Bank Relationships, Business Cycles, and Financial Crisis

Galina Hale*

Federal Reserve Bank of San Francisco

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Abstract

Recent literature argues that the structure of a banking network is important for its stability. We use network analysis to formally describe bank relationships in the global banking network between 1980 and 2009 and analyze the effects of recessions and banking crises on these relationships. We construct a novel data set that builds a bank-level global network from loan-level data on syndicated loans to financial institutions. Our network consists of 7938 banking institutions from 141 countries. We find that the network became more interconnected and more asymmetric, and therefore potentially more fragile, prior to 2008, and that its expansion slowed in recent years, dramatically so during the 2008-09 crisis. We use a stylized model to describe potential effects of banking crises and recessions on bank relationships. Empirically, we find that the structure of a global banking network is not invariant to banking crises nor to recessions, especially those in the United States. While recessions appear to encourage banks to make new connections, especially on the periphery of the network, the global financial crisis of 2008-09 made banks very cautious in their lending, meaning that almost no new connections were made during the crisis, particularly in 2009. We also find that during country-specific recessions or banking crises past relationships become more important as few new relationships are formed.

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*Galina.b.hale@sf.frb.org.

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1 Introduction

In the wake of the global financial crisis, the complex structure of bank relationships started to garner attention in the literature. One direction of this analysis turned to representing banking systems as graphs, or a networks, to explore how the structure of the banking network is related to its fragility and to the mechanism of the propagation of shocks.[1]

While the literature on this topic is still relatively young, one conclusion seems clear — the structure of the banking network matters for the stability of the banking system and for the potential spread of contagion. There is also some recent evidence that bank relationships are an important determinant of international capital flows. Given this importance of bank relationships that form banking networks, we attempt to understand the effects of economic and financial shocks on bank relationships in a stylized model in which bank relationships arise endogenously and respond to shocks. We use micro-level data on international syndicated bank loans to construct a global banking network, analyze the dynamics of its structure, and address the following specific questions: Do U.S. recessions negatively affect bank relationships? Did global financial crisis do more damage than a regular recession? Do recessions and banking crises in other countries negatively affect bank relationships?

Many recent papers on financial networks analyze the potential for the spread of contagion in various exogenous network structures using simulation methods (Battiston et al., 2009; May & Arinaminpathy, 2010; Mirchev et al., 2010; Nier et al., 2007; Sachs, 2010). Others empirically analyze the structure or the development of country-specific and global banking networks (Cocco et al., 2009; Craig & von Peter, 2010; Garratt et al., 2011; von Peter, 2007). A handful of papers model

[1] Some recent papers are Chan-Lau et al. (2009); Haldane (2009) and Haldane & May (2011). The application of the network approach to financial markets follows recent literature on networks in social interactions and firm theory. Karlan et al. (2009) offers a theoretical model of networks in social interactions, while papers by Bottazzi et al. (2009); Guiso et al. (2009) and Lehmann & Neuberger (2001) provide some discussion of the importance of trust and social interactions for investment, economic exchange, and lending. The work on social capital pioneered by Putnam (1995) is the seed of much of this literature.

how relationships between banks form networks endogenously (Allen & Gale, 2000; Castiglionesi & Navarro, 2007; Delli Gatti et al., 2010). The findings of our paper suggest that the structure of a global banking network responds to economic and financial shocks and therefore it may not be appropriate to model banking networks as static and exogenous in a dynamic setting, especially when analyzing the effects of financial shocks.

Unlike some recent empirical analysis of banking and financial networks that build on aggregate country-level bilateral bank lending from the Bank for International Settlements (BIS) data and bilateral asset holdings from the International Monetary Fund's (IMF) Coordinated Portfolio Investment Survey (CPIS) (Garratt et al., 2011; Kubelec & Sá, 2010; Minoiu & Reyes, 2011; von Peter, 2007), this paper constructs a global banking network at the bank level. We use loan-level data from Loan Analytics provided by Dealogic, something that has not been done before.[2] There are two main reasons why loan-level data are more suitable for the construction of the network than BIS statistics. First, the BIS reports stocks of claims and does not provide information on the origination time of these claims. The BIS computes "flows" as a change in stocks, and therefore such flows include, in addition to loan origination, repayments and changes in valuations of these stocks. As a result, such data cannot provide clean information on the formation of new relationships between banks (or countries, in case of BIS data). Second, country-level data do not distinguish between cases with many loans of smaller amounts made in many different pairs of banks and cases where only a few large loans are made between a small number of bank pairs. Loan-level data address both of these concerns — they give the date of the loan origination and allow us to compute network statistics at the bank level before aggregating them to the country level.

The Loan Analytics database provides information on syndicated banks loans, including those

[2]Craig & von Peter (2010) use data from the German interbank market to test for tiering in the banking network; Cocco et al. (2009) build, for the Portuguese interbank market, "borrower preference" and "lender preference" indexes based on loans between banks, but do not go so far as to create a network of banks, which would take into account indirect relationships.

extended to financial institutions. For our purposes, syndicated loans are a good proxy for bank relationships because they tend to be of much longer maturities than interbank loans and thus represent a larger commitment and the potential for information flows. The bank-to-bank syndicated loan market is relatively large — in the late 1990s syndicated bank loans extended to banks and reported in Loan Analytics amounted to over 30 percent of total bank claims on banks as reported by the BIS. This ratio fell to below 20 percent by the end of our sample as interbank lending ballooned prior to the global financial crisis. In 2007, prior to the crisis, 4.7 trillion USD worth of syndicated loans were extended to banks.

Using these data, we construct a global network of banks in which relationships are formed by banks extending loans to each other. In constructing the network we take into account the direction of the lending and the amount lent. For each bank we then compute a set of statistics that would describe its role in the network. Because we are interested in the dynamics of these network statistics, we construct two panel data sets, each at bank-year level. One, noncumulative panel, is based on the assumption that bank relationships depreciate every year and consists of separate new networks based on loans made in each of the years between 1980 and 2009. The other, cumulative panel, is based on the assumption that bank relationships never depreciate and is constructed by adding new loans to the network that starts in 1980 and expands through 2009. In both cases we compute network characteristics of each bank in each year. We also aggregate this information across banks for each country for each year to construct country-year panel data sets.

First, we analyze the dynamics of the overall network structure and some aspects of network statistics distribution for each year. For the first part of our analysis we use measures that describe the overall network for each year and the distribution of some of the network statistics in each year. This part of the analysis is informal, as we only have one observation or distribution per year. Much attention in the theoretical financial network literature is devoted to network density. Allen

& Gale (2000) showed that increased density of the network tends to lead to a more stable system, but more recently Battiston et al. (2009) demonstrated that if the financial accelerator is taken into account, an increase in network density beyond a certain level would actually increase systemic risk, while Nier et al. (2007) found the opposite relationship — at the low level of connectivity, contagion risk increases as connectivity grows, while it declines when connectivity is already high. In addition, Rotemberg (2008) finds that when banks are more interconnected, the liquidity needs of the system are greater. We observe an increase in noncumulative network density starting about a decade prior to the global financial crisis, suggesting a possibility that this increased density, if indeed associated with higher fragility and greater liquidity needs, could be partly responsible for the dramatic propagation of the global financial crisis in 2008-09.

Sachs (2010) shows that not only the density but also the distribution of linkages in the network matter — the more asymmetric the network, the more fragile it is. We find that asymmetry of the network, in terms of lending, has increased substantially during our sample period, potentially also contributing to the propagation of the crisis. We further demonstrate the effects of recessions and crises on the overall structure of the network: the network expansion slowed in recent years, especially during the 2008-09 crisis; during recessions in the United States, clusters tend to become less common in the network, while the span of the network tends to shrink. We also observe a dramatic decline in the span of the network and the number of new relationships established during the recent global financial crisis.

Before turning to the regression analysis of bank-level network statistics, we present a stylized two-country model of bank relationships that arise endogenously and respond to shocks such as demand, supply, and cost of capital. The model predicts that local recessions in small countries can increase the number of new connections established between the banks initially, but will lower them in the long run. A recession in the United States (a larger country and "the world banker") would increase the number of new connections made because U.S. banks would seek investment abroad. A local systemic banking crisis in a small country, represented by an increase in the cost of funding in this country, would lead to an increase in the number of new relationships formed. A global banking crisis, however, if thought of as a decline in the value of future relationships, would result in fewer new connections.

We next turn to the regression analysis of bank-level network statistics: measures of the number of direct connections established through borrowing and lending for each bank and two measures of centrality of each bank. We test for the effects of U.S. recessions, local small country recessions, local banking crises, and the global 2008-09 financial crisis on these network statistics, controlling for country fixed effects and total borrowing and lending. To distinguish between the existing and newly formed relationships, we conduct our analysis for both cumulative and noncumulative networks, as described earlier.

We find that during U.S. recessions, banks tend to diversify their loan portfolios by making new connections through lending, including to banks on the periphery of the network, which is consistent with the intuition obtained from the model. Even though the recession continued into 2009, we find that in that year banks were cautious in lending, in that they lent to fewer counterparties. Moreover, in 2009 large banks mostly lent to previously established relationship borrowers, and there was less or no lending to banks on the periphery of the network, consistent with our model's prediction for the effects of a global banking crisis. During local recessions, small banks in the affected countries need to be more central to be able to borrow and tend to borrow from lenders they have borrowed from in the past. We also find that small banks in countries with local recessions become less important as intermediaries, consistent with the idea that local recessions destroy existing relationships. We further find that during local banking crises most borrowing in affected countries is conducted by banks that borrow from many lenders. Banks that do lend during banking crises tend to lend to a larger number of borrowers, possibly diversifying away from their own country, but do not form more new lending or borrowing relationships.

We make the following conclusions from the analysis. The structure of the global banking network prior to the global financial crisis has likely made the network more fragile. Recessions, especially those in the United States, as well as banking crises, have an important effect on the development of the global banking network through altering the number of new connections banks make and the ways in which banks make new connections. While recessions appear to encourage banks to make new connections, especially on the periphery of the network, the global financial crisis of 2008-09 made banks very cautious in their lending, meaning that almost no new connections were made during the crisis, especially in 2009, and suggesting that the structure of the global banking network is more sensitive to banking crises than to recessions. We also find that during country-specific recessions or banking crises past relationships become more important as few new relationships are formed. Thus, we show that in addition to real costs of banking crises (Reinhart & Rogoff, 2009; Schularick & Taylor, 2010), there are costs associated with deterioration of bank relationships. More generally, our findings demonstrate that a global banking network is not invariant to economic and financial shocks and therefore should not be taken as exogenous in any dynamic model.

The paper is organized as follows. Section 2 presents our data and methodology, mostly focusing on the construction of the global banking network and the network statistics. Section 3 describes the evolution of the network structure over time. Section 4 presents a stylized model of the formation of bank relationships. Section 5 presents the results of our regression analysis. Section 6 concludes.

2 Constructing global banking network

We assume that each loan from bank to bank creates a relationship, or link, thus contributing to the network. Our data consist of syndicated bank loans with median maturity of about 5 years. Thus, the relationships we define are long-term relationships between banks. Since we do not know how fast the relationships depreciate, we take an agnostic approach and proceed by making two extreme assumptions: one, that bank relationships depreciate fully every year, thus constructing a new global banking network for each year (noncumulative network panel); the other, that bank relationships never depreciate, thus constructing for each year a network by adding new loans to the ones that existed in the prior year (cumulative network panel).

The unit of analysis for noncumulative network will be a network statistic, while for the cumulative network it will be percentage change in a network statistic for each year from previous. In terms of interpretation, the noncumulative network shows what type of relationships were prevalent in each year's borrowing and lending, while changes in the cumulative network demonstrate the impact of newly formed connections on existing network statistics.

2.1 Data sources and manipulation

Dealogic's Loan Analytics database (a.k.a. Loanware) provides information on international syndicated bank loans (with some domestic syndicated loans included as well). It has exhaustive information on the terms of the loan, as well as some information on borrowers and lenders. From this database, we downloaded information on loans extended between January 1, 1980, and December 31, 2009, to private- and public-sector banks, a total of 15,324 loans. Out of these, 84 loans had to be dropped due to missing deal values and 151 had to be dropped due to missing lenders field, which left us with the total of 15089 loans.

Syndicated loans are an important portion of bank-to-bank lending. Figure 1 shows total amount outstanding of claims of BIS reporting banks on banks against the total syndicated loan amount signed to banks from Loan Analytics, as well as their ratio. While these numbers are not directly comparable, because Loan Analytics data do not include repayments, we can still see from the chart that syndicated bank-to-bank lending is a large market.[3]

[3]BIS reports in its Table 10 in the Annex to Quarterly Report "total amount of syndicated loans signed," which

We retained the following variables: name of the borrower or borrowers (327 loans had multiple borrowers), deal nationality, all bank involvement (list of all lenders, administrators, and lead arrangers), loan signing date, and total deal value in millions of U.S. dollars, which we deflate by the seasonally adjusted U.S. consumer price index (CPI) from the U.S. Bureau of Labor Statistics. Since the loans are syndicated, they have on average about seven participants, with the median of two participants. Because information on individual lender participation is only available for a handful of the cases, we split each loan amount equally among lenders and then among borrowers, in the case of multiple borrowers, replicating observations for each borrower-lender pair and dividing the total deal value equally among all pairs. We then collapse our data by borrower-lender pair in each year, adding up the amounts, so that in each year each borrower-lender pair enters only once.

Our list of loans, thus, includes 4880 unique institutions (banks and nonbanks) as lenders only, 2535 unique banks as borrowers only, and 1110 unique banks that appear as both borrowers and lenders, for a total of 8525 banks.[4] For 7938 of the banks we were able to confidently match banks to countries.[5] On average, for each year we have about 500 loans with about 1000 unique participants as either borrowers or lenders from about 70 countries.

2.2 Constructing networks

To construct our noncumulative panel of network statistics, we create a separate network for each year. To do so, for each of the 30 years covered in the data, we create a list that has only three elements: borrower, lender, and nominal loan amount, referred to as the "edge list." Using a

is substantially smaller than what we find in our data. This is because BIS excludes the following loans: all loans with maturity less than three years, all loans where there is only one lender, and all loans where nationality of all lenders is the same as that of a borrower. This excludes a large portion of the loans, especially taking into account that BIS includes loans to nonfinancial institutions in its Table 10 data.

[4]While we are restricting borrower type to be a bank, for technical reasons we cannot restrict lenders to be banks. In our data set, out of 5990 lenders (including those that also appear as borrowers), a maximum of 1710 are nonbanks, e.g., insurance companies and special purpose vehicles.

[5]If a given institution was associated with country X in one observation and country Y in another, we eliminate both observations.

custom Mata code for Stata (Miura, 2010), we create for each year a network and compute network statistics at the network and bank-level as described below.[6] We construct for our regression analysis a bank-year panel, heavily unbalanced, by combining each year's network statistics for each bank in one data set. Table 1 shows the number of loans and banks in each year, as well as some characteristics of the noncumulative panel described below.

For cumulative panel, we create a set of edge lists, where for each subsequent year we add loans to those in previous years. Thus, we have edge lists including loans extended in 1980, 1980 and 1981, 1980 through 1982, etc. all the way through the full set of loans extended between 1980 and 2009. From each edge list we, once again, construct a network, but this time the network is larger every year and the network statistics for year t are based on the network made out of loans between 1980 and t. We combine this information into a cumulative bank-year panel and compute percentage changes in network statistics for each bank for each year from a previous year. The cumulative panel contains more observations because once a bank enters the network, it stays in the network throughout the sample.

Note that our networks are directed, that is the direction of relationship matters, in that bank A borrowing from bank B is not the same as bank B borrowing from bank A. For both noncumulative and cumulative panels we also construct country-level data sets of weighted averages of network statistics using as weights the amounts borrowed and lent by each bank, converted to U.S. dollars using the exchange rate on the day the loan contract was signed and deflated by the monthly U.S. CPI.

[6] We check our computations, when possible, against MatlabBGL version 4.0, which makes use of the Boost Graph Library.

2.3 Network statistics

Some terminology needs to be introduced to describe precisely the network statistics used in this paper. The vertices (nodes) of the network, banks in our case, are indexed by $i = 1, ..., I$. The edges (direct connections) between each pair of nodes i and j, loans in our case, are denoted by c_{ij}, which is binary $\{0, 1\}$. Not every pair of nodes is connected by edges. The edges carry the weights which measure the intensity of the connection, or loan amount, which we denote as w_{ij}. Note that $w_{ij} > 0$ if $c_{ij} = 1$ and $w_{ij} = 0$ if $c_{ij} = 0$. The edges are directed so that $c_{ij} \neq c_{ji}$ and $w_{ij} \neq w_{ji}$. We will denote c_{ij} and w_{ij} as connections going from node i to node j, i.e. a loan from bank i to bank j.

A *path* between each pair of nodes i and j is a sequence of edges that connect i to j. There could be many paths connecting each pair of nodes and, because the network is directed, paths from i to j do not generally coincide with paths from j to i. For our purposes, the *length* of a path is the number of edges that comprise that path regardless of the weight; the weight is only used later when we aggregate network statistics across banks. A *geodesic path* is a path between two given nodes that has the shortest possible length. We denote the *length* of the geodesic path from node i to node j as g_{ij}. Note that each pair of nodes i and j can have more than one geodesic path which will, by definition, have the same length. Because the network is directed, there are pairs of nodes for which there is a path in one direction but not in the other. We denote the *number* of geodesic paths from i to j as p_{ij}. We denote the number of geodesic paths that go from i to j *through* k as p_{ikj}.

We first construct the statistics that describe the network as a whole

- **Density** is the number of edges as a share of possible number of edges: $\sum_i \sum_j (c_{ij} + c_{ji})/(N(N-1))$. Density is $\in [0; 1]$ and describes how connected the nodes are within the network, it is sometimes referred to as connectivity or connectedness of a network;

- **Diameter** is the length of the longest geodesic path in the network: $\max_{ij} g_{ij}$. It measures the span of the network;

- **Global clustering coefficient** is the number of closed triplets over total number of triplets in the network, where a closed triplet is a triplet of nodes with density 1;

- **Average local clustering coefficient** is computed for each node as the density of the network composed of the node's immediate neighbors and is averaged across nodes.

We next calculate the following measures for each node:

- **OutDegree** is the number of edges originating from node i: $\sum_i c_{ij}$;

- **InDegree** is the number of edges terminating in node i: $\sum_i c_{ji}$;

- **OutFarness** is the length of an average geodesic path originating from node i: $\sum_j g_{ij} / \sum_j (p_{ij} + p_{ji})$;

- **InFarness** is the length of an average geodesic path terminating in node i: $\sum_j g_{ji} / \sum_j (p_{ij} + p_{ji})$;

- **Betweenness** is the average ratio of geodesic paths between any pair j and k that go through node i to the total number of geodesic paths between j and k: $\sum_j \sum_k (p_{jik}/p_{jk})$.

In- and outdegree statistics measure how many direct connections each bank has in terms of borrowing and lending, respectively. Infarness, outfarness, and betweenness are measures of centrality of a bank. Farness measures how remote the bank is from the center of the network, while betweenness measures how central the bank is in terms of intermediating bank flows. These two measures are not highly correlated: betweenness tends to be high for banks that connect two separate clusters within the network and are not necessarily close to the highly clustered network center.

Table 2 summarizes node-level statistics for cumulative and noncumulative networks overall, and for U.S. banks only, for comparison. We can see that U.S. banks tend to have fewer direct connections and are more central in terms of farness, but less central in terms of betweenness than the average bank in the network. Table 3 shows overall correlation coefficients between our five node-level network statistics for cumulative and noncumulative panels.

To aggregate network statistics by country-year, we construct average network statistics for each country-year as weighted averages, using as weights total lending of each bank in this year for outdegree and outfarness, total borrowing of each bank in this year for indegree and infarness, and the sum of lending and borrowing for betweenness. For the cumulative network panel we compute year-to-year percentage changes in statistics at the bank level prior to aggregation.

2.4 Recessions and banking crises

To identify years with recessions in the U.S., we use NBER recession dates. To identify local recessions we use data on real GDP growth from the IMF's International Financial Statistics (IFS) (line 99b) with missing observations filled in with World Economic Outlook (WEO) data if available. Since IFS does not report the data for Iceland and Taiwan, we take these series entirely from WEO. We construct the indicator of local recessions as equal to one whenever the GDP growth rate is below its linear trend, which is a broader definition than is commonly used but a transparent one and feasible to compute for most countries.[7] Dates of systemic banking crises are taken directly from Laeven & Valencia (2008).

Table 4 presents the number of local recessions and banking crises per year, as well as an indicator of the US recession. Note, importantly, that given our data source for banking crises, 2008 and 2009 are not coded as banking crises in any country. This is not a problem, however,

[7] For the US, 1995, 2002, and 2007 are classified as recession years by our definition, in addition to all the years identified as recession years by NBER.

because in all regressions we will include dummy variables for 2008 and 2009. In the regression analysis we lag recession indicators and a banking crisis indicator by one year.

3 Evolution of the global banking network

We begin our analysis informally, by plotting network characteristics and average node-level characteristics for each year for cumulative and noncumulative networks over time to see any trends in these characteristics and the effects of U.S. recessions and of the global financial crisis in 2008-2009.

The charts for our informal analysis are presented on Figures 2-5. The top panel in each figure presents year-on-year percentage changes in each of the statistics from our cumulative network panel, while the bottom panel presents actual network statistics and unweighed means of node-level statistics for each of the years in the noncumulative network panel. Because the percentage changes are very high and volatile in the first few years of the cumulative network, we only plot charts starting in 1985 for the cumulative network panel, while we start from 1980 for the noncumulative network.

Figure 2 shows the evolution of the global banking network size and density. The top panel shows that the expansion of the network over the years has slowed down: if in the late 1980s and early 1990s over 10 percent of banks and edges were added to the network each year, less than 5 percent of banks and edges were added each year since 1997. There does not appear to be a noticeable effect of U.S. recessions, and, while the pace of network expansion declined in 2008 and 2009, it is hard to tell without observing post-crisis data whether this decline was due to a continuing downward trend or whether it was crisis-specific. The density of the network declined throughout the period, as one would expect when the network is growing. As the network's pace of expansion slowed down so did the pace of decline of the network density.

The bottom panel of Figure 2 shows the size of the network constructed from only new loans in each year — the noncumulative network panel. This information, along with other measures, is also presented in Table 1. We can see that there was a spike in participating banks in the mid-1990s, but otherwise the number of banks in each year's network was around 1000 since the mid-1980s until 2009, when it dropped drastically to 557, even though almost the same number of loans was made in 2009 as was in previous years. We can also see that the newly formed networks became more dense in the last decade as the number of banks fell, while the number of connections remained more or less the same as in the previous period. This means that prior to the global financial crisis of 2008-09, most lending and borrowing was conducted by more interconnected banks, which made the global banking network potentially more fragile. As the number of edges dropped dramatically from almost 3000 in 2008 to less than 1000 in 2009, network density also fell in that year.[8] There is also some tendency for the edge count and therefore density to decline around U.S. recessions, but it is not very pronounced.

Figure 3 shows changes in the network clustering over time. These measures show how common the clusters are within the global network in which all the banks are connected to each other. Even though both the change in clustering in the cumulative panel and clustering of each year's noncumulative network are rather volatile, we can see quite clearly that both clustering measures tend to decline during U.S. recessions and also declined quite dramatically in the 2008-09 crisis. We can also see more clustering of newly created connections in the decade prior to the crisis. Since the clustering coefficient can be thought of as the local density of the cluster, this also suggests that the global financial network and its parts may have had a more fragile structure prior to 2008.

Figure 4 combines the information on network diameter, a network-level measure, with the unweighed average of node-level farness measures, describing the span of the network. Diameter measures the length of the longest geodesic path in the network, while average infarness and outfarness represent the average length of the geodesic inpaths and outpaths in the network. We

[8]These last two findings are consistent with findings of Minoiu & Reyes (2011) that are based on BIS country-level locational statistics.

can see from the top panel that as our cumulative network grew so did the average path length, while the diameter remained more or less the same. In the bottom panel we see a small upward trend in infarness over the years, suggesting that throughout our sample period more and more of remote borrowers were able to obtain bank credit. We can also see that the span of the network as measured by diameter and farness tend to fall during U.S. recessions and fell particularly sharply during the recent crisis. As one can see from Table 1, the diameter of the noncumulative network was eight in 2007 and fell to five in 2008 and only 4 in 2009. This is consistent with our intuition since banks are likely to be more cautious in dealing with remote borrowers during recessions and in particular during the global financial crisis. This also suggests a propagation mechanism because networks that are more concentrated are prone to larger systemic risk (Nier et al., 2007).

Figure 5 reports unweighed average values of remaining node-level statistics: degree, which is the number of direct connections of each bank, and betweenness, which measures how many paths between all other pairs of nodes go through a given node. Much like the network size, the number of direct connections and betweenness appear to have been growing throughout our sample period, but the growth rate has slowed since 1998. We can see this from the rate of change of these statistics in the cumulative network in the top panel or from the levels of these statistics in noncumulative networks in the bottom panel. It appears that the number of direct links does not increase as fast during U.S. recessions as it does in normal times and that the banks in noncumulative networks formed during recession years tend to have fewer direct links and lower betweenness. It is very clear that in 2008 and 2009 there were basically no new links formed in the cumulative network and the noncumulative networks formed in these years had a lot fewer links on average — this number declined from 4.5 in 2007 to 3.2 in 2008 and only 1.7 in 2009.

Much discussion in the literature has been devoted to the structure of the network, in particular, tiering, core-periphery structure, or asymmetry of the network. One way to measure the presence of such properties is to analyze the skewness of the distribution of the connections in the network.

Figure 6 shows the evolution of the skewness in degree (in- and out-) over time in the cumulative and noncumulative networks. We observe a steady increase in the asymmetry of the network in terms lending throughout the sample period, while the skewness of the distribution of indegree, representing borrowing, remained about the same. We can see a similar pattern (with the exception of the last year in the data) for noncumulative networks, which means that an increase in asymmetry was at least partly due to new connections forming in a more and more asymmetric way, especially after 2009. The fact that an increase in asymmetry in lending is much more pronounced for the cumulative network suggests that a larger share of new connections was formed by banks that already had disproportionately many connections. According to findings by Sachs (2010) this implies that the global banking network became more fragile during our sample period. While the skewness of the degree distribution appears to be pretty much acyclical, there is a pronounced increase in 2009 — when most borrowing and lending was conducted by just a few banks.

To summarize this section: we find that the structure of the global banking network likely became more fragile prior to the 2008-09 crisis and that network expansion slowed in recent years, especially during the 2008-09 crisis. We find that network clustering, average farness, diameter, and the number of direct links tend to decline during U.S. recessions. We also observe a dramatic decline in diameter, betweenness, and the number of direct links during the recent global financial crisis. Moreover, we observe an increase in network asymmetry in terms of lending throughout our sample period with a spike in 2009.

4 A simple model of bank relationships

To fix ideas on how macroeconomic shocks can affect bank relationships, we present a simple model that takes the macroeconomy as given but in which international bank relationships are formed endogenously. In our model banks have to establish relationships with banks in a foreign country in order to finance foreign projects — our short-cut for the idea that banks facilitate capital flows between countries through intermediation or otherwise.

4.1 Model setup with no relationships, one period

Suppose the world consists of two countries, home and foreign. We denote variables pertaining to the foreign country with *. In each country, banks finance investment projects, which have heterogeneous returns R. We assume that banks can perfectly select projects with the highest available return and therefore the return on the marginal project financed is a declining function of the number of projects financed: $R'(x) < 0$, $R''(x) > 0$, where x is the number of projects financed. We allow this function to be different in the foreign country, but have the same properties: $R^{*\prime}(x) < 0$, $R^{*\prime\prime}(x) > 0$. We assume that projects succeed with probability π, and otherwise fail with zero return. We assume that the probability of success is the same in both countries but varies by the state of nature — it can be either high π_H with probability $1 - \rho$ or low π_L with probability ρ. We interpret the state of nature with a low probability of success as recession, and ρ as recession probability. Thus, the expected return on marginal project x is $((1 - \rho)\pi_H + \rho\pi_L)R(x) = \phi R(x)$, where $\phi = (1 - \rho)\pi_H + \rho\pi_L$.

There are N and N^* identical risk-neutral banks in domestic and foreign countries that face exogenous costs of funding: D and D^*, respectively. They decide whether to invest in domestic projects, foreign projects, or not to invest at all. Each bank can only finance one project. In order to invest in a project in a different country, a bank has to pay a fee F to a bank in that country for intermediation. For simplicity, we assume that banks either invest in projects or serve as intermediaries. Since banks that intermediate do not invest their own money, they don't have to pay costs of funding. Thus, we also assume that the cost of intermediation is zero and that the only cost associated with intermediation is an opportunity cost of not being able to finance a domestic project. Banks that choose to invest in foreign projects have to pay an intermediation fee in addition to the cost of funding prior to realization of the return on the project. We denote as

α, α^* the share of banks that finance domestic projects.

Autarky. Suppose N and N^* are sufficiently large so that $\phi R(N) < D$ and $\phi R^*(N^*) < D^*$. Because of an additional fee required to finance foreign projects, in this case α and α^* solve $\phi R(\alpha N) = D$ and $\phi R^*(\alpha^* N^*) = D^*$. This is a market equilibrium as well as the social optimum because only projects with positive expected net returns are financed and all of such projects are financed at a minimum cost. We abstract from the question of which banks do and which do not end up financing projects. One can think of either random or sequential assignment, it does not affect the predictions of the model.

Foreign financing. In order to construct an equilibrium in which foreign financing is present, we simply assume that the foreign country does not have a sufficient number of banks, so that even if all banks engage in financing, the marginal project will still have a positive expected net return, that is $\phi R^*(\alpha^* N^*) > D^*$. One can interpret this assumption in a number of ways: as representing an underdeveloped financial system in foreign country; as representing a lower level of economic development in a foreign country, and thus higher return on investment; as a lower level of savings, for institutional or other reasons, which limits the amount of domestic funds available for investment.

In the home country all projects with positive net expected returns will be financed by home banks, so that α is still given by $\phi R(\alpha N) = D$. For the marginal bank to be indifferent between financing a domestic or a foreign project, the expected return on the foreign project should be equal to the expected return on the home project. These returns will be zero unless there is still a positive net return on foreign projects after all interested home and foreign banks have chosen to invest in them — this case is less interesting, so we assume N is sufficiently large to rule it out. Given that α is the share of home banks investing in domestic projects, denote as $\delta(1-\alpha)$ the share of all domestic banks that choose to invest in foreign projects. This gives us demand for intermediation.

Foreign banks have a choice between financing their domestic projects or intermediating. We assume that all foreign banks that do not invest in domestic projects have an equal chance of intermediating, which they take as given. Thus, in equilibrium foreign banks will be indifferent between the expected returns from investing in their domestic projects and the expected fees from participating in the intermediation lottery. Thus, supply of intermediation is jointly determined with financing of foreign projects by foreign banks.

The total number of home projects financed will still be αN, while the total number of foreign projects financed will be $\alpha^* N^* + \delta(1-\alpha)N$. The equilibrium is thus a triplet $(\alpha, \alpha^*, \delta)$ that solves the following equations

$$\phi R(\alpha N) = D, \tag{1}$$

$$\phi R^*(\alpha^* N^* + \delta(1-\alpha)N) = F + D, \tag{2}$$

$$\frac{\delta(1-\alpha)N}{(1-\alpha^*)N^*} F = \phi R^*(\alpha^* N^* + \delta(1-\alpha)N) - D^*. \tag{3}$$

4.2 Many periods and formation of relationships

To introduce the value of relationships, we need to extend the benchmark model to include multiple periods. To keep the model simple, we will assume that banks that experience a bad realization of the project they finance simply exit and are replaced by the same number of banks that are identical to those remaining. This way, the number of banks in each country remains constant and we don't have to keep track of each bank's status. The only thing that will be carried from one period to the next is relationships established through intermediation.

For the value of the relationship to be positive, we will assume that the cost of intermediation for banks that have already been engaged in the financing of foreign projects is smaller than the cost of intermediation for banks that are entering the market of financing foreign projects. In particular, we will keep the intermediation fee for new entrants at F and will assume that banks that have already established a relationship will only pay $f < F$ in each of the periods when they choose to finance foreign projects. We will make a slight change for the purpose of model interpretation by allowing ϕ in the home country to be different from ϕ^* in the foreign country.

We consider an equilibrium with an interior solution, as above, in each period. Period t will start with $\gamma_t N$ banks in the home country that have financed foreign projects in period $t-1$; γ represents the share of home banks that have established relationships with foreign banks in previous periods. These banks have a lower cost of financing foreign projects in period t than other banks and we assume that they will always choose to finance foreign projects. Thus, $\gamma_t = \pi^*_{t-1}(\gamma_{t-1} + \delta_{t-1}(1-\gamma_{t-1}))$, where π^*_{t-1} is the realization of project success probability in the foreign country in period $t-1$ and is therefore the probability that a bank that established relationships in period $t-1$ will survive in period t, γ_{t-1} is the share of banks that already had relationships at the start of period $t-1$, δ_{t-1} is the share of banks that neither had prior relationships nor were financing domestic projects that chose to finance foreign projects in $t-1$ (and pay the fee F). In each period, therefore, γ is predetermined. Since all time periods are *a priori* identical, we will drop the time subscript.

There is now an additional value to financing foreign projects — the value of relationships that will with probability ϕ^* bring rents next period and in every following period s with probability ϕ^{*s} in the amount of $F-f$. This implies the present value of the relationship, $V_t = \sum_{s=t+1}^{\infty}(F-f) = \frac{\phi^*}{1-\phi^*}(F-f)\ \forall t$.

In the benchmark model, the zero-profit condition for the home banks makes the number of new connections independent of home economic conditions — whenever α changes to satisfy equation (1), δ adjusts accordingly. Since we are interested in the effects of home economic conditions on bank relationship, we make another modification to our benchmark mode here, assuming that regardless of the number of home projects financed they pay fixed returns $\bar{R}$ in the case of success, thus expected return on the home project is $\phi\bar{R}$. We assume that $\bar{R}$ is sufficiently small so that a) home banks with existing relationships still prefer to invest in foreign projects, and b) foreign banks are still not interested in investing in home projects. The choice of α is now irrelevant — share δ of banks that don't have relationship will invest in foreign projects, the rest of them will invest in home projects.

In equilibrium with an interior solution, home banks without relationships will be indifferent between financing domestic projects or foreign projects. Foreign banks with relationships will collect a smaller intermediation fee than banks that provide intermediation for new foreign projects financing banks. To make the model interesting and keep it simple, we will assume that foreign relationship banks all engage in financing of their domestic projects in addition to collecting the fee of f. This assumption represents a possibility that maintaining relationships is less costly for the intermediary than establishing new ones, and thus there is no opportunity cost of maintaining existing relationships.

As before, remaining $N^* - \gamma N$ foreign banks are indifferent between financing their domestic project and entering the lottery for intermediation of new foreign investments by home banks, given that γN domestic projects are already taken by relationship banks. Share α^* of these remaining banks will finance projects, while the rest will enter the lottery. Denote the number of new connections formed as a share of N, $\nu = \delta(1-\gamma)$. Then the total number of foreign projects financed will be $\gamma N + \alpha^*(N^* - \gamma N) + (\gamma + \nu)N$. The equilibrium for each period is thus a pair (α^*, ν) that solves the following equations given γ

$$\phi^* R^*(\Psi) + V = F + \phi\bar{R}, \tag{4}$$

$$\frac{\nu N}{(1-\alpha^*)(N^* - \gamma N)} F = \phi^* R^*(\Psi) - D^*, \tag{5}$$

where $\Psi = \alpha^*(N^* - \gamma N) + (2\gamma + \nu)N$ is the total number of projects in the foreign country that are financed by all banks.

The Appendix shows that this equilibrium will be stable as long as $\phi\bar{R} - D^* > V$ and presents the conditions that need to hold for the solution to be in the interior, that is $0 < \alpha^* < 1$, $0 < \nu < 1$. It also presents all the derivatives used for comparative statics below.

An expected equilibrium path can be computed using the fact that in expectation γ should be the same in all periods. Thus an expected equilibrium path is values of (α^*, ν, γ) that solve equations (4)-(5) and

$$\gamma = \phi^*(\gamma + \delta(1 - \alpha - \gamma)) = \phi(\gamma + \nu). \tag{6}$$

We will interpret changes to one-period equilibrium described by equations (4)-(5) as short-run effects and changes to the expected equilibrium path as long-run effects.

4.2.1 Interpretation and comparative statics

We will now consider the interpretation of our model and the implications of parameter changes for the expected equilibrium path as well as for each period's equilibrium. As we are interested in banking crises and business cycles, we consider the effects of the following perturbations:

Recession-demand: a bad state of nature (realization $\pi = \pi_L$) could be thought of as a recession that is due to an adverse demand shock, as fewer projects are successful. The only effect of such a shock in a foreign country will be to lower γ in the beginning of the period. We can also think of a permanent adverse demand shock that would increase ρ, a probability of the bad state of nature, and thus lower ϕ in case of the home country and ϕ^* in case of the foreign country.

Recession-supply: we can model a supply-side recession as a decline in returns on projects for any given number of projects financed, that is, decline in $R(\cdot)$ or $R^*(\cdot)$.

Cost of funding: we can think of an increase in the cost of funding D and D^* as banking crises in home and foreign countries, respectively.

Intermediation fees: we can think of a global banking crisis as an increase in the costs of intermediation, especially in the cost of establishing new connections, F, which can be interpreted as an increased counterparty risk premium, although we do not model such risk specifically. An increase in f for a given F can be thought of as a decreased value of relationships for lenders, which could also be an outcome of a crisis in banks' confidence.

The Appendix shows formally the effects of these perturbations on the number of new connections formed, ν. Here we provide an informal discussion and intuition of the results.

A temporary adverse demand shock in the foreign country would lead to a larger than usual destruction of existing relationships, both in home and in foreign countries. As a result, more new connections will be made in the following period. A permanent adverse demand shock in the foreign country, that is, a lower average probability of project success, would lead to a decline in the number of new connections made, both in the short and, to a lesser extent, in the long run. A permanent adverse supply shock in the foreign country, that is, a lower return on projects for any given number of projects financed, would lead to a decline in the number of new connections made both in the short and the long run.

Overall, the model predicts that while a temporary demand shock would lead to an increase in the number of new connections, recessions that are more long-lasting, regardless whether they are demand- or supply-driven, will result in the reduction of the number of new connections. The intuition from this result is as follows — temporary shocks may destroy existing connections that need to be replaced, giving a temporary boost to the number of new connections made. In the long run, however, a reduction in profitability of investing in the foreign country is more important, reducing the incentive for home banks to form new connections.

Permanent adverse demand or supply shocks in the home country increase the number of new connections formed as more home banks turn to financing foreign projects due to a now lower opportunity cost of not investing in home projects.

A local banking crisis exhibited as an increase in the cost of funding in the foreign country will give comparative advantage to home banks and therefore lead to an increase in the number of new connections formed. While in our benchmark model an increase in the cost of funding in the home country would lower the number of new connections formed by giving comparative advantage to foreign banks, in this set-up home banks incur the same cost of investing in home and in foreign projects and therefore this cost has no effect on the number of new connections.

An increase in the cost of intermediation holding the value of relationship constant has an ambiguous effect on a number of connections formed. This result comes from the fact that home banks are discouraged from forming new connections by the higher intermediation fee, while at the same time the intermediation fee is received by foreign banks as pure rent and thus an increase in this fee reduces the number of foreign banks that are willing to finance their domestic projects. For the resulting effect to decrease the number of new connections formed we would need to assume that return on foreign projects declines quickly with an increase in the number of projects financed, so that the effect on home banks dominates. A decline in the value of the relationship holding the intermediation fee constant would lead to fewer new connections made, quite intuitively.

Translating these findings to empirical terms,we interpret the home country as the U.S., or a core country in the global banking network. We find that local recessions in countries other than U.S. are likely to increase the number of new relationships established by banks initially, but then lower it as lost connections are replaced. A recession in the U.S. would increase the number of new connections made by U.S. banks. A local banking crisis that results in a higher cost of funding for banks would lead to an increase in the number of new relationships formed. In case of a global banking crisis, which we could think of as a destruction of trust between banks that lowers the value of relationships, fewer new connections will be made.

The above model does not create a network of relationships, but it is clear that it could be extended to include more countries. Differences in the returns to projects, in costs of funding, as well as the wedge that arises from intermediation fees would allow for a given country's banks to receive foreign investment from a country with more banks while at the same time investing in the country with fewer banks. Consistent with findings in the literature that banking networks tend to have a core-periphery structure, we would obtain a network with countries that only receive funding on the periphery and countries that receive funding and also fund foreign projects in the core. All of the intuition obtained in the two-country model could readily be extended to such a network.

5 Regression analysis

A natural measure of what in the model we call a number of connections is outdegree for lenders and indegree for borrowers. For additional insights, we also analyze two measures of centrality: farness (which we can separate into infarness and outfarness) and betweenness, as described earlier. The analysis of centrality measures allows us to distinguish the effects that recessions and crises have on banks that are in the center versus the periphery of the network.

We now turn to regression analysis to verify the above observations with respect to the dynamics of the network structures and to see whether the predictions of our model are consistent with the data. Since network-level measures don't vary by country, we have to limit our analysis of the effects of country-specific recessions and banking crises to the node-level statistics. We conduct our analysis in two parts: first at a country level, using country-year weighted averages of node-level network statistics; second, to isolate composition effects, at the bank level, clustering standard errors on country to avoid downward bias (Moulton, 1990). The results are reported in Tables 5 through 8.

5.1 Country-level regressions

For the regressions in Tables 5 and 6 we aggregate network statistics across banks for each country and year using as weights each bank's lending in constant U.S. dollars for out- measures, borrowing for in- measures, and the sum of borrowing and lending for betweenness. Table 5 reports the results for the noncumulative network panel, where the level of network statistics for each year is on the left-hand side, in logs. Table 6 reports the results for the cumulative panel, where year-on-year percentage changes in network statistics are on the left-hand side. These percentage changes are computed at the bank level and then aggregated for each country and year. Both tables include indicators of U.S. recessions, local recessions, local banking crises, dummies for 2008 and 2009, and linear trend as explanatory variables. All regressions include country fixed effects.

Overall trends are consistent with the evolution of the network size presented in Figure 1. We can see that the network expanded over time: we observe an increase in outdegree, outfarness, and betweenness, as indicated by positive coefficients on trend in Table 5 and positive constant term in Table 6. Cumulative panel analysis also shows an increase in indegree and infarness. We can further see that the pace of increase of all network measures slowed throughout the sample period, as indicated by negative coefficients on trend in Table 6, where the dependent variable is a change in network characteristics.

Focusing first on the results with respect to the number of new connections, as measured by indegree and outdegree, we observe patterns that are consistent with our model predictions. During recessions in the United States we find that lenders tend to lend to more banks on average, and specifically tend to establish more new connections, relative to trend (coefficients on U.S. recession indicator are positive and statistically significant in both noncumulative and cumulative regressions). In 2008 and especially in 2009, however, we also observe the effects of the global financial crisis — the total number of connections and the number of new connections declined in these years. Since these years are also classified as recessions in U.S., coefficients on 2008 and 2009 indicators can be interpreted as pure effect of the global financial crisis. Adding up the coefficients, we can see that the overall effect was negative in 2009, thus the global financial crisis effect clearly dominated recession effects.

Local recessions do not seem to alter significantly the pattern of new connections in either specification. We observe an increase in the average number of connections of the banks in countries affected by systemic banking crises, but no increase in the number of new connections made, through borrowing or lending. This finding is consistent with the composition effect — banks that lend or borrow during local banking crises in their countries are banks that had a larger number of existing connections, which is also broadly consistent with our model. In addition, we observe a decline in average indegree during U.S. recessions — banks that borrow during these periods are banks that have fewer connections, suggesting that lenders are not only looking to make new connections, but are seeking to lend to banks that are less connected.

Turning to the results with respect to centrality, we find that lending in networks that are formed during U.S. recessions does not extend as much to periphery banks (infarness is smaller), that banks that are further from the center of the network lend more (outfarness is higher), and at the same time betweenness is lower, which is consistent with lower clustering in the network overall, as betweenness tends to be high for banks that connect different clusters within the network. That is, networks built during U.S. recessions tend to be dominated by banks that are less remote as borrowers but more remote as lenders. These networks also rely more on direct connections, as betweenness is lower on average. These effects were reversed in 2009, when we observe that most lending was conducted by banks that were more central to banks that were more remote (positive coefficient on infarness and negative coefficient on outfarness in Table 5). Consistently, new connections established in 2008 increased the average remoteness of borrowers (positive coefficient on infarness in Table 6), while connections added in 2009 lowered the remoteness of lenders (negative coefficient on outfarness in Table 6).

We find that banks in countries with country-specific recessions tend to have lower betweenness, possibly because they are not able to intermediate capital flows as efficiently during their country's recessions, or because their borrowers and lenders find counterparties in countries not affected by recessions. Local banking crisis places a country's lenders and borrowers more to the periphery of the network, as indicated by positive coefficients on infarness and outfarness in Table 5, but it appears that only banks that were more central than average based on past connections are able to make new connections (coefficients on infarness and outfarness in Table 6 are negative).

Magnitudes of the coefficients can be interpreted as follows. Since our regressors are 0/1 indicators, we can compare coefficients in noncumulative network regressions to the moments of the dependent variables reported in Table 2. We can see that some of the coefficients are large — increase in infarness and decline in outfarness in 2009 are almost as large as two standard deviations of these variables. In the cumulative network regressions the dependent variable is a percentage change in network statistics, thus coefficients simply tell us by how many percentage points these statistics change as a result of recessions and banking crises relative to (quadratic) trend. For instance, outdegree tends to increase by 5 percentage points during U.S. recessions, which is roughly equivalent to the average annual increase in outdegree in the second half of our sample period (see top panel of Figure 5).

To tie these results together, it appears that during U.S. recessions banks tend to diversify their loan portfolios by making new connections through lending, including to banks on the periphery of the network. This observation is consistent with the possibility that banks are diversifying away from lending to U.S. banks, since, as we saw in Table 2, maximum infarness for U.S. banks is substantially lower than the network average (3.7 vs. 4.8), indicating that U.S. banks are on average more central. Even though 2009 was also a recession year in the U.S., we find that in 2009 banks were cautious in lending, in that they lent to fewer counterparties. Moreover, large banks mostly lent to previously established relationship borrowers, and there was less or no lending to banks on the periphery of the network. This latter observation is consistent with our intuition, as well as with the results of our informal analysis, where we found a decline in diameter, a slowdown in network expansion, and a decline in the number of direct links during the financial crisis.

Our findings that infarness and outfarness and in some cases indegree and outdegree respond differently to external shocks also have a methodological implication. Analyzing banking networks, empirically or via simulations, it may be important to model networks as directed, the way we do in this paper, taking into account the direction of lending flows, because some of the effects modeled in undirected network may cancel out.

To assure the robustness of our findings, we attempted additional specifications, most importantly controlling for total borrowing or lending or the sum of the two, depending on the left-hand-side measure. Our results are not at all affected by including these controls and they do not enter significantly, which is why we do not include them in our reported results. We also experimented with excluding offshore financial centers and the United States from the regressions, as well as excluding the first five years of our sample. The results remain the same, indicating that neither the United States nor offshore financial centers, nor highly volatile early periods of our sample are driving our findings. These results are not reported in the interest of space but are available upon request.

5.2 Bank-level regressions

Because the above results may be driven by changes in relative weights of banks with different network characteristics rather than by network characteristics themselves, we repeat the above analysis in bank-level regressions with no weights. Comparing the above results with bank-level regression results allows us to identify whether the above results are driven by changes in weights or changes in network statistics. We continue to view the above results as benchmark, because from the country point of view, which is a unit of our analysis, weighted averages of network measures are more meaningful.

Results of bank-level regressions are reported in Tables 7 and 8. The right-hand side variables are the same as before, including country fixed effects, but now we also add controls for a country's total lending, borrowing, or the sum of the two. While in the country-level regressions these controls were not significant and did not affect the results, now we find that they matter and report the results with these controls. Note that including these controls takes away the trend effect in the noncumulative levels regressions, since lending and borrowing both increase over time, but not the second time derivative — the trend effects are significant in the cumulative regressions where the left-hand-side variables are percentage changes in network characteristics. All bank-level regressions' standard errors are clustered on country.

Some of the results in bank-level regressions are consistent with those obtained in country-level regressions, while others are different. Because of the difference in weights, differences in results could be interpreted as being driven by larger or smaller banks. For example, if we observe a significant effect in the country-level but not in the bank-level regression, we can infer that the result is driven by a few banks that were bigger lenders or borrowers. If, instead, we observe a significant effect in the bank-level but not in the country-level regression, we can infer that the result is driven by banks that were small borrowers or lenders and therefore did not enter in an important way into the country-level analysis.

Consistent with our model predictions and with the results in the country-level regressions, we find that more connections on average and more new connections were made during U.S. recessions and that there were fewer connections on average in 2009. Similarly, consistent with country-level results, we find that more lending, in particular more new lending, during U.S. recessions is conducted by periphery banks, while in 2009 banks that were more central before were the ones lending. We also continue to find that during the global financial crisis more loans went to periphery banks. Finally, only banks that are near the periphery of the network and those that had already relatively more direct connections were lending during banking crises in their countries.

One of the important differences is an increase in indegree above trend in the bank-level cumulative panel regression in 2009, which we did not find in country-level regressions. It appears that in 2009 small banks had to borrow from new lenders, while large banks could continue to borrow from the ones they borrowed from previously. While we found no effect of local recession on new connections in country-level regressions we now find in the cumulative panel, Table 8, that during local recessions banks in the affected countries approached fewer new lenders and were more central in terms of borrowing but less central in terms of betweenness. This implies that during local recessions small banks in the affected countries need to be more central to be able to borrow, that they borrow mostly from lenders that they have borrowed from in the past, and that small banks in countries with local recessions become less important as intermediaries.

While we found an increase in indegree and infarness during local banking crisis in country-level regressions, we found no such effects in bank-level regressions, suggesting that during local banking crises larger banks from the periphery of the network borrow more and become more central in terms of borrowing. Also in contrast with country-level results, we do not observe any effects of local banking crises on new connections formed by banks in affected countries compared to trend.

6 Conclusion

In this paper we introduced formal measures to describe bank relationships in the global banking network. Using loan-level data, we constructed networks for each of the years between 1980 and 2009 and computed network statistics for each of the banks that appeared as either a borrower or a lender in the syndicated loan market during our sample period. We find that the expansion of the global banking network has slowed in recent years, dramatically so during the global financial crisis. We also find that prior to the global financial crisis the network became more dense, more clustered, and less symmetric, all of which is likely to have increased its fragility and potential for contagion. It is reasonable to conclude, therefore, that the structure of the global banking network was indeed one of the culprits in the rapid spread of the global financial crisis.

We find that recessions, especially those in the United States, as well as banking crises have an important systematic effect on the development of the global banking network through altering the ways in which banks make new connections. While recessions appear to encourage banks to make new connections, especially on the periphery of the network, the global financial crisis of 2008-09 made banks very cautious in their lending, meaning that almost no new connections were made during the crisis, especially in 2009. We also find that during country-specific recessions or banking crises, past relationships become more important as few new relationships are formed. These findings are consistent with predictions of our stylized model in which bank relationships form endogenously and respond to shocks.

Our findings have two important implications. A methodological implication is that the structure of a global banking network responds to economic and financial shocks, and it may therefore not be appropriate to model banking networks as static and exogenous in a dynamic setting, especially when the effects of financial shocks are analyzed. A policy-related implication is that, while banking crises are more likely to spread faster through a more concentrated network, as prior literature shows, banking crises themselves make the network more concentrated, thus accelerating the propagation of the crisis. Thus, policies that encourage less concentration in a banking network have the potential to increase its stability.

References

Allen, F. & Gale, D. (2000). Financial contagion. *Journal of Political Economy*, *108*, 1–33.

Battiston, S., Delli Gatti, D., Gallegati, M., Greenwald, B. C., & Stiglitz, J. E. (2009). Liaisons dangereuses: Increasing connectivity, risk sharing, and systemic risk. NBER Working Paper 15611.

Bottazzi, L., Da Rin, M., & Hellmann, T. (2009). The importance of trust for investment: Evidence from venture capital. CentER Discussioin Paper No. 2009-43, Tilburg University.

Castiglionesi, F. & Navarro, N. (2007). Optimal fragile financial networks. Tilburg University Center for Economic Research Discussion Paper 2007-100.

Chan-Lau, J., Espinosa-Vega, M. A., Giesecke, K., & Solé, J. (2009). *Assessing the Systemic Implications of Financial Linkages*, volume April, chapter 2. International Monetary Fund.

Cocco, J. a. F., Gomes, F. J., & Martins, N. C. (2009). Lending relationships in the interbank market. *Journal of Financial Intermediation*, *18*, 24–48.

Craig, B. & von Peter, G. (2010). Interbank tiering and money center banks. BIS Working Paper 322.

Delli Gatti, D., Gallegati, M., Greenwald, B., Russo, A., & Stiglitz, J. E. (2010). The financial accelerator in an evolving credit network. *Journal of Economic Dynamics and Control*, *34*(9), 1627–50.

Garratt, R., Mahadeva, L., & Svirydzenka, K. (2011). Mapping systemic risk in the international banking network. Bank of England Working Paper 413.

Guiso, L., Sapienza, P., & Zingales, L. (2009). Cultural biases in economic exchange. *Quarterly Journal of Economics*.

Haldane, A. G. (2009). Rethinking the financial network.

Haldane, A. G. & May, R. M. (2011). Systemic risk in banking ecosystems. *Nature*, *469*, 351–355.

Karlan, D., Mobious, M., Rosenblat, T., & Szeidl, A. (2009). Trust and social collateral. *Quarterly Journal of Economics*.

Kubelec, C. & Sá, F. (2010). The geographical composition of national external balance sheets: 1980-2005. Bank of England Working Paper No. 384.

Laeven, L. & Valencia, F. (2008). Systemic banking crises: A new database. IMF working paper 08/224, International Monetary Fund.

Lehmann, E. & Neuberger, D. (2001). Do lending relationships matter? evidence from bank survey data in germany. *Journal of Economic Behavior and Organization*.

May, R. M. & Arinaminpathy, N. (2010). Systemic risk: the dynamics of model banking systems. *Journal of the Royal Society Interface*, *7*, 823–838.

Minoiu, C. & Reyes, J. A. (2011). A network analysis of global banking: 1978-2009. IMF Working Paper 11/74.

Mirchev, L., Slavova, V., & Elefteridis, H. (2010). Financial system transformation: A network approach. Working Paper.

Miura, H. (2010). Network sgl: Stata graph library for network analysis. Technical report, Federal Reserve Bank of San Francisco, San Francisco, CA. under review by the *Stata Journal*.

Moulton, B. R. (1990). An illustration of a pitfall in estimating the effects of aggregate variables on micro units. *The Review of Economics and Statistics*, *72*(2), 334–338.

Nier, E., Yang, J., Yorulmazer, T., & Alentorn, A. (2007). Network models and financial stability. *Journal of Economic Dynamics and Control*, *31*(6), 2033–60.

Putnam, R. (1995). Bowling alone: America's declining social capital. *Journal of Domocracy*.

Reinhart, C. M. & Rogoff, K. S. (2009). The aftermath of financial crises. Paper prepared for presentation at the American Economic Association meetings in San Francisco.

Rotemberg, J. J. (2008). Liquidity needs in economies with interconnected financial obligations. NBER Working Paper 14222.

Sachs, A. (2010). Completeness, interconnectedness and distribution of interbank exposures a parameterized analysis of the stability of financial networks. Deutsche Bundesbank Duscussion Paper 08/2010.

Schularick, M. & Taylor, A. M. (2010). Credit booms gone bust: Monetary policy, leverage cycles and financial crises, 1980-2008. Paper presented at the FRBSF conference on Monetary Economics.

von Peter, G. (2007). International banking centres: a network perspective. *BIS Quarterly Review*.

Appendix

Here we show the conditions for our full model equilibrium to be stable and for the interior equilibrium, that is $0 < \alpha^* < 1$ and $0 < \nu < 1$, and the derive comparative statics discussed in the text. Remember that equilibrium is described in the short run by equations (4)-(5) given γ.

Let $\xi = R^{*-1}\left(\frac{F+\phi\bar{R}-V}{\phi^*}\right)$ with $\partial R^{*-1}(x)/\partial x = G < 0$. Recall that

$$\Psi = \alpha^*(N^* - \gamma N) + (2\gamma + \nu)N.$$

Thus, we can rewrite (4) as

$$\alpha^* = \frac{\xi - 2\gamma N}{N^* - \gamma N} - \frac{N}{N^* - \gamma N}\nu. \tag{7}$$

Substituting (4) into (5) and rearranging, we get

$$\alpha^* = 1 - \frac{N}{(N^* - \gamma N)y}\nu, \tag{8}$$

where $y = (F + \phi\bar{R} - V - D^*)/F$.

We can solve these two equations to obtain the short-run solution

$$\alpha^{*SR} = \frac{y(N^* - \gamma N) - (\xi - 2\gamma N)}{(N^* - \gamma N)(y-1)}, \tag{9}$$

$$\nu^{SR} = \frac{y(\xi - \gamma N - N^*}{N(y-1)}. \tag{10}$$

One can show graphically that the equilibrium is stable if (7) is steeper than (8), that is $y > 1$, which means that $\phi\bar{R} - V - D^* > 0$. We can also simply show that both $0 < \alpha* < 1$ and $0 < \nu < 1$ if the following binding conditions hold:

$$\xi > N^* + \gamma N,$$

$$y - 1 > \frac{\xi - (N^* + \gamma N)}{N^* - \gamma N} > 0.$$

We can also derive

$$\frac{\partial \nu^{SR}}{\partial \gamma} = -\frac{y}{y-1} < 0,$$

since $y > 1$ is required for stability of the equilibrium and for interior solution.

In the long run, (6) has to also hold, which implies that

$$\gamma = \frac{\phi^*}{1 - \phi^*}\nu. \tag{11}$$

Note that γ is not a function of α^*. Thus, we can simply substitute (11) into (10) to obtain

$$\nu^{LR} = \frac{y(\xi - N^*)(1-\phi^*)}{N(y-1+\phi^*)}. \tag{12}$$

We now derive comparative statics for ν^{SR} and ν^{SR} with respect to parameters of the model. We have already shown that $\partial\nu^{SR}/\partial\gamma < 0$. The rest follow:

$$\frac{\partial\nu^{SR}}{\partial\phi^*} = \frac{1}{N(y-1)^2(1-\phi^*)}\left[\frac{(F-f)(\xi-\gamma N-N^*}{F(1-\phi^*)} - G\frac{y(y-1)(F+\phi\bar{R}-(2F+\phi\bar{R}-f)\phi^{*2}}{\phi^{*2}(1-\phi^*)}\right] > 0;$$

$$\frac{\partial\nu^{LR}}{\partial\phi^*} = \frac{1}{N(y-1+\phi^*)^2}\left[(\xi-N)(1-\frac{f}{F}-y^2) - G\frac{(y-1+\phi^*)(F+\phi\bar{R}-(2F+\phi\bar{R}-f)\phi^{*2}}{\phi^{*2}(1-\phi^*)}\right],$$

which is ambiguous because the first term in the brackets is negative given $y > 1$ and the second term is positive given $G < 0$. The difference between the effects on ν^{SR} and ν^{LR} is the adjustment of γ. We will assume that these effects are second-order and therefore overall effect of ϕ^* on the number of new connections made is positive. We will make a similar assumption in similar cases in what follows.

If there is an increase in returns on foreign project for any number of projects financed (an upward shift in R^*), this also implies an increase in ξ for given level of other parameter values. It follows that such an increase in R^* will increase ν both in short and in long run, because

$$\frac{\partial\nu^{SR}}{\partial\xi} = \frac{y}{N(y-1)} > 0, \quad \frac{\partial\nu^{LR}}{\partial\xi} = \frac{y(1-\phi^*)}{N(y-1+\phi^*)}.$$

Since ϕ and $\bar{R}$ always enter together, their effects will be the same, hence we simply take derivative with respect to their product $\phi\bar{R}$:

$$\frac{\partial\nu^{SR}}{\partial(\phi\bar{R})} = -\frac{1}{N(y-1)^2}\left[\frac{\xi-\gamma N-N^*}{F} - G\frac{y(y-1)}{\phi^*}\right] < 0,$$

$$\frac{\partial\nu^{LR}}{\partial(\phi\bar{R})} = -\frac{1}{N(y-1+\phi^*)^2}\left[\frac{\xi-N^*}{F} - G\frac{y(y-1+\phi^*)}{\phi^*(1-\phi^*)}\right] < 0.$$

Next,

$$\frac{\partial\nu^{SR}}{\partial D^*} = \frac{\xi-\gamma N-N^*}{FN(y-1)^2} > 0,$$

$$\frac{\partial\nu^{LR}}{\partial D^*} = \frac{(\xi-N^*)(1-\phi^*)^2}{FN(y-1+\phi^*)^2} > 0.$$

The fee for establishing a new connection F has two effects — it increases a cost of establishing a new connection, but it also increases the value of relationship if f remains constant. Since we want to disentangle these two effects, we will examine separately an increase in fee for a new connection holding the value of relationship V constant (that is, an increase in F and f of equal magnitude), and a decline in the value of relationship holding fee for a new connection constant (that is, and increase in f holding F constant).

$$\frac{\partial \nu^{SR}}{\partial F}|_{V=const.} = \frac{1}{N(y-1)^2}\left[\frac{(\phi\bar{R} - D^* - V)(\xi - \gamma N - N^*}{F^2} + G\frac{y(y-1)}{\phi^*}\right],$$

$$\frac{\partial \nu^{LR}}{\partial F}|_{V=const.} = \frac{1}{N(y-1+\phi^*)^2}\left[\frac{(\phi\bar{R} - D^* - V)(\xi - N^*}{F^2} + G\frac{y(y-1+\phi^*)}{\phi^*(1-\phi^*)}\right],$$

which are both ambiguous unless we want to make assumptions on the shape of R^* function. There are two opposing effects at play — when F increases, home banks are less interested in financing foreign projects, while foreign banks are also less interested in financing their projects because return on intermediation increases. Finally,

$$\frac{\partial \nu^{SR}}{\partial f} = -\frac{1}{N(y-1)^2}\left[\frac{\phi^*(\xi - \gamma N - N^*}{F(1-\phi^*)} - G\frac{y(y-1)}{(1-\phi^*)}\right] < 0,$$

$$\frac{\partial \nu^{LR}}{\partial f} = -\frac{1}{N(y-1+\phi^*)}\left[\frac{\phi^*(\xi - N^*}{F} - G\frac{y(y-1+\phi^*)}{1-\phi^*}\right] < 0.$$

Figure 1: Relevance of the syndicated bank loan market

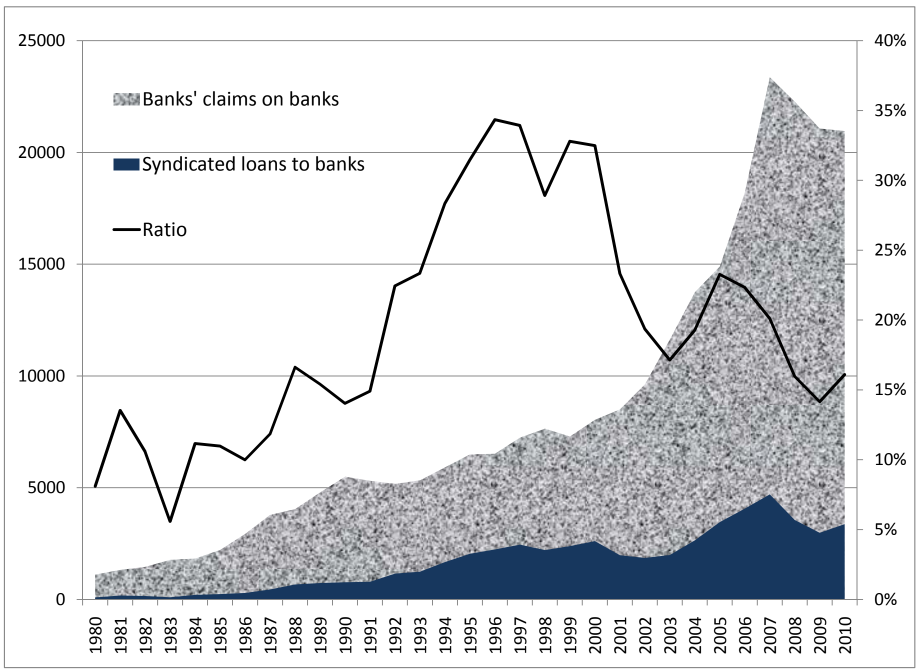
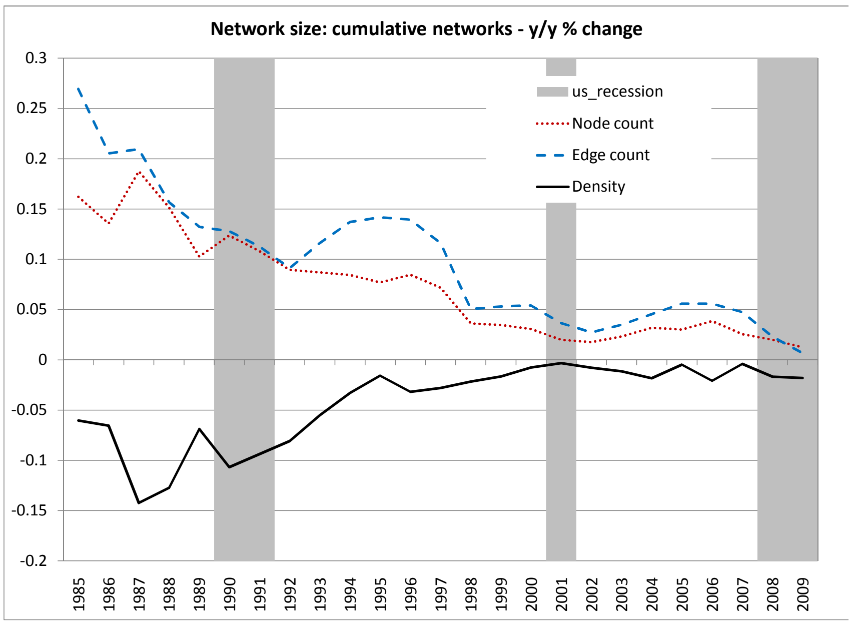


Figure 2: Network size and density



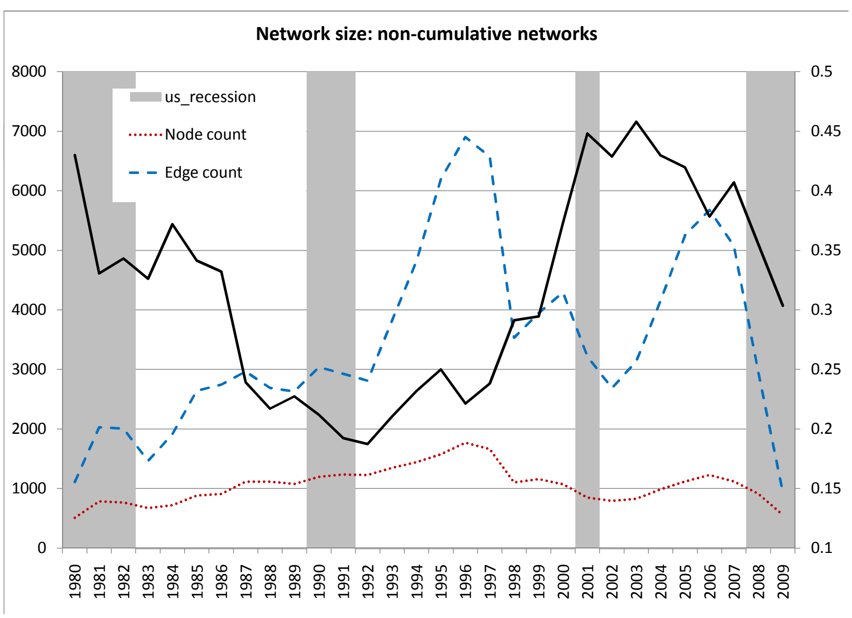


Figure 3: Network clustering

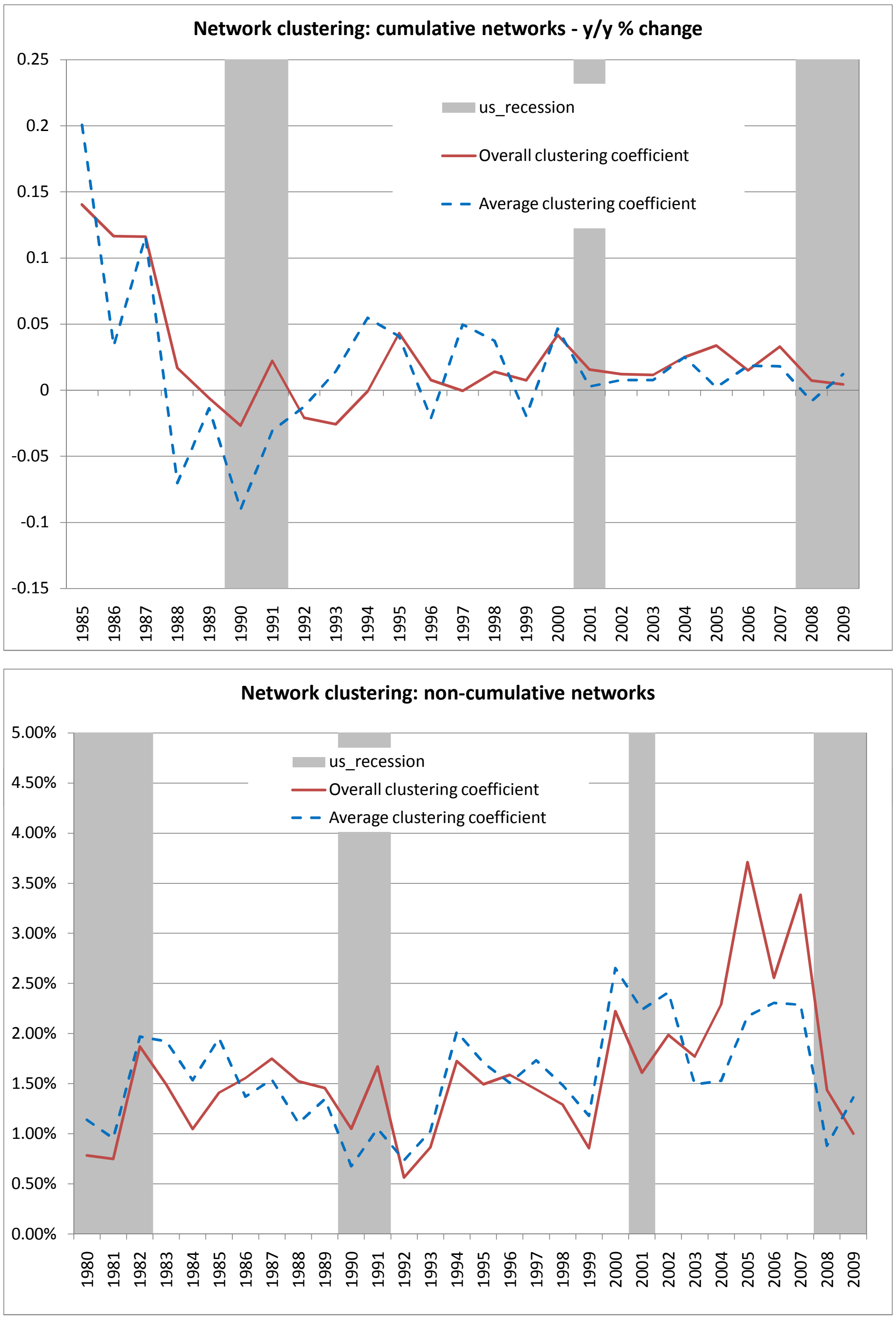
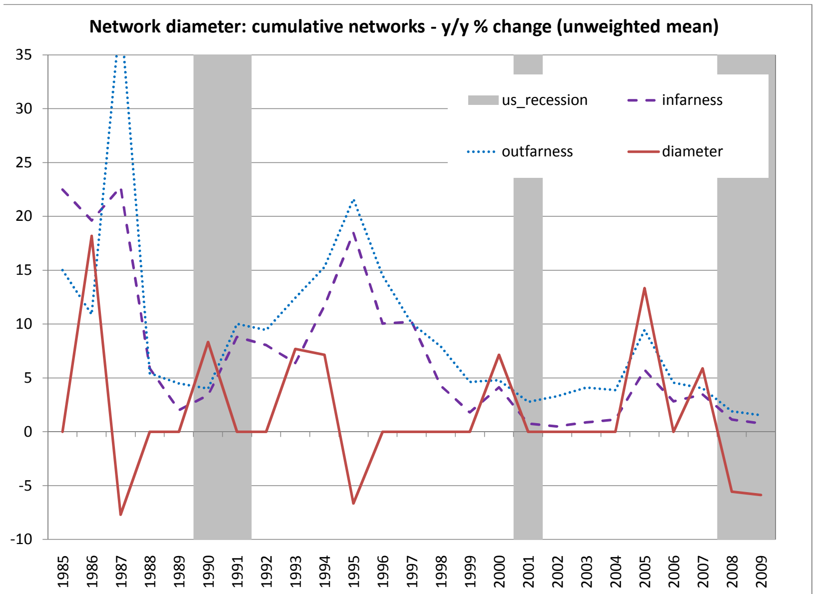


Figure 4: Network diameter and farness



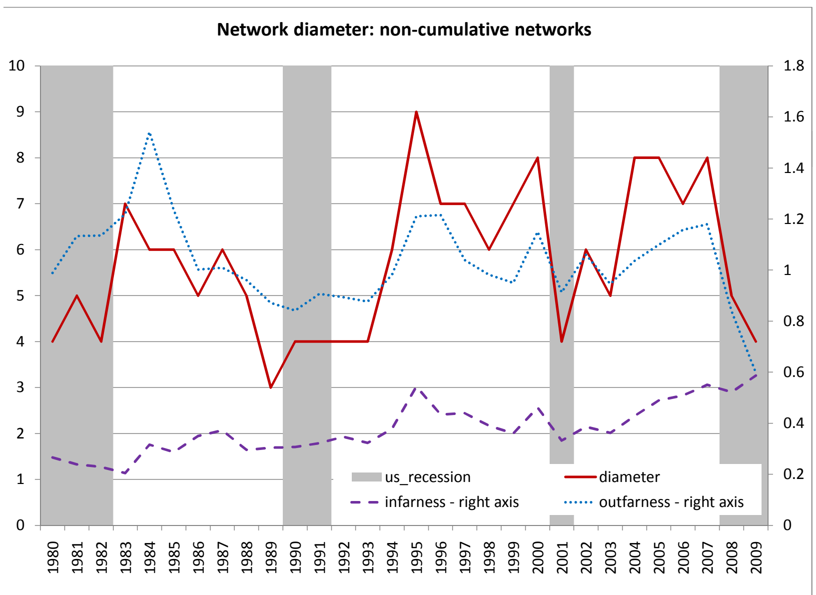


Figure 5: Number of direct links and betweenness

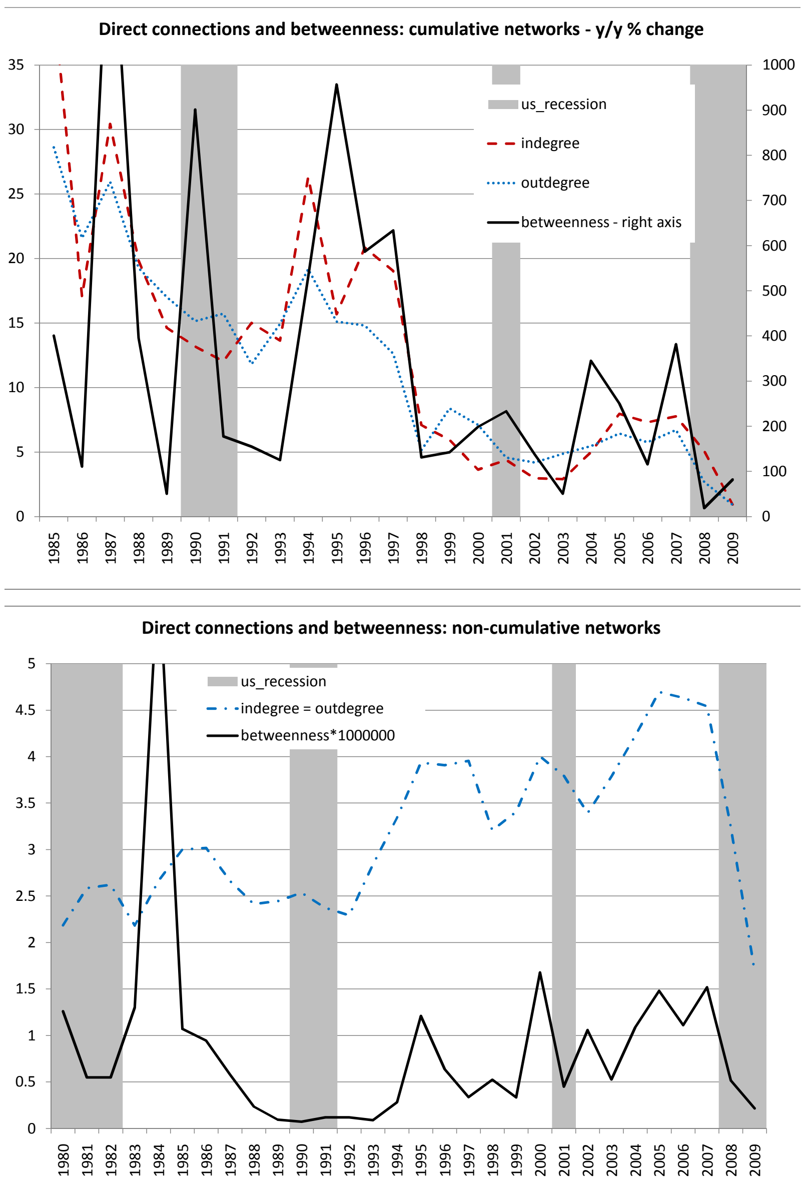
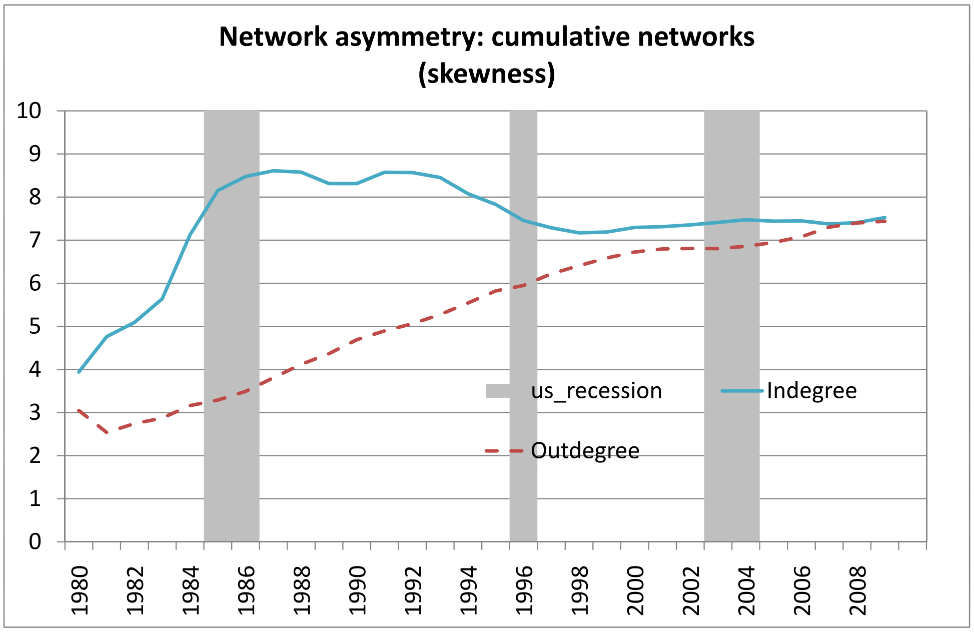


Figure 6: Network asymmetry



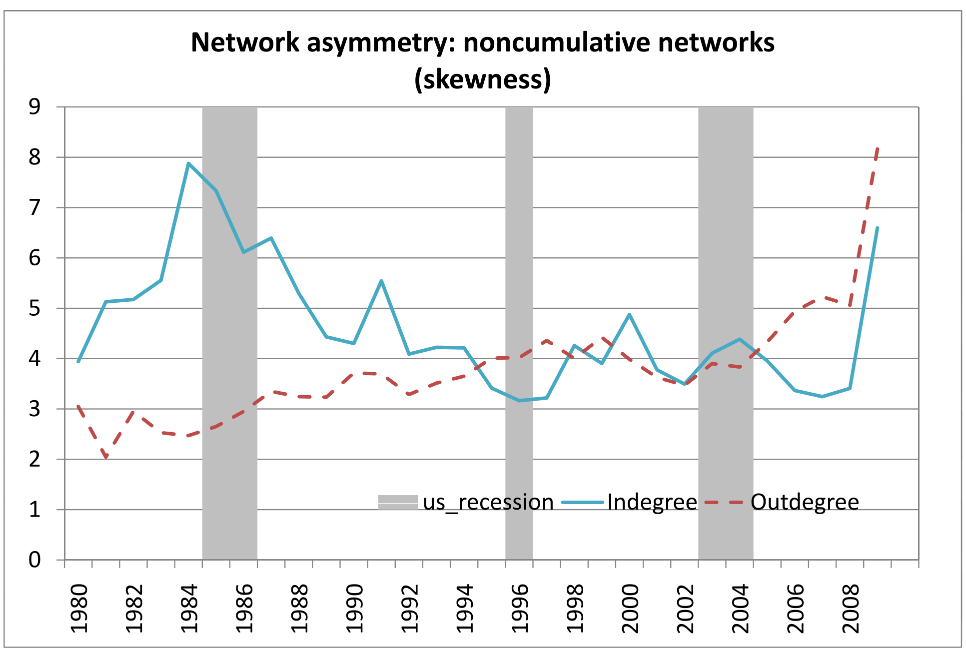


Table 1: Size of networks by year — noncumulative panel

Year	Loans	Banks	Countries	Edges	Geopaths	Amount	Diameter	Density
1980	149	509	60	1112	2185	20	4	0.43%
1981	246	783	68	2025	3688	25	5	0.33%
1982	192	765	70	2006	3806	26	4	0.34%
1983	143	670	59	1462	3665	19	7	0.33%
1984	205	717	58	1910	11130	19	6	0.37%
1985	291	880	62	2640	6883	46	6	0.34%
1986	417	910	58	2747	7409	99	5	0.33%
1987	513	1114	58	2966	7451	96	6	0.24%
1988	438	1114	63	2690	4883	101	5	0.22%
1989	408	1076	61	2631	3707	86	3	0.23%
1990	509	1198	59	3037	4144	148	4	0.21%
1991	509	1234	65	2927	4742	162	4	0.19%
1992	534	1225	64	2808	4560	325	4	0.19%
1993	536	1348	70	3825	5701	270	4	0.21%
1994	700	1442	71	4820	10406	392	6	0.23%
1995	823	1575	77	6196	27061	337	9	0.25%
1996	868	1767	79	6904	23687	260	7	0.22%
1997	882	1662	83	6571	15147	313	7	0.24%
1998	582	1102	74	3534	7870	352	6	0.29%
1999	549	1158	71	3945	7047	312	7	0.29%
2000	587	1073	73	4293	14030	183	8	0.37%
2001	350	848	74	3219	5579	74	4	0.45%
2002	401	792	67	2686	6131	69	6	0.43%
2003	417	828	78	3136	5430	75	5	0.46%
2004	515	984	88	4156	9618	81	8	0.43%
2005	834	1120	91	5258	16972	103	8	0.42%
2006	820	1225	99	5674	19003	125	7	0.38%
2007	671	1117	95	5073	18040	141	8	0.41%
2008	639	914	99	2965	5709	102	5	0.36%
2009	596	557	84	940	1263	67	4	0.30%

Table 2: Network summary statistics — no weights

Variable	Observations	Mean	Std. Dev.	Min	Max
noncumulative: Total banks:	**7938**				
Indegree	30093	3.324062	9.077033	0	159
Outdegree	30093	3.330077	6.79563	0	129
Infarness	30093	.390488	.6643994	0	4.777778
Outfarness	30093	1.032019	.7973926	0	5.371428
Betweenness	30093	7.40e-06	.000136	0	.015775
Cumulative: Total banks:	**7938**				
Indegree	134561	7.826844	24.53938	0	624
Outdegree	134561	7.765943	22.7729	0	489
Infarness	134561	1.306464	1.973535	0	8.616158
Outfarness	134561	2.226515	2.225817	0	13.46041
Betweenness	134561	.0000614	.00071	0	.0381075
noncumulative: US banks:	**1313**				
Indegree	3845	2.273862	7.265778	0	73
Outdegree	3845	2.990117	6.548499	0	80
Infarness	3845	.3289405	.5508336	0	3.700935
Outfarness	3845	.9238481	.7286909	0	4.446429
Betweenness	3845	2.60e-06	.0000453	0	.001816
Cumulative: US banks:	**1313**				
Indegree	23478	3.869963	11.87048	0	198
Outdegree	23478	5.271872	18.14035	0	392
Infarness	23478	1.078367	1.789915	0	7.828805
Outfarness	23478	1.917332	2.26462	0	12.47361
Betweenness	23478	.0000227	.0002701	0	.0085077

Table 3: Correlation between network statistics, borrowing, and lending at the bank level

noncumulative panel

	Indegree	Outdegree	Infar	Outfar	Between	Lending	Borrowing
Indegree	1.0000						
Outdegree	-0.1268	1.0000					
Infarness	0.6138	-0.2025	1.0000				
Outfarness	-0.3328	0.3262	-0.5595	1.0000			
Betweenness	0.1804	0.0528	0.1136	0.0539	1.0000		
Lending	-0.0297	0.2160	-0.0496	0.0979	0.0215	1.0000	
Borrowing	0.1972	-0.0278	0.1973	-0.1257	0.0483	0.0280	1.0000

Cumulative panel

	Indegree	Outdegree	Infar	Outfar	Between	Lending	Borrowing
Indegree	1.0000						
Outdegree	0.0115	1.0000					
Infarness	0.4036	-0.0374	1.0000				
Outfarness	-0.1005	0.1712	-0.3668	1.0000			
Betweenness	0.4160	0.2310	0.0991	0.0479	1.0000		
Lending	0.0114	0.3167	-0.0127	0.0269	0.1114	1.0000	
Borrowing	0.3952	0.1320	0.2024	-0.0625	0.2650	0.1011	1.0000

Table 4: Number of countries affected by banking crises and local recessions per year

Year	I(US rec.)	Number of banking crises	Number of local recessions
1980	1	2	24
1981	1	3	38
1982	1	4	49
1983	0	4	47
1984	0	0	24
1985	0	0	34
1986	0	0	33
1987	0	1	32
1988	0	4	27
1989	0	3	34
1990	1	4	43
1991	1	6	50
1992	0	4	50
1993	0	3	52
1994	0	7	32
1995	0	6	36
1996	0	4	40
1997	0	7	33
1998	0	7	51
1999	0	0	60
2000	0	1	41
2001	1	1	72
2002	0	1	69
2003	0	1	61
2004	0	0	23
2005	0	0	29
2006	0	0	19
2007	0	2	23
2008	1	0	82
2009	1	0	119
Total	8	75	1327

Table 5: Effects of U.S. and local recession and banking crises on noncumulative network characteristics

	Indegree	Outdegree	Infarness	Outfarness	Betweenness
I(Year=2008)	-0.270	-0.358**	0.169	-0.200	-0.868
	(0.268)	(0.139)	(0.207)	(0.176)	(0.532)
I(Year=2009)	0.419	-1.148***	1.310***	-1.047***	-0.866
	(0.310)	(0.228)	(0.249)	(0.296)	(0.640)
L.US recession	-0.378**	0.165*	-0.292**	0.305***	-0.721**
	(0.178)	(0.088)	(0.135)	(0.115)	(0.313)
L.local recession	-0.165	0.005	-0.024	0.021	-0.877***
	(0.129)	(0.067)	(0.097)	(0.089)	(0.243)
L.banking crisis	0.562*	0.384*	0.478*	0.544**	0.937
	(0.327)	(0.204)	(0.260)	(0.275)	(0.895)
Trend	0.006	0.036***	-0.003	0.018***	0.051***
	(0.010)	(0.004)	(0.007)	(0.006)	(0.019)
Constant	-1.478***	-2.057***	-2.846***	-3.150***	-1.057***
	(0.192)	(0.092)	(0.145)	(0.122)	(0.362)
R^2	0.440	0.571	0.452	0.514	0.321

Logs of network statistics are on the left-hand-side.
1718 observations, 29 years and 119 countries in all regressions.
Country fixed effects are included in all regressions.
Robust standard errors are in parentheses.

Table 6: Effects of U.S. and local recession and banking crises on cumulative network characteristics

	Indegree	Outdegree	Infarness	Outfarness	Betweenness
I(Year=2008)	1.044	0.337	1.428*	-1.259	-21.944
	(2.063)	(1.806)	(0.788)	(1.332)	(14.905)
I(Year=2009)	-0.269	-4.474**	1.522	-2.825**	-37.725
	(2.460)	(1.999)	(1.661)	(1.439)	(31.300)
L.US recession	0.456	5.095***	0.803	2.068**	29.016
	(2.166)	(1.679)	(1.355)	(0.871)	(27.480)
L.local recession	-1.249	-0.997	-1.204	-1.499	-12.063
	(2.547)	(0.961)	(0.948)	(0.982)	(13.326)
L.banking crisis	-5.022	-0.620	-3.488***	-1.128*	-19.190
	(4.199)	(1.805)	(1.317)	(0.636)	(14.990)
Trend	-0.616***	-0.354***	-0.432***	-0.106**	0.119
	(0.114)	(0.085)	(0.085)	(0.049)	(0.656)
Constant	16.777***	9.792***	10.897***	4.387***	20.908**
	(2.645)	(1.694)	(2.100)	(1.061)	(9.528)
R^2	0.071	0.088	0.050	0.067	0.048

Percentage changes in network statistics are on the left-hand-side.
3007 observations, 29 years and 141 countries in all regressions.
Country fixed effects are included in all regressions.
Robust standard errors are in parentheses.

Table 7: Effects of U.S. and local recession and banking crises on noncumulative network characteristics: bank-level regressions

	Indegree	Outdegree	Infarness	Outfarness	Betweenness
I(year=2008)	0.028	-0.091	0.089*	-0.071	0.037
	(0.069)	(0.088)	(0.050)	(0.083)	(0.077)
I(year=2009)	0.016	-0.548***	0.328***	-0.399***	-0.061
	(0.103)	(0.099)	(0.060)	(0.076)	(0.127)
L.US recession	0.002	0.056*	-0.011	0.075***	0.027
	(0.035)	(0.032)	(0.025)	(0.023)	(0.034)
L.recession	-0.026	0.031	-0.010	0.029	-0.021
	(0.032)	(0.030)	(0.022)	(0.024)	(0.048)
L.bankcris	-0.123	0.180*	-0.083	0.126*	0.116
	(0.113)	(0.098)	(0.071)	(0.064)	(0.089)
Country lending	0.117***		0.076***		
	(0.016)		(0.010)		
Country borrowing		0.139***		0.101***	
		(0.040)		(0.031)	
Lending+borrowing					0.106***
					(0.032)
Trend	-0.002	0.002	-0.001	-0.002	0.002
	(0.005)	(0.006)	(0.004)	(0.004)	(0.006)
Constant	-1.882***	-0.960***	-2.043***	-1.062***	-5.134***
	(0.111)	(0.265)	(0.079)	(0.220)	(0.248)
R^2	0.300	0.247	0.307	0.269	0.060

Logs of network statistics are on the left-hand-side.
30085 observations, 7933 banks, 29 years and 119 countries in all regressions.
Country fixed effects are included in all regressions.
Robust standard errors clustered on country are in parentheses.

Table 8: Effects of U.S. and local recession and banking crises on cumulative network characteristics: bank-level regressions

	Indegree	Outdegree	Infarness	Outfarness	Betweenness
I(year=2008)	0.562	1.110**	0.273	-0.168	-1.570
	(0.410)	(0.536)	(0.248)	(1.507)	(1.127)
I(year=2009)	1.648***	0.057	1.606***	-2.052	0.315
	(0.551)	(0.650)	(0.321)	(1.607)	(1.035)
L.US recession	-0.332	0.786***	-0.330	3.025***	-0.069
	(0.462)	(0.280)	(0.315)	(1.033)	(0.846)
L.recession	-0.780**	-0.769	-0.508**	-0.974	-1.280*
	(0.370)	(0.473)	(0.208)	(1.046)	(0.701)
L.bankcris	0.041	-1.091	-0.065	-0.181	1.385
	(0.739)	(0.699)	(0.421)	(2.052)	(1.382)
Country lending	0.629**		0.373*		
	(0.292)		(0.215)		
Country borrowing		-1.906**		-1.731	
		(0.756)		(1.108)	
Lending+borrowing					-1.482
					(1.042)
Trend	-0.428***	-0.387***	-0.286***	-0.505***	-0.369***
	(0.058)	(0.115)	(0.034)	(0.181)	(0.127)
Constant	5.323*	33.042***	4.081**	35.446***	30.510***
	(2.694)	(6.211)	(1.936)	(8.300)	(10.619)
R^2	0.015	0.045	0.007	0.009	0.009

Percentage changes in network statistics are on the left-hand-side.
126503 observations, 7833 banks, 29 years and 141 countries in all regressions.
Country fixed effects are included in all regressions.
Robust standard errors are in parentheses.

Table 9: Country averages of noncumulative network across years
(for each year, weighted average across banks)

Country	Indegree	Outdegree	Infar	Outfar	Between	Borrowing	Lending	Banks
Albania	0.75	0.25	0.75	0.25	0.00E+00	6.83	3.33	1.50
Algeria	4.89	0.16	0.59	0.09	0.00E+00	914.53	5.76	3.10
Angola	1.39	0.17	0.72	0.51	0.00E+00	31.48	1.30	1.33
Argentina	3.84	0.25	0.33	0.17	5.22E-06	1250.11	46.58	5.81
Armenia	0.97	0.00	0.65	0.00	0.00E+00	20.59	0.00	2.17
Australia	0.47	0.43	0.07	0.10	5.45E-06	10615.63	2930.76	20.76
Austria	0.09	0.97	0.04	0.10	4.66E-07	1546.20	1275.35	18.27
Azerbaijan	2.00	0.23	0.36	0.24	2.13E-06	142.14	0.79	4.63
Bahamas	1.89	0.65	0.47	0.50	6.75E-07	211.45	25.62	1.88
Bahrain	0.21	0.82	0.02	1.08	1.04E-07	12.65	33.47	2.24
Bangladesh	1.50	0.00	1.00	0.00	0.00E+00	59.12	0.00	1.00
Belarus	2.53	0.09	0.67	0.09	0.00E+00	88.38	0.92	2.64
Belgium	1.24	0.76	0.08	0.11	2.15E-07	2799.72	1206.60	15.00
Benin	1.00	0.00	1.00	0.00	0.00E+00	36.93	0.00	1.00
Bolivia	2.10	0.00	0.80	0.00	0.00E+00	33.07	0.00	1.40
Bosnia&Herz	7.54	0.00	0.79	0.00	0.00E+00	128.35	0.00	1.56
Brazil	1.94	0.11	0.23	0.09	3.25E-07	1541.66	62.41	10.50
Brunei	1.00	0.00	1.00	0.00	0.00E+00	47.13	0.00	1.00
Bulgaria	5.07	0.09	0.66	0.09	0.00E+00	206.24	4.70	3.45
Burundi	0.00	1.00	0.00	1.00	0.00E+00	0.00	4.54	1.00
Canada	0.14	0.77	0.05	0.14	4.88E-08	1856.88	2155.48	12.57
Cayman Islands	1.39	0.63	0.27	0.36	0.00E+00	612.18	65.42	4.92
Chile	3.43	0.31	0.35	0.24	1.40E-06	511.41	12.58	4.42
China	5.54	1.24	0.25	0.38	9.18E-05	1525.36	226.46	9.67
Colombia	2.03	0.17	0.51	0.14	0.00E+00	225.00	9.01	3.26
Congo	1.50	0.00	1.00	0.00	0.00E+00	5.73	0.00	1.00
Cote D'Ivoire	3.33	1.33	0.33	0.67	0.00E+00	10.30	137.38	1.00
Croatia	8.34	0.12	0.62	0.14	6.11E-07	249.87	4.31	2.53
Cuba	5.78	0.08	0.81	0.08	0.00E+00	77.88	3.22	1.75
Cyprus	0.88	1.13	0.21	0.96	0.00E+00	13.53	3.28	1.00
Czech Republic	8.27	0.29	0.64	0.18	1.40E-06	236.67	37.25	3.41
Denmark	1.03	1.57	0.14	0.23	3.18E-07	1500.99	749.70	9.20
Dominican Rep.	0.50	0.33	0.50	0.33	0.00E+00	12.39	2.10	1.33
Ecuador	3.92	0.07	0.73	0.07	0.00E+00	113.28	0.35	1.86
Egypt	0.84	1.28	0.15	0.51	5.16E-06	140.84	131.17	4.70

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Table 9 – continued from previous page

Country	Indegree	Outdegree	Infar	Outfar	Between	Borrowing	Lending	Banks
El Salvador	5.62	0.03	0.99	0.03	0.00E+00	70.74	1.36	1.70
Estonia	4.14	0.15	0.80	0.15	1.37E-07	152.95	1.47	2.13
Ethiopia	6.00	0.00	1.00	0.00	0.00E+00	36.29	0.00	1.00
Faroe Islands	16.00	0.00	1.20	0.00	0.00E+00	172.72	0.00	1.00
Fiji	1.00	0.00	1.00	0.00	0.00E+00	0.42	0.00	1.00
Finland	0.65	1.54	0.14	0.39	1.53E-05	982.61	381.52	4.37
France	0.51	0.60	0.04	0.05	3.70E-06	6902.71	8237.66	33.07
Gambia	0.00	1.00	0.00	1.00	0.00E+00	0.00	6.73	1.00
Georgia	2.57	0.00	0.98	0.00	0.00E+00	104.11	0.00	2.80
Germany	0.60	0.39	0.03	0.04	4.88E-08	10729.16	21191.97	50.57
Ghana	0.79	1.52	0.34	0.72	0.00E+00	29.88	132.40	1.80
Greece	2.80	1.52	0.36	0.39	2.78E-06	178.17	140.10	3.54
Guatemala	3.00	0.00	1.00	0.00	0.00E+00	46.78	0.00	1.00
Guyana	1.00	0.00	1.00	0.00	0.00E+00	9.57	0.00	1.00
Honduras	2.60	0.10	0.90	0.10	0.00E+00	56.76	0.53	1.20
Hong Kong	0.12	0.10	0.02	0.03	6.28E-07	3927.38	4641.57	93.80
Hungary	3.20	0.80	0.39	0.53	6.16E-06	337.14	66.60	5.71
Iceland	3.64	0.10	0.50	0.06	5.71E-07	473.01	6.94	3.85
India	2.78	0.49	0.32	0.21	1.20E-05	777.48	76.54	7.45
Indonesia	1.57	0.14	0.16	0.16	8.95E-07	1041.95	26.07	15.57
Iran	2.01	0.61	0.58	0.63	4.98E-06	356.23	7.11	2.60
Iraq	10.14	0.00	1.29	0.00	0.00E+00	575.81	0.00	1.00
Ireland	0.87	0.63	0.14	0.33	1.30E-06	2843.86	371.80	11.43
Israel	0.50	1.69	0.12	0.69	2.56E-07	21.17	163.89	2.93
Italy	0.68	0.29	0.04	0.04	7.46E-07	5074.71	2795.02	40.17
Jamaica	4.50	0.00	1.00	0.00	0.00E+00	55.46	0.00	1.00
Japan	0.18	0.34	0.03	0.03	2.48E-07	3114.61	6375.45	59.80
Jordan	0.48	3.30	0.05	0.99	3.50E-06	17.23	112.27	1.97
Kazakhstan	4.40	0.13	0.48	0.07	2.05E-06	1354.92	15.91	6.80
Kenya	1.25	0.00	1.24	0.00	0.00E+00	9.64	0.00	1.00
Kyrgyzstan	0.91	0.00	0.83	0.00	0.00E+00	11.46	0.00	1.50
Latvia	5.97	1.45	0.68	0.27	3.79E-05	337.83	27.38	3.36
Lebanon	0.36	0.58	0.23	0.60	3.99E-08	142.94	18.56	2.53
Libya	0.69	1.85	0.08	1.34	0.00E+00	16.57	24.25	1.00
Lithuania	5.50	0.14	0.85	0.11	4.57E-06	41.29	2.31	1.85
Luxembourg	0.19	0.59	0.03	0.06	2.96E-07	1816.79	2133.20	29.17
Macao	1.01	0.98	0.22	0.78	1.27E-06	12.29	24.04	1.80

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Country	Indegree	Outdegree	Infar	Outfar	Between	Borrowing	Lending	Banks
Macedonia	7.26	0.12	1.39	0.03	0.00E+00	211.95	0.97	1.55
Madagascar	4.33	0.00	1.00	0.00	0.00E+00	10.12	0.00	1.00
Malaysia	1.52	0.64	0.17	0.36	2.31E-06	397.99	165.10	9.48
Maldives	1.00	0.00	1.00	0.00	0.00E+00	2.37	0.00	1.00
Malta	0.00	5.20	0.00	1.94	0.00E+00	0.00	44.39	1.09
Mauritius	5.00	0.00	1.00	0.00	0.00E+00	41.68	0.00	1.00
Mexico	3.70	0.22	0.35	0.21	2.35E-07	997.82	25.97	4.17
Moldova	0.81	0.00	0.67	0.00	0.00E+00	17.30	0.00	1.75
Mongolia	0.47	2.03	0.47	0.47	0.00E+00	4.98	13.96	1.67
Montenegro	1.00	0.00	1.00	0.00	0.00E+00	22.60	0.00	1.00
Mozambique	1.00	0.00	1.00	0.00	0.00E+00	6.69	0.00	1.00
Namibia	12.50	0.00	1.34	0.00	0.00E+00	39.25	0.00	1.00
Nepal	1.00	0.00	1.00	0.00	0.00E+00	4.05	0.00	1.00
Netherlands	0.33	0.94	0.06	0.09	8.53E-07	7533.38	4180.45	17.40
Neth. Antilles	0.00	0.83	0.00	0.83	0.00E+00	0.00	33.30	1.33
New Zealand	2.86	0.31	0.67	0.16	4.47E-07	1371.13	104.51	2.72
Niger	1.79	0.00	0.50	0.00	0.00E+00	39.58	0.00	2.00
Nigeria	0.42	0.48	0.28	0.47	4.78E-09	236.81	7.59	4.43
Norway	1.09	0.38	0.12	0.14	2.27E-06	1714.19	212.72	12.00
Oman	0.00	9.60	0.00	1.35	0.00E+00	0.00	57.17	1.00
Pakistan	0.26	1.17	0.07	0.82	0.00E+00	14.29	20.00	1.68
Panama	1.94	1.33	0.27	0.37	2.61E-07	101.50	72.26	3.58
Paraguay	1.00	0.00	0.75	0.00	0.00E+00	33.37	0.00	1.50
Peru	3.45	0.10	0.63	0.15	0.00E+00	206.55	2.53	2.38
Philippines	2.89	0.18	0.54	0.16	0.00E+00	389.92	16.14	4.25
Poland	2.09	1.48	0.35	0.21	2.75E-06	468.21	98.49	5.95
Portugal	0.73	0.57	0.13	0.19	9.08E-07	498.95	294.67	8.40
Qatar	2.08	1.52	0.27	0.67	1.34E-05	222.82	76.44	2.40
Romania	4.93	0.89	0.55	0.29	3.05E-06	267.57	22.36	3.21
Russia	13.34	0.57	0.58	0.21	1.22E-06	3901.91	998.66	16.10
Rwanda	0.50	0.00	0.50	0.00	0.00E+00	10.98	0.00	2.00
Saint Lucia	1.00	0.00	1.00	0.00	0.00E+00	16.00	0.00	1.00
San Marino	0.00	1.50	0.00	1.00	0.00E+00	0.00	17.73	1.00
Saudi Arabia	0.41	1.08	0.04	0.36	4.06E-07	88.82	178.06	5.70
Senegal	1.00	0.00	1.00	0.00	0.00E+00	37.53	0.00	1.00
Serbia	5.48	0.00	0.81	0.00	0.00E+00	52.67	0.00	1.89
Seychelles	2.00	0.00	1.33	0.00	0.00E+00	21.37	0.00	1.00

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Country	Indegree	Outdegree	Infar	Outfar	Between	Borrowing	Lending	Banks
Singapore	0.26	0.20	0.05	0.06	2.58E-08	274.71	1446.29	46.07
Slovak Rep.	2.95	1.10	0.65	0.45	9.44E-07	30.08	12.09	1.77
Slovenia	8.33	0.36	0.54	0.13	6.42E-06	576.74	15.53	3.95
South Africa	4.14	0.36	0.32	0.20	1.26E-06	960.25	35.24	5.37
South Korea	3.20	0.11	0.10	0.09	2.87E-05	4160.58	277.70	21.57
Spain	0.18	1.29	0.05	0.15	4.85E-07	303.59	1169.18	12.53
Sri Lanka	9.32	0.03	1.20	0.03	0.00E+00	98.84	0.68	1.45
Sudan	0.00	1.00	0.00	1.00	0.00E+00	0.00	4.36	1.00
Sweden	0.60	0.83	0.12	0.27	1.38E-07	1879.23	653.64	7.67
Switzerland	0.62	0.72	0.07	0.13	4.81E-06	912.89	3103.75	14.57
Syria	17.50	0.00	2.87	0.00	0.00E+00	147.64	0.00	1.00
Taiwan	1.46	0.20	0.29	0.08	2.19E-08	241.10	819.07	22.29
Tajikistan	0.83	0.00	0.83	0.00	0.00E+00	4.79	0.00	1.50
Tanzania	8.21	0.00	1.04	0.00	0.00E+00	77.22	0.00	1.11
Thailand	1.82	0.29	0.31	0.29	2.71E-08	690.60	27.78	7.81
Togo	1.00	0.00	1.00	0.00	0.00E+00	79.12	0.00	1.00
Trin&Tobago	10.66	0.26	0.86	0.14	0.00E+00	83.62	8.27	1.50
Tunisia	1.81	1.72	0.29	0.70	0.00E+00	48.21	25.56	2.29
Turkey	2.98	0.34	0.15	0.14	1.22E-06	2920.37	58.54	15.52
Turkmenistan	3.80	0.00	1.07	0.00	0.00E+00	308.17	0.00	1.00
Uganda	2.17	0.00	1.00	0.00	0.00E+00	13.73	0.00	1.00
Ukraine	2.70	0.09	0.33	0.08	1.30E-08	1009.79	38.88	11.50
UAE	0.00	1.44	0.00	1.14	0.00E+00	0.00	64.22	1.13
United Kingdom	0.11	0.18	0.01	0.02	1.71E-07	18960.37	57739.66	123.97
United States	0.15	0.13	0.01	0.01	3.42E-07	33110.93	20349.23	128.17
Uruguay	2.81	0.06	0.80	0.06	0.00E+00	44.70	0.99	1.56
Uzbekistan	4.36	0.00	0.96	0.00	0.00E+00	83.54	0.00	1.18
Venezuela	1.40	0.19	0.47	0.13	1.17E-06	410.85	36.54	3.19
Vietnam	5.48	0.00	1.08	0.00	0.00E+00	53.41	0.00	1.71
Yemen	4.33	0.56	0.39	0.56	0.00E+00	51.68	5.72	1.33
Zambia	1.00	0.00	1.00	0.00	0.00E+00	11.81	0.00	1.00
Zimbabwe	2.59	0.00	0.88	0.00	0.00E+00	45.57	0.00	1.45
Overall	2.71	0.56	0.54	0.25	2.05E-06	1100.68	1054.32	8.12