROA. The variables ROA, ROE, equity/assets, and assets are winsorized at the 1st and 99th percentiles. Direct current exposures are expressed in constant (2005) billion USD. Sources: Authors' calculations based on Loan Analytics, Bankscope, and Laeven and Valencia (2012).

Table 2: Effect of crises inside and outside home country on bank performance

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
Crisis in home country	-0.872*** (0.047)	-0.876*** (0.056)	-0.735*** (0.060)	-0.727*** (0.053)	-0.697*** (0.070)	-0.693*** (0.065)
Year FE	no	yes	yes	yes	yes	yes
Bank nationality FE	no	no	yes	yes	yes	yes
Bank nationality*Year FE	no	no	no	no	yes	yes
Other bank-level controls	no	no	no	yes	no	yes
Observations	14,955	14,955	14,955	11,374	14,955	11,374
R-squared	0.045	0.054	0.168	0.336	0.481	0.544
Panel B	(1)	(2)	(3)	(4)	(5)	(6)
Crisis in home country	-1.014*** (0.049)	-1.156*** (0.070)	-0.800*** (0.084)	-0.783*** (0.079)	-0.802*** (0.093)	-0.807*** (0.094)
No. of crises elsewhere	-0.085*** (0.007)	-0.102*** (0.014)	-0.022 (0.014)	-0.017 (0.012)	-0.040*** (0.015)	-0.033** (0.015)
Year FE	no	yes	yes	yes	yes	yes
Bank nationality FE	no	no	yes	yes	yes	yes
Bank nationality*Year FE	no	no	no	no	yes	yes
Other bank-level controls	no	no	no	yes	no	yes
Observations	14,763	14,763	14,763	11,326	14,763	11,326
R-squared	0.059	0.065	0.164	0.339	0.487	0.548

Notes: The dependent variable is ROA. The number of crises elsewhere refers to the number of systemic banking crises occurring each year outside the bank's home country. Other bank-level controls refer to equity-to-assets ratio, size (log-total assets), and bank entity and specialization dummies. Standard errors are clustered on bank. Sources: Authors' calculations based on Loan Analytics, Bankscope, and Laeven and Valencia (2012).

Table 3: Effect of counterparty performance on bank performance

	(1)	(2)	(3)	(4)	(5)
ROA _j (unweighted)		0.024*** (0.005)	0.008* (0.004)		
ROA _j (weighted)				2.308*** (0.710)	1.655*** (0.550)
Equity/Assets	0.126*** (0.002)	0.130*** (0.002)	0.130*** (0.002)	0.130*** (0.002)	0.130*** (0.002)
Log-assets	0.081*** (0.004)	0.062*** (0.005)	0.058*** (0.005)	0.062*** (0.005)	0.058*** (0.005)
Crisis in home country	-0.496*** (0.013)	-0.456*** (0.016)	-0.278*** (0.023)	-0.469*** (0.015)	-0.278*** (0.023)
Constant	-1.370*** (0.087)	-1.024*** (0.106)	-1.138*** (0.116)	-0.989*** (0.105)	-1.121*** (0.116)
Year FE	no	no	yes	no	yes
Other bank-level controls	yes	yes	yes	yes	yes
Observations	54,118	25,150	25,150	25,150	25,150
R-squared	0.460	0.515	0.532	0.514	0.532

Notes: The dependent variable is lending bank ROA (ROA_i) and the variable of interest is borrowing bank ROA (ROA_j). The specifications are estimated on the sample of bank pairs that are connected in the EGBN. The “weighted” ROA_j is weighted by dollar exposure. Other bank-level controls refer to bank entity and specialization dummies (coefficients not shown). Standard errors are clustered on borrowing bank. Sources: Authors’ calculations based on Loan Analytics, Bankscope, and Laeven and Valencia (2012).

Table 4: Effect of direct exposures on bank performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Top	Bottom	All	All	Top	Bottom
Direct US\$ non-crisis exposure (total)	-0.000 (0.000)	-0.000 (0.001)	0.020 (0.037)				
Direct US\$ crisis exposure (total)	-0.003*** (0.001)	-0.000 (0.001)	-0.694** (0.312)				
Direct US\$ non-crisis exposure (banks)				-0.002 (0.002)	-0.003 (0.004)	-0.001 (0.004)	-0.163 (0.279)
Direct US\$ crisis exposure (banks)				-0.026*** (0.008)	-0.038** (0.015)	-0.035* (0.018)	-0.258 (1.117)
Direct US\$ non-crisis exposure (non-banks)					0.000 (0.001)	-0.000 (0.001)	0.030 (0.041)
Direct US\$ crisis exposure (non-banks)					0.002 (0.003)	0.005 (0.003)	-0.738* (0.394)
Equity/Assets	0.089*** (0.010)	0.077*** (0.021)	0.103*** (0.010)	0.089*** (0.010)	0.089*** (0.010)	0.077*** (0.021)	0.103*** (0.010)
Log-assets	0.092*** (0.013)	0.078*** (0.027)	0.118*** (0.018)	0.092*** (0.012)	0.092*** (0.013)	0.078*** (0.027)	0.118*** (0.018)
Crisis in home country	-0.729*** (0.053)	-0.413*** (0.058)	-0.814*** (0.079)	-0.730*** (0.053)	-0.730*** (0.054)	-0.414*** (0.058)	-0.813*** (0.079)
Observations	11,374	3,321	6,811	11,374	11,374	3,321	6,811
R-squared	0.336	0.417	0.325	0.336	0.336	0.417	0.325

Notes: The dependent variable is ROA. Column heading “top” refers to top 500 banks by total banking exposures, and column heading “bottom” refers to the remaining banks. Exposures are lagged 1 year, crises are contemporaneous. Variables labeled “US\$” are dollar exposures computed on the weighted EGBN. All specifications include bank entity and specialization dummies, bank nationality, and year fixed effects. A constant term is included in all specifications, but the coefficient is not shown. Standard errors are clustered on bank. Sources: Authors’ calculations based on Loan Analytics, Bankscope, and Laeven and Valencia (2012).

Table 5: Effect of direct and indirect exposures on bank performance

	(1)	(2)	(3)	(4)	(5)	(6)
	All	Top	Bottom	All	Top	Bottom
Direct US\$ non-crisis exposure (total)	-0.000 (0.000)	-0.001 (0.000)	0.020 (0.039)	-0.001 (0.000)	-0.001 (0.000)	0.018 (0.039)
Direct US\$ crisis exposure (total)	0.002 (0.002)	0.003 (0.002)	-0.762** (0.332)	0.002 (0.002)	0.003 (0.002)	-0.752** (0.330)
Direct 0-1 non-crisis exposure (banks)	0.000 (0.001)	0.001 (0.001)	-0.006 (0.011)	-0.000 (0.001)	0.001 (0.001)	-0.003 (0.012)
Direct 0-1 crisis exposure (banks)	-0.019*** (0.006)	-0.014** (0.007)	0.000 (0.016)	-0.016** (0.006)	-0.013* (0.007)	0.005 (0.016)
Indirect 0-1 non-crisis exposure (banks)				0.106 (0.171)	0.305 (0.203)	0.003 (0.462)
Indirect 0-1 crisis exposure (banks)				-0.820* (0.469)	-0.489 (0.595)	-2.105*** (0.547)
Equity/Assets	0.090*** (0.012)	0.079*** (0.021)	0.112*** (0.012)	0.089*** (0.013)	0.078*** (0.021)	0.111*** (0.013)
Log-assets	0.106*** (0.015)	0.082*** (0.029)	0.147*** (0.021)	0.108*** (0.016)	0.079*** (0.029)	0.156*** (0.022)
Crisis in home country	-0.763*** (0.060)	-0.442*** (0.065)	-0.841*** (0.090)	-0.767*** (0.061)	-0.453*** (0.066)	-0.844*** (0.093)
Observations	9,552	3,064	5,246	9,063	2,982	4,849
R-squared	0.343	0.424	0.333	0.339	0.419	0.329

Notes: The dependent variable is ROA. Column heading “top” refers to top 500 banks by total banking exposures, and column heading “bottom” refers to the remaining banks. Exposures are lagged 1 year, crises are contemporaneous. Variables labeled “US\$” are dollar exposures and are computed on the weighted EGBN; variables labeled “0-1” are computed on the binary EGBN. All specifications include bank entity and specialization dummies, bank nationality, and year fixed effects. A constant term is included in all specifications, but the coefficient is not shown. Standard errors are clustered on bank. Sources: Authors’ calculations based on Loan Analytics, Bankscope, and Laeven and Valencia (2012).

Table 6: Effect of direct and indirect exposures on net charge-offs as potential mechanism

	(1)	(2)	(3)	(4)	(5)	(6)
	All	All	Top	Top	Bottom	Bottom
Direct US\$ non-crisis exposure (total)	-0.000 (0.001)	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)	-0.096* (0.054)	-0.105* (0.058)
Direct US\$ crisis exposure (total)	-0.001 (0.002)	-0.001 (0.003)	-0.003 (0.002)	-0.002 (0.003)	0.590 (0.412)	0.696 (0.433)
Direct 0-1 non-crisis exposure (banks)		-0.002 (0.002)		-0.003** (0.001)		0.020 (0.024)
Direct 0-1 crisis exposure (banks)		0.005 (0.007)		-0.000 (0.005)		0.019 (0.024)
Indirect 0-1 non-crisis exposure (banks)		-0.402* (0.209)		-0.136 (0.172)		-0.041 (0.604)
Indirect 0-1 crisis exposure (banks)		-0.430 (0.748)		-0.400 (0.726)		-0.923 (1.688)
Equity/Assets	0.026** (0.012)	0.034** (0.014)	0.019 (0.019)	0.039* (0.023)	0.013 (0.014)	0.017 (0.019)
Log-assets	0.061*** (0.022)	0.075*** (0.025)	0.060 (0.039)	0.130*** (0.030)	0.120** (0.048)	0.106* (0.054)
Crisis in home country	0.797*** (0.091)	0.913*** (0.103)	0.436*** (0.107)	0.508*** (0.104)	1.017*** (0.122)	1.131*** (0.147)
Observations	6,545	5,372	2,081	1,891	3,652	2,674
R-squared	0.228	0.226	0.230	0.247	0.255	0.251

Notes: The dependent variable is net charge-offs (NCO). Column heading “top” refers to top 500 banks by total banking exposures, and column heading “bottom” refers to the remaining banks. Exposures are lagged 1 year, crises are contemporaneous. Variables labeled “US\$” are dollar exposures and are computed on the weighted EGBN; variables labeled “0-1” are computed on the binary EGBN. All specifications include bank entity and specialization dummies, bank nationality, and year fixed effects. A constant term is included in all specifications, but the coefficient is not shown. Standard errors are clustered on bank. Sources: Authors’ calculations based on Loan Analytics, Bankscope, and Laeven and Valencia (2012).

Table 7: Key intermediaries

Rank	Country	# banks	Selected examples
<i>A. Advanced economies</i>			
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, Macquarie 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
<i>B. Emerging market economies</i>			
1	China	7	Bank of China, Agricultural Bank of China, ICBC, China Development Bank, China Construction Bank
2	Turkey	6	Akbank, Garanti, Turk Ekonomi 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 reports the top advanced economies and emerging market countries with key intermediaries in the 2010 EGBN. Sources: Authors' calculations based on Loan Analytics.

Table 8: Effect of global connectivity profile on bank performance

	(1)	(2)	(3)	(4)	(5)
	All	All	All	Top	Bottom
Direct US\$ non-crisis exposure (total)	-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)	0.018 (0.039)
Direct US\$ crisis exposure (total)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.003 (0.002)	-0.783** (0.347)
Direct 0-1 non-crisis exposure (banks)	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.012 (0.012)
Direct 0-1 crisis exposure (banks)	-0.014** (0.007)	-0.017** (0.007)	-0.016** (0.007)	-0.013* (0.008)	0.011 (0.018)
Indirect 0-1 non-crisis exposure (banks)	0.100 (0.174)	0.089 (0.173)	0.085 (0.174)	0.284 (0.206)	-0.135 (0.437)
Indirect 0-1 crisis exposure (banks)	-0.832 (0.549)	-0.801 (0.552)	-0.806 (0.551)	-0.290 (0.690)	-2.168*** (0.573)
Key intermediary	-0.162*** (0.061)	-0.029 (0.057)	-0.010 (0.063)	-0.111 (0.075)	0.117 (0.096)
Key intermediary * Crisis in home country		-0.535*** (0.157)	-0.517*** (0.159)	-0.012 (0.123)	-0.942*** (0.239)
Key intermediary * No. of crises elsewhere			-0.003 (0.004)	0.001 (0.005)	-0.011 (0.007)
Equity/Assets	0.088*** (0.013)	0.088*** (0.013)	0.088*** (0.013)	0.078*** (0.021)	0.110*** (0.012)
Log-assets	0.113*** (0.016)	0.111*** (0.016)	0.112*** (0.016)	0.077** (0.030)	0.162*** (0.022)
Crisis in home country	-0.788*** (0.063)	-0.736*** (0.062)	-0.739*** (0.063)	-0.463*** (0.067)	-0.742*** (0.094)
Observations	8,734	8,734	8,734	2,866	4,715
R-squared	0.341	0.344	0.344	0.418	0.342

Notes: The dependent variable is ROA. Key intermediary is an indicator for banks with positive betweenness centrality. Column heading “top” refers to top 500 banks by total banking exposures, and column heading “bottom” refers to the remaining banks. Key intermediary and exposures are lagged 1 year, crises are contemporaneous. Variables labeled “US\$” are dollar exposures and are computed on the weighted EGBN; variables labeled “0-1” are computed on the binary EGBN. All specifications include bank entity and specialization dummies, bank nationality, and year fixed effects. A constant term is included in all specifications, but the coefficient is not shown. Standard errors are clustered on bank. Sources: Authors’ calculations based on Loan Analytics, Bankscope, and Laeven and Valencia (2012).

Table 9: Effect of direct, indirect exposures, and global connectivity profile on bank performance - Robustness

	(1)	(2)	(3)	(4)	(5)	(6)
	ROE	Double clustering	Drop Citi	ROE	Double clustering	Drop Citi
Direct US\$ non-crisis exposure (total)	-0.008 (0.006)	-0.001 (0.000)	-0.000 (0.000)	-0.008 (0.006)	-0.001 (0.000)	-0.000 (0.001)
Direct US\$ crisis exposure (total)	0.053 (0.037)	0.002 (0.002)	0.002 (0.002)	0.052 (0.041)	0.001 (0.002)	0.001 (0.002)
Direct 0-1 non-crisis exposure (banks)	0.006 (0.016)	-0.000 (0.001)	-0.000 (0.001)	0.013 (0.017)	0.001 (0.001)	0.001 (0.001)
Direct 0-1 crisis exposure (banks)	-0.277** (0.111)	-0.016** (0.007)	-0.016** (0.007)	-0.284** (0.125)	-0.016** (0.007)	-0.017** (0.007)
Indirect 0-1 non-crisis exposure (banks)	0.095 (1.674)	0.106 (0.170)	0.099 (0.153)	-0.169 (1.697)	0.085 (0.195)	0.077 (0.178)
Indirect 0-1 crisis exposure (banks)	-3.955 (6.045)	-0.820*** (0.257)	-0.786* (0.452)	-4.504 (7.218)	-0.806** (0.337)	-0.767 (0.555)
Key intermediary				-0.038 (0.788)	-0.010 (0.083)	-0.010 (0.064)
Key intermediary * Crisis in home country				-4.019* (2.151)	-0.517*** (0.200)	-0.519*** (0.163)
Key intermediary * No. of crises elsewhere				-0.019 (0.052)	-0.003 (0.004)	-0.002 (0.004)
Equity/Assets	0.262*** (0.081)	0.089*** (0.006)	0.088*** (0.006)	0.251*** (0.081)	0.088*** (0.006)	0.087*** (0.013)
Log-assets	1.186*** (0.186)	0.108*** (0.015)	0.105*** (0.016)	1.210*** (0.191)	0.112*** (0.018)	0.108*** (0.016)
Crisis in home country	-10.110*** (0.773)	-0.767*** (0.162)	-0.764*** (0.158)	-9.768*** (0.793)	-0.739*** (0.164)	-0.737*** (0.063)
Observations	9,062	9,063	8,960	8,733	8,734	8,631
R-squared	0.205	0.339	0.340	0.205	0.344	0.345

Notes: The dependent variable is ROA in all columns except 1 and 5 where it is ROE. In columns 2 and 5 st. errors are double clustered on bank and year (in all other columns they are clustered on bank). In columns 3 and 6 we drop all the entities of Citigroup. Variables labeled "US\$" are dollar exposures and are computed on the weighted EGBN; variables labeled "0-1" are computed on the binary EGBN. All specifications include bank entity and specialization dummies, bank nationality, and year fixed effects. A constant term is included in all specifications, but the coefficient is not shown. Regressions are run on the full sample. Sources: Authors' calculations based on Loan Analytics, Bankscope, and Laeven and Valencia (2012).

Appendix. EGBN Construction

To construct our dataset we proceed as follows:

- Step 1. We download from Loan Analytics about 150,000 syndicated loan deals (structured in almost 1,000,000 loan tranches) signed between January 1990 and December 2010. To construct the EGBN we retain only the loans extended to financial institutions.

We drop the deals for which the lender is recorded as “unknown” or “undisclosed [Asian, French, German, Japanese] bank”. We also drop the 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 are recorded in Loan Analytics with 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 EGBN is constructed using the full set of about 5,500 banks that appear as lenders or borrowers in the loan syndication market during 1990-2010.

- Step 3. After cleaning the bank names, we match all banks – by 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 website¹⁴ and Bloomberg Businessweek.¹⁵ 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 loan syndication market and report to Bankscope contains about 2,000 distinct banks.

¹⁴<http://www.ffiec.gov/nicpubweb/nicweb/SearchForm.aspx>

¹⁵<http://investing.businessweek.com/research/company/overview/overview.asp>