Social Networks in the Global Banking Sector *

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Abstract

We construct a variety of social network measures within the global banking system, using the board connections from banks in 16 countries between 2000 and 2010. We show that connected banks partner more often in the syndicated loan market and that central banks in the network play dominant roles in various interbank transactions, indicating that social connections facilitate business connections. However, consistent with "group-think" concerns, we find that the more central banks in the network contribute significantly to the systemic risk of the global banking system, suggesting there may also be a downside to having a strong social network.

Key words: Top global banks, director social networks, pairwise connection, network centrality, loan syndication, interbank transactions, systemic risk, financial crisis

JEL classification: G20, G24, G28

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1 Introduction

In recent years, a number of interesting papers have highlighted the myriad ways in which personal connections influence financial transactions. For example, there is evidence that portfolio managers are more likely to invest in firms in which they share social connections (Cohen et al., 2008), and that connections between board members and CEOs influence the level and structure of executive compensation (Hwang and Kim, 2009; Engelberg et al., 2012[a]). Another part of this literature has shown that connections between borrowers and lenders affect the pricing and structure of bank loan agreements (Engelberg et al., 2012[b]; Ferreira and Matos, 2012). At the same time, there is somewhat conflicting evidence regarding how the connections between merging firms influence the market's response to the merger's announcement (Cai and Sevilir, 2011; Fracassi and Tate, 2012).

The personal connections between firm managers have also been shown to influence corporate decision-making. For example, Duchin and Sosyura (2012) show that division managers who have stronger social ties to the firm's CEO are more inclined to receive internal capital from headquarters. In another study, Fracassi (2012) demonstrates that firms with stronger personal ties tend to have more similar investment policies. Looking more directly at the possible value of social networks, Larcker et al. (2012) show that firms that play a more "central" role in the social network generate higher risk-adjusted stock returns and a higher growth in ROA. Similar evidence is found for venture capital firms that hold central positions in their syndication networks (Hochberg et al., 2007).

From a broader perspective, we might expect that these connections would generate both "micro" and "macro" effects. On a micro level, stronger personal ties may lead to enhanced trust that helps create valuable soft information. On the other hand, these connections may foster a "group-think" mentality that limits valuable independent thought. This concern becomes serious on a macro level if managers of the firms at central positions in the network promote the "group-think" mentality in systematic ways.

In an attempt to better understand the importance and relative value of these influences, we examine the social connections among the largest 99 global banks in the Boardex database ranked by their total assets in 2003 over the 2000-2010 time period. For many reasons, the banking industry over this time period provides an interesting laboratory to study these issues. A large long-standing literature (e.g. Rajan, 1992; Houston and James, 1996; Detragiache et al., 2000; Berger et al., 2001; Champagne and Kryzanowski, 2007; Morrison and Wilhelm, 2007; Sufi, 2007; Ivashina, 2009) has emphasized the importance of banking relationships and the vital role that soft information plays within these relationships. Consequently, we might expect that social connections among banks' board members are particularly important, and that stronger connections between them may make it easier for banks to engage in a wide variety of valuable inter-bank transactions through enhanced information sharing between them.[1] The concern, however, is that these connections may cause banks to make similar bets that ultimately increase the systemic risk of the banking system. These concerns are particularly relevant in the aftermath of the recent financial crisis.

With these concerns in mind, we address three specific issues. First, we provide what we think is the first detailed evidence regarding the degree of social connections within the global banking industry. More specifically, we look at two broad types of measures. One set of measures calculates, for each possible pair of global banks in our sample, the number of connections among the respective board members in a given year. The other set of measures estimates the extent to which the bank is "central" to the overall social network of banking firms. Our results strongly

[1] For each pair of banks, we consider social connections between both their managers (employee board members) and their non-manager board members (non-employee board members). These non-manager board members not only conduct a supervisory role but also provide useful information or advice to banks' managers (See Coles et al., 2012 and Larcker et al., 2012, among others). The latter function of these non-manager board members is important to promote an informative managerial decision making, and thus, their connections would serve as an important information bridge among banks.

indicate that network connections in banking are meaningful and have become increasingly important over time. Average pairwise connectedness between two global banks in our sample has increased by 47% over the 2000-2010 period, and there has also been a steady increase in connections between U.S. and non-U.S. banks over this same time period. Moreover, we find that on average, government credit institutions, investment banks, and bank holding companies hold more central positions in the network relative to commercial banks and other savings institutions.

Second, we explore whether these extensive social connections within the global banking sector lead to more active business partnerships and/or similar investments among connected banks. Here we find that connected banks are more likely to partner together in loan syndicates, and that more central banks in the social network are more likely to lead or co-lead large syndicates. These results suggest that the central banks in the network promote and send signals of common investment ideas to the banks that are adjacent to them in the network, and stack up the common assets through the connected party transactions in loan syndicates. In this regard, we argue that these central banks play a crucial role in the financial system to the extent they serve as "intermediaries among intermediaries". We further confirm this notion of network central banks by documenting that they are net lenders in the interbank market. However, these net positive interbank asset positions held by network central banks could also raise concerns about a greater risk concentration among the small set of banks that are relatively well-connected to other banks within the network system.

In this regards, we ask our third question - whether the structure of social connections has had an influence on the systemic risk of the banking industry. We find that there is a strong link between the measures of centrality and the $\Delta CoVaR$ measure of systemic risk (Adrian and Brunnermeier, 2011). Put together with our earlier findings, these results suggest that connected banks make similar bets and that systemic risk is concentrated among banks that play central roles in the social network. Arguably, these linkages may be a valuable by-product of the shared information generated from these connections or they simply reflect a group-think mentality. Regardless, to the extent they enhance systemic risk; these results suggest that there may be a dark side to social connections.

Beyond these main results, we also examine whether the recent financial crisis influenced the effects of social networks within the global banking industry. Stepping back, one could envision two scenarios. One scenario is that networks became increasingly important during the financial crisis, causing banks to continue to rely exclusively on trusted partners. The other scenario is that the magnitude of the crisis transformed both the networks and the industry in ways that diminished the value of previous connections. In our tests, we find that banks were still likely to partner with connected banks in the syndicated loan market during the financial crisis. Interestingly, however, we find that these effects are primarily driven by cases where the partnered banks operate in the same country. By contrast, we find that during the crisis, the value of social connections was significantly reduced when the paired banks operate in different countries. This result is consistent with other areas of the literature, which have demonstrated a "flight to home market" effect in the global banking transactions during the crisis (De Haas and Van Horen, 2012; Giannetti and Laeven, 2012).

Looking further, we also find that during the crisis, central banks are no longer significantly more likely to serve as leads or co-leads in the syndicated loan market. Moreover, we find that while network central banks were able to offer lower loan spreads in the pre-crisis period, this effect disappeared during the crisis period. Given that we do not find any evidence on the disproportionately declining performance of the network central banks during the crisis, on balance, we conclude that the crisis transformed the value of centralized information flow within the global banking network.

Arguably, our results are sensitive to how we choose to define the banking network. We think it is appropriate to focus on a global network of large banking institutions, which arguably represent the key players whose operations are truly global and whose decisions are more likely to have a profound effect on the overall health and stability of the banking system. Despite the merits of our approach, our evidence suggests that banking networks are locally clustered and one could argue that their formations are endogenously determined by omitted factors that are not included as part of our controls.

To address these concerns, we include a series of bank pair-level dummies, which help alleviate concerns related to potential omitted variables. We find that our results are robust to including these effects, which gives us comfort that the observed connections are not solely driven by other common factors that are also correlated with the social connections within the local or regional network. At the same time, one could also argue that at least some of our results could be driven by reverse causality. Rather than network connections influencing bank decision making, the process could be reversed: bankers engaging in similar activities may generate new social connections. To alleviate this specific concern, we construct a series of robustness tests similar to those employed by Engelberg et al. (2012^b) and Hochberg et al. (2007). We use a much more restrictive definition of network connections that only includes (1) educational ties between board members and/or (2) professional ties that were generated well in advance of the later transactions by more than five years. Using this pre-existing network measure with a long time lag, we show that our results are robust to this specific channel of reverse causality.[2]

We believe that our results provide a number of insights that are relevant to bank regulators and other policymakers. Most notably, our evidence suggests that network measures calculated among a sample of the largest global banks, have a significant influence on the level of systemic

[2]Our test on reverse causality does not rule out a possibility that banks appoint new board members who are socially connected, anticipating that these connected board members will generate future business opportunities. This potential channel of reverse causality along the temporal dimension, if true, would re-confirm our main argument that pre-existing network connections have an important influence on subsequent business transactions. Moreover, we also find that our results are robust to excluding the observations with any board structure change one- to three years prior to each business transaction, which helps alleviate concerns about this particular channel of reverse causality.

risk. While it is well recognized that large banks are more likely to contribute to systemic risk, our findings suggest that network centrality may be another key indicator of systemic risk. In this regard, rather than simply being "too-big-to-fail", some banks may be "too-connected-to-fail." While it may be difficult, if not impossible, for regulators to specifically limit social ties within the global banking sector, our results do suggest that policymakers may want to pay particular attention to banks that play a key central role within the banking network. In this regard, our results may also be relevant to the current debate regarding the appropriateness of policies designed to break up banks that are viewed as too-big-to-fail.

Apart from these policy implications, we believe that our study provides a valuable contribution to four areas of the literature. First, our study contributes to the social network literature and provides further evidence that personal connections matter (Cohen et al., 2008, 2010; Hwang and Kim, 2009; Duchin and Sosyura, 2012; Engelberg et al., 2012[a]; Fracassi and Tate, 2012). We particularly emphasize the importance of board connections as an information bridge between banks (Cai and Sevilir, 2011; Engelberg et al., 2012[b]; Ferreira and Matos, 2012; Larcker et al., 2012). Second, our results add to the literature that focuses on the importance of banking relationships. In particular, our results suggest that personal connections between bank managers and directors create important inter-bank relationships that have real effects on a variety of bank transactions (Allen and Babus, 2008; Engelberg et al., 2012[b]). Third, our results add to the literature that looks at the factors influencing the stability of the banking system, and the resulting implications for bank regulators and other policy makers (Acharya et al., 2012; Brunnermeier et al., 2012; Cai et al., 2012). Cai et al. (2012) derive the interconnectedness of banks in their syndicated loan portfolios and identify such asset commonality as a major source of systemic risk for U.S. banks. In many respects, our results reinforce their findings and suggest that social connections are an important source of the links that are created through syndication partnerships. Beyond highlighting the importance of social connections, our findings are also distinct in that we focus on a global sample of banks from 16 countries. Finally, our paper adds to the growing literature that highlights the various effects related to the recent financial crisis (Chari et al., 2008; Ivashina and Scharfstein, 2010; Afonso et al., 2011; Erkens et al., 2012; De Haas and Van Horen, 2012; Giannetti and Laeven, 2012).[3]

The rest of the paper proceeds as follows: In Section 2, we introduce our data and our main network measures, and describe both the pairwise connection and centrality measures. In Section 3, we describe the patterns and trends of the social network in the global banking sector. Next, we investigate the effects that our network measures have on loan syndication and interbank transaction decisions in Section 4. We present the systemic risk results related to the centrality measures in Section 5. Section 6 presents the results of the network effects before and after the financial crisis and provide some potential explanations for our findings related to the financial crisis effects. Section 7 concludes.

2 Measures of social connectedness

2.1 Data

We use the Boardex database to construct our various social network measures. This database contains extensive information regarding the characteristics of board members and top management for major banks listed in Europe, North America, and Australia. The data include board size and composition along with each board member's complete history of other board memberships and socio-demographics such as age, gender, education, and nationality. We supplement the Boardex data with accounting information from Bankscope and equity prices from CRSP for

[3]These papers address the effect the crisis had on 1) the non-financial sector in the economy (Chari et al., 2008); 2) the level of bank lending in the syndicated loan market (Ivashina and Scharfstein, 2010); 3) the Fed funds market (Afonso et al., 2011); 4) the relationship between the corporate governance and a bank's performance (Erkens et al., 2012); the markets focused by international lenders (De Haas and Van Horen, 2012; Giannetti and Laeven, 2012).

North American banks and Compustat World for European and Australian Banks.

Our focus is on the most important financial institutions worldwide over the 2000 - 2010 time period, and we therefore include the 99 largest banks in the Boardex database ranked by their total assets in 2003 that we have complete access to their board members' vitae. We list these sample banks in the Appendix.

Panel A of Table 1 gives a quick picture of the main characteristics of our sample banks. All variables in the table are winsorized at the 1% level in both the left and right tails. The average book value of total assets of our sample banks is 437 billion USD. Their average beta coefficient calculated from daily industry CAPM regressions using the STOXX Global 1800 Banks index as a global banking sector index is 0.976.[4] The average value of $\Delta CoVaR$, the systemic risk measure for our sample banks, is -2.886. The definitions and construction details of $\Delta CoVaR$ will be discussed later in Section 5.

[Insert Table 1 here]

Using the DealScan database, we also collect information on the 300 largest global syndicate packages (based on their total package amounts denominated in USD) for each year during the 2000-2010 period. These deals, on average, represent roughly half (44.5%) the total dollar amount of syndicate packages reported each year in the entire DealScan database. Each package has multiple facilities with multiple lenders who are classified broadly into the following three categories: 1) lead arranger, 2) co-agent, and 3) participant lender.[5] We map each lender in each facility to its ultimate parent holding company.[6] To minimize any measurement error in this mapping process,

[4]The industry CAPM regressions are run at the end of each year over a 250-day moving window.

[5]We use co-agent and co-lead arranger interchangeably in the text.

[6]This mapping requires the information on dynamic subsidiary-ultimate parent link for all 99 top global banks in our sample over the 2000-2010 sample period. This process is done by the following two steps: First, we use a computer-based matching to utilize the dynamic subsidiary-ultimate parent company link file that was kindly provided by Cai et al. (2012) for the top 100 lead arrangers in the U.S. syndicated loan market. Second, we manually inspect the link for the remaining banks in our sample by utilizing the information provided by either

we focus on just the first two types of lenders; lead arrangers and co-agents. After completing this mapping process, we obtain each lender's identifier in the Bankscope database, which is the key variable that links the syndicate structure data to our social networks and financial data. Summary statistics of the 300 largest global syndicate packages in each year are provided in Panel B of Table 1.

The sample consists of 1,644 borrowers from 66 countries. The average package is 4.303 billion USD and includes 2.128 facilities. On average, each facility has 4.344 lead arrangers and 9.892 lead or co-lead arrangers. The average facility is 2.050 billion USD, and this average value does not vary significantly between the deals syndicated within and outside the U.S. Arguably, the information produced by social networks may vary depending on whether there is available public information on the borrower's characteristics. We classify 33% of our borrowers as "opaque" - these are either private entities or public companies without a published rating.

2.2 Network measures

2.2.1 Pairwise connections

Boardex allows us to retrieve all the connections between board members of each bank pair. Connections are established either through common educational institutions, or past or present membership on a corporate board, government institution, medical institution, or charity. Two people are considered connected if they were active members of the same institution at the same time. To avoid double counting one individual cannot contribute more than one connection between two banks. Similar to the social network index (*sni*) that Fracassi (2012) calculated for his sample of non-financial firms, we create a measure of connectedness: *Sni*, which is the sum of all connections between two banks, established both through current or past common affiliations,

the National Information Center (http://www.ffiec.gov/nicpubweb/nicweb/nichome.aspx), or each bank's company web page, or both, if necessary.

scaled by the average board size of the two banks.

Sni comprehensively captures both educational and professional ties between the board members of two banks. Even though we mainly focus on the broader *sni* measure throughout our regression analyses, it is also interesting to see how the patterns of each of the two types of connections vary over time. Thus we decompose *sni* into the following two sub-components: *edu* and *professional*. *Edu* is defined exclusively based on the educational ties, whereas *professional* captures all potential connections between two banks' board members except the educational ties. Both *edu* and *professional* are also scaled by the average board size of two banks.

In addition to these three "scaled" pairwise connection measures - *sni*, *edu*, and *professional*, we also construct for each measure a simple "unscaled" version that takes a binary value, either zero or one, depending on whether two banks are connected. For example, for *sni*, the unscaled version of *sni* takes a value of one if there is at least one connection between the board members of two banks through any type of social connections, either educational or professional. For the other two scaled pairwise connection measures, we similarly construct their unscaled counterparts.

[Insert Table 2 here]

The summary statistics of both the scaled and unscaled versions of *sni*, *edu*, and *professional* are all provided in Panel A of Table 2. This panel depicts how the average values of these different pairwise connectivity measures change from 2000 to 2010.[7] In that panel, we see that *sni*, both scaled and unscaled, increases over time, and the professional social connections between two banks (*professional*) seem to drive this upward trend. We find the opposite trend in educational connections, which decline over our sample period. In Panel B of the table, we show that the scaled versions of the three pairwise connection measures are highly correlated. In the later Section 3,

[7]Even though Boardex database spans the time-period since 1997, the coverage till 1999 is limited to only European institutions. Because our study examines the global nature of network connections among the largest banks around the world, we exclusively focus on the post-2000 period.

we will take a closer look at the patterns of these average pairwise connection measures across different regions throughout our sample period.

2.2.2 Centrality

In addition to the pairwise connectedness measures described above, we also construct a series of network centrality measures. These centrality measures are designed to capture how each bank is positioned in the global network, and how much information flows through each bank. Each centrality measure can be computed using any of the three above-mentioned definitions of pairwise connectedness - *sni*, *edu*, and *professional*. For the time being, we restrict ourselves however to the full measure of pairwise connectivity, *sni*. Based on this pairwise connection measure, each year we first construct an nXn unweighted adjacency matrix whose (i, j)-element is a dummy which takes a value of one if bank-i and bank-j are socially connected.[8] Here n denotes the total number of banks in the global banking network. Using this unweighted adjacency matrix, we construct each centrality measure on a bank-year level, following approaches similar to those used in Hochberg et al. (2007) and Larcker et al. (2012). More specifically, we construct the following four measures of network centrality:[9]

- *Betweenness*

  Betweenness captures the frequency in which a given bank lies on the shortest path between all sets of possible bank pairs within the sample. Presumably, if a bank is part of many paths that connect other banks to each other, then it is likely to have informational or relational importance within the networks since it is vital in connecting banks to each other. This

[8] In other words, this unweighted adjacency matrix is constructed using the value of the unscaled *sni* for each pair of banks.

[9] The measures are computed using Hirotaka Miura's network package for Stata and are computed as described in its documentation (Miura, 2012). Since the composition of the banks in our sample changes year by year, we end up with an unbalanced panel for the years 2000-2010. However, it should be noted that our results are robust to these concerns about the changing composition of the global network system throughout our sample period. See Appendix Table 1 in Appendix B.

betweenness measure captures the importance of a bank not only in the first-degree (direct) links but also in the multiple-degree (indirect) links that connect any given pair of banks. In that sense, *betweenness* broadly captures the degree of the importance of a given node in the whole network. Suppose P_{ij} denotes the number of shortest paths from bank-i to bank-j. Let $P_{ij}(k)$ then denote the number of the shortest paths that bank-k lies on. *Betweenness* centrality of bank-k is then formally defined as

$$\sum_{i,j:i\neq j,k\notin i,j} \frac{P_{ij}(k)}{P_{ij}}$$

- *Eigenvector*

  Eigenvector centrality gives large values to those banks that have many links with other important banks that are central within the system. A bank has large value of *eigenvector* centrality if the bank is connected to other important nodes in the networks through both the first degree and multiple-degree links. Hence this *eigenvector* centrality of a given bank depends on the centrality of other important banks in the networks. The formal definition of this *eigenvector* centrality is more mathematical than the other centrality measures, and requires computation of the eigenvalues of each node in the network. See Bonacich (1972) for more details on the computational procedures.

- *Closeness*

  Closeness computes the inverse value of the average distance between bank-i and all other banks in the networks where the distance is defined as the number of steps in each shortest path that two banks lie on. Let D_{ij} denote the number of steps in the shortest path between bank-i and bank-j. The *closeness* measure of centrality of bank-i is formally defined as

$$\frac{n-1}{\sum_{j \neq i} D_{i,j}}$$

where n denotes the total number of banks in the networks. *Closeness* can be seen as a measure of the speed in which information from an individual bank spreads through the network.

- *Degree*

  For each bank, *degree* counts the number of other banks in which it shares a first-degree connection. Let $I_{i,j}$ be the indicator that bank-i and bank-j are connected through a first-degree link. We use a normalized version of the *degree* centrality that scales by the total number of banks in the networks other than the given bank-i. The *degree* measure of centrality of bank-i is formally defined as

$$\frac{1}{n-1} \sum_{j \neq i} I_{i,j}$$

  where n denotes the total number of banks in the networks.

[Insert Table 3 here]

Summary statistics for the centrality measures are provided in Panel A of Table 3. On average, investment banks and government credit institutions hold more important positions within the network compared to the other types of institutions. At the other extreme, institutions classified as savings banks play, on average, the most peripheral roles within the network. Panel B of Table 3 shows that the four different centrality measures are highly correlated.

3 Global banking networks

Table 2 illustrated that the average pairwise connections in the global banking sector have been steadily increasing over time. In this section, we want to take a closer look at the regional and cross-regional patterns of the pairwise connectedness.

[Insert Figures 1, 2, and 3 here]

Figures 1 - 3 show the snapshots of the following three different networks taken at the year 2006: 1) Global network (Figure 1), 2) U.S. regional network that includes only the U.S. banks as the network vertices (Figure 2), and 3) non-U.S. network (Figure 3) that includes only the non-U.S. banks in the network. In all three figures, the thicker the line between two banks, the more connections between these two institutions. As shown in Figure 1, the global banking network has two heavily interconnected centers formed by large banking corporations, a European (BNP Paribas, Deutsche Bank AG, RBS Holdings NV (the former ABN AMRO Group NV), UBS AG, among others) and an American one (Citi Group Inc, Merrill Lynch & Co, MetLife, Inc, Morgan Stanley, among others). Grouped around these two centers are smaller banks that seem to form more regional centers. In Figure 2 and 3, we further look at the patterns and formations of both the U.S. only and the non-U.S. only networks, respectively. In the U.S. network, one can see that Goldman Sachs Group, Inc, JP Morgan Chase & Co, and Morgan Stanley are placed at more central positions in the network. The more peripheral institutions (Popular, Inc, PNC Financial Services Group, Inc, State Street Corporation, among others) are connected to the one of those central banks in the network. Similar patterns are found in the non-U.S. network where Barclays Plc, BNP Paribas, and Deutsche Bank AG serve as the regional central banks within the non-U.S. network.

[Insert Figure 4 here]

Figure 4 graphically illustrates how average pairwise connectedness changes over time in the post-2000 period. We first consider the pairwise measure based on the global network (Global: *sni*). These results confirm our earlier findings in Table 2 which showed that both the scaled and unscaled versions of *sni* steadily increased from 2000 to 2010. For the scaled *sni* measure, we can see that there is a net 47% (=0.0245/0.0167-1) increase in the average pairwise connectedness between two global banks in our sample. Next, we focus on the U.S. regional network, constructing the pairwise connection measures exclusively with the U.S. bank pairs (U.S. only: *sni*). In that panel, we see that the scaled *sni* measure increases from 0.03 to 0.047, which corresponds to a net 57% increase in the average pairwise connectedness between two U.S. banks during the 10-year time period. We also find similar upward patterns in the pairwise connections between non-U.S. banks (Non-U.S. only: *sni*). Finally, when we look at the cross-regional connections between the U.S. and the non-U.S. networks (U.S. to Non-U.S.: *sni*), we also find increased connectedness between banks that operate in different regions. However, this pattern is slightly reversed following the 2007 financial crisis. Overall, these results strongly indicate that network connections in banking are meaningful and have become increasingly important over time.

4 Network effects: Global loan syndication structure and interbank transactions

4.1 Are connected banks more likely to partner together in the syndicated loan market?

In this section, we consider whether global banks that share a common (pairwise) connection are more likely to partner together in the syndicated loan market. Evidence supporting these partnerships would suggest that social connections provide valuable information that translates into business connections. To explore these links, we gather information on the top 300 largest global syndicated loan packages for each year in our sample period. As emphasized earlier, these deals are quite representative of global syndication activity recorded in the DealScan database in the post-2000 time period. For each loan facility in each syndicate package, we focus on the facility's lead or co-lead arrangers and create a partnership dummy for each possible pair of banks that exist in our sample of global banks.

Thus, the main dependent variable in our regression analysis is a dummy, $pair_{i,j,k,t}$, which takes a value of one if bank-i, a lead (or, co-lead) arranger in facility-k, partners with bank-j as another lead (or, co-lead) arranger of this facility-k in year-t.[10] Each facility has a unique borrower-b. We use a unique pair for any two banks in our top global banks sample, eliminating any duplicates due to permutations. Following Cai et al. (2012), we run a linear probability regression with the lagged value of the scaled version of our pairwise measure, $sni_{i,j,t-1}$, as the main right-hand-side (RHS) variable:

$$\begin{aligned} pair_{i,j,k,t} = \quad & \alpha_0 + \alpha_t + \beta_{i,t-1} + \beta_{j,t-1} + \beta_{i,b,t-1} + \beta_{j,b,t-1} + \beta_{b,t-1} \\ & + \gamma \cdot sni_{i,j,t-1} + \delta' X_{i,j,t-1} + \epsilon_{i,j,k,t} \end{aligned} \tag{1}$$

where α_0 is an overall constant, and α_t is the vector of year fixed effects.

Some banks may lend more than other banks in the syndicated loan market. $\beta_{i,t-1}$ (or $\beta_{j,t-1}$) captures this bank-level heterogeneity in the loan origination activity. We use the cumulative number of syndicated loan facilities that a bank-i (or j) has lent to any borrower in our sample prior to the year of the syndication of facility-k and denote this bank-level variable by $cum.lending_{i,t-1}$ (or $cum.lending_{j,t-1}$). To control for any prior lending relationship between each bank and the borrower, we additionally control for $\beta_{i,b,t-1}$ (or $\beta_{j,b,t-1}$). For this bank-borrower level variable, we

[10] When we form these bank pairs, we require that at least one bank from our sample of global banks should lead (or, co-lead) the facility-k.

use the total number of facilities that bank-i (or j) has lent to the borrower-b of facility-k prior to the year of syndication of facility-k divided by the total number of facilities that the bank has lent to any borrower in our sample prior to the year of the syndication. We denote this bank-borrower pair-level variable by $cum.lending_{i,b,t-1}$ (or $cum.lending_{j,b,t-1}$). Lastly, banks may avoid lending to informationally opaque borrowers. To capture this borrower-level heterogeneity, we control for $\beta_{b,t-1}$, which we proxy for using *opaque* borrower dummies.

Having controlled for these variations in $pair_{i,j,k,t}$ along the bank-, the bank-borrower pair-, and the borrower-levels, all remaining variations in $pair_{i,j,k,t}$ would be captured by our main RHS variable, $sni_{i,j,t-1}$, which is defined at the bank pair level. The coefficient γ on $sni_{i,j,t-1}$ is our main interest. One might expect that banks from the same country and of the same institutional type may make similar investments. To control for these same country and same institutional type fixed effects, we have included same country (*country*) and same institutional type dummies (*type*) on the RHS of the regression as additional bank pair-level controls, $X_{i,j,t-1}$. We also cluster the standard errors at the bank pair level.[11]

[Insert Table 4 here]

Table 4 shows the results. In column (1), we find that connected banks are more likely to form a syndicate partnership. The point estimate of $sni_{i,j,t-1}$ is 0.510, which is statistically significant at the 1% level. For a one standard deviation increase of $sni_{i,j,t-1}$ (0.047), there is a 2.397% (=0.047*0.510) increase in the likelihood of syndicate partnership. This effect corresponds to 24.459% (=2.397%/9.8%) of the unconditional probability of two banks forming a partnership in our sample (9.8%), which is an economically significant effect. In column (2), where we use the unscaled version of *sni* on the RHS of the regression, we find similar effects both statistically and

[11] We find a similar result when we use an alternative clustering algorithm of the regression residuals - the dual clustering algorithm by Petersen (2009) for each of two banks in a pair.

economically.[12]

In column (3), we extend our bank pair level controls, $X_{i,j,t-1}$. In addition to the same *country* and *type* dummies, we further control for the effects of similar size and leverage on two banks' partnership decisions. Specifically, we create the following five matched buckets for the size (TA) and leverage (*leverage*) variables respectively, all based on their lagged values: hh, hm, hl, ml, and ll where h, m, and l respectively denote high, median, and low buckets based on the terciles of each of the two variables. Due to the overall constant term (α_0) in the regression, the mm case is naturally ruled out when we assign bank pairs into these tercile buckets. In column (3), we find that our results carry through even after controlling for these additional time-varying controls at the bank pair level.

Next, we address the concerns about potential omitted variable biases by additionally controlling for various fixed effects. In column (4), we first additionally control for borrower fixed effects.[13] As shown in that column, the point estimate of $sni_{i,j,t-1}$ (0.128) is little changed from that in column (3), which indicates that the omitted constant factors defined at the borrower level do not materially affect our main findings.

Some facilities may be more difficult to coordinate than others, possibly due to different seniorities and loan types. We additionally control for these facility fixed effects in column (5). It should be noted that year and borrower fixed effects are all embedded in the facility fixed effects since each facility belongs to a specific year and a specific borrower of the loan syndication. The point estimate of $sni_{i,j,t-1}$ (0.123) in column (5) is hardly changed from that in column (3).

Another legitimate concern is that geographical similarity or any similarities in institutional characteristics that are not captured by our control variables - *country* and *type* - may determine the patterns of social networks among our sample banks. Such constant factors defined at each

[12]There is a 26.392% (=0.424*0.061/9.8%) increase in the likelihood of syndicate partnership from the sample average for a one standard deviation increase in the unscaled $sni_{i,j,t-1}$ (0.424).

[13]We consequently drop the *opaque* variable on the RHS of the regression.

bank pair level could be also correlated with two banks' decisions on syndicate partnership. To address this concern, we conduct an additional robustness test in column (6), where we use our regression specification in column (3), but additionally control for bank pair fixed effects. There we find the robustness of our results to the inclusion of these bank pair level dummies. The lagged *sni* significantly explains more frequent partnership between socially connected banks at the 1% level.

Even though we use the lagged value of *sni* in our main analysis, reverse causality could still be an issue when we interpret our results. Our analysis assumes that past and current connections induce bankers to partner together, but there is a legitimate concern that the causality is reversed if the co-lending experience may foster new social connections between the board members of the two banks. This concern exists if the two banks persistently form business partnerships over times. To tackle this potential endogeneity of personal relationship between the board members of the two banks, we follow the approach used in Engelberg et al. (2012^b). Specifically, we replace our one-year lagged *sni* with the predetermined pairwise connectedness, *sni(old)*, where the social connections between two banks' board members are based exclusively on (1) educational ties whose formation predates the co-lending experience by several years or decades and/or (2) the professional ties that are formed at a third-party institution other than the two banks by more than five years prior to the date of syndication.[14] Given that we measure the board structures of partnering banks prior to the date of each syndication, the long lag between the formation of the *sni(old)* and the co-lending experience between the two banks naturally rules out concerns related to reverse causality. In column (7), where we still control for year- and bank pair fixed effects, we find a statistically significant positive association between the lagged *sni(old)* and the syndicate partnership dummy at the 1% level.

[14]This new pairwise connection measure, *sni(old)*, is also scaled by the average board size of the two banks.

4.2 Do central banks in the network play a predominate role in syndicate arrangement?

By definition, banks that play a central role in the global network have many banks directly adjacent to them. This central place in the social network may enable these banks to have access to the information created by their adjacent banks. The resulting information advantage might naturally create an environment in which the central banks in the network would be expected to play more predominant roles in originating large international syndicates. In this section, we test whether socially central banks are more likely to lead or co-lead large international syndicates.

In syndicate lending, leads and co-agents typically play more senior roles in conducting various managerial functions within the syndicate. Pure participants simply contribute their capital to the syndicate, and are not generally responsible for screening and monitoring the borrower. Given this background, in our empirical tests we create a new dummy, $arranger_{i,k,t}$, as our main left-hand-side (LHS) variable. This dummy variable takes a value of one if bank-i takes a senior role such as a lead or a co-lead for facility-k in year-t. We denote the borrower of the facility-k by b. We use the one-year lagged values of the four measures of network centrality as our main RHS variables - *betweenness*, *eigenvector*, *closeness*, and *degree*:

$$\begin{aligned} arranger_{i,k,t} &= \alpha_0 + \alpha_t + \alpha_b + \alpha_{i,country} + \alpha_{i,specialization} \\ &\quad + \beta \cdot centrality_{i,t-1} + \gamma' X_{i,t-1} + \epsilon_{i,k,t} \end{aligned} \tag{2}$$

where where α_0 is an overall constant, α_t the vector of year fixed effects, α_b the vector of borrower fixed effects, $\alpha_{i,country}$ the vector of country fixed effects of the bank-i, and $\alpha_{i,specialization}$ the vector of specialization fixed effects of the bank-i.

The coefficient β on $centrality_{i,t-1}$ is our main interest. As additional bank-level time-varying controls ($X_{i,t-1}$), we consider the market-to-book equity ratio ($mtb_{i,t-1}$), leverage ($leverage_{i,t-1}$), and size ($TA_{i,t-1}$ in trillion USD). The standard errors are clustered at the year level following Cai et al. (2012). However, we further show the robustness of our results to the persistent temporal error terms within each bank panel by clustering the errors at each bank level.

[Insert Table 5 here]

Table 5 shows the results. In column (1), we use lagged *betweenness* centrality and find that central banks are decidedly more likely to lead or co-lead large international syndicates. The point estimate of *betweenness* is 1.827, which is statistically significant at the 1% level. For a one standard deviation increase in *betweenness* (0.012), there is a 34.967% (=0.012*1.827/0.0627) increase in the probability of a bank to lead or co-lead the syndicates from the sample average (6.27%). This is an economically significant effect. The results are not driven by any constant omitted variables defined at the year, country, and specialization of a bank, and also at the borrower levels. Moreover, they are robust to the various bank level characteristics such as lagged values of market-to-book equity ratio, leverage, and size. These results confirm our prior that central banks have information advantages that make it more viable for them to provide senior roles within a syndicate.

In the columns (2) to (4), we repeat the same analysis using different network centrality measures. We use lagged *eigenvector* in column (2), lagged *closeness* in column (3), and lagged *degree* in column (4). In each case, we find results that are both qualitatively and quantitatively similar to those reported using the *betweenness* measure of centrality. These results do not appear to be driven by any omitted factors defined at the loan facility levels (column 5) and are also robust to the use of standard errors clustered at the bank level (column 6).[15]

In column (7), we again address the reverse causality concern - in this case, the concern would be that the process of arranging large syndicates enables the bank to increase its network

[15]In column (5) of Table 5, year and borrower fixed effects are implicitly controlled since we control for the facility fixed effects.

centrality. To address this concern, we use a new centrality measure, $betweenness_{i,t-1}(old)$, that is based solely on predetermined social ties such as educational ties and the ties that were formed at least five years prior to the date of loan origination. The results in column (7) confirm the robustness of our results to reverse causality. A similar approach to ours is also employed by Hochberg et al. (2007) to address reverse causality concerns in VC network centrality measures. They measure the VC network centrality using syndication data for the five preceding years for a fund of a given vintage year.

Put together, socially central banks appear to play an important intermediary role by inducing other socially peripheral banks to make joint investments. In this regard, the potential information advantage that the central banks have through their well-connected directors enables them to serve as "intermediaries among intermediaries" in the global syndicated loan market.

4.3 Do central banks play a predominant role in the interbank market?

Besides their loan originations to corporate borrowers, banks also transact with one other in the interbank market. In the interbank market, some banks play a particularly important role in providing liquidity, which helps other banks with their day-to-day operations and assists them in preserving their minimum capital requirement. In this interbank transaction, information asymmetry on the counterparty plays a key role in credit rationing (see Flannery, 1996; Freixas and Jorge, 2008; and Heider, Hoerova, and Holthausen, 2009, among others). In the context of our analysis, we might expect that socially central banks would be more willing to lend without rationing due to the information advantages that stem from their extensive social connections.

We examine the relations between centrality and interbank lending and borrowing using the regression specification in Equation (3) below. We use the ratio of interbank loans to total assets (*interbank loans*) and the ratio of interbank deposits to total assets (*interbank deposits*) as our main LHS variables. On the RHS, we have one of the four centrality measures and additionally control for the market to book ratio (*mtb*), total capital ratio (*capital ratio*), and bank size (TA), all in lagged forms.

$$\begin{aligned} \textit{interbank loans } (\text{or } \textit{deposits})_{i,t} &= \alpha_0 + \alpha_t + \alpha_{country} + \alpha_{specialization} \\ &+\beta \cdot centrality_{i,t-1} + \gamma' X_{i,t-1} + \epsilon_{i,t} \end{aligned} \tag{3}$$

where where α_0 is an overall constant, α_t the vector of year fixed effects, $\alpha_{country}$ the vector of country fixed effects, and $\alpha_{specialization}$ the vector of specialization fixed effects. We cluster the standard errors at the bank level.

[Insert Table 6 here]

Table 6 shows the results of the network effects on interbank lending and borrowing. The first four columns of Table 6 clearly demonstrate that a bank's willingness to lend in the interbank market critically depends on its position within the network. For each of our four centrality measures, there is a positive and statistically significant coefficient, confirming that banks with a central position in the global banking network lend more to their peers relative to banks that hold more peripheral network positions. Similar results are found in column (5), where we use the $betweenness(old)$ on the RHS of the regression to mitigate concerns regarding reverse causality.

The next four columns (6) to (9) of Table 6 show the corresponding results for deposits received in the interbank market. We first find negative point estimates for all four centrality measures, and a similar negative relation between the interbank deposit ratio and the lagged $betweenness(old)$ is also found in the last column (10). These results indicate that banks at more peripheral positions in the networks tend to receive deposits from other banks in the system.

Taken together, the results from interbank lending and interbank borrowing indicate that banks that are central in the network are net lenders. These results reconfirm the notion that central banks play important roles serving as the "intermediaries among intermediaries." However, the net positive interbank asset positions held by network central banks could raise concerns about a greater risk concentration among this small set of banks that are relatively well-connected to other banks within the network system. In the following section, we primarily investigate such possibilities.

5 Do network connections promote systemic risk?

The previous results suggest that connected banks often partner together and invest in similar ways. Moreover, central banks in the network appear to play an important role in hosting these similar investing and financing decisions, creating systematic signals in bank operations. From these results, one obvious concern is that the systematically coordinated actions among global banks could reflect a form of "group think" that ultimately leads to greater systemic risk in the global banking sector.

To explore this possibility, we investigate whether banks that play a more central role in the social network are more likely to contribute to the risk of the global banking sector. This question asks whether the collapse of a more centrally connected bank has a more severe impact on the stability of the financial system than the collapse of a less connected institution. In order to address this issue we use the $\Delta CoVaR$ measure introduced by Adrian and Brunnermeier (2011). $\Delta CoVaR$ is defined as the difference between the Value at Risk of the banking sector conditional on one individual bank being in distress and the Value at risk of the banking sector conditional on this bank operating in its median state. More formally, using the same notation as in Adrian and Brunnermeier (2011), the value at risk of the financial system conditional upon bank-i performing at its worst q% quantile ($CoVaR_q^{system|i}$) is defined as

$$Prob(R^{system} \leq CoVaR_q^{system|i} | R^i = VaR_q^i) = q,$$

where R^{system} is the asset-level return of the banking system, R^i the asset-level return of bank-i and VaR_q^i the Value at Risk of bank-i at the q% quantile. Similarly the value at risk of the financial system conditional upon bank-i performing at its median state ($CoVaR_q^{system|i,median}$) is defined as

$$Prob(R^{system} \leq CoVaR_q^{system|i,median} | R^i = VaR_{median}^i) = q$$

and therefore bank-i's contribution to systemic risk is defined as

$$\Delta CoVaR_q^i = CoVaR_q^{system|i} - CoVaR_q^{system|i,median}.$$

In our analysis, we apply the approaches used in Adrian and Brunnermeier (2011), where we define the banking system to be our set of the 99 largest global banks. For each bank, we transform its book value of total assets into a market value using its market-to-book equity ratio.[16] From these estimates of the market-valued total assets, we compute their weekly asset-level returns. We estimate $\Delta CoVaR$ at the 1% level by running quantile regressions on weekly data for each bank. First, we predict each individual bank's VaR at the 1% level and at the median level using a vector of lagged state variables. Time varying $VaR_{1\%}^i$ and $VaR_{50\%}^i$ are then calculated as the fitted values from these regressions. We then estimate the Value at Risk of the banking sector conditional on the same lagged state variables and the contemporaneous performance of each individual bank. And we calculate $CoVaR_{1\%}^{system|i}$ and $CoVaR_{1\%}^{system|i,median}$ using $VaR_{1\%}^i$ and $VaR_{50\%}^i$. $\Delta CoVaR_{1\%}^i$ of bank-i is then the difference between the two $CoVaR$ values.

[16]See Section 2.4 of Adrian and Brunnermeier (2011) for the details of this transformation procedure. The market value of equity is updated on a daily basis whereas the book value of equity is updated quarterly. For each daily date of the market value of equity, we use the information on the book value of equity from the most recent fiscal quarter end date.

Here the asset-level return of the banking system is defined as the weighted average of the constituent banks' weekly asset-level returns using their 1-week lagged market-valued total assets as weights. The state variables used in the quantile regressions correspond to those used by Adrian and Brunnermeier (2011): Market volatility is the 60 day standard deviation of S&P 500 returns, market returns are proxied by the weekly S&P 500 returns, liquidity risk is captured using the difference between the three month LIBOR rate and the three month Treasury bill rate, interest rate risk is the change in the three month Treasury bill rate, the change in the yield curve slope is the change in the difference between the 10 year Treasury rate and the three month Treasury rate, and default risk is proxied by the change in the credit spread between BAA rated corporate bonds and the ten year Treasury rate.

Panel A of Table 1 reports the summary statistics related to our systemic risk measure. The statistics indicate that the average value of $\Delta CoVaR$ for our top 99 global banks (-2.886) is more negative than the value reported by Adrian and Brunnermeier (2011) (-1.16). It is notable, however, that their study looked at a much longer time period (1986-2010) and focused on both small and large banks in the U.S.

To examine the effect of network centrality on the systemic risk of global banking sector, we regress $\Delta CoVaR$ on the lagged value of one of our four centrality measures using the following specification:

$$\begin{aligned} \Delta CoVaR_{i,t} &= \alpha_0 + \alpha_t + \alpha_{country} + \alpha_{specialization} \\ &+ \beta \cdot centrality_{i,t-1} + \gamma' X_{i,t-1} + \epsilon_{i,t} \end{aligned} \tag{4}$$

where where α_0 is an overall constant, α_t the vector of year fixed effects, $\alpha_{country}$ the vector of country fixed effects of the bank-i, and $\alpha_{specialization}$ the vector of specialization fixed effects of the bank-i. Standard errors are clustered at the bank level.

It should be noted that we do not unsign the negative value of $\Delta CoVaR$ in this analysis. As the time-varying bank-level controls ($X_{i,t-1}$) of this regression, we include mtb, size (TA) and its non-linear effects on $\Delta CoVaR$ (TA^2 and TA^3), *leverage*, and the systematic risk measured by *beta* from banking sector CAPM, all in the lagged forms. The expected sign of our point estimate of interest, β, is negative. The expected signs for the lagged *mtb*, TA, *leverage*, and *beta* are also all negative.

[Insert Table 7 here]

Table 7 shows the results. There we see that banks that hold more central positions in the network contribute more to the systemic tail risk of the global banking sector. In all columns, the point estimates of the four centrality measures are significantly negative at least at the 10% level. For a one standard deviation increase in *betweenness* (0.012), there is an 8.375% increase in $\Delta CoVaR$ relative to its sample average value (-2.886), which appears to be both economically and statistically significant.

The point estimates of our additional control variables mostly confirm their expected signs except the size-related variables (TA, TA^2, and TA^3). Our sample banks are the 99 largest banks around the world, and thus, the relationship between the size and the systemic risk around this extreme part of the banks' size distribution could be different from that associated with the normal-sized banks. However, their estimated coefficients are generally not statistically significant.

Overall, it appears that socially central banks are significant contributors to the instability risk of global banking sector throughout the whole sample period. These results suggest that in order to ensure stable financial sector around the world, particular attention should be paid to the banks that play a key central role within the global banking network. The network centrality measures we introduce in this paper could be useful to identify systemically important entities in the global banking industry. The measures are based on personal connections generated by individual directors in the global banking system and, therefore, shed light on another important aspect of global banking operations - the human side of banking.

6 Network effects before and after the crisis

One might expect that the financial crisis transformed the value of social networks. In one respect, we might expect that banks are even more likely to rely on strong existing relationship during difficult times. If so, we would expect that banks were more likely to partner with connected banks during the crisis period. At the same time, the crisis transformed the business models of many top banks, which may have instead dramatically reduced the value of existing connections. Moreover, to the extent the crisis influenced banks willingness to engage in global transactions, the effects of this shifting environment on banking transactions could be different depending on whether the connected banks operate within the same country. In this section, we empirically examine these possibilities.

[Insert Table 8 here]

Table 8 shows the results. In column (1) of the table, we repeat the regression in column (1) of Table 4 with the *crisis* interaction term with the lagged *sni* as an additional RHS variable. The *crisis* is a dummy variable for the post-2007 period. We find that socially connected banks continue to form a strong partnership in their loan syndication even during the crisis period. The point estimate of $sni_{i,j,t-1}$ during the crisis period ($crisis = 1$) is 0.501 (=0.515-0.014), which is 97.282% of the point estimate of $sni_{i,j,t-1}$ during the pre-crisis period (0.515), and is significantly different from zero with the p-value of 0.000 based on a Wald test using an F-distribution.

While this result suggests that the crisis did not reduce the value of social connections, we might expect differential effects depending on whether the connected banks operated within the same country. In columns (2) and (3), we re-run the regressions dividing the sample according to whether the paired banks operated within the same country. The results reported in column (2) demonstrate that the value of social connections was not diminished during the crisis in those cases where the paired banks operated in the same country.[17] However, when the paired banks operate in different countries, we see in column (3) that the links between social connections and lending connections were significantly weakened during the crisis. Looking at the estimated coefficients, we see that during the crisis socially connected firms in different countries were still more likely to partner together in the syndicated loan market, but the magnitude of this effect was 25% less (-.193/.772) than it was during the pre-crisis period. We find similar results in columns (4) and (5), where we further control for borrower fixed effects and conduct the within-firm variation test to alleviate concerns about loan demand side effects. All in one, we find that the crisis had a significantly more negative impact on the value of social connections between lenders when these lenders operated in different countries. This result suggests that during the financial crisis, lenders rely more on their domestic connections. This effect is consistent with the results of other papers that have shown that the crisis generated a "flight to home market" (De Haas and Van Horen, 2012; Giannetti and Laeven, 2012).

To further explore the effects of the crisis, we also test whether central banks continued to be more likely to lead or co-lead large loans after the crisis. In Table 9, we report results where we re-run the regressions in the first four columns of Table 5. Here we find a statistically significant reduction in the likelihood that a bank at the central position of the network leads or co-leads a large global syndicate during the crisis period. For instance, in column (1) of the table, the point estimate of the interaction term between the lagged *betweenness* and the *crisis* dummy is -3.921 and statistically significant at the 1% level. Given that the point estimate corresponding to the standalone *betweenness* measured on a standalone basis is 2.888, the negative interactive effect between *betweenness* and *crisis* is substantial. We find similar tendency throughout the remaining columns (2) to (4) of Table 9 for the other three centrality measures.

[17] The standard deviation of $sni_{i,t-1}$ for lenders in the same country is 0.091, which is twice as large as that for lenders in different countries (0.043). Therefore, the smaller point estimate of $sni_{i,t-1}$ in columns (2) does not mean that the social network effects are smaller for lenders in the same country during the pre-crisis period.

[Insert Table 9 here]

Why were socially central banks less likely to originate syndicated loans during the crisis period? One explanation is that the central banks in the network, which are primarily the large global investment banks, might have suffered disproportionately during the crisis, which in turn caused them to reduce their involvement in this important market. Alternatively, the value of centralized information flows might have become less valuable to the extent the crisis "changed the game", and reduced the benefits of historical relationships. We continue to investigate which channel among the two is more likely to explain the diminished roles played by the socially central banks during the crisis period.

To this end, in Table 10, we report the fundamental characteristics of the following two groups of banks, before and after the crisis: (1) the banks at more central positions in the network based on *betweenness* centrality (High) and (2) the banks at more peripheral positions in the network (Low). We use the median value of *betweenness* in each sub-period as the cutoff to define the two groups of banks, before and after the 2007 financial crisis. For these two groups of banks, we provide the average values of the natural logarithm of the book value of total assets ($ln(TA)$), return on assets (roa), leverage, equity return, total annualized equity return volatility ($sigma$), and two CAPM betas (one for domestic stock market index and the other for global banking sector index) before and after the 2007 financial crisis. Then we compute the difference in differences (DiD) of these fundamental characteristics between the two groups, before and after the crisis.

[Insert Table 10 here]

Column (9) of Table 10 shows the results of the DiD. First of all, we find a positive and statistically significant (at the 10% level) DiD in *betweenness*, indicating that the social network in the global banking industry becomes more centralized in the post-crisis period. However, during that time period, we do not find any significant deterioration of the fundamentals of the socially central banks. None of the key measures, *roa*, *leverage*, and *sigma* appears to be disproportionately affected for the socially central banks in the network. Indeed, by one key measure (*equity return*), the central banks outperform the peripheral banks during the crisis compared to their relative performance in the pre-crisis period. Moreover, the difference between the central and the non-central banks in the two systematic risk proxies, *beta* (domestic market index) and *beta* (global banking index), seems to decrease during the crisis.

On balance, the results in Table 10 provide little support for the argument that central banks played a diminished role because they suffered disproportionately during the crisis. Consequently, these findings alternatively suggest that during the crisis period, both the quantity and quality of information that flowed through the network tended to depreciate, in turn reducing the roles played by the banks at the central positions of the global banking network. To further address this possibility, we explore whether observed loan spreads are significantly correlated with the centrality measures, and whether these links changed during the crisis.

These results are reported in Table 11, where we run a series of regressions where the LHS variable is the natural logarithm of the syndicated loan's all-in-drawn spread. The explanatory variables that are of main interest are the average values of four centrality measures of lead arrangers of the loan facility. The results of each centrality measure are reported in columns (1) through (4). In these regressions, we control for a variety of loan-specific and deal-specific characteristics, as well as borrower characteristics. We employ fixed effects at the year, industry and country levels. The standard errors are also clustered by country. Looking at columns (1) through (4), we see that loan spreads are negatively correlated with each of the four centrality measures, which is consistent with the argument that more central banks have greater information flows that enable them to price loans at lower rate. Next, we re-run these regressions including an interactive term related to the crisis. These results are reported in columns (5) through (8). The results indicate that the links between centrality and loan spreads disappear during the crisis. To the extent this finding suggests that the transformative effects of the crisis eliminated the central bank's information advantages, this may help explain why the crisis eliminated the association between centrality and the propensity to lead or co-lead syndicated loans.

[Insert Table 11 here]

7 Conclusion

This study highlights three important points. To the best of our knowledge, our paper is the first to provide a detailed analysis of the director social network that exists within the global banking system. Our results suggest that network connections across banks are common, and have become increasingly prevalent over time. Second, we show that banks that share connections are more likely to partner together and operate in a similar fashion. More specifically, banks that are connected with one another are more likely to partner together in the syndicated loan market, and banks that play a more central role in the social network are more likely to play a leading role in the syndicated loan originations. Moreover, we find that the links between network connections and bank activity were significantly altered during the recent financial crisis.

In some respects, these results may suggest that network connections play a valuable role in that they lead to enhanced trust which leads to greater information flows and expanded business opportunities. At the same time, these connections may cause banks to operate more similarly. With this concern in mind, the final part of our study provides evidence that network connections may indeed contribute to systemic risk.

In this regard, our findings dovetail nicely with the recent work of Cai et al. (2012) who show that the level of systemic risk is related to the extent to which banks share common business connections. In some respects, our analysis of the social network provides a foundation for a better understanding of these common business conditions. More broadly, our study contributes to the growing literature illustrating the fundamental importance of social networks.

On balance, we think our results provide a challenge to policymakers who are charged with controlling the systemic risk of the global banking system. In one respect, our findings suggest that policymakers may want to have a better understanding of both the common connections and common actions made by key players in the global system. At the same time, they may want to focus specific attention on those banks that play a particularly central role within the social network, since these institutions are shown to make the greatest contribution to overall systemic risk. The challenge, however, is that unlike other common regulatory metrics, managing and controlling social connections seems to be an inherently problematic exercise.

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Tables and Figures

Table 1: Summary statistics of sample banks and syndicate packages.
The data period is from 2000 to 2010. In panel A, we summarize the fundamental and risk characteristics of our sample banks. Our sample banks are from 16 countries, and they are the 99 largest banks in the Boardex database by total assets in the year 2003. Leverage is the ratio of the book value of total assets to the book value of total equity. Market-to-book ratio is the ratio of market value to book value of equity. *Roa* is the return on assets. Total capital ratio is the ratio of the sum of tier-1 and tier-2 capital to total assets. Interbank loans is the ratio of interbank lending to total assets, and interbank deposits is the ratio of interbank borrowing to total assets. Total equity return volatility, *sigma*, is the annualized daily standard deviation of equity returns over a 250 day window. *Beta* is the beta coefficient from a daily CAPM regression using STOXX Global 1800 Banks index as a global banking sector index over a 250-day moving window. $\Delta CoVaR$ is a proxy for systemic risk as defined by Adrian and Brunnermeier (2011). In panel B, we summarize the characteristics of the top 300 largest global syndicate packages in each year from DealScan database. $Termloan$, *secured*, *senior*, and $financial\ borrower$ are indicators for a term loan, a secured facility, a senior facility, and a financial borrower. *Opaque* is a dummy variable for a private borrower or a public borrower without any agency rating.

Panel A: Summary statistics of the 99 banks in our sample

Variable	Mean	Std. Dev.	N
Total assets in bil.USD (TA)	437.298	541.511	888
Leverage	21.149	13.058	888
Market-to-book ratio (*mtb*)	1.993	1.507	870
Return on assets in % (*roa*)	0.775	0.947	888
Total capital ratio in % (*capital ratio*)	12.531	2.376	728
Interbank loans	0.084	0.076	833
Interbank deposits	0.132	0.087	526
Total equity return volatility (*sigma*)	0.377	0.261	884
Global banking sector CAPM beta (*beta*)	0.976	0.408	887
$CoVaR$	-9.998	5.511	893
$\Delta CoVaR$	-2.886	2.738	893

Panel B: Summary statistics of the 300 largest global syndicate packages in each year

Variable	Mean	Std. Dev.	N	Sum
	Package-level summary			
Package amount in bil.USD	4.303	4.746	3,300	1.4e+04
Number of facilities	2.128	1.661	3,300	7,022
	Facility-level summary			
Facility amount in bil. USD	2.050	2.830	6,939	1.4e+04
U.S. facility amount in bil. USD	2.003	2.365	2,663	5,335.178
Non-U.S. facility amount in bil. USD	2.079	3.084	4,276	8,889.572
Number of lenders	9.892	9.219	6,956	
Number of leads	4.344	4.782	6,956	
Ln(All-in-drawn spread (bps))	4.707	1.048	5,351	
Maturity (months)	56.518	47.747	6,617	
Fraction of foreign banks	0.595	0.283	6,956	
Term loan	0.354	0.478	6,956	
Secured	0.327	0.469	6,956	
Senior	0.993	0.085	6,795	
Financial borrower	0.143	0.350	6,956	
Opaque	0.330	0.470	6,956	

Table 2: Summary statistics of pairwise connections.
Sni is the most comprehensive measure of pairwise connections that counts the sum of the all social connections between two banks. The measure considers any type of the social activities that include the activities through common educational institutions, or past or present membership on a corporate board, government institution, medical institution, or charity. We scale the sum of all these social connections by the average board size of the two banks (scaled). This scaled *sni* is mainly used in our regression analyses. On the other hand, *edu* takes into accounts exclusively the educational connections, whereas *professional* accounts for all other types of the social connections except the educational ties. We also scale these two additional pairwise connection measures by the average board size of the two banks. The unscaled versions of these three pairwise connections (unscaled) take a binary value, either zero or one, depending on whether there is at least one connection between the board members of two banks. Thus, these unscaled connection measures do not take into account the strength of the connections between the two banks.

Panel A: Pairwise connection measures over time

	Scaled (by the average board size)			Unscaled (binary)			
Year	sni	edu	professional	sni	edu	professional	N
			Mean only				
2000	0.017	0.006	0.010	0.220	0.112	0.145	2,850
2001	0.018	0.007	0.012	0.235	0.118	0.159	3,486
2002	0.020	0.006	0.013	0.237	0.107	0.168	3,828
2003	0.018	0.006	0.012	0.212	0.092	0.150	4,753
2004	0.019	0.006	0.013	0.224	0.096	0.160	4,560
2005	0.020	0.006	0.014	0.229	0.099	0.165	4,465
2006	0.021	0.006	0.016	0.246	0.094	0.185	4,186
2007	0.022	0.006	0.016	0.250	0.089	0.192	3,741
2008	0.024	0.005	0.019	0.252	0.084	0.201	2,850
2009	0.024	0.005	0.019	0.248	0.077	0.207	2,485
2010	0.025	0.004	0.020	0.249	0.063	0.215	2,346
			Mean (Std. Dev.)				
Total	0.020	0.006	0.015	0.235	0.095	0.174	39,550
	(0.047)	(0.019)	(0.039)	(0.424)	(0.293)	(0.379)	

Panel B: Correlations across different pairwise connection measures (Scaled)

Variable	sni	edu	professional
sni	1.000		
edu	0.575	1.000	
professional	0.920	0.208	1.000

Table 3: Summary statistics of centrality measures.
Betweenness centrality is the number of shortest paths between all bank pairs that a bank lies on. *Eigenvector* centrality gives large values to those banks that have many links, links that are important or both. *Closeness* centrality is defined as the inverse value of the average distance between a bank and all other banks in the networks where distance is defined as the shortest path. *Degree* centrality denotes the number of first-degree links that a bank has in the network. All measures are calculated based on the social connections between banks according to *sni* (unscaled). Specializations are as reported by Bankscope. Sample period is 2000-2010.

Panel A: Centrality and bank specialization

Specialization	betweenness	eigenvector	closeness	degree	N
	Mean (Std. Dev.)				
Bank holding companies	0.012	0.105	0.550	0.261	550
	(0.012)	(0.055)	(0.068)	(0.013)	
Commercial banks	0.010	0.073	0.523	0.201	278
	(0.013)	(0.045)	(0.060)	(0.118)	
Investment banks	0.014	0.136	0.586	0.323	28
	(0.007)	(0.024)	(0.028)	(0.060)	
Savings banks	0.0010	0.022	0.438	0.075	11
	(0.001)	(0.014)	(0.047)	(0.032)	
Real estate, mortgage banks	0.007	0.066	0.510	0.181	27
	(0.008)	(0.052)	(0.061)	(0.117)	
Government credit institutions	0.020	0.173	0.624	0.419	9
	(0.012)	(0.026)	(0.027)	(0.055)	
Total	0.011	0.095	0.541	0.241	903
	(0.012)	(0.055)	(0.067)	(0.132)	

Panel B: Correlations across different centrality measures

Variable	betweenness	eigenvector	degree	closeness
betweenness	1.000			
eigenvector	0.770	1.000		
degree	0.792	0.958	1.000	
closeness	0.830	0.981	0.975	1.000

Table 4: Pairwise connections and global syndicate partnership.
We run a linear probability model with the dependent variable, $pair_{i,j,k,t}$, which takes a value of one if bank-i, a lead (or, co-lead) arranger in facility-k, invites bank-j as another lead (or, co-lead) arranger of this facility-k in year-t. The main explanatory variable is $sni_{i,j,t-1}$, the one-year lagged value of the pairwise connectedness between two banks, i and j, through any type of social connections. $Cum.lending_{i,b,t-1}$ (or $cum.lending_{j,b,t-1}$) denotes the total number of facilities that bank-i (or j) has lent to the borrower-b of facility-k prior to the year of syndication of facility-k divided by the total number of facilities that the bank has lent to any borrower in our sample prior to the year of the syndication. $Cum.lending_{i,t-1}$ (or $cum.lending_{j,t-1}$) denotes the cumulative number of syndicated loan facilities that a bank-i (or j) has lent to any borrower in our sample prior to the year of the syndication of facility-k. The reported point estimates of $Cum.lending_{i,t-1}$ (or $cum.lending_{j,t-1}$) are the inflated values of original point estimates of the variables by 1,000. *Opaque* is a dummy for a private firm or a firm without rating. *Country* is the same country dummy, and the *type* is the same specialization dummy. Each bank's specialization is defined based on the specialization definition in the Bankscope. *Size*(.) and *leverage*(.) respectively denote similar size and leverage dummies for each pair of banks based on the one-year lagged values of the two variables. Standard errors are clustered at each bank pair level, and they are reported in the parentheses. ***,**, and * denotes the statistical significance at the 1%, 5%, and 10% level, respectively.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$sni_{i,j,t-1}$	0.510***		0.133***	0.128***	0.123***	0.125***	
	(0.051)		(0.046)	(0.045)	(0.044)	(0.026)	
$sni_{i,j,t-1}$(unscaled)		0.061***					
		(0.005)					
$sni_{i,j,t-1}$(old)							0.144***
							(0.044)
$cum.lending_{i,b,t-1}$	0.074**	0.100***	0.244***	0.127***	0.330***	-0.022	-0.024
	(0.036)	(0.036)	(0.033)	(0.033)	(0.036)	(0.029)	(0.029)
$cum.lending_{j,b,t-1}$	3.821***	3.836***	3.668***	3.452***	3.650***	3.626***	3.626***
	(0.283)	(0.284)	(0.268)	(0.254)	(0.260)	(0.264)	(0.264)
$cum.lending_{i,t-1}$	-0.018***	-0.017***	-0.017***	-0.016***	-0.001	-0.005***	-0.005***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
$cum.lending_{j,t-1}$	0.488***	0.489***	0.429***	0.418***	0.423***	0.314***	0.314***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
opaque	-0.005***	-0.005***	-0.006***			-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)			(0.001)	(0.001)
country	-0.034***	-0.027***	0.015*	0.027***	0.032***		
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)		
type	0.011**	0.010**	0.017***	0.017***	0.017***		
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)		
size(hh)			0.123***	0.141***	0.155***	0.109***	0.109***
			(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
size(hm)			0.011***	0.026***	0.038***	0.039***	0.039***
			(0.003)	(0.003)	(0.004)	(0.005)	(0.006)
size(hl)			-0.035***	-0.022***	-0.010***	-0.000	-0.000
			(0.003)	(0.003)	(0.003)	(0.006)	(0.006)
size(ml)			-0.031***	-0.034***	-0.036***	-0.024***	-0.024***
			(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
size(ll)			-0.041***	-0.048***	-0.060***	-0.051***	-0.051***
			(0.005)	(0.005)	(0.005)	(0.008)	(0.008)
leverage(hh)			-0.048***	-0.043***	-0.041***	-0.031***	-0.031***
			(0.006)	(0.006)	(0.006)	(0.004)	(0.004)
leverage(hm)			-0.032***	-0.030***	-0.029***	-0.019***	-0.019***
			(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
leverage(hl)			-0.035***	-0.033***	-0.033***	-0.017***	-0.017***
			(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
leverage(ml)			-0.001	-0.001	-0.002	0.000	-0.000
			(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
leverage(ll)			-0.009	-0.011*	-0.014**	-0.003	-0.003
			(0.007)	(0.006)	(0.006)	(0.004)	(0.004)
Fixed Effect (FE)	Year	Year	Year	Year, Borrower	Facility	Year, Pair	Year, Pair
Adj. R^2	0.121	0.121	0.168	0.195	0.210	0.280	0.280
N	3,228,076	3,228,076	3,228,076	3,228,076	3,228,076	3,228,076	3,228,076

Table 5: Centrality and lead/co-lead arranging global syndicates.
We run a linear probability model with various fixed effects and additional bank level controls. The dependent variable is $arranger_{i,k,t}$, which takes a value of one if bank-i takes a senior role such as a lead or a co-lead for facility-k in year-t, and zero otherwise. We use the one-year lagged values of the following measures of network centrality as our main explanatory variables - *betweenness*, *eigenvector*, *closeness*, and *degree*. $betweenness_{i,t-1}(old)$ is the betweenness centrality that is constructed based on the pairwise connectedness of banks whose formation date precedes the date of loan syndication by more than five years. *Mtb* is the ratio of market value to book value of equity, and *leverage* is the ratio of the book value of total assets to the book value of total equity. *TA* denotes the book value of total assets in trillion USD. Standard errors are clustered at the year level in all columns except column (6), where we cluster the standard errors at the bank level. The standard errors are reported in the parentheses, and ***,**, and * denotes the statistical significance at the 1%, 5%, and 10% level, respectively.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{betweenness}_{i,t-1}$	1.827***				1.827***	1.827***	
	(0.424)				(0.426)	(0.677)	
$\text{eigenvector}_{i,t-1}$		0.420***					
		(0.087)					
$\text{closeness}_{i,t-1}$			0.290***				
			(0.069)				
$\text{degree}_{i,t-1}$				0.166***			
				(0.035)			
$\text{betweenness}_{i,t-1}\text{(old)}$							0.650**
							(0.208)
$\text{mtb}_{i,t-1}$	-0.004***	-0.003***	-0.003**	-0.003***	-0.004***	-0.004	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)
$\text{leverage}_{i,t-1}$	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\text{TA}_{i,t-1}$	0.146***	0.144***	0.148***	0.144***	0.146***	0.146***	0.157***
	(0.020)	(0.019)	(0.020)	(0.019)	(0.020)	(0.027)	(0.019)
Year FE	Yes	Yes	Yes	Yes		Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes		Yes	Yes
Facility FE					Yes		
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specialization FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Year	Year	Year	Year	Year	Bank	Year
Adj. R^2	0.171	0.171	0.170	0.171	0.177	0.171	0.170
N	492,278	492,278	492,278	492,278	492,278	492,278	492,278

Table 6: Centrality and interbank loan and deposit ratios.
The dependent variables are interbank loans (columns 1 to 5) and interbank deposits ratios (columns 6 to 10) to total assets. We use the one-year lagged values of the following measures of network centrality as our main explanatory variables - *betweenness*, *eigenvector*, *closeness*, and *degree*. In columns (5) and (10), we use the one-year lagged *betweenness* based on only the predetermined network connections that were formed at least five years prior to the beginning of the year-t when the dependent variables are measured. *Mtb* is the ratio of market value to book value of equity, *leverage* the ratio of the book value of total assets to the book value of total equity, and *TA* the book value of total assets in trillion USD. Year, country, and specialization fixed effects are controlled in all columns, and the standard errors are clustered at the bank level. The standard errors are reported in the parentheses. ***, **, and * denote the statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variable			interbank loans$_{i,t}$					interbank deposits$_{i,t}$		
betweenness$_{i,t-1}$	2.423***					-0.313				
	(0.901)					(0.578)				
eigenvector$_{i,t-1}$		0.725***					-0.072			
		(0.239)					(0.204)			
closeness$_{i,t-1}$			0.529***					-0.092		
			(0.176)					(0.159)		
degree$_{i,t-1}$				0.289***					-0.033	
				(0.096)					(0.076)	
betweenness$_{i,t-1}$(old)					1.009**					-0.421
					(0.414)					(0.285)
mtb$_{i,t-1}$	0.005	0.006	0.007	0.006	0.003	-0.010***	-0.010***	-0.010***	-0.010***	-0.009***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
capital ratio$_{i,t-1}$	0.010**	0.010**	0.009**	0.010**	0.009**	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
TA$_{i,t-1}$	-0.021	-0.030	-0.026	-0.032	-0.017	-0.019	-0.019	-0.017	-0.019	-0.015
	(0.020)	(0.021)	(0.021)	(0.022)	(0.021)	(0.016)	(0.015)	(0.015)	(0.016)	(0.015)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specialization FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Adj. R^2	0.245	0.277	0.268	0.277	0.241	0.524	0.523	0.524	0.523	0.531
N	596	596	596	596	596	385	385	385	385	385

Table 7: Centrality and systemic risk, $\Delta CoVaR$.
This table shows the results of the regression of the systemic risk measure, $\Delta CoVaR$ (Adrian and Brunnermeier, 2011), on the lagged values of different centrality measures - *betweenness*, *eigenvector*, *closeness*, and *degree*. *Mtb* is the market-to-book ratio, TA, TA^2, and TA^3 denote the book value of a bank's total assets, and its square and cube values. *Leverage* is the ratio of the book value of total assets to the book value of total equity. *Beta* is the beta coefficient from a daily CAPM regression using STOXX Global 1800 Banks index as a global banking sector index over a 250-day moving window. The sample period is 2000 till 2010. Year, country, and specialization fixed effects are controlled in all columns, and the standard errors are clustered at the bank level. The standard errors are reported in the parentheses. ***,**, and * denotes the statistical significance at the 1%, 5%, and 10% level, respectively.

Variable	(1)	(2)	(3)	(4)
betweenness$_{i,t-1}$	-20.142*			
	(11.276)			
eigenvector$_{i,t-1}$		-7.831**		
		(3.402)		
closeness$_{i,t-1}$			-6.221**	
			(2.689)	
degree$_{i,t-1}$				-3.404**
				(1.380)
mtb$_{i,t-1}$	-0.073	-0.070	-0.076	-0.070
	(0.114)	(0.106)	(0.105)	(0.105)
TA$_{i,t-1}$	0.974	1.756	1.722	1.890*
	(1.198)	(1.125)	(1.148)	(1.119)
TA$^2_{i,t-1}$	-0.247	-0.734	-0.703	-0.769
	(1.022)	(0.966)	(0.972)	(0.963)
TA$^3_{i,t-1}$	0.059	0.149	0.140	0.150
	(0.207)	(0.198)	(0.198)	(0.197)
leverage$_{i,t-1}$	-0.012	-0.010	-0.011	-0.011
	(0.015)	(0.015)	(0.015)	(0.015)
beta$_{i,t-1}$	-0.373	-0.322	-0.315	-0.316
	(0.265)	(0.266)	(0.261)	(0.263)
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Specialization FE	Yes	Yes	Yes	Yes
Cluster	Bank	Bank	Bank	Bank
Adj. R^2	0.438	0.443	0.444	0.445
N	766	766	766	766

Table 8: Effects of pairwise connections before and after the 2007 financial crisis.
This table reports the results of the crisis period interaction effects with pairwise connections. *Crisis* is a dummy variable for the post-2007 period. In column (1), we repeat the Table 4 analysis using the interaction term between $sni_{i,t-1}$ and the *crisis* period dummy as an additional explanatory variable. In the remaining columns of this table, we compare the syndicate partnership decisions among socially connected banks from the same country to those among the connected banks from different countries during the crisis period. Standard errors are reported in the parentheses, and ***, **, and * denotes the significance at the 1% , 5%, and 10% level, respectively.

Variable	(1)	(2)	(3)	(4)	(5)
$\text{sni}_{i,t-1}$	0.515***	0.321***	0.772***	0.310***	0.792***
	(0.057)	(0.084)	(0.074)	(0.079)	(0.074)
$\text{sni}_{i,t-1}$ X crisis	-0.014	0.038	-0.193***	-0.019	-0.188***
	(0.042)	(0.067)	(0.064)	(0.067)	(0.064)
$\text{cum.lending}_{i,b,t-1}$	0.074**	1.300***	0.048	1.035***	-0.091***
	(0.036)	(0.305)	(0.035)	(0.280)	(0.035)
$\text{cum.lending}_{j,b,t-1}$	3.821***	3.464***	3.835***	3.240***	3.623***
	(0.283)	(1.035)	(0.291)	(0.973)	(0.277)
$\text{cum.lending}_{i,t-1}$	-0.018***	-0.017	-0.017***	-0.012	-0.014***
	(0.003)	(0.011)	(0.003)	(0.010)	(0.003)
$\text{cum.lending}_{j,t-1}$	0.488***	0.483***	0.486***	0.476***	0.479***
	(0.009)	(0.026)	(0.010)	(0.026)	(0.009)
opaque	-0.005***	-0.004**	-0.005***		
	(0.001)	(0.002)	(0.001)		
country	-0.034***				
	(0.008)				
type	0.011**	0.041***	0.005	0.043***	0.005
	(0.005)	(0.013)	(0.005)	(0.012)	(0.005)
FE	Year	Year	Year	Year, Borrower	Year, Borrower
Cluster	Pair	Pair	Pair	Pair	Pair
Sample	All	Same country	Different countries	Same country	Different countries
Adj. R^2	0.121	0.089	0.130	0.121	0.158
N	3,228,076	587,547	2,640,529	587,547	2,640,529

Table 9: Centrality effects on lead/co-lead arranging global syndicates before and after the 2007 financial crisis. This table reports the results of the crisis period interaction effects with network centralities on lead/co-lead arranging global syndicates. *Crisis* is a dummy variable for the post-2007 period. We repeat the Table 5 analysis using the interaction term between each of our four lagged centrality measures and the *crisis* period dummy. Standard errors are reported in the parentheses, and ***, **, and * denote the statistical significance at the 1%, 5%, and 10% level, respectively.

Variable	(1)	(2)	(3)	(4)
$\text{betweenness}_{i,t-1}$	2.888***			
	(0.525)			
$\text{betweenness}_{i,t-1}$ X crisis	-3.921***			
	(0.783)			
$\text{eigenvector}_{i,t-1}$		0.590***		
		(0.090)		
$\text{eigenvector}_{i,t-1}$ X crisis		-0.620***		
		(0.130)		
$\text{closeness}_{i,t-1}$			0.452***	
			(0.081)	
$\text{closeness}_{i,t-1}$ X crisis			-0.535***	
			(0.104)	
$\text{degree}_{i,t-1}$				0.249***
				(0.042)
$\text{degree}_{i,t-1}$ X crisis				-0.281***
				(0.055)
$\text{mtb}_{i,t-1}$	-0.002	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)
$\text{leverage}_{i,t-1}$	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$\text{TA}_{i,t-1}$	0.166***	0.155***	0.160***	0.157***
	(0.022)	(0.020)	(0.021)	(0.020)
FE	Year, Borrower, Country, Specialization			
Cluster	Year			
Adj. R^2	0.178	0.175	0.175	0.176
N	492,278	492,278	492,278	492,278

Table 10: Network central banks before and after the crisis: Difference in differences.
In this table, we analyze the fundamental characteristics of the network central banks before and after the crisis. These variables include the average values of the natural logarithm of total assets ($ln(TA)$), return on assets (*roa*), leverage, equity return, total annualized equity return volatility (*sigma*), and two CAPM betas (one for *domestic* stock market index and the other for *global* banking sector index). We decompose our sample banks into the central (High) and the non-central (Low) banks based on *betweenness* centrality and compare each group's fundamental characteristics before and after the crisis. More specifically, we use the median value of *betweenness* in each sub-period as the cutoff to define the two groups of banks, before and after the crisis. DiD in column (9) of this table reports the difference in differences of the fundamental characteristics between the two groups of banks before and after the 2007 financial crisis. The p-value of DiD is reported in column (10) of this table. ***,**, and * denotes the statistical significance at the 1%, 5%, and 10% level, respectively.

Variable	(1)		(2)		(3)	(4)	(5)		(6)		(7)	(8)	(9)	(10)
	pre-crisis (2000-2006)						post-crisis (2007-2010)						diff-in-diff (DiD)	
	High	N	Low	N	Diff	p-val	High	N	Low	N	Diff	p-val	DiD	p-val
betweenness	0.019	301	0.002	310	0.017***	0.00	0.021	145	0.002	139	0.019***	0.00	0.002*	0.086
ln(TA)	19.570	300	18.344	303	1.226***	0.00	20.378	142	18.881	143	1.498***	0.00	0.271*	0.086
roa	0.970	300	1.063	303	-0.093*	0.081	0.264	142	0.265	143	-0.002	0.990	0.091	0.562
leverage	20.786	300	20.792	303	-0.006	0.995	23.493	142	20.457	143	3.036	0.368	3.042	0.390
equity return	0.000	296	0.000	297	0.000	0.729	0.000	145	0.000	139	0.000*	0.076	0.000*	0.071
sigma	0.010	296	0.010	297	0.000	0.180	0.021	145	0.021	139	0.000	0.832	0.000	0.580
beta (*domestic*)	0.899	296	0.639	297	0.260***	0.000	1.297	145	1.142	139	0.156**	0.017	-0.105	0.143
beta (*global*)	0.982	296	0.746	297	0.236***	0.000	1.184	145	1.043	139	0.141***	0.001	-0.095*	0.043

Table 11: Centrality effects on facility pricing before and after the 2007 financial crisis.
This table shows how the average centrality of lead arrangers of a given facility affects the facility pricing. We measure the price of a facility using the all-in-drawn spread of the facility. A natural logarithm of the all-in-drawn spread is used as a dependent variable in this regression. Standard errors are reported in the parentheses, and ***, **, and * denote the statistical significance at the 1%, 5%, and 10% level, respectively.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{betweenness}_{i,t-1}$	-7.903***				-9.965***			
	(1.400)				(1.312)			
$\text{eigenvector}_{i,t-1}$		-1.711**				-2.793***		
		(0.732)				(0.929)		
$\text{closeness}_{i,t-1}$			-1.393**				-2.740***	
			(0.650)				(0.920)	
$\text{degree}_{i,t-1}$				-0.779***				-1.388***
				(0.289)				(0.373)
$\text{betweenness}_{i,t-1}$ X crisis					7.447*			
					(4.070)			
$\text{eigenvector}_{i,t-1}$ X crisis						2.783**		
						(1.113)		
$\text{closeness}_{i,t-1}$ X crisis							2.607**	
							(1.003)	
$\text{degree}_{i,t-1}$ X crisis								1.311***
								(0.435)
ln(# of lenders)	-0.121***	-0.123***	-0.123***	-0.122***	-0.119***	-0.119***	-0.119***	-0.118***
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.029)	(0.029)	(0.028)
fraction of foreign banks	-0.276***	-0.264***	-0.268***	-0.266***	-0.282***	-0.272***	-0.272***	-0.275***
	(0.058)	(0.064)	(0.063)	(0.064)	(0.059)	(0.064)	(0.065)	(0.066)
term loan	0.385***	0.384***	0.385***	0.384***	0.386***	0.384***	0.384***	0.384***
	(0.030)	(0.029)	(0.029)	(0.029)	(0.030)	(0.029)	(0.029)	(0.029)
secured	0.770***	0.778***	0.777***	0.775***	0.774***	0.781***	0.780***	0.779***
	(0.094)	(0.091)	(0.093)	(0.092)	(0.095)	(0.090)	(0.091)	(0.090)
senior	-1.334***	-1.337***	-1.336***	-1.335***	-1.337***	-1.337***	-1.338***	-1.336***
	(0.054)	(0.052)	(0.052)	(0.053)	(0.056)	(0.053)	(0.053)	(0.054)
opaque	0.257***	0.254***	0.256***	0.254***	0.256***	0.251***	0.251***	0.249***
	(0.060)	(0.063)	(0.062)	(0.062)	(0.060)	(0.063)	(0.063)	(0.062)
financial borrower	0.211**	0.196*	0.194*	0.192*	0.214**	0.197*	0.200*	0.196*
	(0.098)	(0.102)	(0.102)	(0.102)	(0.102)	(0.106)	(0.107)	(0.107)
FE	Year, Industry, Country							
Cluster	Country							
Adj. R^2	0.588	0.586	0.586	0.587	0.589	0.588	0.587	0.588
N	4,693	4,693	4,693	4,693	4,693	4,693	4,693	4,693

Figure 1: The global banking network in the year 2006. Thicker lines indicate more connections between two financial firms.

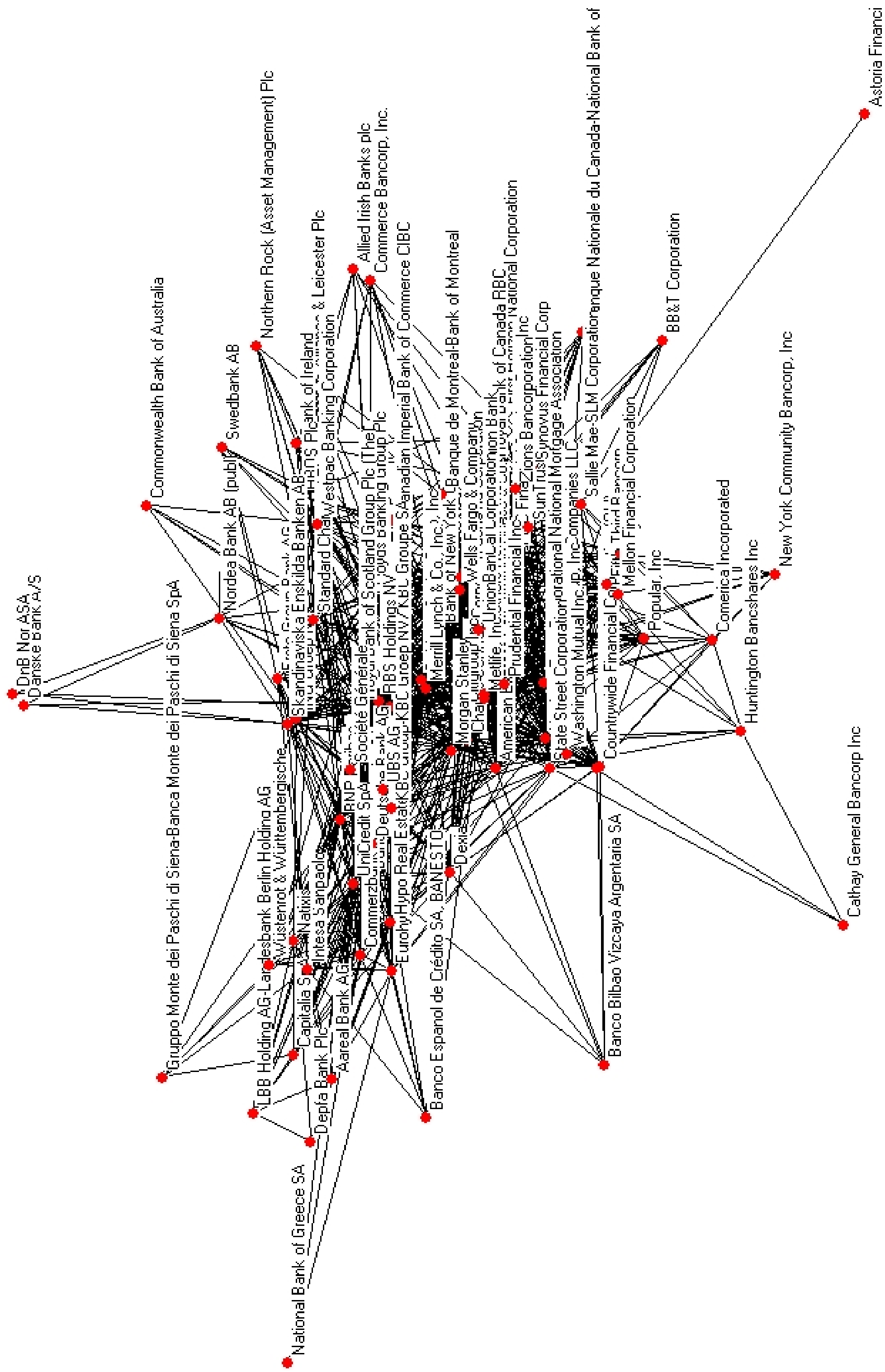


Figure 2: The U.S. only banking network in the year 2006. Thicker lines indicate more connections between two financial firms.

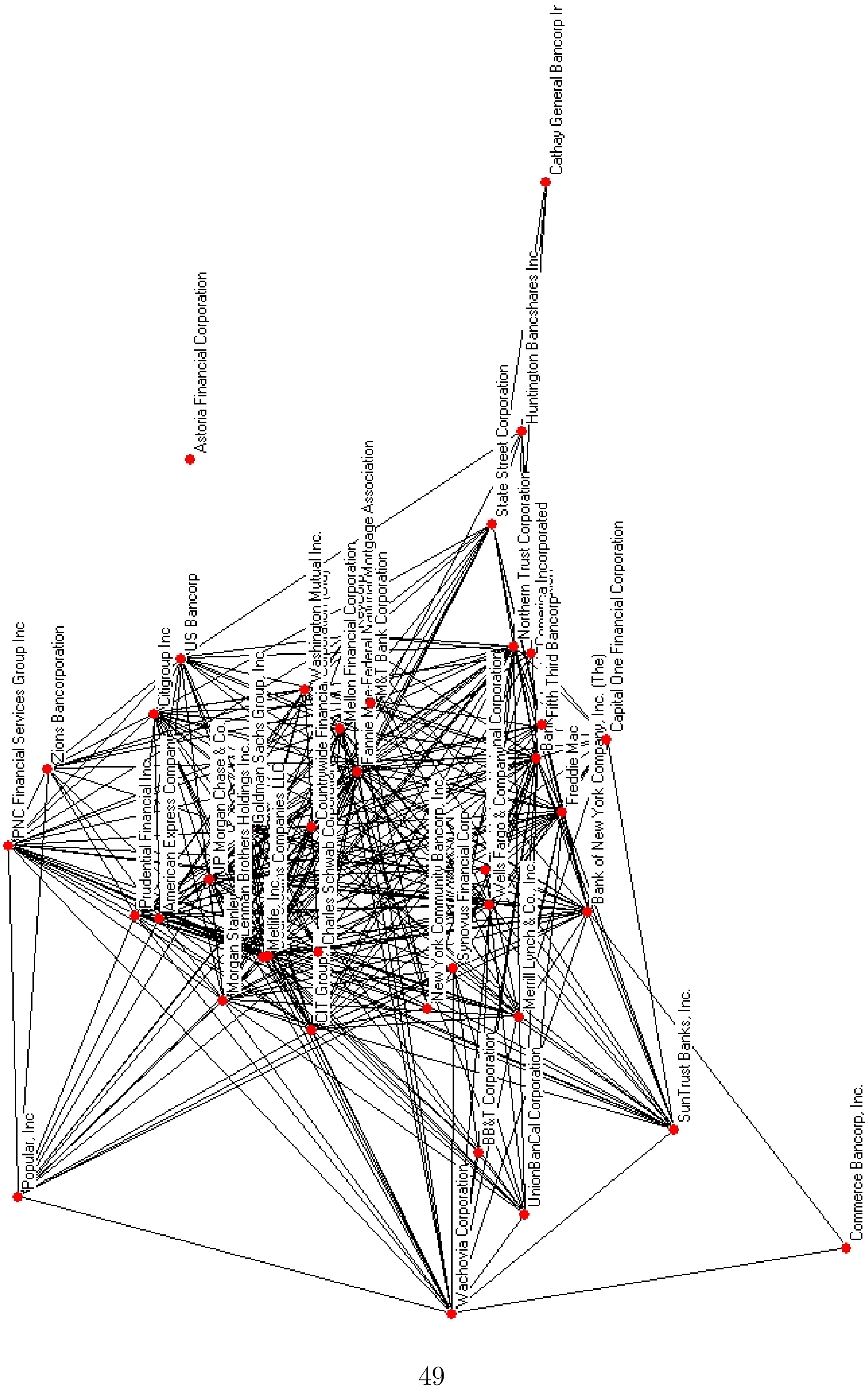


Figure 3: The non-U.S. only banking network in the year 2006. Thicker lines indicate more connections between two financial firms.

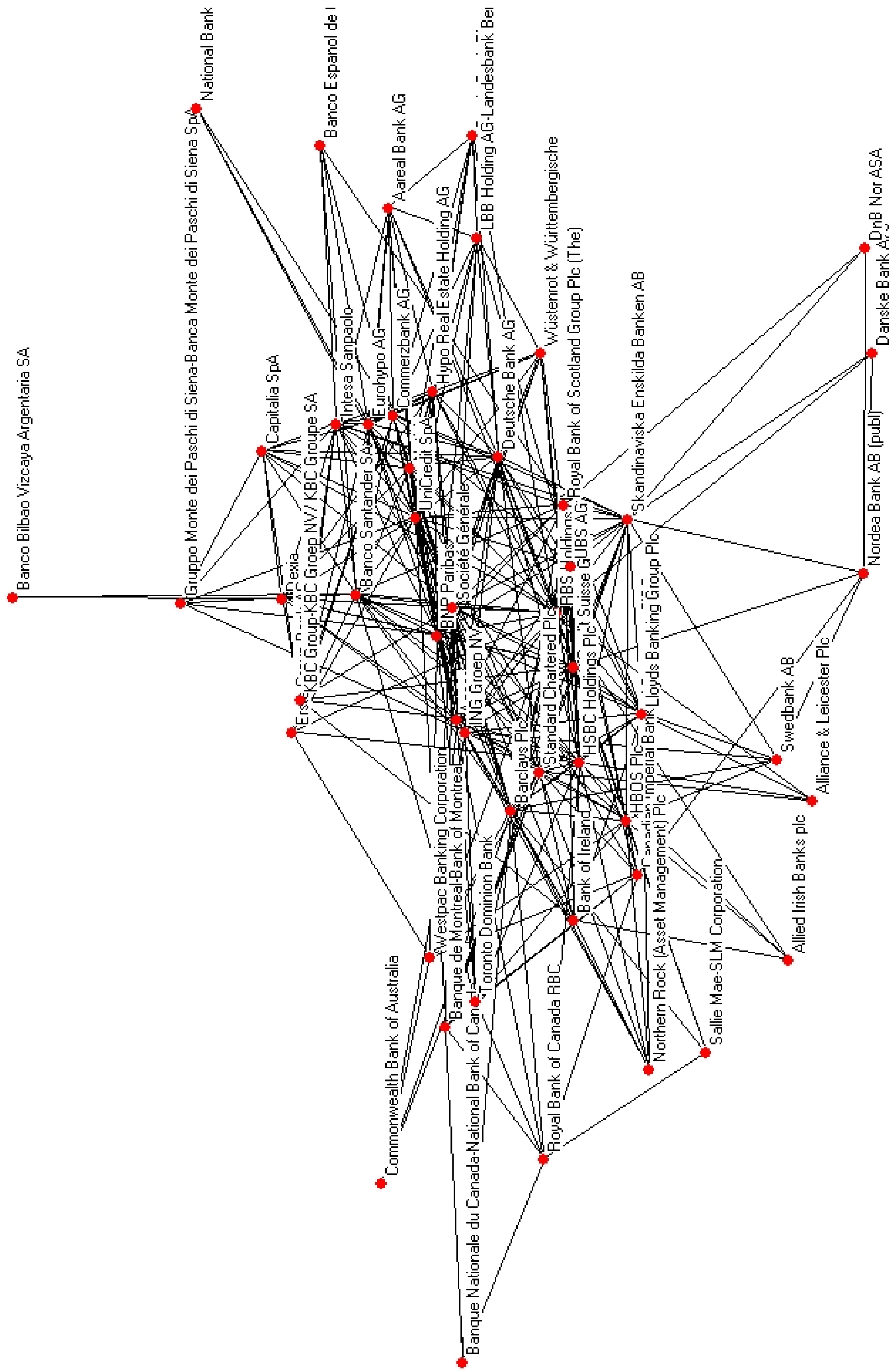
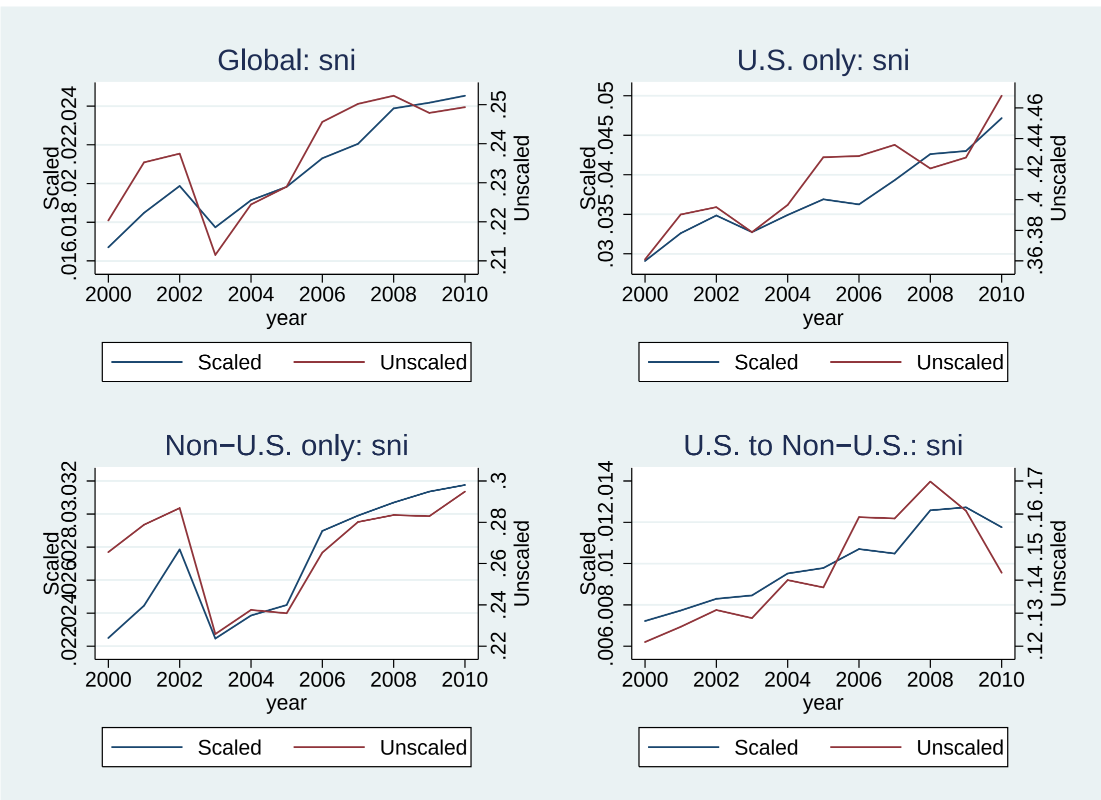


Figure 4: The average pairwise connections: *Sni*.
Scaled *sni* is the sum of all types of social connections between two banks scaled by their average board size. Unscaled *sni* is a binary variable that takes a value of one if two banks have at least one social connection between them, regardless of the type of connection. Global panel shows the average values of both versions of *sni* each year for all global bank pairs in our sample. U.S. only panel shows the average values of both versions of *sni*, exclusively for the U.S. banks in the local U.S. only network. Non-U.S. only panel shows the average values, exclusively for the non-U.S. bank to the non-U.S. bank pairs in the non-U.S. only network. Lastly, U.S. to Non-U.S. panel shows the average values exclusively for the cross-regional network such as the U.S. bank to the Non-U.S. bank pairs. Sample period is from 2000 to 2010.



Appendix

A Sample banks

Name	Start	End
Aareal Bank AG	2002	2010
Ageas	2000	2010
Alliance & Leicester Plc	2000	2007
Allied Irish Banks plc	2000	2010
Almanij	2000	2003
AmSouth Bancorporation	2000	2005
American Express Company	2000	2009
Astoria Financial Corporation	2000	2010
BB&T Corporation	2000	2010
BNP Paribas	2000	2010
Banco Bilbao Vizcaya Argentaria SA	2000	2010
Banco Espanol de Cr.dito SA, BANESTO	2000	2010
Banco Santander SA	2000	2010
Bank of America Corporation	2000	2010
Bank of Ireland	2000	2010
Bank of New York Company, Inc.	2000	2006
National Bank of Canada	2003	2010
Banque de Montreal-Bank of Montreal	2003	2010
Barclays Plc	2000	2010
Bear Stearns Companies LLC	2000	2007
CIT Group, Inc	2003	2010
Canadian Imperial Bank of Commerce CIBC	2003	2010
Capital One Financial Corporation	2000	2010
Capitalia SpA	2002	2006
Cathay General Bancorp Inc	2003	2010
Charles Schwab Corporation	2000	2010
Citigroup Inc	2000	2010
Comerica Incorporated	2000	2010
Commerce Bancorp, Inc.	2000	2006
Commerzbank AG	2000	2010
Commonwealth Bank of Australia	2003	2010
Countrywide Financial Corporation	2000	2007
Credit Suisse Group AG	2000	2010
Danske Bank A/S	2001	2010
Depfa Bank Plc	2002	2006

Deutsche Bank AG	2000	2010
Dexia	2000	2010
DnB Nor ASA	2003	2010
Erste Group Bank AG	2000	2010
Eurohypo AG	2002	2007
Fannie Mae-Federal National Mortgage Association	2000	2008
Fifth Third Bancorp	2000	2010
First Horizon National Corporation	2000	2010
FleetBoston Financial Corporation	2000	2002
Freddie Mac	2001	2008
Golden West Financial Corp	2000	2005
Goldman Sachs Group, Inc	2000	2010
Gruppo Monte dei Paschi di Siena	2000	2010
HBOS Plc	2001	2007
HSBC Holdings Plc	2000	2010
Huntington Bancshares Inc	2000	2010
Hypo Real Estate Holding AG	2003	2008
ING Groep NV	2000	2010
Intesa Sanpaolo	2001	2010
JP Morgan Chase & Co.	2001	2010
KBC Group-KBC Groep NV/ KBC Groupe SA	2000	2010
KeyCorp	2000	2010
LBB Holding AG-Landesbank Berlin Holding AG	2000	2010
Lehman Brothers Holdings Inc.	2000	2007
Lloyds Banking Group Plc	2000	2010
M&T Bank Corporation	2000	2010
MBNA Corporation	2000	2004
Mellon Financial Corporation	2000	2006
Merrill Lynch & Co., Inc.	2000	2008
Metlife, Inc.	2000	2010
Morgan Stanley	2000	2010
National Bank of Greece SA	2000	2010
Natixis	2000	2010
New York Community Bancorp, Inc	2000	2010
Nordea Bank AB	2000	2010
North Fork Bancorporation, Inc	2000	2005
Northern Rock Plc	2000	2007
Northern Trust Corporation	2000	2010
PNC Financial Services Group Inc	2000	2010
Popular, Inc	2000	2010
Prudential Financial Inc	2001	2010
RBS Holdings NV	2000	2007

Royal Bank of Canada RBC	2003	2010
Royal Bank of Scotland Group Plc	2000	2010
Sallie Mae-SLM Corporation	2000	2009
Skandinaviska Enskilda Banken AB	2000	2010
Societe Generale	2000	2010
Southtrust Corporation	2000	2003
Standard Chartered Plc	2000	2010
State Street Corporation	2000	2010
SunTrust Banks, Inc.	2000	2010
Swedbank AB	2000	2010
Synovus Financial Corp	2000	2010
Toronto Dominion Bank	2003	2010
UBS AG	2000	2010
US Bancorp	2001	2010
UniCredit SpA	2000	2010
UnionBanCal Corporation	2000	2007
Wachovia Corporation	2001	2007
Washington Mutual Inc.	2000	2007
Wells Fargo & Company	2000	2010
Westpac Banking Corporation	2003	2010
Wustenrot & Wurttembergische	2000	2009
Zions Bancorporation	2000	2010

B Appendix Table

Appendix Table 1: Robustness tests to the changing composition of the banks during our sample period. In this table, we test the robustness of our main results to the changing composition of the banks during our sample period. We compute *betweenness* centrality exclusively for the banks that are present throughout the whole 2000-2010 time period. With this fixed set of the banks, we test our three centrality models previously reported in Table 5 (*arranger* in the LHS), 6 (*interbank loans* and *interbank deposits* in the LHS), and 7 ($\Delta CoVaR$ in the LHS). Standard errors are reported in the parentheses, and ***, **, and * denotes the significance at the 1% , 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
	Table 5	Table 6		Table 7
Variable	arranger$_{i,j,t}$	interbank loans$_{i,t}$	interbank deposits$_{i,t}$	$\Delta CoVaR_{i,t}$
betweenness$_{i,t-1}$	0.721***	2.423***	-0.313	-20.142*
	(0.208)	(0.901)	(0.578)	(11.276)
mtb$_{i,t-1}$	-0.002	0.005	-0.010***	-0.073
	(0.003)	(0.006)	(0.002)	(0.114)
leverage$_{i,t-1}$	-0.000			-0.012
	(0.001)			(0.015)
capital ratio$_{i,t-1}$		0.010**	-0.002	
		(0.004)	(0.004)	
TA$_{i,t-1}$	0.135***	-0.021	-0.019	0.974
	(0.024)	(0.020)	(0.016)	(1.198)
$\text{TA}^2_{i,t-1}$				-0.247
				(1.022)
$\text{TA}^3_{i,t-1}$				0.059
				(0.207)
beta$_{i,t-1}$				-0.373
				(0.265)
Year FE	Yes	Yes	Yes	Yes
Borrower FE	Yes			
Country FE	Yes	Yes	Yes	Yes
Specialization FE	Yes	Yes	Yes	Yes
Cluster	Year	Bank	Bank	Bank
Adj. R^2	0.188	0.245	0.524	0.438
N	294,463	596	385	766