Social Networks in the Global Banking Sector *

Joel F. Houston, Jongsub Lee, and Felix Suntheim†

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Abstract

We construct a wide variety of social network measures within the global banking system using the board connections of top global banks from 16 countries in the post-2000 period. Our measures illustrate that social networks among top banks are extensive and have become increasingly important over time. We hypothesize that these connections may facilitate valuable information flows, but they may also foster a "group-think" mentality that could lead to instability in the global banking sector. Indeed, we find evidence supporting both views. Connected banks are more likely to partner together in the global syndicated loan market, which suggests that social connections generate valuable information which translates into 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 that there is also a potential dark side to having a strong social network.

Key words: Top global banks, social networks, pairwise connection, network centrality, loan syndication, equity correlation, systemic risk, financial crisis
JEL classification: G20, G24, G28

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†Correspondence information: Joel F. Houston is the John B. Hall Chair Professor of Finance at the University of Florida, U.S.A. (Email: joel.houston@warrington.ufl.edu, Tel: +1-352-392-7546), and Jongsub Lee is an Assistant Professor of Finance at the University of Florida, U.S.A. (Email: jongsub.lee@warrington.ufl.edu, Tel: +1-352-273-4966). Felix Suntheim is from the Financial Conduct Authority, U.K. (Email: felix.suntheim@fca.org.uk).

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 the extent to which 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 there is both a "bright" side and a "dark" side to these connections. In one respect, 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 more serious 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 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

[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.

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".

Third, we ask whether the structure of social connections has had an influence on the systemic risk of the banking industry. As a starting point, we examine the pairwise equity correlations of the banks in our sample, and we find that these correlations are significantly more positive when the banks share a social connection. We find that this effect particularly holds for the systematic component of the equity correlations. Perhaps even more important, we find throughout the entire time period, that there is a strong link between the measures of centrality and the $\Delta CoVaR$ measure of systemic risk (recently popularized by Adrian and Brunnermeier, 2011). Put together, 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 by-product of the valuable 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 way in which the social network influenced operations within the global banking industry. Stepping back, one could envision two scenarios. One scenario is that networks become increasingly important during the financial crisis, causing banks to rely more 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.

Here our evidence is decidedly mixed. In one respect, we find that banks were even more likely to partner with connected banks in the syndicated loan market during the financial crisis. This finding suggests that banks are more likely to rely on partners with shared connections during difficult times. On the other hand, we find that during the financial crisis, socially central banks played a diminished role (relative to their involvement in the pre-crisis period) in the syndicated loan markets. Moreover, we find that the systematic correlations of equity returns of connected banks significantly declined during the financial crisis, whereas the links between connections and the idiosyncratic component of the equity correlation remained unchanged during the crisis. Most notably, we find that the links between centrality and the $\Delta CoVaR$ measure of systemic risk became even stronger during the financial crisis period.

We consider two possibilities for why the central banks in the social network had a diminished role during the crisis. One explanation is that centralized information flows became less valuable as a result of the crisis. An alternative explanation is that the more central banks in the network (primarily the large investment banks) suffered disproportionately during the crisis and their declining performance limited their ability to participate in syndicate lending. On balance, our evidence provides little support for the second view, leading us to conclude that the crisis transformed the value of playing a central role in the 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.

We use two strategies to address these concerns. First, when estimating the likelihood of two banks forming a business connection, 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. Second, we also re-estimate our pair-wise findings, together with our findings on leading or co-leading roles played by network central banks in loan originations, using alternative network measures that are locally defined. More specifically, we create a network of exclusively US banks, a network of exclusively non-US banks, and a cross regional network. Interestingly, we find that the results on both pair-wise measures and network centralities are strongest within the cross-regional network. These findings strongly suggest that the relevant banking network is globally defined, and once again it gives us further comfort that our main results are not driven by local endogeneity concerns within our network measures.

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 educational ties between board members that were typically generated well in advance of the later transactions. 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.

However, using educational ties still leaves room for another potential channel of reverse causality - the endogenous board structure. Though we measure the board structure strictly prior to each business transaction, one could still argue that banks appoint board members that graduated from the same institutions, anticipating that these educational ties will generate future business opportunities. However, in many respects while the direction of causation might remain uncertain, this potential channel just re-confirms our main argument: pre-existing network connections have an important influence on subsequent business transactions.[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 networks have a significant influence on the level of systemic risk. 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, the network centrality measures employed in our study could be useful to detect these systemically important banks in the global banking system. More indirectly, to the extent that the

[2]It should be also noted that this second potential channel of reverse causality is less likely to be a concern for network centrality because an individual bank's measured network centrality depends on other banks' centralities, and therefore, one bank cannot freely determine its own network position by changing its board composition.

size and distribution of banks influence the structure of the social network in banking, 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; Fracassi, 2012; 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).[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. We also decompose the global network into the U.S., the non-U.S.,

[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 syndicate 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).

and the cross-regional sub-networks. Next, we investigate the effects that our network measures have on loan syndication decisions and demonstrate how the financial crisis transformed the role that social networks played within the syndicated loan market in Section 4. In Section 5, we examine the equity correlation of our sample banks before and after the crisis, and then we present the systemic risk results related to the centrality measures in Section 6. Section 7 discusses some potential explanations for our various results related to the financial crisis, and also provides some robustness tests, including those that are designed to address reverse causality concerns and also the effects of using alternative constructions of our network measures. Section 8 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 North American banks and Compustat World for European and Australian Banks.

Our focus is on the most important financial institutions worldwide over 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 provide the list of these sample banks in Appendix A.

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 left and right tails. The definitions and construction details of each bank's risk characteristics (*sigma, beta,* $CoVaR$, $\Delta CoVaR$) will be discussed later in Section 5 and 6. The average book value of total assets of our sample banks is 437 billion USD, and these banks have high *beta* coefficients (0.976, on average) from the daily industry CAPM regressions using STOXX

Global 1800 Banks index as a global banking sector index.[4]

[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[5], and 3) participant lender. We map each lender in each facility to its ultimate parent holding company.[6] To minimize any measurement error in this mapping process, 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 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 4,303.29 million USD and includes 2.11 facilities. On average, each facility has 4.56 lead arrangers and 9.89 lead or co-lead arrangers. The average facility is 2,049.97 million 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 the extent to which there is available public information on the borrower's characteristics. We classify 32.97% of our borrowers as "opaque" - these are either private entities or public companies without a published rating.

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

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, 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. One advantage of this decomposition is that educational ties are formed several years or decades prior to the board members appointed to our sample banks. Thus these predetermined connections could help us identify clear causal links between our connection measures and any potential outcome that we are interested to analyze for our sample banks during the sample period. 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 derive 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, 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 theoretically be computed based on one of the three-abovementioned 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]

[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.

[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

- *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 *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

year by year, we end up with an unbalanced panel for the years 2000-2010.

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 spreads through the networks from a specific bank-i.

- *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. As can be seen in Appendix A the composition of banks in our sample changes over time due to corporate restructuring events such as merger and acquisitions (M&As). Such changes in the total number of banks in the networks might affect our measure of centrality in a mechanical way. To address these concerns, we run robustness tests in Section 7.2, dropping banks that are not present during the whole sample period. Our results are robust to these different measures of sample construction.

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*). Interestingly, 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. Overall, these results strongly indicate that network connections in banking are meaningful and have become increasingly important over time.

4 Network connections and the structure of global loan syndications

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 lead or co-lead arrangers of that facility 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, $pair_{i,j,k}$, 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.[10] We use a unique pair for any two banks in our top global banks sample, eliminating any duplicates due to permutations. Hence, unique pairs of lead to lead, or lead to co-agent, or co-agent to co-agent are used throughout our tests.[11]

Following Cai et al. (2012), we run a linear probability regression with the lagged value of the scaled version of our pairwise measure, *sni*, denoted by $L.sni$, as the main right-hand-side (RHS) variable. We use the scaled *sni* measure since it captures both the existence and the strength of the connections between two banks. We believe that both dimensions are equally relevant to the two banks' joint investment decisions. Consequently, we mainly use the scaled version of the pairwise connection measures throughout our remaining analyses. In our regressions, we use various fixed effects models, defined at the year, borrower, facility, and bank pair levels.

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 and same institutional type dummies as additional explanatory variables, each of which is denoted by *country* and *type*, respectively. The information on each bank's country and institutional type is from Bankscope.

To control for any prior lending relationship between each bank and the borrower, we additionally include *rel-bank-borrower* for both banks in a pair, i and j, in the RHS of the regression. Each *rel-bank-borrower* is defined as the total number of facilities that bank-i (or j) has lent to the borrower 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 further control for the effects of similar size and leverage (or total capital ratio) on the partnership decisions for each pair of banks. Specifically, we create the following five matched buckets for the size and capital ratio variables respectively, all based on their lagged values: hh, hm, hl, ml, and ll where h, m, and l respectively denote high,

[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.

[11]We get similar results, in terms of economic magnitude and statistical significance, when we limit the definition of a partnership to lead to lead and lead to co-lead pairs.

median, and low buckets based on the terciles of each of the two variables.[12] In the interest of brevity, we do not report the point estimates of these similar size and capital ratio dummies. Standard errors are clustered at the bank pair level.[13]

[Insert Table 4 here]

Table 4 shows the results. In column (1), we control for year fixed effects and find that connected banks are more likely to form a syndicate partnership. The point estimate of $L.sni$ is 0.464, which is statistically significant at the 1% level. For a one standard deviation increase of the lagged sni (0.0472), there is a 2.2% (=0.0472*0.464) increase in the likelihood of syndicate partnership. This effect corresponds to 22.4% (=2.2%/9.8%) of the unconditional probability of two banks forming a partnership in our sample (9.8%), which is an economically significant effect.

Next, we address the concerns about potential omitted variable biases by additionally controlling for various fixed effects. In column (2), we first additionally control for borrower fixed effects. As shown in that column, the point estimate of $L.sni$ (0.450) is hardly changed from that in column (1), which indicates that the omitted constant factors defined at the borrower level do not materially affect our main findings.

Some banks may lend more than other banks in this syndicated loan market. To show that our results are not driven by this concern, we construct a variable named *cum. lending freq. bank* for both banks-i and j that measures 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. We control for these two additional variables in column (3) and continue to find that the point estimate of $L.sni$ (0.348), which is statistically significant at the 1% level.

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 (4). 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

[12]Due to the overall constant term in the regression, the mm case is naturally ruled out when we assign bank pairs into the tercile buckets.

[13]We find a similar result that is statistically significant at the 1% level 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. The results are reported in column (1) of Appendix Table 1 in Appendix B.

loan syndication. Hence, this specification in column (4) nests those in columns (1) to (3), while it further controls for additional omitted constant factors defined at the loan facility levels. As shown in column (4), the point estimate of $L.sni$ (0.339) is hardly changed from that in column (3), which indicates that the omitted constant factors defined at the loan facility level do not materially affect our main findings.

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 lagged *sni* with lagged *edu*, where *edu* is similarly constructed to *sni*, but it is based exclusively on educational ties whose formation predates the co-lending experience by several years or decades. 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 educational ties and the co-lending experience between the two banks naturally rules out concerns related to reverse causality. The new pairwise connection measure, *edu*, is also scaled by the average board size of the two banks. The results using this new measure are reported in column (5). Here we find a statistically significant positive association between the lagged *edu* and the syndicate partnership dummy, *pair*, at the 10% level (p-value=0.068).

Though we prove that our results are not driven by newly generated social connections between two banks following their business partnerships, there is another potential channel of reverse causality that is still not resolved. More specifically, two banks could appoint new board members from the same alma mater in anticipation of their future business partnerships. To tackle this second channel of reverse causality, we need an exogenous shock to the board compositions of two partnering banks such as director deaths (Fracassi, 2012). For example, Fracassi (2012) used the deaths of connected directors (treatment group) and non-connected directors (control group), and identified the treatment effect on the similarity in two firms' corporate investment policies through a difference-in-differences (DiD) framework. To utilize this identification strategy, we collect director deaths sample for 3,786 directors who served at our sample banks using the Boardex database. However, we found that only 60 directors died during our sample period, and that none of them were connected directors. For these reasons, we could not proceed with the DiD setup to address this unresolved channel of reverse causality. However, as explained in the introduction, this additional channel of reverse causality, if it exists, would just reconfirm the importance of network connections in business partnerships, and therefore, is consistent with our main hypothesis, which suggests that social connections are important in banking transactions.

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 pattens of social networks among our sample banks. Such constant factors defined at each 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 baseline regression specification in column (1), 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. *L.sni* significantly explains more frequent partnership between socially connected banks at the 1% level.

Next, in column (7), we investigate whether the tendency of connected banks to form a partnership in syndicate lending becomes even stronger when lending to informationally opaque borrowers, since these are circumstances where the soft information produced from past connections may be particularly valuable. *Opaque* is a dummy variable that takes a value of one if the borrower is either a private firm or an unrated public firm, and zero otherwise. Using the baseline specification in column (1), we interact lagged *sni* with *opaque* in this analysis. The point estimate of this interaction term is 0.054, which is statistically significant at the 1% level. This implies that partnerships among connected banks are more likely to be formed when the borrower's quality is more opaque. Relatedly, we find a statistically negative point estimate of *opaque*, -0.011, at the 1% level in that column. This confirms that there is also a direct effect in which any pair of banks (regardless of the degree of social connections) are less likely to form a partnership to provide lending to opaque borrowers.[14]

[14]Sufi (2007) documents that when the information asymmetry between lenders and a borrower is severe, the lead bank retains a larger share of the syndicate facility and the lenders tend to be closer

We also might expect that the financial crisis transformed the level of information asymmetry between borrowers and lenders. As discussed in the introduction, this shifting environment may have induced lending banks to partner more frequently with trusted bankers with whom they shared a social connection. At the same time, the crisis itself may have reduced the value of their shared information (which was based on lending during a more tranquil time). In these instances, we would expect to see less frequent partnership between connected banks during the crisis.

To address this issues, we empirically investigate the effect of the crisis by running the same baseline regression in column (1), but now we include an additional interaction term between lagged pairwise connection measure, $L.sni$, and a *crisis* dummy. The dummy variable takes a value of one for the years from 2007 onwards, and zero otherwise. In column (8) of Table 4, we find a positive point estimate of this interaction term with *crisis* dummy. The point estimate of the interaction term, $L.sni\ X\ crisis$, is 0.150, and is statistically significant at the 1% level. This implies that the partnership likelihood of two connected banks increases substantially by 0.150/0.407=36.9% during the crisis. The results appear to support the view that lenders rely more on their network connections during troubled times in which they face greater information asymmetry regarding the quality of potential borrowers.

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. At the same time, during the crisis when the quality of information deteriorates, and the information slowly flows through the networks, the central banks' information advantage could also depreciate. If true, one might expect central banks to

to the borrower, both geographically and in terms of previous lending relationships, to mitigate the information asymmetry problems.

play less active roles in originating the large syndicates during the financial crisis. To jointly investigate these two possibilities, we test whether central banks are more likely to lead or co-lead large international syndicates, and whether there is any change in the role played by the socially central banks during the crisis.

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, $arranger_{i,k}$, 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. We use the lagged values of the four measures of network centrality as our main RHS variables - *betweenness*, *eigenvector*, *closeness*, and *degree*, and interact each of them with the *crisis* dummy. We run this regression with various fixed effect dummies and also control for fundamental characteristics of each bank. In this analysis, year, country, specialization, and borrower fixed effects are either explicitly or implicitly controlled. The standard errors are clustered at the year level following Cai et al. (2012). However, we further show the robustness of our results to an alternative choice of error clustering approach - the bank level standard error clustering.

[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 1.947, which is statistically significant at the 1% level. Interestingly, this tendency becomes substantially weaker during the crisis. The interaction term between *betweenness* and *crisis* has a point estimate of -1.661, which implies that during the crisis, the likelihood that a central bank leads or co-leads a syndicate facility is reduced by almost 85.3%. This effect is statistically significant at the 5% level. These results confirm our prior that the information advantage of the central banks implies that they provide more senior roles within a syndicate before the crisis, but the incentive diminishes during the crisis, possibly due to the non-durability of the information that flows through the network. 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 ratio ($L.mtb$), total capital ratio ($L.capital\ ratio$), and size ($L.ln(TA)$).

In the remaining 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 all columns (2) to (4), we find similar results to that with *betweenness* centrality, both qualitatively and quantitatively. Only in column (3) where the lagged *closeness* centrality is used, does the centrality measure, itself, become statistically insignificant. However, the negative sign and statistical significance of the interaction term with *crisis* are still confirmed. Overall, we find that central banks in the global network tend to lead or co-lead syndicate facilities before the crisis. However, this effect significantly declines during and after the crisis. 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 centrality. Among the two potential channels of reverse causality explained in Section 4.1, here we focus on the possibility that directors of banks that play a leading role in large syndicates are able to generate new social connections within the director networks, which ultimately leads to an increase in its measured centrality.[16] To address this concern, we use a new centrality measure, $betweenness - edu$, that is based solely on educational ties. The results in column (7) confirm the robustness of our results, and hopefully alleviate concerns related to reverse causality.[17]

We also checked the robustness of our results by using the frequency of a bank to lead

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

[16]It should be noted again that the network centrality tends to be more exogenous than the pairwise connectedness because a bank cannot freely determine its network position by its own discretion - a bank's centrality closely depends on other banks' centralities. For these reasons, for our network centrality results, we are less concerned about the second additional channel of reverse causality that goes through the endogenous board compositions.

[17]A similar approach is employed by Hochberg et al. (2007) to address reverse causality concerns in VC network centrality measures. For a fund of a given vintage year, they measure the VC network centrality using syndication data for the 5 preceding years.

or co-lead a syndicate facility as an alternative LHS variable. Once again we find the same tendencies - central banks are more likely to serve as operating agents before the crisis, but this effect diminishes during and after the crisis. Though not reported in Table 5, these results are available in columns (2) to (5) of Appendix Table 1 in Appendix B.

Put together, socially central banks appear to play an important role in intermediating other socially peripheral banks to make joint investments. 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.

We confirm this notion of a socially central bank by examining the connections between centrality and banking transactions in another important market - interbank market. We find that socially central banks are more likely to lend to, but not borrow from the banks that are peripheral and adjacent to them in the network. Moreover, socially central banks tend to have high interbank assets to liabilities ratios. These additional results from interbank transactions further confirm that socially central banks serve as intermediaries among intermediaries in various banking transactions. These interbank market results are reported in Appendix Table 2 and 3 in Appendix B.

5 Do connected banks operate in a similar fashion? Evidence from equity correlations

The findings in the previous sections demonstrate that social connections have an important influence on how banks operate within the syndicated loan market. Beyond this specific market, we might in a broader sense expect that connected firms with similar experiences would undertake a whole host of similar operating, investing and financing decisions. If so, on average we would expect that connected firms would ultimately demonstrate a higher correlation in their equity returns.

To test these ideas, we calculate the pairwise equity correlations for each pair of banks in our sample. To explore this issue in more detail, we separately calculate the correlations of the unconditional, systematic and idiosyncratic returns. More specifically, we first calculate the weekly pairwise correlation over a 52 weeks window at year-end for each bank pair. This unconditional correlation is denoted by *R52*. Second, we estimate an industry CAPM by regressing banks' daily equity returns on a global banking index, the STOXX Global 1800 Banks index, after which we calculate the weekly pairwise correlations using the fitted values from the CAPM regression. We call this the systematic component of equity correlations, *R52_systematic*. Third, using the global banking sector CAPM residuals, we construct the idiosyncratic equity correlation and denote it by *R52_abnormal*.

To address the effects that the financial crisis had on the relationship between connectedness and correlations, we include the interaction term between the lagged value of our measure of social connectedness, *L.sni*, and the *crisis* dummy in this analysis. We control for the similarity in size and leverage and further control for the same *country* and *type* dummies in this regression.[18] Standard errors are clustered at the bank pair level and the regressions commonly include year dummies. In the interest of brevity, the point estimates of similar size and leverage dummies are not reported.

[Insert Table 6 here]

These results are reported in Table 6. In the first two columns, we show the results when we use the unconditional equity correlations as our main LHS variable. Column (1) employs only year fixed effects, whereas column (2) includes fixed effects related to the pair of banks along with year fixed effects. In each case, there is a significant positive link between the lagged *sni* variable and the unconditional correlation - indicating that banks that share a common social network connection are more likely to have a higher correlation in their equity returns. At the same time, the interactive variable linking lagged *sni* and the *crisis* dummy has a negative (and statistically significant) coefficient. We find similar results in columns (3) and (4), where we use the systematic correlations, *R52_systematic*, as our main dependent variables.

In column (5) where we use idiosyncratic correlations as our LHS variable, we once again find a positive and statistically significant point estimate of *L.sni*, but in this case, the interaction term with *crisis* is no longer statistically significant. Furthermore, looking at column (6) where we use the same idiosyncratic correlations but now also controlling for bank pair fixed effects, we see that none of the results remain statistically significant.

[18] In this analysis, we define the similarity in leverage using total capital ratio, which is consistent with what was done in Table 4.

In this regard, the findings in Table 6 suggest that the network connections primarily influence the systematic correlations, and have less of a pronounced effect on the idiosyncratic correlations. One interpretation is that the pattern of systematic correlations before and after the crisis reflected the changing role of the network central banks in the syndicated loan market, whereas the more peripheral banks in the network tend to move more in an idiosyncratic way without being affected by any systematic signal generated from the network central banks. Thus, in many respects, these results in Table 6 are consistent with our earlier analysis related to the loan syndication process.[19]

6 Do network connections promote systemic risk?

The previous results suggest that connected banks often partner together and operate in similar ways. One obvious concern is that these actions reflect a form of "group think" that ultimately leads to greater systemic risk. Consistent with this concern, the results in the previous section indicate that greater network connections lead to higher pairwise equity correlations - indeed confirming that connected banks are inclined to make similar bets. In this section, we further explore the correlation between network connections and systemic risk.

More specifically, we now 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. As an initial benchmark, we first explore whether there is a relation between the measures of network centrality and the bank's systematic risk (*beta*, estimated from the industry CAPM with the STOXX Global 1800 Banks index), total risk (*sigma*, the total annualized equity return volatility), and idiosyncratic risk (the volatility of the residual component from the industry CAPM). These results, presented in Appendix Table 4 in Appendix B, consistently show no significant relation between centrality and these banks own risk measures.[20]

[19]All of these results are robust to the use of the pairwise connection measures that are based solely on educational ties - *edu*. The results are reported in Panel A of Table 9. From this point on forth, every analysis is repeated using the network measures exclusively based on the educational ties. Our results are mostly robust to the use of *edu* and centrality measures built on *edu*.

[20]It should be noted that we find a positive and then negative relation between *beta* and all of our four network centrality measures before and after the crisis. Though their effects are not statistically significant, this reversing pattern of the effect of the four centrality measures on *beta* is consistent with

While an individual bank's centrality in the network does not appear to explain its own systematic risk, we are still interested in the larger question of whether tighter networks lead to greater systemic risk for the banking system. Put somewhat differently, 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.[21] From these estimates of the market-valued total assets, we compute

our earlier results related to the syndicated loan arrangements.

[21] 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

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 $VaR^i_{1\%}$ and $VaR^i_{50\%}$ 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 $CoVaR^{system|i}_{1\%}$ and $CoVaR^{system|i,median}_{1\%}$ using $VaR^i_{1\%}$ and $VaR^i_{50\%}$. $\Delta CoVaR^i_{1\%}$ of bank-i is then the difference between the two $CoVaR$ values.

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 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. It should be noted that we do not unsign the negative value of $\Delta CoVaR$ in this analysis. We control for *mtb*, size (TA) and its non-linear effects on $\Delta CoVaR$ (TA^2 and TA^3), systematic risk measured by *beta* from banking sector CAPM, all in the lagged forms. To compare the signs of point estimates of the main control variables to those reported in Adrian and Brunnermeier (2011), we use the lagged value of *leverage*, instead of *capital*

equity from the most recent fiscal quarter end date.

ratio, following the specification used in Adrian and Brunnermeier (2011). We control for year, country, and specialization fixed effects and cluster the standard errors at each bank level. The expected signs for the lagged *mtb*, TA, *leverage*, and *beta* are all negative.

[Insert Table 7 here]

Table 7 shows the results. In the first four columns, 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* (0.0118), there is an 8.2% increase in $\Delta CoVaR$ relative to its sample average value (-2.886), which appears to be both economically and statistically significant. In columns (5) to (8), we include the interaction term between each centrality measure and the *crisis* dummy. Here we find significant incremental impact of the network centrality on $\Delta CoVaR$ during the crisis. Even though the statistical significance of the interaction terms are somewhat marginal in two columns (5) and (7), their economic impact seem quite substantial when we compare the point estimate of the interaction term to that of each standalone centrality measure. The point estimates of our additional control variables mostly confirm their expected signs except the size-related variables (TA, TA^2, and TA^3).[22] However, the 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, and these effects were maintained during the financial crisis. 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.

[22]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.

7 Discussion

7.1 Network central banks before and after the crisis

During the crisis period, socially central banks were less likely to originate syndicated loans. 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. In this section, we 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 8, 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 subperiod as the cutoff to define the two groups of banks, before and after the crisis. For these two groups of banks, we provide the average values of size ($ln(TA)$), operating profitability (roa), leverage, equity return, total 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 of these fundamental characteristics between the two groups, before and after the crisis.

[Insert Table 8 here]

Column (9) of Table 8 shows the results of the DiD. Notably, 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 8 provide little support for the argument that central banks played a diminished role because they suffered disproportionately during the crisis. Consequently, these findings lead us to conclude 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.

7.2 Robustness tests

In this section, we test the robustness of our main results with respect to the following concerns: 1) reverse causality, 2) the changing composition of the global network system throughout our sample period, and 3) potential endogeneity in the formation of the regional social networks. The first concern was first raised in Section 4, whereas the second concern was discussed in Section 2.2.2 when we introduced our four measures of network centrality. It should be noted that our results using pairwise network connections as the main explanatory variables are robust to the second concern. The third concern centers around potential omitted variables that are defined at each regional network level that jointly affect both the patterns of regional social networks and the decisions that banks make in their syndicate lending. We addressed this third concern partly in Table 4 where we regress the syndicated loan partnership dummy on the lagged *sni* while also controlling for bank pair fixed effects on the RHS of that regression. In this section, we further examine this issue by breaking down the global banking social networks into regional and cross-regional sub-networks. Here we show that most of our earlier results are driven by strong "cross-regional" connections between U.S. and non-U.S. bank pairs. These results help alleviate the third concern that our results are primarily driven by endogenously formed local social networks.

Panel A of Table 9 first shows the robustness checks related to reverse causality. There we replicate our earlier analysis using the more narrow network measures that are based exclusively on educational ties whose formation occur well before the various transactions between our sample banks. Such a long lag between the dates of the network formation and the financial transactions helps alleviate concerns related to reverse causality. More specifically, as our key network measures, we now use *edu* for pairwise connections and *eigenvector* $-$ *edu* for the centrality measure.[23]

[Insert Table 9 here]

Looking at Panel A of Table 9, we find in all columns that our main results are quite robust to the reverse causality concern.

Next, in Panel B of Table 9, we further show the robustness of our main results to the potential change in the composition of our sample banks in each year. To address this concern, we focus exclusively on the banks that are present during the complete sample period, 2000-2010. Using this fixed set of the banks over the complete sample period, we compute *eigenvector* centrality and re-run the previously tested centrality models with this new measure of *eigenvector* centrality (Table 5 and 7). These results are reported in columns (1) and (2) of Panel B of Table 9. There we find that the most of our earlier findings in the centrality models remain robust to the use of this new measure of network centrality.

Related to this concern, the Boardex database is known to add smaller and newer (less socially connected) companies during the 2000-2003 time period.[24] To show the robustness of our results to this structural break of the Boardex database, we re-run the two centrality models exclusively focusing on the post-2003 sample period. The results are reported in columns (3) and (4) of the same panel. There we confirm that our results are not influenced by the structural break in the Boardex data.

Overall, the results in Panel B of Table 9 confirm that our previous findings are applicable to both the static and dynamic components within the global banking network and are robust to the potential structural break issues in the Boardex data. More specifically, the results in the first two columns of that panel alleviate the concerns that our results might have been solely driven by the effects that M&As among the top global banks had on the centrality measures.

Lastly, in Panel C of Table 9, we present the results of two tables 4 and 5 on syndicated loan transactions, using pairwise connectedness (columns (1) to (3)) and network centrality (columns (4) to (6)) constructed with one of the following three regional and/or

[23] In Section 4.2, we already showed the robustness of the results reported in Table 5 using the alternative centrality measure, *betweenness* $-$ *edu*.

[24] We are grateful for Cesare Fracassi to point out this issue.

cross-regional networks exclusively: 1) the U.S. regional (U.S.-U.S.), 2) the non-U.S. regional (Non-U.S.-Non-U.S.), and 3) the U.S. to the non-U.S. cross-regional (U.S.-Non-U.S.) networks exclusively. The row labelled "Network Type" in that panel denotes which sub-network is used to construct either of the two types of social network measures, *sni* and *eigenvector*, in each analysis.

Looking at the first three columns of that panel, we find that the earlier result that socially connected banks are more likely to form a syndicated loan partnership, continues to hold when using two of the sub-networks - the non-U.S. only and/or the U.S. to the non-U.S. cross-regional network connections. When we further examine in which network central banks are more likely to lead or co-lead global loan syndications, we find a very interesting pattern in columns (4) to (6). Here we find that socially central banks in the U.S. to the non-U.S. cross-regional network are those that lead or co-lead the large syndicates before the 2007 financial crisis, and that these central banks in the cross-regional network are also those diminished their loan originations in the aftermath of the crisis.

Put together, the results reported in Panel C of Table 9 suggest that our main results are primarily driven by the strong cross-regional network connections rather than either the U.S. bank only or non-U.S. bank only local networks, whose patterns are presumably more likely to be endogenized by omitted local factors.

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

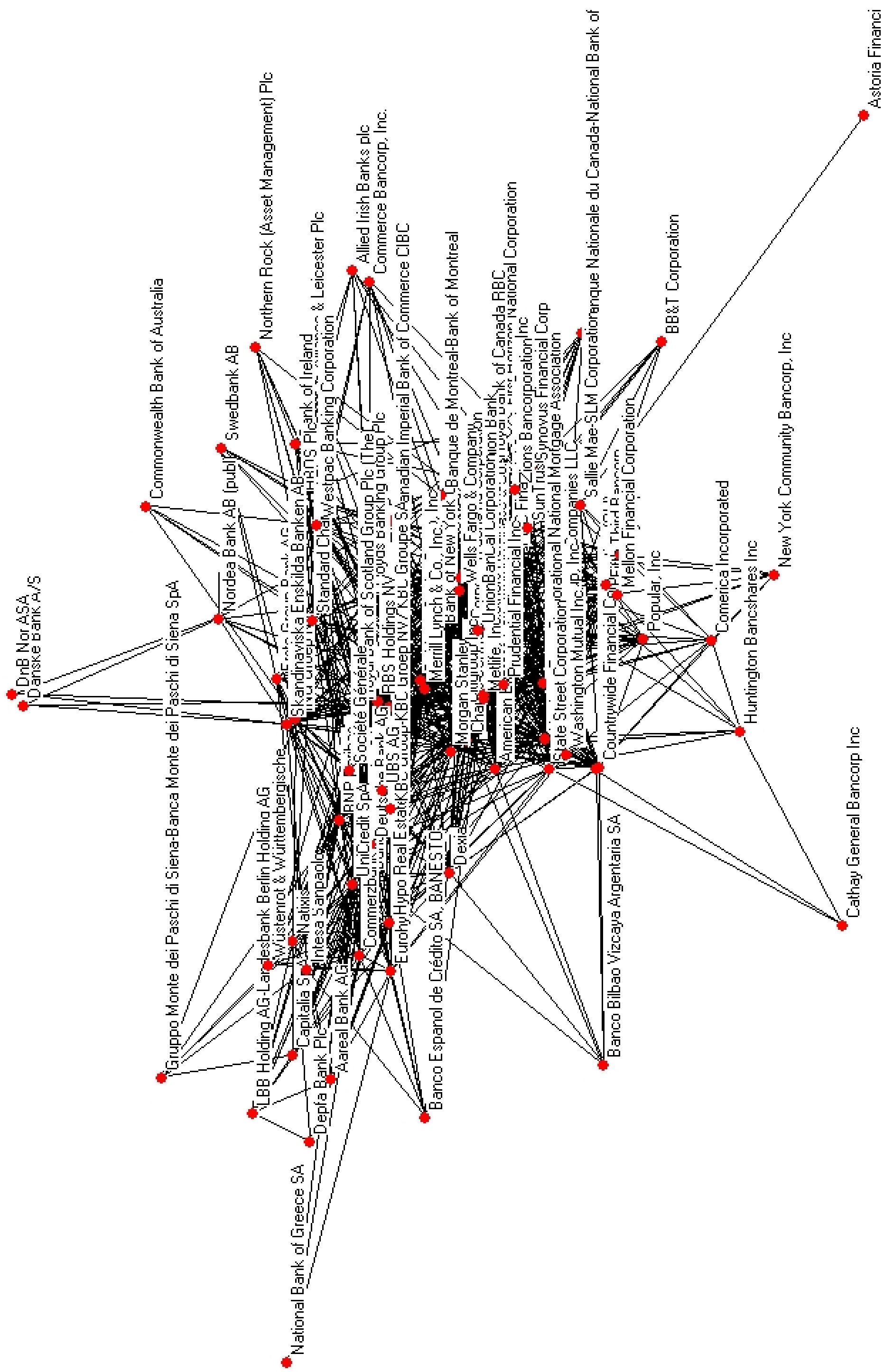

Figure 2: The U.S. only banking network in the year 2006. Thicker lines indicate more connections between two financial firms.

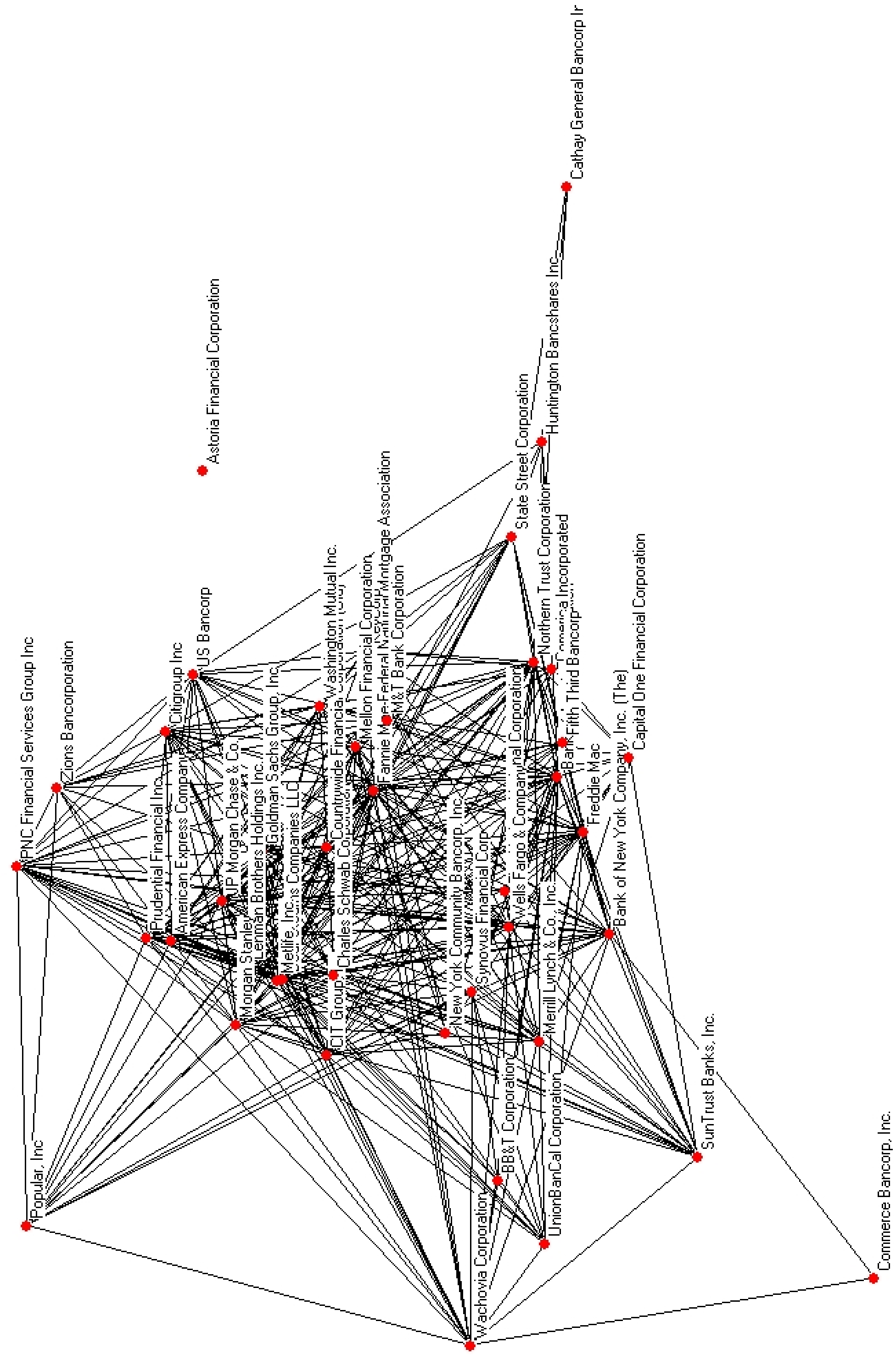

Figure 3: The non-U.S. only banking network in the year 2006. Thicker lines indicate more connections between two financial firms.

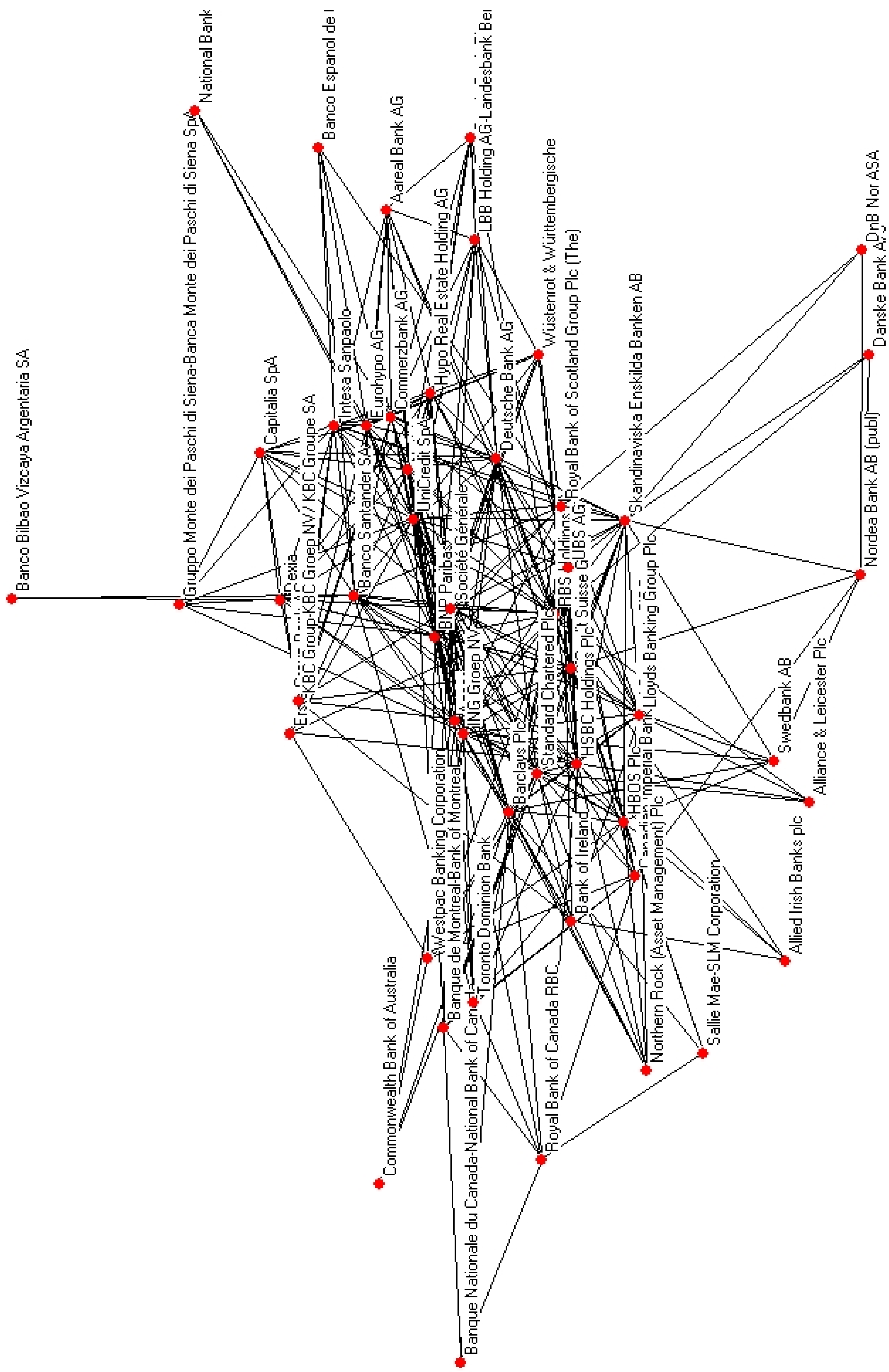

Figure 4: The average pairwise connections: *Sni*.

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 connections. 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 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.

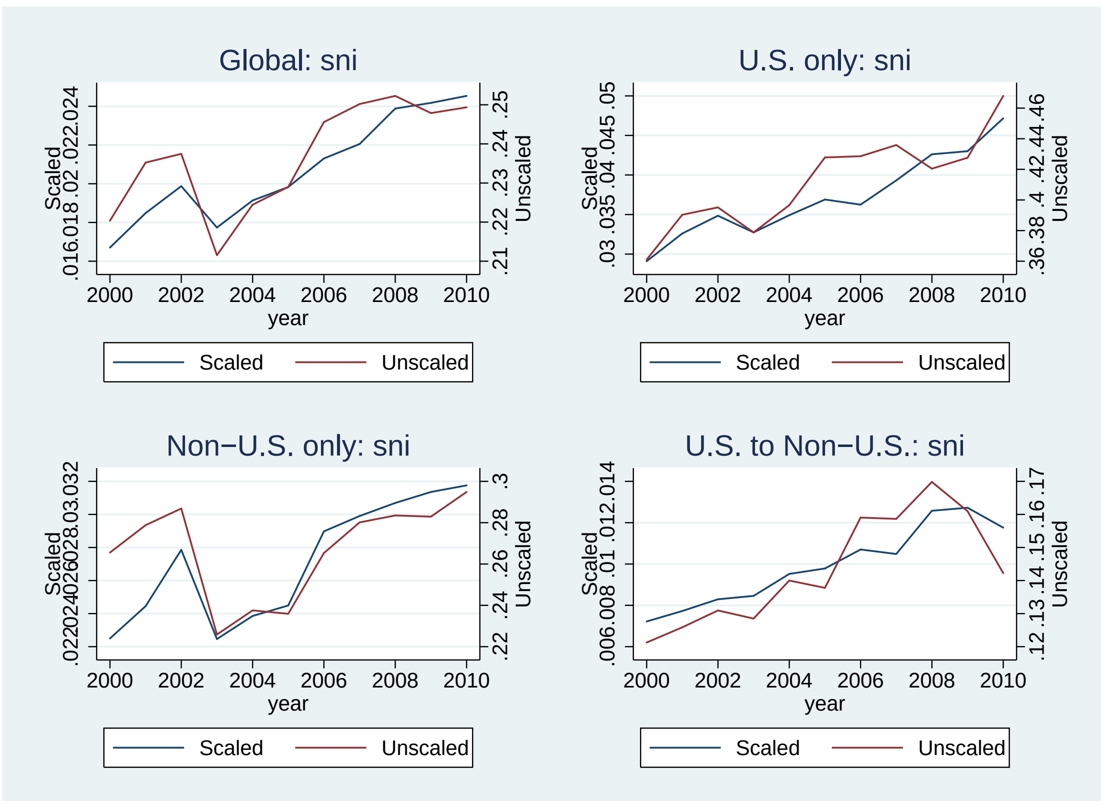

Table 1: Summary statistics of sample banks and syndicate packages.
The data period is from 2000 to 2010. In panel A, we summarize the fundamental and risk characteristics of our sample banks. Our sample banks are from 16 countries, and they are the 99 largest banks in the Boardex by total assets in the year 2003. Total capital ratio is the ratio of the sum of tier-1 and tier-2 capital to total assets. Leverage is the ratio of the book value of total assets to the book value of total equity. Non-interest ratio is the ratio of non-interest operating income to operating profit. Market-to-book ratio is the ratio of market value to book value of equity. *Sigma* is the annualized daily standard deviation of equity returns over a 250 days 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. *Secured* and *senior* are dummy variables for the facilities that are secured and senior, respectively. *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	542	888
Return on assets (roa)	0.775	0.947	888
Total capital ratio ($capital\ ratio$)	12.531	2.376	728
Leverage	21.149	13.058	888
Non-interest ratio	2.623	14.194	888
Market-to-book ratio (mtb)	1.993	1.507	870
Total volatility of equity return ($sigma$)	0.377	0.261	884
Global banking sector CAPM beta ($beta$)	0.976	0.407	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
Regional summary				
Num. of syndication country	66			
Num. of borrower country	66			
Package-level summary				
Package amount in mil.USD	4,303.29	4,746.33	3,300	1.42e+07
Num. of facilities	2.11	1.63	3,300	
Facility-level summary				
Facility amount in mil.USD	2,049.97	2,829.87	6,939	1.42e+07
U.S. facility amount in mil.USD	2,003.45	2,365.09	2,663	5.33e+06
Non-U.S. facility amount in mil.USD	2,078.95	3,084.04	4,276	8.89e+06
Num. of lenders	9.89	9.22	6,956	
Num. of leads	4.56	4.94	6,956	
Maturity (months)	56.52	47.75	6,617	
Secured	0.3265	0.4690	6,956	
Senior	0.9928	0.0846	6,795	
Opaque	0.3297	0.4702	1,644	

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	0.0167	0.0064	0.0103	0.2204	0.1116	0.1446	2,850
2001	0.0185	0.0068	0.0117	0.2352	0.1185	0.1595	3,486
2002	0.0199	0.0065	0.0134	0.2375	0.1071	0.1680	3,828
2003	0.0177	0.0056	0.0122	0.2116	0.0924	0.1503	4,753
2004	0.0191	0.0058	0.0134	0.2245	0.0956	0.1602	4,560
2005	0.0198	0.0060	0.0138	0.2290	0.0988	0.1654	4,465
2006	0.0213	0.0056	0.0157	0.2456	0.0939	0.1851	4,186
2007	0.0221	0.0056	0.0165	0.2502	0.0887	0.1919	3,741
2008	0.0239	0.0052	0.0187	0.2523	0.0842	0.2014	2,850
2009	0.0242	0.0049	0.0193	0.2479	0.0769	0.2068	2,485
2010	0.0245	0.0043	0.0203	0.2494	0.0631	0.2148	2,346
			Mean (Std. Dev.)				
Total	0.0204	0.0058	0.0146	0.2350	0.0951	0.1739	39,550
	(0.0472)	(0.0190)	(0.0395)	(0.4240)	(0.2933)	(0.3791)	

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

Variable	sni	edu	professional
sni	1.000		
edu	0.5754	1.000	
professional	0.9196	0.2078	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	0.0116	0.1052	0.5500	0.2609	550
	(0.0115)	(0.0548)	(0.0683)	(0.0133)	
Commercial Banks	0.0097	0.0727	0.5234	0.2008	278
	(0.0129)	(0.0452)	(0.0599)	(0.1178)	
Investment Banks	0.0135	0.1359	0.5861	0.3233	28
	(0.0068)	(0.0237)	(0.0281)	(0.0597)	
Savings Bank	0.0009	0.0216	0.4382	0.0747	11
	(0.0006)	(0.0139)	(0.0471)	(0.0316)	
Real Estate, Mortgage banks	0.0068	0.0661	0.5099	0.1814	27
	(0.0078)	(0.0517)	(0.0608)	(0.1172)	
Government Credit Institutions	0.0203	0.1732	0.6240	0.4188	9
	(0.0120)	(0.0255)	(0.0271)	(0.0549)	
Total	0.0109	0.0946	0.5411	0.2413	903
	(0.0118)	(0.0546)	(0.0674)	(0.1315)	

Panel B: Correlations across different centrality measures

Variable	betweenness	eigenvector	degree	closeness
betweenness	1.000			
eigenvector	0.7697	1.000		
degree	0.7924	0.9577	1.000	
closeness	0.8304	0.9807	0.9750	1.000

Table 4: Pairwise connections and global syndicate partnership.
The dependent variable is $pair_{i,j,k}$, 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. The main RHS variables are the lagged values of the scaled version of *sni* and *edu*, each of which measures the fraction of the directors in the two banks, i and j, who are connected through any type of social connections that include the common alma maters, common previous job affiliations, common charity and other forms of organizations (*sni*), or exclusively through the common alma mater connections (*edu*). *Opaque* is a dummy for a private firm or a firm without rating, and *crisis* is a dummy for the period since 2007 and onwards. The reported point estimates of *cum. lending freq. bank* variables are the inflated values of original point estimates of the variables by 1,000. In all columns, we additionally control for similar size and capital ratio dummies for each pair of banks, all based on their lagged values. Their point estimates are not reported in this table for brevity. 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)	(8)
L.sni	0.464***	0.450***	0.348***	0.339***		0.168***	0.447***	0.407***
	(0.053)	(0.051)	(0.044)	(0.043)		(0.029)	(0.054)	(0.058)
L.edu					0.174*			
					(0.096)			
opaque							-0.011***	
							(0.001)	
L.sni X opaque							0.054***	
							(0.018)	
L.sni X crisis								0.150***
								(0.049)
country	-0.022***	-0.009	-0.003	0.003	0.015**		-0.022***	-0.022***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)		(0.008)	(0.008)
type	0.011**	0.012**	0.010**	0.010**	0.011***		0.011**	0.011**
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)		(0.005)	(0.005)
rel-bank1-borrower	0.364***	0.089**	0.046	0.227***	0.042	-0.035	0.353***	0.362***
	(0.043)	(0.042)	(0.034)	(0.037)	(0.034)	(0.029)	(0.043)	(0.043)
rel-bank2-borrower	5.080***	4.693***	3.608***	3.798***	3.627***	3.659***	5.073***	5.080***
	(0.381)	(0.355)	(0.269)	(0.275)	(0.271)	(0.267)	(0.381)	(0.381)
cum. lending freq. bank1			-0.016***	-0.002	-0.013***	-0.003		
			(0.003)	(0.003)	(0.003)	(0.002)		
cum. lending freq. bank2			0.438***	0.442***	0.446***	0.320***		
			(0.011)	(0.010)	(0.011)	(0.008)		
Additional controls	Similar size and leverage dummies							
Fixed effects	Year	Year, Borrower	Year, Borrower	Facility	Facility	Year, Pair	Year	Year
Cluster	Pair	Pair	Pair	Pair	Pair	Pair	Pair	Pair
Adj. R^2	0.075	0.107	0.172	0.188	0.169	0.275	0.075	0.075
N	3,228,052	3,228,052	3,228,052	3,228,052	3,228,052	3,228,052	3,228,052	3,228,052

Table 5: Centrality and lead/co-lead arranging global syndicates.
The dependent variable is $arranger_{i,k}$, which takes a value of one if bank-i takes a senior role such as a lead or a co-lead for facility-k, and zero otherwise. We use the lagged values of the following measures of network centrality as our main RHS variables - *betweenness*, *eigenvector*, *closeness*, and *degree*, and interact each of them with *crisis*. *Crisis* is a dummy for the period since 2007 and onwards. We run a linear probability model with various fixed effects and additional bank level controls. Standard errors are clustered at the year level in all columns except column (6) where we cluster the errors 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)	(5)	(6)	(7)
L.betweenness	1.947***				1.947***	1.947*	
	(0.435)				(0.438)	(1.026)	
L.betweenness X crisis	-1.661**				-1.660**	-1.661**	
	(0.682)				(0.686)	(0.713)	
L.eigenvector		0.351***					
		(0.077)					
L.eigenvector X crisis		-0.387**					
		(0.136)					
L.closeness			0.091				
			(0.062)				
L.closeness X crisis			-0.260*				
			(0.115)				
L.degree				0.126***			
				(0.032)			
L.degree X crisis				-0.154**			
				(0.057)			
L.betweenness-edu							0.731***
							(0.180)
L.betweenness-edu X crisis							-1.134***
							(0.268)
Lmtb	-0.003**	-0.003**	-0.002**	-0.002**	-0.003**	-0.003	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)
Lcapital ratio	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)
L.ln(TA)	0.067***	0.068***	0.075***	0.069***	0.067***	0.067***	0.072***
	(0.006)	(0.004)	(0.005)	(0.005)	(0.006)	(0.018)	(0.005)
Year	Yes	Yes	Yes	Yes		Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specialization	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower	Yes	Yes	Yes	Yes		Yes	Yes
Facility					Yes		
Cluster	Year	Year	Year	Year	Year	Bank	Year
Adj. R^2	0.183	0.182	0.182	0.182	0.188	0.183	0.188
N	384,391	384,391	384,391	384,391	384,391	384,391	345,105

Table 6: Pairwise connections and equity correlations.
This tables shows the results of the regression of the pairwise equity correlation on the lagged value of pairwise social connectedness measure, *sni* (scaled). *Sni* is the total number of connections between two banks scaled by the average size of their boards. The dependent variables are 1) *R52*, the unconditional pairwise correlation of weekly equity returns, calculated over a 52 weeks window, 2)*R52_systematic*, the pairwise correlation of the weekly fitted values from the daily industry CAPM regression on the STOXX Global 1800 Banks index, calculated over a 52 weeks window, and 3) *R52_abnormal*, the pairwise correlation of the weekly residuals from the daily industry CAPM regression on the STOXX Global 1800 Banks index, calculated over a 52 weeks window. More specifically, we run the daily industry CAPM regression first, and then convert both the fitted and residual values of the regression into weekly values. Using these weekly converted values, we construct both *R52_systematic* and *R52_abnormal* for each year over the 52 weeks window. *Country* takes a value of one if both banks come from the same country and zero otherwise. *Type* takes a value of one if both banks have the same specialization according to the Bankscope and zero otherwise. *Crisis* is a dummy that takes value one for the years 2007 till 2010. We additionally control for the similarity in size and capital ratio for each pair of banks, however, their point estimates are not reported for brevity. Standard errors are clustered at the bank pair level, and they are reported in the parentheses. ***,**, and * denotes the statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	*R52*		*R52_systematic*		*R52_abnormal*	
L.sni	0.283***	0.0736*	0.0682**	0.127***	0.328***	0.0256
	(0.0449)	(0.0433)	(0.0340)	(0.0325)	(0.0505)	(0.0541)
L.sni X crisis	-0.185***	-0.242***	-0.233***	-0.266***	-0.0202	-0.0598
	(0.0473)	(0.0432)	(0.0341)	(0.0334)	(0.0636)	(0.0583)
country	0.169***		0.0557***		0.232***	
	(0.00465)		(0.00319)		(0.00509)	
type	0.0375***		0.0188***		0.0239***	
	(0.00344)		(0.00283)		(0.00371)	
Additional controls	Similar size and leverage dummies					
Fixed effects	Year	Year, Pair	Year	Year, Pair	Year	Year, Pair
Cluster	Pair	Pair	Pair	Pair	Pair	Pair
Adj. R^2	0.408	0.638	0.096	0.418	0.274	0.526
N	34,261	34,261	34,261	34,261	34,261	34,261

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*. *Crisis* is a dummy for the period since 2007 and onwards. *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. 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)	(5)	(6)	(7)	(8)
L.betweenness	-20.143*				-12.549*			
	(11.276)				(6.708)			
L.eigenvector		-7.831**				-4.690		
		(3.402)				(3.148)		
L.closeness			-6.221**				-3.657**	
			(2.689)				(1.415)	
L.degree				-3.404**				-2.066***
				(1.380)				(0.627)
L.betweenness X crisis					-23.446			
					(21.397)			
L.eigenvector X crisis						-8.938**		
						(4.437)		
L.closeness X crisis							-6.985	
							(4.170)	
L.degree X crisis								-3.508*
								(1.872)
L.mtb	-0.073	-0.070	-0.076	-0.070	-0.071	-0.078	-0.078	-0.075
	(0.114)	(0.106)	(0.105)	(0.105)	(0.050)	(0.103)	(0.047)	(0.048)
L.TA	0.097	0.176	0.172	0.189*	0.069	0.128	0.124**	0.136**
	(0.120)	(0.113)	(0.115)	(0.112)	(0.063)	(0.125)	(0.054)	(0.055)
L.TA^2	-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)	(0.000)	(0.000)
L.TA^3	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)	(0.000)	(0.000)
L.leverage	-0.012	-0.010	-0.011	-0.011	-0.011	-0.009	-0.009	-0.009
	(0.015)	(0.015)	(0.015)	(0.015)	(0.012)	(0.015)	(0.012)	(0.012)
L.beta	-0.373	-0.322	-0.315	-0.316	-0.376	-0.313	-0.326	-0.319
	(0.265)	(0.266)	(0.261)	(0.263)	(0.232)	(0.271)	(0.224)	(0.232)
Fixed effects	Year, Country, Specialization							
Cluster	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Adj. R^2	0.438	0.443	0.444	0.445	0.439	0.449	0.449	0.450
N	766	766	766	766	766	766	766	766

Table 8: Network central banks before and after the crisis: Difference in difference.
In this table, we analyze the fundamental characteristics of the network central banks before and after the crisis. 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	0.02	301	0.00	310	0.02***	0.00	0.02	145	0.00	139	0.02***	0.00	0.00*	0.09
ln(TA)	19.57	300	18.34	303	1.23***	0.00	20.38	142	18.88	143	1.50***	0.00	0.27*	0.09
roa	0.97	300	1.06	303	-0.09*	0.08	0.26	142	0.27	143	0.00	0.99	0.09	0.56
leverage	20.79	300	20.79	303	-0.01	1.00	23.49	142	20.46	143	3.04	0.37	3.04	0.39
equity return	0.00	296	0.00	297	0.00	0.73	0.00	145	0.00	139	0.00*	0.08	0.00*	0.07
sigma	0.01	296	0.01	297	0.00	0.18	0.02	145	0.02	139	0.00	0.83	0.00	0.58
beta (Domestic market index)	0.90	296	0.64	297	0.26***	0.00	1.30	145	1.14	139	0.16**	0.02	-0.10	0.14
beta (Global banking index)	0.98	296	0.75	297	0.24***	0.00	1.18	145	1.04	139	0.14***	0.00	-0.09*	0.04

Table 9: Robustness tests.
In Panel A of this table, we test the robustness of our main results to reverse causality. In that panel, we repeat the same analyses done in the previous tables, 5, 7, and 6, using the network measures exclusively based on the educational ties whose formation predates the date of action for each LHS variable of the regression by several years or decades. Control variables are the same as those used in the three tables. In Panel B of this table, we further test the robustness of our main results to the changing composition of the banks during our sample period. In columns (1) and (2) of that panel, we compute *eigenvector* 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 two centrality models previously reported in Table 5 (*arranger* in the LHS) and 7 ($\Delta CoVaR$ in the LHS). Control variables are the same as those used in the two tables. In the remaining columns (3) and (4) of the same panel, we exclusively focus on the 2004-2010 time period and run the same centrality analyses. We focus on this post-2003 time period since Boardex database is known to add smaller and newer (less socially connected) companies during the 2000-2003 time period. In Panel C of this table, we show the results of Table 4 and 5 using the following three regional and/or cross-regional sub-networks: 1) the network with only the U.S. bank pairs (U.S.-U.S.), 2) the network with only the non-U.S. bank pairs (Non-U.S.-Non-U.S.), and 3) the U.S. bank to the non-U.S. bank cross-regional newtork (U.S.-Non-U.S.). In columns (1) to (3) of that panel, control variables include similar size and capital ratio dummies, *rel-bank-borrower*'s for both banks. In the remaining columns (4) to (6), control vairables are the same as those used in Table 5. In all panels of this table, standard errors are reported in the parentheses, and ***, **, and * denotes the significance at the 1% , 5%, and 10% level, respectively.

Panel A: Reverse causality

	(1)	(2)	(3)	(4)	(5)
	Centrality model		Pair model		
	Table 5	Table 7	Table 6		
Variable	arranger	$\Delta CoVaR$	equity correlation		
		OLS	unconditional	systematic	abnormal
L.eigenvector-edu	0.139**	-2.051*			
	(0.060)	(1.246)			
L.eigenvector-edu X crisis	-0.344***				
	(0.077)				
L.edu			0.255***	0.317***	0.010
			(0.078)	(0.041)	(0.098)
L.edu X crisis			-0.201*	-0.579***	0.337
			(.117)	(0.051)	(0.152)
Year	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes
Type	Yes	Yes	Yes	Yes	Yes
Borrower	Yes				
Controls	Yes	Yes	Yes	Yes	Yes
Cluster	Year	Bank	Pair	Pair	Pair
Adj. R^2	0.19	0.47	0.40	0.09	0.27
N	345,105	691	34,261	34,261	34,261

Panel B: Results using different sample of banks and different sample period

	(1)	(2)	(3)	(4)
	Banks that were present throughout the entire sample period		Only the post-2003 sample period	
Variable	Table 5 arranger	Table 7 $\Delta CoVaR$	Table 5 arranger	Table7 $\Delta CoVaR$
L.eigenvector-robust	0.176*	-10.356**		
	(0.079)	(4.053)		
L.eigenvector-robust X crisis	-0.299**			
	(0.107)			
L.eigenvector			0.386**	-9.699**
			(0.120)	(3.776)
L.eigenvector X crisis			-0.354*	
			(0.189)	
Year	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
Type	Yes	Yes	Yes	Yes
Borrower	Yes		Yes	
Controls	Yes	Yes	Yes	Yes
Cluster	Year	Bank	Year	Bank
Adj. R^2	0.19	0.48	0.18	0.47
N	251,377	488	283,488	540

Panel C: Effects of regional and cross-regional networks

Variable	(1)	(2) Table 4 pair	(3)	(4)	(5) Table 5 arranger	(6)
L.sni	0.018	0.580***	0.484***			
	(0.073)	(0.068)	(0.078)			
L.eigenvector				-0.146	-0.086	0.858***
				(0.115)	(0.090)	(0.095)
L.eigenvector X crisis				-0.405***	-0.051	-0.592***
				(0.112)	(0.143)	(0.123)
Network Type	U.S.-U.S.	Non-U.S.-Non-U.S.	U.S.-Non-U.S.	U.S.-U.S.	Non-U.S.-Non-U.S.	U.S.-Non-U.S.
Year	Yes	Yes	Yes	Yes	Yes	Yes
Type	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Pair	Pair	Pair	Year	Year	Year
Adj-R^2	0.06	0.07	0.07	0.20	0.22	0.20
N	497,939	1,137,522	1,592,766	205,738	147,732	291,476

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 tables

Appendix Table 1: Untabulated results.
This table reports the results that are discussed but are not reported in our main tables in the manuscript. In column (1), we show the results of Table 4 using an alternative clustering algorithm of the regression residuals - the dual clustering algorithm by Petersen (2009) for each of two banks in a pair. The dual-clustered standard errors are reported in the parentheses. In the remaining columns (2) to (5), we report the results of Table 5 using an alternative regression specification. In this analysis, we use the frequency of a bank to lead or co-lead a syndicate facility in a given year as a main dependent variable, and thus, the regression has each bank-year observation as its base unit. The alternative dependent variable is formally defined as the total number of facilities that a given bank leads or co-leads during a given year divided by the total number of facilities that any bank in our sample leads or co-leads during that year. We use the lagged values of the following measures of network centrality as our main RHS variables - *betweenness*, *eigenvector*, *closeness*, and *degree*, and interact each of them with *crisis*. *Crisis* is a dummy for the period since 2007 and onwards. Year fixed effects are further controlled. The standard errors are clustered at the bank level, and they are reported in the parentheses. In all columns of this table, ***, **, and * denote the statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)		(2)	(3)	(4)	(5)
	Table 4				Table 5	
Variable	pair		The frequency of a bank to lead or co-lead a syndicate facility			
L.sni	0.463***	L.betweenness	2.884***			
	(0.124)		(0.841)			
country	-0.022	L.betweenness X crisis	-1.912***			
	(0.017)		(0.708)			
type	0.011	L.eigenvector		0.833***		
	(0.008)			(0.267)		
rel-bank1-borrower	0.361***	L.eigenvector X crisis		-0.574***		
	(0.128)			(0.191)		
rel-bank2-borrower	5.063***	L.closeness			0.616***	
	(1.106)				(0.185)	
		L.closeness X crisis			-0.503***	
					(0.152)	
		L.degree				0.335***
						(0.105)
		L.degree X crisis				-0.240***
						(0.078)
Controls	Similar size and leverage dummies		Lagged values of mtb, total capital ratio, ln(TA)			
Year	Yes		Yes	Yes	Yes	Yes
Cluster	Dual Clustering		Bank	Bank	Bank	Bank
Adj. R^2	0.075		0.608	0.624	0.611	0.619
N	3,228,052		457	457	457	457

Appendix Table 2: Centrality and interbank loan and deposit ratios.
The dependent variables are interbank loans (columns (1) to (4)) and interbank deposits ratios (columns (5) to (8)) to total assets. We use the lagged values of the following measures of network centrality as our main RHS variables - *betweenness*, *eigenvector*, *closeness*, and *degree*, and interact each of them with *crisis*. *Crisis* is a dummy for the period since 2007 and onwards. 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)
Variable		interbank loans				interbank deposits		
L.betweenness	1.899*				-0.780			
	(0.984)				(0.692)			
L.betweenness X crisis	-0.060				-0.201			
	(0.530)				(0.617)			
L.eigenvector		0.681**				-0.354		
		(0.306)				(0.277)		
L.eigenvector X crisis		-0.072				0.024		
		(0.129)				(0.163)		
L.closeness			0.528**				-0.261	
			(0.239)				(0.194)	
L.closeness X crisis			-0.098				-0.026	
			(0.088)				(0.113)	
L.degree				0.277**				-0.145
				(0.127)				(0.100)
L.degree X crisis				-0.045				0.011
				(0.045)				(0.062)
L.roa	-0.016**	-0.016**	-0.016**	-0.015**	-0.012	-0.011	-0.011	-0.011
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
L.mtb	0.007	0.008	0.008	0.008	-0.009***	-0.010***	-0.010***	-0.010***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.002)	(0.002)	(0.002)	(0.002)
L.capital ratio	0.011**	0.011***	0.010**	0.011***	-0.002	-0.002	-0.002	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
L.ln(TA)	0.002	-0.006	-0.005	-0.006	0.004	0.008	0.008	0.009
	(0.010)	(0.012)	(0.012)	(0.012)	(0.010)	(0.010)	(0.010)	(0.010)
Fixed effects				Year, Country, Specialization				
Cluster	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Adj. R^2	0.248	0.272	0.268	0.271	0.518	0.520	0.523	0.522
N	596	596	596	596	385	385	385	385

Appendix Table 3: Centrality and interbank assets to liabilities ratio.
The dependent variable is the interbank assets to liabilities ratio. We use the lagged values of the following measures of network centrality as our main RHS variables - *betweenness*, *eigenvector*, *closeness*, and *degree*, and interact each of them with *crisis*. *Crisis* is a dummy for the period since 2007 and onwards. 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)
L.betweenness	673.875			
	(675.336)			
L.betweenness X crisis	-378.741			
	(696.768)			
L.eigenvector		471.916*		
		(251.759)		
L.eigenvector X crisis		-261.588		
		(208.256)		
L.closeness			280.379*	
			(151.532)	
L.closeness X crisis			-148.869	
			(138.064)	
L.degree				166.632*
				(93.529)
L.degree X crisis				-82.070
				(73.862)
L.roa	5.770	2.758	4.196	3.685
	(11.973)	(11.526)	(11.617)	(11.535)
L.mtb	0.807	1.836	1.785	1.744
	(2.949)	(3.072)	(2.981)	(3.010)
L.capital ratio	5.370*	4.482	4.799	4.434
	(3.135)	(3.041)	(3.086)	(3.080)
L.ln(TA)	-16.803	-23.137	-21.206	-23.467
	(14.399)	(13.832)	(13.715)	(13.987)
Fixed effects	Year, Country, Specialization			
Cluster	Bank	Bank	Bank	Bank
Adj. R^2	0.210	0.223	0.218	0.220
N	349	349	349	349

Appendix Table 4: Systematic risk, total and idiosyncratic volatilities: Centrality model.
The first four columns (1) to (4) show the results of the regressions of each bank's own systematic risk, *beta*, on the different centrality measures: 1)*betweenness*, 2)*eigenvector*, 3)*closeness*, and 4)*degree*. The *beta* coefficient is from the daily global CAPM regression with the STOXX Global 1800 Banks index over a 250-day moving window. In columns (5) and (6), we respectively use the total annualized equity return volatility (*sigma*) and the idiosyncratic volatility from the global CAPM regression as the LHS variables. *Crisis* is a dummy that takes a value of one for the years 2007 till 2010, and the sample period is 2000 till 2010. Standard errors are clustered at the bank level, and they are reported in the parentheses. ***, **, and * denote the statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Variable		*beta*			*sigma*	*idiosyncratic vol.*
L.betweenness	0.895				-0.844	-0.047
	(2.275)				(0.804)	(0.045)
L.betweenness X crisis	-3.352				1.352	0.060
	(2.355)				(1.499)	(0.083)
L.eigenvector		0.327				
		(0.447)				
L.eigenvector X crisis		-0.597				
		(0.529)				
L.closeness			0.529			
			(0.366)			
L.closeness X crisis			-0.503			
			(0.405)			
L.degree				0.185		
				(0.188)		
L.degree X crisis				-0.282		
				(0.213)		
L.mtb	0.013	0.011	0.011	0.011	-0.015***	-0.001***
	(0.011)	(0.011)	(0.010)	(0.011)	(0.005)	(0.000)
L.TA	0.064***	0.062***	0.055***	0.059***	0.013**	0.000
	(0.016)	(0.016)	(0.015)	(0.015)	(0.006)	(0.000)
L.TA^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.TA^3	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.leverage	0.001	0.000	0.001	0.001	0.003*	0.000**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.000)
L.sigma	0.934***	0.934***	0.928***	0.932***		
	(0.087)	(0.086)	(0.086)	(0.086)		
Fixed effects			Year, Country, Specialization			
Cluster	Bank	Bank	Bank	Bank	Bank	Bank
Adj. R^2	0.405	0.405	0.406	0.405	0.701	0.631
N	763	763	763	763	771	771