

Bank Relationships, Business Cycles, and Financial Crisis

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Abstract

Last recession was special in many ways. Using the analysis of the global banking network for last 30 years this paper demonstrates that the breakdown of banking relationships was an important feature of the recent crisis. Specifically, it shows that during U.S. recessions, and for a year afterwards, international banking network tends to shrink, in the sense of diminished reach and the degree of intermediation of an average bank within a network, for a given amount of interbank lending. Moreover, in 2008 and 2009 connections between banks suffered further decline than during other recessions, even controlling for the fact that total lending collapsed. That is, as a result of the crisis global banking network became more concentrated above and beyond the mechanical effect of diminished lending and the macroeconomic effect of recession. The effects of local recessions and banking crises on the network are less important. We find that decline in bank relationships has real economic costs of meaningful magnitude in terms of lower GDP growth, higher unemployment, and lower growth rate of the bank credit to the private sector, thus propagating the crises. Finally we investigate whether regulation can protect bank relationships from breaking down during downturns. One of the paper contributions is a novel data set that builds bank-level global network from loan-level data.

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Key words: networks, international banking, crises, bank relationships

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1 Introduction

Recent studies demonstrate that banking crises have a number of direct costs in terms of economic activity (Reinhart and Rogoff, 2009; Schularick and Taylor, 2010). This paper shows that in addition to tangible costs, such as amount of credit and GDP growth, there are intangible costs of such crises, namely the destruction of the stock of banking relationships. The global financial crisis demonstrated that at the height of the liquidity crunch relationships between banks break down due to the loss of confidence and trust. One may expect that it will take years for the relationships to be rebuilt and that the destruction of these relationships will have real costs in terms of less bank lending and ultimately lower economic growth, thus propagating the effects of the crisis.

This paper attempts to understand empirically the effects of economic shocks on bank relationship and evaluate the potential for such propagation mechanism. The specific questions we study in this paper are the following: 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? How long do the effects last? Are there real macroeconomic costs of a destruction in bank relationships? What can be done in terms of bank supervision and regulatory policies to protect bank relationships from breaking down during crises?

There is rich literature in both finance and international finance on the importance of relationships and information flows between institutions, especially financial institutions. For example, Veldcamp and Van Nieuwerburgh (2010, forthcoming) show that information acquisition by investors can be endogenous and may affect investment patterns. The global liquidity crisis also demonstrated the importance of the relationships between financial institutions, not only within a country but also across national borders. However, measuring the extent of relationships and information flows is an elusive target.

This paper attempts at hitting this target by applying network analysis, which is becoming more and more popular in social interactions and firm theory literature,¹ to international banking. Unlike some recent analysis of banking network that builds on aggregate bilateral bank lending from the BIS data (von Peter, 2007), this paper constructs global banking network at the bank level, using loan-level data from Loanware, something that has not been done before.²

Nier, Yang, Yorulmazer, and Alentorn (2008) present a theoretical model that demonstrates how banking systems can be very naturally represented by networks in which individual banks are connected to each other in specific ways. We apply this approach empirically, creating 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. We use loan-level data to construct our network with banks as nodes. 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 a separate global banking network for each of the 30 years between 1980 and 2009. We rely on four main statistics: farness, ineccentricity, and outeccentricity, which measure the reach of the bank in the network, and betweenness, which measures the importance of the bank in intermediation. Having constructed global banking network for each of the years in our sample, we can analyze how network properties of banks are affected by global and country-specific shocks.

We find that the reach of the network and the level of intermediation tend to fall during the U.S. recessions and that they have declined even further during the global financial crisis of 2008-2009. Importantly, the data allow us to control for the total amount lent and borrowed, that is,

¹Karlan, Mobious, Rosenblat, and Szeidl (2009) offers a theoretical model, while papers by Bottazzi, Da Rin, and Hellmann (2009); Guiso, Sapienza, and Zingales (2009) and Lehmann and 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.

²Cocco, Gomes, and Martins (2009) build, for Portuguese interbank market, “borrower preference” and “lender preference” indexes based on loans between banks, but do not go as far as creating a network of banks, which would take into account indirect relationships.

evaluate the effects of crises on banking relationships beyond the mechanical effect of a decline in lending. We can interpret these results as follows: during U.S. recessions, and especially during the global financial crisis, international banking network became more concentrated, in a sense that interbank lending was made within a tightly knit core of banks, while banks on the periphery were less involved, if at all. Importantly, Nier, Yang, Yorulmazer, and Alentorn (2008) show in a theoretical model that more concentrated banking systems are prone to larger systemic risks. Our results therefore suggest that this additional propagation mechanism of the banking crisis is present in the data — crisis makes the banking network more concentrated which makes it more fragile.

Singling out emerging markets, we test the claim made by Eichengreen (2009), that emerging markets will be less able to outsource intermediation to foreign banks and that in general we should expect some de-globalization of banking in the aftermath of the global financial crisis. [To be completed]

We find that country-specific recessions and banking crises have less important effect on the network characteristics. Specifically, when controlling for the U.S. recessions, local recessions only affect the degree of intermediation, but not the reach of the banks in the affected country. Local banking crises only have negligible effects.

We show that negative effects of the U.S. recessions on the global banking network persist for a year after the U.S. recessions are over, but not beyond that. We also show that decline in bank relationships, as measured by our network statistics, have real costs in terms of lower GDP growth, higher unemployment, and lower growth rate of bank credit to the private sector. The magnitudes of these costs are economically meaningful.

Finally, to evaluate potential policy recommendation, we exploit cross-country variances in order to link the effects of crises on bank relationships to the regulatory environment. [To be completed]

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 presents the results of our empirical analysis. Section 4 concludes.

2 Data and Methodology

This paper uses a novel data set, namely a bank-level global network that is constructed from Loanware data on interbank loans. We combine these data with conventional data sources, as described below.

2.1 Global banking network

Dealogic’s Loan Analytics data base (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 data base, we downloaded information on loans extended between January 1, 1980 and December 31, 2009 to private and public sector banks, a total of 15324 loans. Out of these, 84 loans had to be dropped due to missing deal value and 151 had to be dropped due to missing lenders field, which left us with the total of 15089 loans.

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, borrower type (private or public sector), and total deal value in million U.S. dollars. Since the loans are syndicated, they have on average about 7 participants, with the median of two participants. Because information on individual lender’s participation is only available for a handful of the cases, we split each loan equally among lenders, and then among borrowers, in 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 non-banks) as lenders only, 2535 unique banks as borrowers only, and 1110 unique banks that appear as both borrowers and lenders, for the total of 8525 banks.³ On average, for each year we have about 500 loans with about 1000 unique participants as either borrowers or lenders from about 70 countries. Average loan amount (after splitting each loan by borrower-lender pairs) is about 1.7 million 2000 U.S. dollars.

One challenge that we face is with respect to assigning banks to countries. While deal nationality informs us on the nationality of the borrower, there is no information on the nationality of the lender in the Loanware. Thus, we proceed in three steps. First, we download from the universe of information in Loanware all the variables that match institutions with nationalities. Using the data from these variables, we form a list, where each observation is a unique institution name with an associated country name.⁴ We merge the list to our list of banks and call it $C1$ — it is not missing for 7961 out of our 8525 banks.

Second, we take advantage of the fact that 2086 banks, mostly those that appear as borrowers, have country names in parentheses that are appended to the bank name. For example, Bank X might be listed as Bank X (United States). In most cases these are branches or subsidiaries of global banks. Since we are interested in cross-border banking flows, we code these branches as separate banks. Given that the country name may serve as an identifier of nationality, we merge the list to our networks samples and call it $C2$.

Third, for the banks for which either both $C1$ and $C2$ are missing, we used online sources

³While 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 non-banks, e.g. insurance companies and special purpose vehicles.

⁴We dropped institutions that were not unique in our list. In other words, if a given institution was associated with country X in one observation and country Y in another, we eliminate both observations.

such as Alacra, Inc. and Mergent, Inc. to help us identify the nationality of the banks. We then assigned nationality to bank as follows: (1) bank i is assigned the nationality in $C1$ if $C1$ is not missing for bank i and $C1$ is not an offshore financial center (OFC);⁵ (2) bank i is also assigned the nationality in $C1$ if $C1$ is an OFC and $C2$ is also an OFC, where $C1$ and $C2$ may or may not be the same; (3) $C2$ is assigned to bank i if $C1$ is missing and $C2$ is not an OFC or if $C1$ is an OFC and $C2$ is not an OFC; and (4) we assign bank i the nationality in $C3$ if both $C1$ and $C2$ is missing, 81 banks, of which six are in OFCs according to $C3$. There are two cases remaining — when $C1$ is missing and $C2$ is an OFC (28 banks), and vice versa (224 banks). We adopted two ways of dealing with these cases. First, we did not assign any country, so that these observations would drop from any analysis that involves country information. Second, we assigned a non-missing OFC as their country.⁶ The first approach leaves us with 7935 banks with countries assigned, while the second approach preserves all banks.

For each of the 30 years covered with the data, we create a list that has only three elements: borrower, lender, and nominal loan amount. Using a custom Java program, we create, from each list, a directed banking network for each of the 30 years, taking into account the amount of each loan, in U.S. dollars.⁷ In this network each bank, whether it is a borrower or a lender, or both, represents a node with connections going to other banks. We compute, for each node of the network, i.e. each bank, network statistics of interest as described below. We work with bank-level and country-level data sets, where country-level data set is generated from bank-level by aggregating across banks.

Some terminology needs to be introduced in order to describe precisely networks statistics used

⁵We use Rose and Spiegel (2007) for the list of offshore financial centers, but exclude from this list larger countries. Thus, countries we classify as OFCs are Andorra, Bahamas, Bahrain, Barbados, Bermuda, Cayman Islands, Cost Rica, Cyprus, Gibraltar, Guernsey, Jersey, Kuwait, Liechtenstein, Macao, Malta, Mauritius, Monaco, Morocco, Netherlands Antilles, Oman, Saint Kitts and Nevis, UAE, and British Virgin Islands.

⁶We will use the second approach for testing the robustness of our results.

⁷Directed networks are networks in which the direction of relationship matters, i.e. bank A borrowing from bank B is not identical to bank B borrowing from bank A. Taking account of the amount of each loan allows us to retain the information on the “intensity” of each relationship, which will be useful for weighing the data for regressions and aggregates and for computing some network statistics, as described below.

in this paper. The vertices (nodes) of the network, banks in our case, are indexed by $i = 1, \dots, I$. 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, 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. loan from bank i to bank j .

The *length* of a path is the number of edges that comprise that path regardless of the weight. 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, and 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} .

In this paper we are interested in the reach of the network and the importance of each country in terms of international financial intermediation. Thus, we limit our analysis to the following four network statistics, of which first three measure the reach and the fourth measures bank's importance in international banking flows.

- **OutEccentricity** (oe_i) is the length of the longest geodesic path originating in node i :

$$oe_i = \max_j g_{ij}.$$
- **InEccentricity** (ie_i) is the length of the longest geodesic path terminating in node i :

$$ie_i = \max_j g_{ji}.$$
- **MeanFarness** (f_i) is the length of an average geodesic path originating or terminating in node i :

$$mf_i = \sum_j (g_{ij} + g_{ji}) / \sum_j (p_{ij} + p_{ji}).$$

- **Betweenness** (b_i) 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 : $b_i = \sum_j \sum_k (p_{jik}/p_{jk})$.

In addition, in order to control for the total amount lent and borrowed and to compute weighted averages we construct two more statistics.

- **Emission** is a sum of values of all edges incident *from* node i divided by the total number of nodes in the network: $EMISSION_i = \sum_j w_{ij}/I$.
- **Reception** is a sum of values of all edges incident *to* node i divided by the total number of nodes in the network: $RECEPTION_i = \sum_j w_{ji}/I$.

Table 1 presents, for each year, the number of loans in our original Loanware list, the number of banks, the number of countries these banks are in, the number of geodesic paths in the network, and the total amount lent, deflated by U.S. CPI. We can see a substantial decline in each of these variables in 2008 and 2009, as we would expect. For instance, whereas on average over 1000 banks participated in borrowing or lending each year, in 2009 the network consisted of only 558 banks.⁸

This table also reports the diameter of the network, which is simply the length of the longest geodesic path in the network, the average degree of the network, which shows the average shortest distance between every pair of two banks, and network density which is the ratio of edges in a network over all possible ones.⁹ Note that as the network becomes more dense, the average length of a geodesic path tends to become smaller. For example, in a complete network, where all the nodes are linked directly to each other, average length of a geodesic path is one.

⁸Of course, there was an unusually high number of bank mergers and acquisitions during the crisis that would automatically lower the number of distinct banks in the network. Two points are worth mentioning here — first, we consider bank branches located in different countries as separate banks, whenever information is available. Insofar as branches retain their names, mergers would not affect much our sample. Second, we are planning to incorporate mergers information, subject to data availability, to the analysis.

⁹Since our network is directed, $c_{ij} \neq c_{ji}$, so the total possible number of edges in the network is $I(I - 1)$, where I is the total number no banks in the network.

- **Diameter** is the length of the longest geodesic path in the network: $d = \max_{ij} g_{ij}$.
- **Average degree** is the average length of geopaths in the network: $ad = \sum_{ij} (g_{ig} + g_{ji}) / \sum_{ij} (p_{ig} + p_{ji})$.
- **Density** is the total number of edges in the network as a share of all possible edges: $\rho = \sum_{ij} (c_{ig} + c_{ji}) / (I(I - 1))$.

We can see that all three measures declined substantially both during the 2001 recession and also in the recent crisis indicating that the international banking network became smaller in a sense of maximum and average length of the path, and more densely linked.

Table 2 presents summary statistics for our network measures for the full sample and for the sample of U.S. and U.K. banks — two countries that dominated the sample. We can see, as we would expect, that both U.S. and U.K. banks were on average more active than an average bank in the entire network — with average U.S. bank receiving more loans and average U.K. banks extending more loans. U.K. banks appear to have further reach in the network, both in terms of farness and in terms of outeccentricity, and seem to have also been more important in intermediation — higher betweenness than for U.S. banks.

2.2 Other data sets

We append bank network statistics with country-level data from the International Financial Statistics (IFS), World Economic Outlook (WEO), World Development Indicators (WDI), and Bloomberg. For each database, the following editions are used: IFS data are taken from April 2010 On-Line edition; WEO data are taken from October 2009 edition (downloaded March 2010); WDI data are taken from 2009 edition. We collect data on nominal GDP in U.S. dollars as a measure of country size, real GDP growth and unemployment as measures of business cycle, bank lending activity as a measure of bank lending to the private sector, exchange rates, inflation rates and U.S. CPI for

scaling nominal variables.

Data on nominal GDP in U.S. dollars consist of series from WDI supplemented with IFS series line 99b converted to U.S. dollars and with WEO data. Nominal GDP in local currency reported in IFS line 99b is converted to U.S. dollars by using the exchange rate series described below. For Euro Area countries, IFS extends nominal GDP in local currency series to present day. Data for Taiwan are taken from WEO. No forecasts are used. Missing WDI data are automatically filled with available IFS data only if the maximum absolute percent difference between the two WDI and IFS series are less than or equal to five percent. For countries reporting percent difference greater than five percent between WDI and IFS series, visual inspection is conducted before manually splicing series. In the splicing process, IFS or WEO data is combined to WDI data at the beginning and/or at the end of the WDI series only if earlier and/or most recent overlapping years, respectively, are relatively similar. In some cases, IFS or WEO data is used for countries for which WDI data is missing entirely. No WEO forecasts are used in the process of constructing nominal GDP in U.S. dollars series.

Data on real GDP growth, unemployment, and inflation rate consist of series from IFS (lines 99b, 67r, and 64x, respectively) with missing observations filled with WEO data if available. Since IFS does not report the data for Iceland and Taiwan, we take these series entirely from WEO. Where WEO data are used, for the most recent years the figures are based on International Monetary Fund (IMF) staff estimates.

Data on other depository corporations' claims on private sector consist of series from IFS line 22d supplemented with series from line 22s for Euro Area countries, excluding Slovak Republic. Data for Slovak Republic is reported in line 22d. For Euro Area countries, data denominated in local currency reported on line 22d is discontinued after countries join the union and is continued on line 22s with figures denominated in Euro. Thus to construct an uninterrupted series for Euro Area countries, series reported in line 22s is converted to local currency using fixed exchange rates

provided by IFS, and then appended to series reported in line 22d. The Netherlands, Luxembourg, France, Belgium and Austria are missing 1998 data, both in IFS line 22d and 22s. Thus we fill in 1998 for these countries by taking the average of adjoining years after constructing combined series from line 22d and 22s.

Data on exchange rates consist of local currency per US dollar series reported in WDI supplemented with series from IFS line rf and WEO. The Euro denominated exchange rate series for Euro Area countries reported in WDI and IFS are converted to local currency using fixed exchange rates provided by IFS. Missing WDI data are filled with IFS data when available. For the following countries, recent IFS data is allowed to be appended to WDI series since although there are large discrepancies in exchange rates earlier in the series, differences disappear in recent years: Brazil, Nicaragua, Afghanistan, Democratic Republic of Congo, and Slovenia. Exchange rate data for Taiwan are calculated by dividing nominal GDP in local currency by nominal GDP in US dollars as reported in WEO. For 2009, Taiwan's exchange rate is taken from Bloomberg via the Federal Reserve Board.

Data on seasonally adjusted US consumer price index is taken from the US Bureau of Labor Statistics via Haver Analytics. The series consist of all items, all urban consumers, with the index set to 100 between 1982 and 1984.

Dates of systemic banking crises are taken directly from Laeven and Valencia (2008). Data on U.S. recessions are from the NBER. We also use Bank Regulation and Supervision Database, updated in June 2008 (Barth, Caprio, and Levine, 2008).

3 Results

We conduct our analysis at the bank level, properly clustering standard error each time to avoid downward bias (Moulton, 1990). We first analyze the effects of U.S. recessions and of the global

financial crisis, then we turn to the analysis of the effects of country-specific recessions and systemic banking crises.

3.1 Effects of U.S. and local recessions and of local banking crises

Table 3 shows the results of bank-level regressions of each of our four network statistics on indicators of U.S. recession and indicators for years 2008 and 2009. Importantly, 2008-09 are also classified as U.S. recession, and therefore the coefficients on indicators for 2008 and 2009 measure the change in the network statistics *in addition* to recession effects. In all regressions we allow for common trend and in the last four regressions we control, in addition, for the total loan amount in each year, which is equal to the sum of all emissions or the sum of all receptions in each year. Regressions reported in Table 3 do not include any fixed effects. However, results are robust to including bank or country fixed effects; in fact, including bank fixed effects increases both the magnitudes and the significance level of the coefficients of interest. Standard errors are clustered on year because the variables of interest only vary year-to-year. The sample includes almost 8000 banks from 141 countries over 30 years.¹⁰

The first three columns of Table 3 demonstrate that the reach of the network tends to decline during U.S. recessions on average and that during global financial crisis (especially in 2009) the reach of the network declined even further than it would have during a regular recession. Average importance of individual banks in intermediating international banking transactions, measured by betweenness, also declines during recessions and also experienced an additional decline during the global financial crisis, both in 2008 and in 2009.

One may be concerned that these effects are simply the result of decline in total lending that tends to occur during U.S. recessions. To make sure that the effects we find are not purely

¹⁰The number of observations and the number of banks are slightly lower in farness and betweenness regressions due to missing values of these statistics for a few banks.

mechanical, we control, in the next four columns of Table 3, for the total amount lent. We continue to find negative effects of both U.S. recessions and of global financial crisis on all four network statistics. This means that network reach and average importance in intermediation tend to decline during U.S. recessions and experienced further decline during global financial crisis *for a given amount of lending*. In what follows, we will continue to control for total lending, separating total emission and total reception when we control for these aggregates by country-year.¹¹

We can interpret these results as follows: during U.S. recessions, and especially during the global financial crisis, international banking network became more concentrated, in a sense that interbank lending was made within a tightly knit core of banks, while banks on the periphery were less involved, if at all. Importantly, Nier, Yang, Yorulmazer, and Alentorn (2008) show in a theoretical model that more concentrated banking systems are prone to larger systemic risks. Our results therefore suggest that this additional propagation mechanism of the banking crisis is present in the data — crisis makes the banking network more concentrated which makes it more fragile.

Table 4 presents the analysis of the effects of country-specific recessions on the global banking network. We define “recessions” as years in which real GDP growth rate was below 30-year linear trend for each country. Appendix Table 1 lists recession years for each country in the sample. To make sure our results are not driven by the U.S. banks, we exclude them from the sample. We also exclude from the sample banks from the OFCs. Including these banks in the sample does not affect the results. Because variables of interest are country-level, we include country fixed effects and total emission and reception for each country in each year, we also cluster standard errors by country-year, although clustering them by year does not change the results. We continue allowing for common trend. Because we exclude U.S. banks and banks from OFCs, we now have about 6500 banks from 130 countries over 30 years.

First four columns of Table 4 show that our network statistics tend to fall during country-

¹¹By construction, total emission is equal to total reception for the entire network. However, for each country emission and reception need not and do not add up to the same number.

specific recessions, and fell even further during global financial crisis, both in 2008 and 2009. Importantly, for 85 percent of the sample 2008 is classified as recession, and for 98 percent of the sample 2009 is classified as a recession. Thus, these results show that global banking network shrunk further during the global financial crisis than it would have during “regular” global recession.

Last four columns of Table 4 control for the U.S. recession. We continue to exclude the U.S. from the sample. As before, the results strongly show that banking network becomes more concentrated during the U.S. recessions and even more so during the global financial crisis. We can see, however, that only for betweenness do we still have a significant effect of country-specific recessions. We interpret these results as showing that the reach of the global banking network tends to decline during U.S. recessions but is not affected by local recessions, while the importance of individual banks in intermediation declines when their countries are undergoing recessions, in addition to its decline due to U.S. recessions. These results make sense intuitively — while the network reach, by construction, depends on conditions in many countries, individual banks’ role in intermediation is likely to be diminished by its home-country recession.

Table 5 provide similar analysis to that of Table 4, except now we study the effects of country-specific banking crises, also listed in Appendix Table 1. To avoid a mechanical effect of banking crises on the network, we lag the measure of banking crises by one year. As before we include common trend, country fixed effects, total emission and reception by country. We exclude banks from OFCs and cluster standard errors by country-year. Because banking crises data are available for fewer countries, we only have about 3700 banks from 102 countries in these regressions. Once again, first four columns do not control for the U.S. recessions, while last four columns do.

We find that local banking crises have negative effects on the reach of the network as measured by outeccentricity and farness, although the size of the effects is small compared to those of U.S. recession or global financial crisis and the coefficient on outeccentricity becomes insignificant if

we exclude banks from the U.S.¹² We find that there is no effect of local banking crises on the importance of the banks in the intermediation. These effects do not change much if we control for the U.S. recession. As before, we continue to find strong negative effects of the U.S. recession and further negative effects of the global liquidity crisis.

To sum up, we find that U.S. recessions lead to the concentration of global banking network and that this concentration was more pronounced during global financial crisis than during a “normal” recession. We further find that local recessions and banking crises have only limited effects on network characteristics, with local recession only affecting the degree of intermediation but not the network reach of the banks in the affected countries.

3.2 How long do the effect lasts?

Bank relationships take time to form. We therefore expect that once they are disrupted during the crises, they may take time to rebuild. To study this possibility, we focus on the effects of the U.S. recessions and construct indicators of one and two years since the end of the U.S. recession.¹³ We exclude 2008 and 2009 from the sample because current recession is not over and we do not want the results to be driven by the global financial crisis. We continue to include trend and total amount lent in each year. Since we no longer include country-level variables, we do not include country fixed effects and we cluster standard errors by year. First four columns of Table 6 present the results without any fixed effects, while second four columns include bank fixed effects. Regressions in Table 6 span 28 years, during which there were about 7700 banks from 134 countries.

Once again, we find strong decline in network measures during the U.S. recessions. We find that the effect is still negative in the first year after the recession. It is somewhat smaller in magnitude than the decline during the recessions and is only statistically significant for inecentricity in the

¹²The results without the U.S. banks are not reported but are available upon request.

¹³We experimented with three and four years, but found that, as can be seen from what follows, including these is unnecessary.

regressions without fixed effects and for three other measures in the regressions with bank fixed effects. In the second year after the U.S. recession the effect becomes even smaller and even turns positive for some measures and is only statistically significant for inecentricity in the regression without bank fixed effects.

We conclude from this analysis that the effects of U.S. recessions on global banking network are less persistent than we would have expected. We find evidence that they are likely to last through a year after the recession is over, but we do not see evidence of the effects persisting beyond that first year.

3.3 What are the costs?

While the findings above are interesting from an academic point of view, we also want to investigate their economic importance. In particular, we want to see whether the concentration of the global banking network, such as occurs during U.S. recessions, has real economic consequences. We measure these consequences by estimating the effects of network measures on GDP growth (percent per year), unemployment rate (percent), and growth rate of the bank credit to the private sector (percent per year, deflated by local CPI). Because our dependent variables are now country-level, we transform our data into a country panel as follows.

First, we construct a first principal component of our four network measures at the bank level — for bank i it is equal to

$$1stPC_i = 0.42 * oe_i + 0.44 * ie_i + 0.59 * f_i + 0.54 * b_i.$$

It has an eigenvalue of 2.0 and captures 50 percent of variance.¹⁴ Next, we compute a simple average of this principal component across banks for each country and year, thus obtaining a

¹⁴Second principal component also has an eigenvalue greater than 1 and captures additional 32 percent of the variance, but does not enter significantly in the regressions and does not affect the results.

country panel.¹⁵ We lag the principal component of network measures by one year.

Table 7 reports the results of our regression analysis. The panel size varies due to limited availability of macro data. We exclude OFCs from all regressions and always control for country fixed effects and common trend. First three columns present the basic specification, second three columns control for U.S. recessions and exclude the U.S. from the sample. Last three columns further exclude 2008 and 2009 from the analysis. The results are consistent across all three sets of the regressions with the only exception of the coefficient on GDP growth that is no longer significant in the third set of the regressions.

We find that higher network measures are associated with higher GDP growth, lower unemployment, and faster increase in the bank credit to the private sector, even when we control for the U.S. recessions that do indeed have negative effect on macroeconomic performance measures even though the U.S. banks are excluded from the sample. It is important to keep in mind that these effects are identified by within country variation in banks' network characteristics and macroeconomic performance and not by cross-country differences.

The magnitudes of these effects are economically meaningful — one standard deviation increase in the principal component (which is equal to about 1 in the aggregated country panel) would increase GDP growth and lower unemployment by about a quarter of a percentage point, while it would increase the growth rate of the bank credit to the private sector by about one percentage point.

We can conclude that strong network relationships are good for the economy and therefore when U.S. recession weakens them, they can function as a propagation mechanism of the crisis.

¹⁵We also experimented with computing weighted average using sum of emission and reception for each bank as a weight and found that our results are robust to such alteration.

3.4 What can be done?

The importance of interbank relationships is relevant for policymakers in terms of requirements on the transparency of the banks, which will reduce both the importance of the relationships and the extent of their break-down during crises. Moreover, providing guarantees for interbank lending may prevent the breakdown in confidence and trust that destroys interbank relationships. To illustrate these points, the paper will exploit cross-country differences in bank regulation to test whether indeed countries with more transparent banking systems or with better guarantees on interbank transactions suffered less of a break-down in banking relationships during crises.

[To be completed]

4 Conclusion

U.S. recessions shrink global banking network.

Global financial crises affected the banking network even more than U.S. recessions would.

Local recessions and banking crises have less of an effect.

Effects of U.S. recessions persist just one year after.

Decline in the network linkages has economically meaningful real costs.

Bank regulation...

[To be completed]

References

- BARTH, J. R., G. CAPRIO, AND R. LEVINE (2008): “Bank Regulations are Changing: For Better or Worse?,” World Bank Policy Research Working Paper No.4646.
- BOTTAZZI, L., M. DA RIN, AND T. HELLMANN (2009): “The Importance of Trust for Investment: Evidence from Venture Capital,” CentER Discussioin Paper No. 2009-43, Tilburg University.
- COCCO, J. A. F., F. J. GOMES, AND N. C. MARTINS (2009): “Lending Relationships in the Interbank Market,” *Journal of Financial Intermediation*, 18, 24–48.
- EICHENGREEN, B. (2009): “Lessons of the Crisis for Emerging Markets,” ADBI Working Paper No. 179.
- GUISSO, L., P. SAPIENZA, AND L. ZINGALES (2009): “Cultural Biases in Economic Exchange,” *Quarterly Journal of Economics*.
- KARLAN, D., M. MOBIOUS, T. ROSENBLAT, AND A. SZEIDL (2009): “Trust and social collateral,” *Quarterly Journal of Economics*.
- LAEVEN, L., AND F. VALENCIA (2008): “Systemic Banking Crises: A New Database,” IMF working paper 08/224, International Monetary Fund.
- LEHMANN, E., AND D. NEUBERGER (2001): “Do lending relationships matter? Evidence from bank survey data in Germany,” *Journal of Economic Behavior and Organization*.
- 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., J. YANG, T. YORULMAZER, AND A. ALENTORN (2008): “Network Models and Financial Stability,” Bank of England Working Paper No.346.
- PUTNAM, R. (1995): “Bowling Alone: America’s Declining Social Capital,” *Journal of Democracy*.
- REINHART, C. M., AND K. S. ROGOFF (2009): “The Aftermath of Financial Crises,” Paper prepared for presentation at the American Economic Association meetings in San Francisco.
- ROSE, A. K., AND M. M. SPIEGEL (2007): “Offshore Financial Centres: Parasites or Symbionts?,” *The Economic Journal*, 117(523), 1310–1335.
- SCHULARICK, M., AND A. M. TAYLOR (2010): “Credit Booms Gone Bust: Monetary Policy, Leverage Cycles and Financial Crises, 1980-2008,” Paper presented at the FRBSF conference on Monetary Economics.
- VELDCAMP, L., AND S. VAN NIEUWERBURGH (2010, forthcoming): “Information Acquisition and Under-Diversification,” *Review of Economic Studies*.
- VON PETER, G. (2007): “International Banking Centres: a Network Perspective,” *BIS Quarterly Review*.

Appendix Country-specific recessions and banking crises

[To be completed]

Table 1: Size of network by year

Year	Loans	Banks	Countries	Geopaths	Amount	Diameter	Avg. Degree	Density (%)
1980	149	509	60	2185	124	6	3.1	0.80
1981	246	783	68	3688	163	15	3.2	0.61
1982	192	765	70	3806	159	11	3.2	0.65
1983	143	670	59	3665	119	10	4.0	0.62
1984	205	717	58	11130	121	17	5.7	0.71
1985	291	880	62	6883	279	19	3.9	0.65
1986	417	910	58	7409	552	17	3.9	0.64
1987	513	1114	58	7451	584	22	4.1	0.46
1988	438	1115	63	4883	572	14	3.2	0.42
1989	408	1079	61	3707	488	12	2.5	0.43
1990	509	1220	59	4144	828	13	2.5	0.40
1991	509	1235	65	4742	990	29	2.9	0.37
1992	534	1225	64	4560	2024	15	2.9	0.36
1993	536	1349	70	5701	1549	14	2.7	0.41
1994	700	1444	71	10406	2250	29	3.6	0.46
1995	823	1576	77	27061	1873	42	5.5	0.48
1996	868	1769	79	23687	1458	42	5.0	0.43
1997	882	1662	83	15147	1769	55	4.1	0.46
1998	582	1103	74	7870	2021	22	3.7	0.56
1999	549	1158	71	7047	1783	21	3.4	0.57
2000	587	1075	73	14030	1039	28	4.7	0.70
2001	350	849	74	5579	434	11	2.8	0.86
2002	401	792	67	6131	401	22	3.6	0.84
2003	417	828	78	5430	439	16	3.0	0.89
2004	515	984	88	9618	475	27	4.0	0.81
2005	834	1220	91	16972	661	42	4.4	0.74
2006	820	1225	99	19003	732	55	4.1	0.72
2007	671	1117	95	18040	831	53	4.4	0.77
2008	639	915	99	5709	576	35	3.3	0.68
2009	596	558	84	1263	374	16	2.6	0.60

Table 2: Network summary statistics

Variable	OBSERVATIONS	Mean	Std. Dev.	Min	Max
Total banks:	7935				
Emission	30104	0.00071	0.0058	0	0.28
Reception	30104	0.00070	0.0042	0	0.22
Outecentricity	30104	2.23	3.96	0	55
Inecentricity	30104	0.92	2.92	0	52
MeanFarness	30085	1.36	0.62	1	5.42
Betweenness	30099	23.9	82.4	0	1899
US banks:	1313				
Emission	3845	0.00078	0.0037	0	0.13
Reception	3845	0.00123	0.0067	0	0.22
Outecentricity	3845	1.78	3.55	0	55
Inecentricity	3845	0.55	1.51	0	26
MeanFarness	3845	1.23	0.51	1	4.55
Betweenness	3845	12.3	38.3	1	959
UK banks:	848				
Emission	3727	0.00216	0.0141	0	0.27
Reception	3727	0.00068	0.0043	0	0.12
Outecentricity	3727	2.97	4.81	0	44
Inecentricity	3727	0.36	1.40	0	37
MeanFarness	3719	1.42	0.67	1	4.62
Betweenness	3727	19.1	65.7	0	1887

Table 3: Effects of U.S. recession and liquidity crisis on network characteristics

	Outeccc.	Inecc.	MFarness	Betweenness	Outecc.	Inecc.	MFarness	Betweenness
I(U.S. recession)	-0.738** (0.342)	-0.300** (0.133)	-0.166** (0.066)	-9.450** (4.010)	-0.946*** (0.325)	-0.339** (0.124)	-0.204*** (0.066)	-12.298*** (3.699)
I(2008)	-0.839 (0.514)	-0.183 (0.195)	0.000 (0.088)	-11.975* (6.388)	-0.925* (0.475)	-0.199 (0.201)	-0.015 (0.079)	-13.160** (5.905)
I(2009)	-1.526*** (0.536)	-0.464** (0.203)	-0.166* (0.092)	-24.041*** (6.677)	-1.589*** (0.494)	-0.476** (0.207)	-0.177** (0.083)	-24.900*** (6.117)
Total loan amount					-0.724** (0.341)	-0.135 (0.149)	-0.131** (0.063)	-9.910** (4.607)
Trend	0.049* (0.025)	0.037*** (0.008)	0.004 (0.004)	0.881*** (0.312)	0.058** (0.023)	0.039*** (0.009)	0.005 (0.004)	1.010*** (0.297)
Constant	1.659*** (0.460)	0.407*** (0.147)	1.343*** (0.090)	12.579** (5.515)	2.131*** (0.472)	0.495*** (0.131)	1.428*** (0.101)	19.043*** (5.262)
Observations	30104	30104	30085	30099	30104	30104	30085	30099
Banks	7935	7935	7933	7935	7935	7935	7933	7935
R ²	0.020	0.012	0.018	0.011	0.025	0.012	0.025	0.013

Standard errors clustered by year are in parenthesis. 30 years. 141 countries.

Table 4: Effects of local recession and liquidity crisis on network characteristics

	Outecc.	Inecc.	MFarness	Betweenness	Outecc.	Inecc.	MFarness	Betweenness
I(country recession)	-0.371** (0.161)	-0.145** (0.057)	-0.064** (0.029)	-5.836*** (1.944)	-0.252 (0.163)	-0.096 (0.058)	-0.038 (0.028)	-4.277** (1.948)
I(2008)	-1.414*** (0.239)	-0.839*** (0.294)	-0.188*** (0.046)	-24.579*** (5.700)	-0.698*** (0.270)	-0.545* (0.299)	-0.028 (0.053)	-15.209** (5.919)
I(2009)	-2.075*** (0.268)	-1.021** (0.405)	-0.339*** (0.044)	-35.221*** (6.410)	-1.367*** (0.293)	-0.731* (0.409)	-0.180*** (0.051)	-25.944*** (6.621)
Country emission	0.460 (1.118)	-0.399* (0.239)	0.051 (0.139)	-11.736 (10.793)	0.275 (1.108)	-0.475** (0.240)	0.010 (0.135)	-14.164 (10.736)
Country reception	-5.159** (2.358)	1.133 (0.963)	-0.435 (0.294)	5.063 (30.965)	-5.271** (2.298)	1.087 (0.948)	-0.460* (0.266)	3.603 (30.020)
I(U.S. recession)					-0.741*** (0.155)	-0.304*** (0.060)	-0.166*** (0.028)	-9.700*** (1.747)
Trend	0.087*** (0.010)	0.013*** (0.003)	0.007*** (0.002)	0.672*** (0.129)	0.075*** (0.011)	0.008** (0.004)	0.005** (0.002)	0.514*** (0.135)
Observations	25987	25987	25968	25982	25987	25987	25968	25982
Banks	6493	6493	6491	6493	6493	6493	6491	6493
R ²	0.093	0.218	0.045	0.063	0.097	0.219	0.053	0.064

Local recession is defined as years when growth was below 30-year trend.

30 years and 130 countries in all regressions, OFCs and the U.S. excluded.

Country fixed effects are included in all regressions.

Standard errors clustered by country-year (1920 clusters) are in parenthesis.

Table 5: Effects of local banking crises and liquidity crisis on network characteristics

	Outecc.	Inecc.	MFarness	Betweenness	Outecc.	Inecc.	MFarness	Betweenness
L.I(banking crisis)	-0.491* (0.257)	-0.171 (0.285)	-0.119** (0.058)	0.877 (7.581)	-0.529* (0.314)	-0.180 (0.276)	-0.126** (0.064)	0.437 (7.788)
I(2008)	-2.436*** (0.307)	-0.907*** (0.333)	-0.225*** (0.049)	-40.923*** (8.781)	-1.133*** (0.356)	-0.589* (0.331)	0.013 (0.058)	-25.733*** (8.815)
I(2009)	-3.519*** (0.341)	-1.260*** (0.411)	-0.458*** (0.039)	-55.299*** (8.391)	-2.213*** (0.386)	-0.942** (0.412)	-0.219*** (0.050)	-40.069*** (8.570)
Country emission	0.461 (1.388)	-0.497*** (0.187)	0.091 (0.157)	-15.408 (12.384)	0.141 (1.326)	-0.575*** (0.183)	0.033 (0.143)	-19.136 (11.982)
Country reception	-6.275*** (2.007)	0.983* (0.539)	-0.814*** (0.233)	-5.767 (23.260)	-6.651*** (1.965)	0.891* (0.529)	-0.883*** (0.221)	-10.145 (22.515)
I(U.S. recession)					-1.281*** (0.180)	-0.313*** (0.063)	-0.234*** (0.030)	-14.939*** (2.090)
Trend	0.134*** (0.014)	0.017*** (0.004)	0.009*** (0.002)	1.097*** (0.172)	0.117*** (0.014)	0.012*** (0.004)	0.006*** (0.002)	0.891*** (0.176)
Observations	16654	16654	16642	16650	16654	16654	16642	16650
Banks	3733	3733	3732	3733	3733	3733	3732	3733
R ²	0.102	0.254	0.049	0.079	0.110	0.255	0.064	0.081

Country fixed effects are included in all regressions.

30 years and 102 countries in all regressions. OFCs excluded.

Standard errors clustered by country-year (1489 clusters) are in parenthesis.

Table 6: How long do the effects of U.S. recession last?

	Outecc.	Inecc.	MFarness	Betweennes	Outecc.	Inecc.	MFarness	Betweennes
I(U.S. recession)	-0.922*** (0.308)	-0.386*** (0.128)	-0.202*** (0.064)	-12.587*** (3.714)	-1.300*** (0.452)	-0.422*** (0.105)	-0.237*** (0.078)	-18.013*** (4.388)
I(Yr1post-recession)	-0.228 (0.276)	-0.243** (0.117)	-0.026 (0.060)	-4.569 (3.279)	-1.365** (0.503)	-0.194 (0.227)	-0.121* (0.071)	-16.921*** (5.040)
I(Yr2post-recession)	0.635 (0.897)	-0.393** (0.185)	0.051 (0.184)	1.301 (8.350)	-0.867 (1.132)	-0.272 (0.207)	-0.069 (0.208)	-13.969 (11.428)
Total loan amount	-0.702** (0.328)	-0.149 (0.140)	-0.129** (0.060)	-9.857** (4.396)	-0.676 (0.428)	-0.050 (0.128)	-0.133* (0.069)	-7.466 (4.732)
Trend	0.058** (0.023)	0.038*** (0.009)	0.005 (0.004)	0.997*** (0.295)	0.110*** (0.032)	-0.003 (0.008)	0.006 (0.004)	0.716** (0.264)
Bank FE	NO	NO	NO	NO	YES	YES	YES	YES
Observations	28697	28697	28680	28692	28697	28697	28680	28692
Banks	7685	7685	7683	7685	7685	7685	7683	7685
R ²	0.024	0.013	0.022	0.012	0.429	0.589	0.352	0.307

Standard errors clustered by year are in parenthesis. 28 years: 2008 and 2009 are excluded. 134 countries.

Table 7: Effects of bank relationships on macroeconomic outcomes

	GDP growth	Unempl.	Bank cred. gr.	GDP growth	Unempl.	Bank cred. gr.	GDP growth	Unempl.	Bank cred. gr.
L.1stPC	0.264** (0.127)	-0.236*** (0.088)	1.099** (0.496)	0.214* (0.125)	-0.245*** (0.088)	1.083** (0.500)	0.128 (0.129)	-0.201** (0.096)	1.423*** (0.542)
I(U.S. rec.)				-2.343*** (0.244)	-0.566*** (0.189)	-2.631** (1.017)	-0.980*** (0.298)	-0.379 (0.238)	-0.770 (1.241)
Trend	0.013 (0.013)	-0.028** (0.011)	0.144*** (0.054)	0.017 (0.013)	-0.020* (0.012)	0.137** (0.055)	0.068*** (0.015)	-0.017 (0.013)	0.193*** (0.063)
Excluded	OFCs	OFCs	OFCs	U.S. & OFCs	U.S. & OFCs	U.S. & OFCs	U.S. & OFCs	U.S. & OFCs	U.S. & OFCs
Sample									
Obs.	1826	1217	1624	1797	1188	1596	1623	1094	1492
Countries	129	76	117	128	75	116	116	74	110
R ²	0.203	0.800	0.225	0.245	0.803	0.227	0.258	0.801	0.240

1stPC is a first principal component of all four network variables which is equal to

$$0.42*Outecc.+0.44*Inecc.+0.59*MFarness+0.54*Betweenness.$$

Country panel regressions. Country fixed effects are included. Standard errors are in parenthesis.