Global Banking Network and Cross-Border Capital Flows

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Abstract

We propose a new factor for understanding aggregate international capital flows: banks' positions in the global banking network (GBN). We construct the GBN at the bank level, using individual syndicated loan data from Loan Analytics for 1980-2007. Using gravity approach to modeling capital flows, we find that country-pairs in which banks are more closely connected within the GBN experience larger inflows and outflows of foreign direct investments, as well as portfolio equity and debt flows between them. After identifying macroeconomic and institutional factors that help explain banks' positions in the GBN and, controlling for their effects, we find in a cross-country regression that countries in which banks were more centrally positioned in the GBN before 2000 experienced higher international capital inflows and outflows in 2001-2007. Network characteristics of banks have large effects and substantially improve the model's fit in gravity and cross-country regressions, but are less important in country fixed-effects panel regressions. Our results suggest that old connections between banks are more important than the new ones.

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1 Introduction

The importance of information flows and relationships between financial institutions, is frequently emphasized in finance and economics literature (Veldcamp & Van Nieuwerburgh, 2010), but is still little understood empirically. The global liquidity crisis of 2007-09 also demonstrated the importance of the relationships between financial institutions, not only within a country but also across national borders. It is therefore not surprising to see an outburst of literature that emphasizes connections between banks. One direction this literature has taken is representation of banking systems as graphs, or networks.[1] The majority of the papers in that area focus on the relationship between the structure of banking network and its stability with respect to shocks.[2] In this paper we take a longer-term perspective and focus on the relationship between long-term international capital flows and connections between banks. Our main question is: How important are connections between individual banks in determining international capital flows at the aggregate level?

Unlike much of 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 (GBN) at the bank level. We use loan-level data from Loan Analytics provided by Dealogic, something that has not been done before.[3] There are many advantages to using bank-level connections to construct the GBN. We

[1]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.

[2]Some recent papers are Battiston et al. (2009); Castiglionesi & Navarro (2007); Chan-Lau et al. (2009); Cocco et al. (2009); Craig & von Peter (2010); Delli Gatti et al. (2010); Garratt et al. (2011); Haldane (2009); Haldane & May (2011); May & Arinaminpathy (2010); Mirchev et al. (2010); Nier et al. (2007); Sachs (2010) and von Peter (2007).

[3]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

emphasize two: First, 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 the BIS data). Second, by constructing the network at the bank level, we can distinguish between the countries or country pairs with many bank-pair connections from countries with few connections that conduct large volume lending activity.

The Loan Analytics database provides information on syndicated banks loans, including those 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 alone 4.7 trillion USD worth of syndicated loans extended to banks are reported in Loan Analytics.

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. We then compute a proximity measure, in the network sense, for each pair of banks, as well as a set of statistics for each bank that would describe the number of direct connections it has (degree) and its position in the GBN (farness and betweenness centrality). For some of our analysis we aggregate these measures at country and country-pair levels.

We construct two separate networks — one based on loans extended between 1980 and 2000, the other based on loans extended between 2001 and 2007. We find that while both networks are rather disperse and not very dense, the global banking network was more concentrated after 2000.

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.

Hale (2011) presents the dynamics of the GBN constructed in a similar fashion at annual frequency. We also construct networks based on loans extended between 1985 and 2000, 1990 and 2000, and 1995 and 2000, in order to analyze relative importance of new and old bank-to-bank connections on international capital flows.

To analyze the effects of banks' position in the GBN on international capital flows we focus on capital flows that are not directly related to bank-to-bank lending: foreign direct investment and portfolio equity and debt flows. We study separately inflows and outflows. We begin the analysis of our main question in the gravity setting using recent data on bilateral assets and liabilities from Milesi-Ferretti et al. (2010). After fitting a benchmark gravity model that explains about 70-90 percent of the variance in bilateral assets and liabilities, we find that our proximity measure has a statistically significant effect: the more closely connected in the GBN are the banks in a country pair, the more capital flows of all types are observed between these countries. The magnitude of this effect is economically significant and adding network proximity measure substantially improves the fit of the model. Moreover, we find that connections between banks do not seem to decay over time, on the contrary, older connections have larger effects. Finally, we find that the effect of geographical distance declines slightly when we include measures of network proximity. These results hold even if we control for the total amount of bank lending between each country pair.

Next we turn to the analysis of aggregate inflows and outflows for each of the 99 countries in our sample, using the Balance of Payments data augmented by Forbes & Warnock (2011) and network measures that describe the position of each of the banks in the GBN aggregated at country level. First, however, we analyze the determinants of bank's position in the global network. In particular, we examine which macroeconomic and institutional variables help understand bank relationships. Explanatory variables are computed as long term averages prior to year 2000: 20-year averages for developed and 10-year averages for developing countries, while banks' positions in the GBn are computed using the network built through lending between 2001 and 2007:H1. We conduct this analysis at the bank level.

We find that for developed countries, the positions of banks in the GBN are affected mostly by the average inflation rate in preceding two decades. Some of the centrality measures for the banks in developed countries are also affected by country wealth, growth rate, and political stability. For developing countries we find that banks' positions in the GBN are affected by their country's size, growth rate, trade openness, exchange rate volatility, political stability, and geographical remoteness. At best, we explain about 10 percent of variance in network characteristics of banks by country-specific variables. This is good news, because it indicates that most of the information we gather from constructing global banking network is orthogonal to macroeconomic and institutional variables.

To analyze the effect of an average bank's position in the GBN on the country's long-term capital flows, we construct a network based on loans extended between 1980 and 2000, and combine it with international capital flows data for 2001-2006 and estimate a cross-country relationship between them. Because some of the same variables can be affecting global banking network in prior to 2000 and capital flows after 2000, we include among our control variables those that we found significant in determining bank's position in the GBN. In addition, we control for total amount lent and borrowed by banks in each country. We find that betweenness centrality is very important in explaining international capital flows — developed countries in which banks are more central tend to experience larger equity inflows, developing countries in which banks are more central tend to experience larger capital inflows and outflows of all types. In addition, debt and equity outflows tend to be lower in developing countries where banks have more direct connections with borrowers or lenders and are more remote in terms of borrowing. The magnitudes of some of these effects are rather large and in many cases the addition of network statistics among explanatory variables substantially improves the fit of the model. We also note that controlling for macroeconomic and institutional factors is important.

We also test whether changes in banks' network positions have short-run effects on capital flows in a subsequent year by constructing country-year panel data of changes in network statistics and estimating a model of annual capital flows in the following year, controlling for country and year fixed effects. For developed countries we find that when new loans increase the number and the remoteness of direct borrowing and lending connections, equity inflows and outflows tend to increase in the following years, which is consistent with the possibility that new bank relationship facilitate an increase in capital flows on the extensive margin, possibly with a diversification purpose. For developing countries we find that an increase remoteness in terms of both borrowing and lending and an increase in the number of borrowing connections is associated with lower FDI and portfolio equity and debt inflows in the subsequent year. Possibly, increased remoteness and the addition of new lenders are symptoms of economic and financial distress, for which we do not fully control with macroeconomic variables, which lead to decline in portfolio capital inflows. The magnitudes of the effects of network statistics in the panel regression are smaller than those we found in cross-country analysis and the improvement in the regression fit is rather small, indicating that changes banks' positions in the GBN network are not very important in driving fluctuations in international capital flows, which is consistent with our finding in the gravity setting that old connections matter more than new ones.

Overall, then, we find that connections between banks play an important role in determining long-term international capital flows — the more closely connected are the banks between the two countries and the more central are the country's banks in the GBN, the larger are the long term FDI and portfolio equity and debt flows. We also find some evidence that for developed countries, creating new and different banking connections tends to facilitate foreign investment. Thus, we provide evidence supporting the idea that relationships between banks are important in facilitating international capital flows other than bank lending.

The paper is organized as follows. Part 2 describes our data, mainly focusing on the construction of the GBN and its description. Part 3 presents bilateral, cross-section, and panel analysis. Part 4 concludes.

2 Data description

We construct the global banking network based on loan–level data from Dealogic's Loan Analytics data base. We use and country–level data from new as well as from conventional sources. In this section we first describe the bank loan data and the network statistics we compute; then, we list the sources of country–level data.

2.1 Loan data and global banking network

We obtain deal–level data on syndicated international and domestic bank loans from Dealogic's *Loan Analytics* database (formerly known as Loanware). As our goal is to capture bank-to-bank lending activity, we download all loans extended to public and private sector banks between 1 January 1980 and 30 June 2007.[4] There are 13,506 loans of this type in our data sample. To get a sense of how representative our data are, consider just one year, 2006. During this year we have about 4 trillion USD worth of new loans extended to public and private sector banks. In December of that same year, 2006, BIS reports total amount of banks' claims on banks, domestic and international, to be about 18 trillion USD. While these numbers are not directly comparable because Loan Analytics reports amounts of loans originated and BIS reports amounts of loans outstanding, they give a sense of the relevance of the syndicated loan market.

Ideally, we would like to ensure that each of the loans in our sample is a bank-to-bank loan, but the Dealogic database only allows us to constrain borrowers' type (which we constrain to be

[4]We end our sample in June 2007 in order for our results not to be affected by the global liquidity crisis that began in August 2007.

either public or private sector bank); it does not allow us to place the same constraints on lenders.[5] Among the loans in our sample over 60% are term credit, revolving loans or CD's while only about 15% are various credit facilities.

While a variety of loan characteristics are available for each of the 13,506 loan deal, we focus on five: name and nationality of borrower (or borrowers), names and nationality of lenders, and total loan amount (in millions of US dollars).[6] We replicate syndicated loans as many times as there are lenders in the syndicate and split the total loan amounts equally among lenders, because for the majority of loans lender-specific amounts are not reported. We also adjust deals with multiple borrowers — there are 315 such cases in our sample — using a similar approach.[7] After completing the replication procedure, we have a data set that contains 106,848 transactions between lenders and borrowers. Each observation has three elements: a borrower name, a lender name, and a divided loan amount.

We proceed to create our networks data set by adjusting the divided loan amount for inflation, using the monthly US "All Urban Consumers" CPI index (2000=100). We also collapse our data set by lender–borrower pair to calculate the *total amount of lending activity* in real terms between each pair. After collapsing the data set we are left with a total of 71,489 unique lender–borrower transactions that would form connections, or edges, in our directed bank network, with each edge carrying a weight equal to the sum of all lending from a given lender to a given borrower in constant 2000 U.S. dollars.[8]

There are 8,138 unique institutions that appear in this data set. Again, we cannot say that all of

[5] As such, some of the lenders within a syndicate may not be banks. We find that the non-bank lenders account for roughly 29% of all lenders in our sample and consist mostly of insurance companies and special purpose vehicles.

[6] When referring to lenders, we are referring to list of all participants in the loan syndicate: lenders, administrators, and lead arrangers. The variable with this list is called *all bank activity* in Dealogic.

[7] If there are x borrowers and y lenders for a given loan, the loan deal is replicated $x \cdot y$ times. Then, the loan amount is divided equally among the borrower–lender pairs.

[8] Directed 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.

the institutions are banks because some of the lenders are non-bank entities. We are, however, able to provide a rough upper bound for the number of non-bank entities as follows. Of the 8,138 unique institutions, 2,354 appear only as borrowers in the data set and 1,028 appear as both borrowers and lenders. Because any institution that appears as a borrower is a bank (as we set this constraint when downloading the data), we know that 3,382 institutions are banks. Thus, we are left with the 4,756 institutions that appear as lenders. By searching through these lenders, we find that 3,093 may be identified as banks, as the word "bank" (in any language) appears in the entity's name. The lower limit on the total number of banks in our sample, therefore, is 6,475, or about 80% of all institutions.

In the empirical analysis, we focus on two smaller networks built from our main data sample: (1) a subsample with loan deals between 1 January, 1980, and 31 December, 2000 — the "early subsample"; and (2) a subsample with loan deals between 1 January, 2001, and 30 June, 2007 — the "late subsample". The two samples are generated exactly as described above. From these, we create two directed bank networks that take into account the loan amounts and compute network statistics that are described in the next section. To do so, we make use of a custom Java code and custom Mata code for Stata (Miura, 2010). We check our computations, when possible, against MatlabBGL version 4.0. After computing the network statistics, we link each banking entity to a country on a locational basis.

2.2 Network statistics

The vertices (nodes) of our network, each representing a bank, 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, 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.

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, 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}.

For each pair of nodes we compute their *proximity* δ_{ij} as an inverse of the length of the geodesic path, that is $\delta_{ij} = 1/g_{ij}$. For each node we also calculate the following measures:

- **OutDegree** (od_i) is the number of edges originating from node i;
- **InDegree** (id_i) is the number of edges terminating in node i;
- **OutFarness** (f_i) is the length of an average geodesic path originating from node i: $of_i = \sum_j g_{ij} / \sum_j (p_{ij} + p_{ji})$;
- **InFarness** (f_i) is the length of an average geodesic path terminating in node i: $if_i = \sum_j g_{ji} / \sum_j (p_{ij} + p_{ji})$;
- **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: $b_i = \sum_j \sum_k (p_{jik}/p_{jk})$;

In- and outdegrees measure how many direct connection each bank has in terms of borrowing and lending, respectively. In- and outfarness and betweenness are measures of centrality of a bank. Farness measures how remote is the bank from the center of the network in terms of borrowing or how remote are the banks that it is ultimately lending to, while betweenness measures how central the bank is in terms of intermediating bank flows.

For part of our analysis, we aggregate network statistics by country and country pair. We compute average proximity between countries A and B as a simple average of proximities between each pair of banks in which one bank is located in country A and the other in country B. For bank-level statistics, we construct weighted averages, using as weights total lending of each bank for outdegree and outfarness, total borrowing of each bank for indegree and infarness, and the sum of lending and borrowing for betweenness.

2.3 Network description

The early subsample includes 6866 banks from 125 countries that are linked by 54204 links. The late subsample includes 2598 banks from 117 countries that are linked by 19471 edges. Appendix Table 6 provides information on network statistics for G-20 countries. As we would expect to see, the United States, the UK, Germany, and, to some extent, Japan are leading in total borrowing, lending, and the number of banking institutions among G-20 nations. Among these same countries, Indonesia, Russia, South Africa, and Turkey in early sample and India, Russia, and Turkey in the late sample have the highest indegree, indicating that these countries' banks on average accessed a large number of banks for credit. Saudi Arabia and Germany in the early sample have the highest outdegree, indicating that banks in these countries lent directly to a large number of banks. Nevertheless, some of these same countries are on the periphery in terms of borrowing and lending, as shown by infarness and outfarness, respectively. Banks in China, Russia, and Korea in the early sample and in India, Indonesia, and Turkey in the late sample had high betweenness, indicating that banks in these countries were important in connecting different clusters of banks.

In addition to the node-level statistics described above, the network can be characterized as a whole. One important characteristic of a network is its *density*, which is equal to the number of edges as a share of all possible edges in the network (which is equal, for a directed network, to $N(N-1)$, where N is the number of nodes). In our case, the density of the early network is 0.11 percent, while the density of a late network is 0.29 percent, indicating that in the last decade the banks became much more connected to each other than in the previous period. This is no surprise given a sharp increase in international capital flows in the early 2000s.

Another important measure is a *diameter* of the network, which reflects how far the network stretches. It is measured as the length of the longest geodesic path in the whole network, i.e. $\max_{i,j} g_{ij}$. The diameter of our early network is 15, while the diameter of our late network is 22. As far as networks go, this diameter is quite large, for two reasons: first, we have a lot of nodes in our networks, second, directed networks tend to have longer geodesic paths because of "one-way" connections. Note that even though the number of banks in our network declined by more than half from early to late sample period, the diameter of the network actually increased, reflecting the fact that more remote banks are now included in the network.

Our final network-wide measures are *clustering coefficients*. They measure the presence of clusters, or cliques, in the network. There are two main ways to measure the clustering of the network — at a network level, a *global clustering coefficient* can be computed — it is equal to the ratio of closed triplets (sets of three nodes which are all connected to each other, in both directions) over the total number of triplets in the network (which is equal to $N(N-1)(N-2)/6$). In our early network global clustering coefficient is 3.8 percent, while in the late network it is 5.3 percent, demonstrating an increased incidence of clusters in the network over time. A *local clustering coefficient* can also be computed for each node — it is equal, simply, to the density of each nodes' immediate neighbors. An average local clustering coefficient in our early network is 4.3 percent, while in our late network it is 4.6 percent.

Overall, our network appears to be rather dispersed and not very dense, especially compared to financial networks constructed based on country-level data such as Kubelec & Sá (2010). This is true by construction. However, it implies that one needs to be careful when making statements about the fragility of the network due to its concentration and density because underlying network is at the bank level, and the density of the bank-level network is low.

Unfortunately, high dimensionality of our network does not allow us to represent it graphically. As an illustration, however, Figure 1 demonstrates a subsection of our late network which includes all banks that are within two degrees of the Hong Kong branch of Credit Agricole Indosuez, the 10th largest lender in our late network.

2.4 International capital flows

Our main goal is to see whether bank relationships help us understand international capital flows. We rely on two newly constructed data sources: bilateral gross external positions in various instruments from Milesi-Ferretti et al. (2010) and capital flows data from the *Balance of Payments Statistics* from the IMF's International Financial Statistics (IFS BOP) augmented by Forbes & Warnock (2011). After deflating the individual flows data by the US annual consumer price index (2000=100), we compute the gross inflows and outflows for each category of interest (foreign direct investment, portfolio equity securities, and portfolio debt securities) over 2001-2006 sample period. For our panel analysis, we simply use the deflated value of these variables for each of the years they are available between 1980 and 2009.

While bilateral data are stocks as of 2007, we interpret them as long-term flows and assert that they were mostly accumulated after 2000, and therefore we use information on bank connections from the network constructed based on loans extended prior to 2001. For our bilateral analysis we focus on the following countries: Canada, China, Hong Kong, Japan, Singapore, Switzerland, United Kingdom, United States. We also include two aggregate regions: Emerging Asia and Euro area. We repeat all our analysis excluding the aggregated regions to make sure these regions do not drive our results.

2.5 Additional data sources

For our country–level macroeconomic and institutional data we use conventional sources. The macroeconomic variables were obtained from the World Development Indicators system of the World Bank, including measures of income, size, openness trade and financial openness, financial indicators, fiscal indicators, current account balance, and inflation.

To account for de jure capital account openness we use the index by Chinn & Ito (2008). We use different databases to account for institutional variables, including indexes for political and institutional development (ICRG and Polity), indexes of financial reform and banking supervision from Abiad et al. (2008), data on private credit rights from Djankov et al. (2007), and data on exchange rate regimes from Ilzetzki et al. (2008). In the analysis we also control for banking and currency crises, using the database on financial crises by Laeven & Valencia (2008). Finally, following recent literature on gravity models of international capital flows, we control for distance, computing a measure of weighted distance from each country to all other countries in the sample.

3 Effects of bank connections on international capital flows

We approach our main question from three angles: the effect of bilateral proximity between two country's banks on the extent of capital flows between these two countries in the gravity analysis context; the effect of banks' positions in the GBN on long-term inflows and outflows of capital in and out of the country where these banks are located in the cross-country regression context; and the effect of changes in banks' positions in the GBN on short-run fluctuations in capital flows in the context of panel regression with country fixed effects. We analyze separately gross inflows (liabilities) and gross outflow (assets) of FDI, portfolio equity, and portfolio debt.

3.1 Gravity regression

We begin our analysis with a standard gravity regression of bilateral gross external positions. There is a prolific empirical literature documenting the robustness of a gravity approach to explain the international capital flows. This approach models financial flows between countries i and j as a function of their size and distance. The role of distance has been rationalized as a proxy for information costs and information asymmetries that agents face (Portes et al., 2001; Portes & Rey, 2005; Buch, 2005). Overall, the literature has found a negative and significant effect of information asymmetries, in particular distance, for all types of financial flows. Portes and Rey (2005) show evidence that a gravity model accounts for up to 70 percent of the variance of gross cross-border bilateral equity transactions. Similar evidence on the role of distance and GDP per capita is presented by Ghosh & Wolf (2000) and by Daude & Fratzscher (2008) for bilateral flows of FDI, debt, bank lending and equity. The Buch (2005) results suggest that a gravity-type model can explain up to 80 percent of variation in cross-border bank assets and show a robust and negative coefficient for distance.[9]

Geographical distance, however, may be picking up the effect of trade in goods or economic ties due to direct investment. Aviat & Coeurdacier (2007) present evidence that, controlling for bilateral trade in goods, the negative coefficient of distance is reduced, although it remains negative and statistically significant. Jain (1986) shows a positive and significant effect of trade in goods and FDI in the international lending of US banks. Similarly, Jain & Nigh (1989) report a positive and significant coefficient of trade in the international lending of US banks, while Goldberg & Johnson (1990) and Dahl & Shrivies (1999) find that FDI flows have a positive significant impact on international lending of US banks. Similar results on the positive effect of trade on bank lending are reported using large country samples by Jeanneau & Micu (2002) in the case of bank's aggregate lending flows, and by Rose & Spiegel (2002) for sovereign lending.

[9] Wei (2000) and Wei & Wu (2001) also estimate gravity-type models and find significant coefficients for size and distance in a small sample using data on international lending 1994-1996.

We follow the set up in Glick & Taylor (2010). For each of the instruments: FDI, portfolio equity, and portfolio debt, we estimate a benchmark gravity regression of gross inflows (liabilities) and outflows (assets):

$$y_{ij} = \alpha_i + \alpha_j + GDPPC_i * GDPPC_j + POP_i * POP_j + D_{ij} + \varepsilon_{ij},$$

where α_i and α_j are country fixed effects, $GDPPC$ is log of real GDP per capita, POP is log of population, D_{ij} is log geographic distance between biggest cities in countries i and j. We find that our benchmark regression has a pretty good fit with R^2 ranging from 0.6 to 0.9. We experiment with including additional control variables that have been used in the gravity literature, but none of them affect our results, so we leave them out of our benchmark regressions.[10] To this benchmark we add our measure of average proximity of banks in each country pair as described above, in logs.

Table 1 summarizes the results of our analysis. Each cell in the table consists of three numbers: coefficient on average proximity with its significance level denoted by *'s, R^2 from the regression that includes this proximity measure, and adjusted R^2 from the corresponding regression that excludes it. This way, we can tell how much regression fit improves when we include network proximity.[11] Rows correspond to different types of capital flows, while columns correspond to various sample periods from which we construct global banking network and compute proximity measures. Finally, left half of the table presents the analysis for the full sample of countries, while the right half excludes emerging Asia and the euro area.

We find that network distance between the two countries has a standard gravity effect on international capital flows — the closer are the countries the more capital flows between them we observe. Except, of course, in our case we measure proximity in global banking network, rather than in

[10] Specifically, we included product of countries' geographical areas, indicator of common language, indicator of colonial link, a dummy variable for whether countries are contiguous, an indicator of common colonizer prior to 1945 and after 1945, and trade flows. In most of the regressions none of these variables entered significantly. The product of areas was significant in some specifications.

[11] Full regression results are not reported in the interest of space, but are available from the authors upon request.

geographical sense.[12] We find that the effect of network proximity is highest for FDI and lowest for portfolio debt flows and that it is the smallest for portfolio debt outflows. We also find, counter to our expectations, that old connections between banks matter more than new connections, as indicated by lower coefficients in regressions where proximity measure is based on a shorter, more recent, network. Excluding regional aggregates only makes effects larger in magnitude.

We also find that in many cases adjusted R^2 increases substantially when network proximity measure is included — the largest increase, from 0.64 to 0.79, is in the regression of FDI outflows on the oldest network proximity measure for the restricted sample that excludes regional aggregates. This means that including our proximity measure explains additional 15 percentage points in the variance of bilateral FDI asset positions for this subsample. The explanatory power of the proximity measure is more modest in other regressions, but is still substantial.

Given that all our variables are included in the regressions in logs, we can also interpret coefficients as elasticities: if average proximity doubles (which would be an equivalent of increasing proximity from sample minimum of 0.17 between Emerging Asia and Canada to sample maximum of 0.31 between Hong Kong and China), FDI liabilities between the two countries will increase by 20 percent. These magnitudes are reasonable — not implausibly larger, yet economically meaningful.

To summarize our bilateral analysis, we find that bilateral external asset and liability positions in 2007 were higher between countries in which banks were more closely connected in the GBN that is based on loans extended by banks to banks prior to 2001. We find that older connections have larger effects than newer connections and that direct investments are more sensitive to network proximity than portfolio investments.

[12] Correlation between proximity and the inverse of the geographical distance is positive, but very low, 0.15. Including network proximity in the regression slightly lowers the coefficient on geographical distance.

3.2 Macro determinants of bank relationships

Before analyzing in the cross-country and panel setting to what extent banks' positions in the global network help us understand aggregate international financial flows, we need to understand the determinants of banks' network statistics themselves. Because the level of financial development is drastically different between the OECD and the developing countries, we analyze the determinants of network measures separately in these two samples. For this part, we use the network statistics constructed from the late sample that only includes loans starting 2001 and we use averages of macroeconomic and institutional variables for the period of 1980-2000 for OECD and 1990-2000 for developing countries.[13]

3.2.1 Potential explanatory variables

To inform our analysis on the determinants of the bank relationships, we turn to the empirical literature on the determinants of international capital flows in general, and banking flows in particular. Following the literature, we can classify the main determinants of international capital flows into three broad categories in addition to gravity variables described before: (i) regulation and institutional characteristics; (ii) macroeconomic variables; and (iii) financial sector indicators.

Institutional variables have been found to determine international capital flows and bank lending by Alfaro et al. (2008), Aviat & Coeurdacier (2007), and Papaioanno (2009). Similar results are reported by Buch (2005) for measures of protection of property rights and by Daude & Fratzscher (2008) for proxies of investor protection and corruption — both studies using international bank lending. In contrast to these findings, Wei (2000) and Wei & Wu (2001) report a positive coefficient for corruption in a gravity-type model of bilateral international lending. Thus, in contrast with

[13] We use the shorter sample of explanatory variables for developing countries for two reasons: First, many developing countries in our sample were affected by the debt crisis in the 1980s, which is not necessarily informative of their international banking relations in post-2000 years. Second, data for the 1980s for developing countries is limited, especially for the Eastern European economies.

other studies, they find that a lower quality of institutions is associated with larger lending flows. Similarly, Wei (2006) and Faria & Mauro (2009) find that higher levels of institutional quality (or lower levels of corruption) are associated with smaller shares of bank loans in a country's foreign liabilities. Differential effects of institutions on different types of capital flows are also found by Daude & Fratzscher (2008).

Most empirical studies don't find a robust association between bank lending and macroeconomic variables once proper controls for institutional quality and gravity-type regressors are introduced in the analysis (Papaioanno, 2009; Jeanneau & Micu, 2002; Buch, 2005).[14] Goldberg (2002) shows that international lending by US banks is uncorrelated with foreign demand conditions but instead responds to business cycles and monetary policy in the US.

In contrast, financial indicators are found to be important drivers of international capital flows. McGuire & Tarashev (2008) reports that the spread of interest rate between countries i and j increases lending to j. Similar results are reported by Moshirian & Bishop (1997) for a small sample of industrial countries. McGuire & Tarashev (2008) also shows evidence that larger lending flows are associated with foreign bank participation and higher bank equity (as measured by stock indexes of financial companies shares). Similarly, Buch (2001) finds that a high share of government ownership in banking, the existence of capital controls and high corporate-tax rates reduce cross-border bank lending.[15] Aviat & Coeurdacier (2007) also report negative and significant coefficients for tax rates on dividends and interest.

Guided by this literature, we put together a list of potential determinants of the banks' positions in the GBN, presented in Appendix 2, each variable calculated as a simple average over the years between the first year in our sample and 2000, unless otherwise specified.

[14] Volatility of the exchange rate and the exchange rate regime may also play a role. Jeanneau & Micu (2002) found that countries with fixed exchange regimes attract larger lending flows.

[15] However, the evidence on capital controls is not strong. Daude and Fratzscher (2007) find no significance of this variable in their specification for bank lending.

3.2.2 Empirical results

The level of financial development is very different in developed and developing countries, we therefore split our sample into high income OECD countries and the rest. As described above, we use 1980-2000 averages for developed and 1990-2000 averages for developing countries. We conduct the rest of our analysis for these two samples separately.

For the sample of banks from industrial countries, indegree is highly positively correlated with infarness and borrowing, while outdegree is only highly positively correlated with lending. For the developing countries we see high correlation between borrowing and indegree and lending and outdegree, while the correlation of infarness and outfarness with borrowing and lending and with indegree and outdegree is weaker. Betweenness is somewhat correlated with both borrowing and lending for developing, but not for industrial countries.

After inspecting correlations between each of the network statistics and each of potential explanatory variables, we retain all variables that have a potential to have explanatory power and do not have too many missing values. Next, we estimate an OLS regression for each of our network statistics, at bank level, which we weigh by the share of each bank's sum of emission and reception in the total network, on a set of explanatory variables that survived our pre-screening. Because all explanatory variables are country-level while the unit of observation is a bank, we cluster our standard errors by country to avoid downward bias (Moulton, 1990).[16] We further drop the variables that do not have explanatory power for any of the regressions and are not essential controls (such as size and wealth).

We report the effects of remaining variables for developed and developing countries' regressions in Tables 2 and 3, respectively. We find that for developed countries, as one would expect, better quality of the government as measured by ICRG index is associated with higher importance of

[16]We repeat our analysis at the country level, used weighted averages of network statistics for each country. We find very similar results, which we do not report in the interest of space.

banks in the network — higher betweenness. We also find that banks in larger countries have lower betweenness. Higher inflation is associated with more remoteness and more direct links in terms of borrowing, but with less remoteness and fewer direct links in terms of lending. Higher inflation is also associated with higher betweenness. Surprisingly, there is no relation between international trade openness and bank network statistics.

For developing countries we find that lower indegree and infarness and higher outdegree and outfarness are observed in countries that are larger, have higher GDP growth, higher trade openness, and lower exchange rate volatility. We also find that betweenness is higher in countries with better quality of the government, countries that are larger, and those that are less remote geographically.

Overall, macroeconomic variables explain a much larger share in the variation of the measures of bank relationships for developing than for developed countries, as measured by R^2. This is not surprising: Developed countries' financial markets are much older than our sample period and many of the global bank headquarters were established in these countries well prior to the time for which we have available data. Developing countries' financial markets, on the other hand, are younger and frequently their development is a function of the overall economic and institutional development of the countries, which is consistent with the results of our analysis.

3.3 Cross-country analysis

We now turn to the cross-country analysis of the impact of banks' positions in the GBN on international capital flows. For this analysis we use the network data that are based on the early sample of bank loans (1980-2000) and aggregate international capital flow data for 2001-2006 as a share of GDP. That is, we are trying to understand how banks' connections formed during two decades prior to 2000 affected international capital flows in the last decade, prior to the liquidity crisis. Because left-hand side variables are at a country level, we use country averages of weighted network statistics as explanatory variables. Because many of the network statistics are highly correlated, we conduct our analysis including them one-by-one. Since betweenness is less correlated with other variables, we include it together with infarness and outfarness in some specifications, but find that our results do not change when we do this. We continue to conduct our analysis separately for developed and developing countries.

As before, we conduct our analysis separately for assets and liabilities for each of the asset types: FDI, portfolio equity, and portfolio debt, as well as for total flows. The results are reported in Table 4, where each row presents a coefficient in the regression of the left-hand side variable (rows of the table) and a network measure (columns of the table). The significance level of the coefficient is indicated by the *s. Below each coefficient, we report the adjusted R^2 of each regression and the adjusted R^2 of the regression in which a network statistic is excluded, for comparison. In each case, for industrial countries, the number of observations is 21, while for the developing countries the number of observations is 78. Both dependent variables and regressors are in logs, which means the coefficients represent elasticities of capital flows with respect to network statistics.[17] The left panel of Table 4 presents the results for industrial countries, while the right panel presents the results for developing countries.

Table 4 includes, in additional to macroeconomic and institutional factors, total lending and borrowing as controls: borrowing for indegree and infarness regressions, lending for outdegree and outfarness regressions, and the sum of lending and borrowing for betwenness regressions. We include these controls to avoid the results that will simply be driven by the fact that some countries are more active in international financial markets of all types than others. Macroeconomic and institutional variables are the ones we found to be important in determining banks' positions in the GBN: GDP growth, trade/GDP, inflation, ICRG government index, GDP per capital, exchange rate volatility, real GDP in USD, and geographical distance. We include these variables as averages over 1980-2000

[17] In the BOP statistics, assets, or outflows, are presented with a negative sign. For the ease of interpretation, we reverse the sign of the coefficient in the regressions of outflows, so that a positive coefficient means that an increase in the explanatory variable is associated with an increase in capital outflows. We deal with negatives as follows: $x = log(y)$ if $y > 0$; $x = -log(-y)$ if $y < 0$; $x = 0$ if $y = 0$.

for industrial and over 1990-2000 for developing countries.

We exclude Ireland, Iceland, and Hong Kong from the sample because they are outliers in terms of capital flows as a share of GDP. We find that developed countries in which banks are more central in terms of betweenness tend to have larger equity inflows, while developing countries with banks that are more central in terms of betweenness tend to have large capital inflows and outflows of all types, except FDI outflows and equity inflows. In addition, we find that developed countries in which banks have more direct connections in terms of borrowing, indegree, tend to have less FDI inflows and more equity outflow, while developing countries in which lending banks are more remote, tend to have higher equity outflows.

Including network statistics substantially improves the fit of the model especially in the case of betweenness: for example, the addition of betweenness to the regression of equity inflows into developed countries increases adjusted R^2 from negative to 0.19, suggesting that over 20 percent of the cross-country differences in equity inflows among developed countries could be attributed to betweenness centrality of these countries banks in the GBN. Similarly, adding betweenness to the regression of equity outflows for developing countries increases the share of variance explained by 12 percentage points.

3.4 Country fixed effects panel analysis

In this section we test for short-term relationship between network statistics and international capital flows in the panel data setting with country and year fixed effects. To do so, we construct the cumulative panel of network statistics as follows. First, we generate a data set on bank loans between 1980 and year t, for each $t \in [1980; 2008]$. For each of these data sets we construct a network and compute network statistics that we then associate with year t and aggregate by country. As a result, we have a country-year panel where network statistics represent connections between banks accumulated since year 1980. We use first differences in these network statistics which measure the effect of new relationships formed in year t on changes in banks' positions in the GBN, lagged one year, as our explanatory variables.

On the left-hand side, we use annual capital flows from IFS BOP statistics augmented by Forbes & Warnock (2011) as a share of GDP. As controls, we include the same set of macroeconomic and institutional control variables as in cross-country regression, lagged one year, first differences in total borrowing or lending, as well as country and year fixed effects. We can still include average distance in the regressions because weights, based on GDP, change over time even though distances do not.

It is important to emphasize that the nature of this exercise is different from the cross-country analysis presented above. In the cross-country analysis we were looking for the long-term correlation between measures of banking relationships established between 1980 and 2000 and average international capital flows in years 2001-2007. Here, instead, we are looking for the short-term effects of changes in banks' positions in the GBN due to newly formed bank relationships on international capital flows in the following year, absorbing all long-term cross-country differences and all common trends by country fixed effects and year fixed effects, respectively.

The results are reported in Table 5. The structure of the table is similar to that of Table 4, where each row presents a coefficient in the regression of the left-hand side variable (rows of the table) and a network measure (columns of the table). The significance level of the coefficient is indicated by the *s. Below each coefficient, we report the adjusted R^2 of each regression and the adjusted R^2 of the regression in which a network statistic is excluded, for comparison.

We first note that while betweenness of banks is an important determinant of cross-country differences in long-term international capital flows, changes in banks' betweenness do not seem to have any effect on capital flows in the following year, with one exception: increase in betweenness tends to increase FDI outflows for developing countries. This is consistent with our intuition — increase in banks' centrality allows country's residents to establish foreign projects more easily.

We find the rest of the results to be very different for developed and developing countries. For developed countries we find that when new loans increase the number of direct borrowing connections, equity outflows tend to increase in the following year, while an increase in the remoteness of lending connections tends to increase equity outflows and lower FDI inflows in a following year. First two of these effects are consistent with the possibility that new bank relationship facilitate an increase in capital flows on the extensive margin, possibly with a diversification purpose.

For developing countries we find that an increase remoteness of lending tends to lower equity inflows, while an increase in the number and in remoteness of borrowing and lending connections additionally lowers portfolio debt inflows. Possibly, increased remoteness and the addition of new lenders are symptoms of economic and financial distress, for which we do not fully control with macroeconomic variables, which lead to decline in portfolio capital inflows.

The improvement in the regression fit is rather small, indicating that changes banks' positions in the GBN network are not very important in driving fluctuations in international capital flows: at best, we observe a 2 percentage points increase in the R^2 when we include network statistics. This is not surprising, especially in light of our finding in the gravity setting that old relationships matter more than new one in determining international capital flows.

4 Conclusion

We demonstrate empirically that connections between banks are important in determining international capital flows. To do so, we construct a bank-level global banking network that is build through banks lending to each other. We show that countries proximity in terms of the position of their banks in the GBN as well as the centrality of individual country's banks tend to be associated with larger long-term international capital flows of all types, even when we account for total amount of bank lending and other variables that are found to be correlated with international capital flows.

We interpret this finding as evidence that banks' intermediation is important not only for bank flows, but also for FDI, portfolio debt and equity flows.

This finding is important in a number of ways. First and foremost, it implies that connections between banks are an important factor in explaining international capital flows that so far has been overlooked, at least in the empirical literature. Second, it supports the view of complementarity between various types of international capital flows as opposed to the views that these different types of capital flows are substitutes. Third, it points to the importance of stable macroeconomic and political environment for fostering banks' connections to the global banking network and therefore encouraging capital flows. Finally, it confirms empirically the argument frequently made in the literature of the importance of relationship and information flows in determining international borrowing, lending, and portfolio asset purchases.

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Figure 1: An illustration of a subset of the network

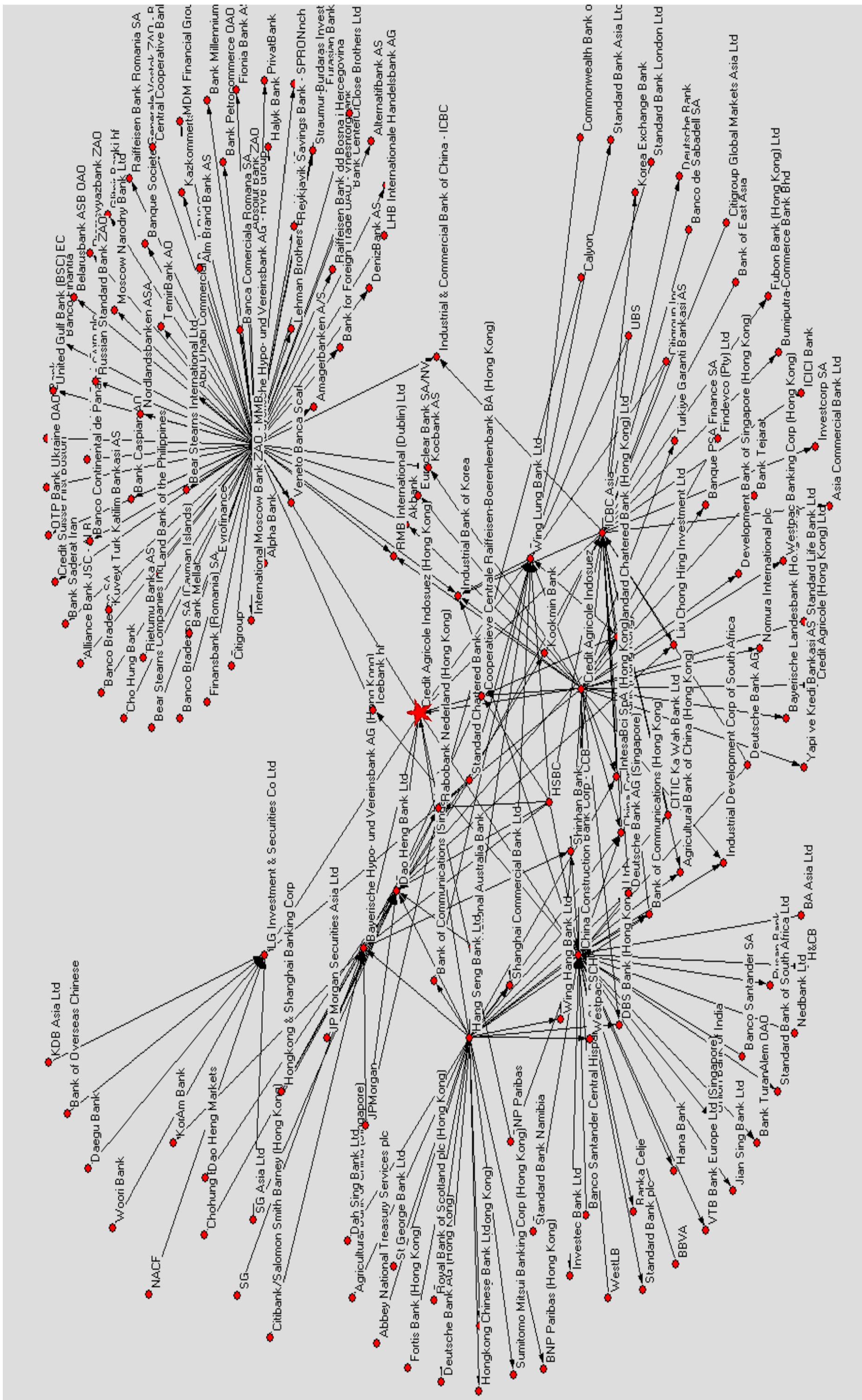

Table 1: Gravity Regressions Summary

	Full sample				No regional aggregates			
	1980-2000	1985-2000	1990-2000	1995-2000	1980-2000	1985-2000	1990-2000	1995-2000
FDI out	19.850***	17.137***	11.045***	8.456**	34.964***	28.882***	14.190***	9.757**
	0.69	0.70	0.69	0.70	0.79	0.70	0.73	0.73
	0.63	0.63	0.63	0.63	0.64	0.64	0.64	0.64
FDI in	18.216**	14.821**	9.503**	8.224**	30.371***	23.745***	11.905**	9.163**
	0.71	0.71	0.70	0.73	0.78	0.71	0.73	0.75
	0.66	0.66	0.66	0.66	0.67	0.67	0.67	0.67
Equity out	11.220**	8.354**	3.310	2.383	17.540***	13.506***	6.293*	3.916*
	0.74	0.73	0.72	0.72	0.79	0.73	0.77	0.76
	0.72	0.72	0.72	0.72	0.75	0.75	0.75	0.75
Equity in	14.037***	11.220***	8.283***	5.160***	17.248***	13.545***	5.607*	3.624
	0.80	0.80	0.81	0.80	0.85	0.80	0.83	0.82
	0.77	0.77	0.77	0.77	0.81	0.81	0.81	0.81
Debt in	13.712***	10.877***	5.803**	4.226**	20.198***	15.771***	6.584**	4.455**
	0.90	0.89	0.89	0.89	0.92	0.89	0.90	0.90
	0.87	0.87	0.87	0.87	0.89	0.89	0.89	0.89
Debt out	8.385	6.833*	5.807**	4.247**	17.726***	13.209**	7.132**	4.699**
	0.89	0.89	0.90	0.90	0.92	0.89	0.91	0.91
	0.89	0.89	0.89	0.89	0.90	0.90	0.90	0.90

Dependent variables are in rows, measured in logs. Control variables are country fixed effects, product of GDP per capita, product of population, and geographical distance, all in logs. 92 observations in full sample, 73 observations in restricted sample. Reported in each cell are coefficient on proximity measure, R^2 of the regression with proximity measure, and R^2 of the regression that excludes proximity measure.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Determinants of banks' network statistics for developed countries.

	(1) indegree	(2) outdegree	(3) infarness	(4) outfarness	(5) betweenness
Avg. GDP Growth	-0.98	-0.42	-0.95	-0.33	-0.84***
	(1.29)	(1.20)	(1.24)	(1.16)	(0.27)
Trade/GDP	-2.11	2.37	-2.06	2.28	0.024
	(1.95)	(1.55)	(1.89)	(1.53)	(0.33)
Inflation	6.48***	-4.72***	6.26***	-4.51***	1.14**
	(2.05)	(1.41)	(1.96)	(1.38)	(0.52)
ICRG government score	1.91	0.27	1.89	0.32	1.46***
	(2.39)	(2.00)	(2.31)	(1.96)	(0.44)
GDP PC, PPP	3.35	-8.50	3.02	-8.77	-3.93**
	(8.30)	(6.55)	(8.02)	(6.48)	(1.43)
Constant	-75.2	78.1	-71.8	79.9	-5.52
	(78.7)	(62.1)	(76.0)	(61.5)	(13.1)
Observations	1416	1416	1416	1416	1416
Adjusted R^2	0.031	0.032	0.031	0.031	0.018

Dependent variables in column headings. Explanatory variables are averages of 1980-2000.

All variables are in logs. Robust standard errors, clustered by country, in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Determinants of banks' network statistics for developing countries.

	(1) indegree	(2) outdegree	(3) infarness	(4) outfarness	(5) betweenness
Avg. GDP Growth 90 to 00	-0.71***	0.89**	-0.66**	0.91***	0.14
	(0.26)	(0.34)	(0.27)	(0.33)	(0.14)
Trade/GDP	-5.25***	6.69***	-5.00***	6.83***	1.10
	(1.40)	(0.86)	(1.39)	(0.86)	(0.68)
CV of NominalExchange Rate	0.34***	-0.39***	0.34***	-0.39***	-0.036
	(0.047)	(0.044)	(0.045)	(0.045)	(0.024)
GNI (nominal)	-1.21*	2.98***	-1.32**	3.02***	1.07***
	(0.65)	(0.76)	(0.65)	(0.74)	(0.32)
ICRG government score	0.78	0.79	0.61	0.83	0.96**
	(0.79)	(0.81)	(0.78)	(0.79)	(0.47)
Average distance	3.54	-13.6	4.23	-13.4	-6.14**
	(8.18)	(8.26)	(8.10)	(8.24)	(2.89)
Constant	8.67	-12.9	4.88	-17.3	-18.2
	(72.0)	(70.6)	(71.2)	(70.3)	(26.7)
Observations	836	836	836	836	836
Adjusted R^2	0.10	0.14	0.098	0.15	0.017

Dependent variables in column headings. Explanatory variables are averages of 1990-2000.

All variables are in logs. Robust standard errors, clustered by country, in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Cross-country Regressions Summary

	Developed countries					Developing countries				
	InD	OutD	InF	OutF	Betw	InD	OutD	InF	OutF	Betw
FDI Out	-0.006	0.0006	-0.007	-0.021	0.0015	-0.0018	0.00089	0.0012	-0.0012	0.00049
	0.71	0.75	0.71	0.81	0.76	-0.079	-0.084	-0.090	-0.078	-0.055
	0.73	0.78	0.73	0.78	0.78	-0.039	-0.037	-0.039	-0.037	-0.032
FDI In	-0.016*	-0.003	-0.006	-0.014	0.002	0.0012	0.0004	0.004	-0.0001	0.0019**
	0.66	0.33	0.37	0.42	0.36	0.37	0.40	0.37	0.40	0.44
	0.41	0.39	0.41	0.39	0.40	0.39	0.43	0.39	0.43	0.40
Equity Out	0.0050	-0.0025	0.0014	-0.0004	0.0011	0.0027	0.0019	0.007*	0.0015	0.0006**
	0.54	0.40	0.50	0.39	0.50	0.21	0.32	0.25	0.31	0.30
	0.55	0.46	0.55	0.46	0.54	0.17	0.28	0.17	0.28	0.18
Equity In	0.016*	0.0064	0.0076	0.0084	0.006**	0.001	0.0013	-0.0026	0.00023	0.00018
	0.079	-0.25	-0.41	-0.31	0.19	0.20	0.21	0.21	0.16	0.17
	-0.35	-0.23	-0.35	-0.23	-0.31	0.23	0.20	0.23	0.20	0.19
Debt Out	0.0045	-0.0055	-0.021	-0.033	0.005	0.0002	-0.0008	0.0018	0.00060	0.00041*
	0.22	0.23	0.29	0.33	0.26	0.56	0.58	0.57	0.58	0.62
	0.30	0.31	0.30	0.31	0.30	0.58	0.60	0.58	0.60	0.60
Debt In	-0.007	-0.0015	-0.019	-0.017	0.0043	-0.002	-0.002	-0.008	-0.001	0.00095**
	-0.53	-0.53	-0.47	-0.51	-0.49	0.13	0.17	0.16	0.17	0.21
	-0.37	-0.36	-0.37	-0.36	-0.36	0.16	0.20	0.16	0.20	0.14

Dependent variables in rows, measured as a share of GDP. Signs of coefficients for outflows are reversed.
Reported in each cell are coefficient on network statistic in column, R^2 of the regression with network statistic, and R^2 of the regression without network statistic. Ireland, Iceland, and Hong Kong are dropped.
In the top panel controls are total borrowing and total lending. In the bottom panel additional controls are GDP growth, trade/GDP, inflation, ICRG government index, GDP per capital, exchange rate volatility, real GDP, geographical distance as averages over 1980-2000 for industrial and 1990-2000 for developing countries, in logs.

Table 5: Panel Fixed Effects Regressions Summary

	Developed countries					Developing countries				
	InD	OutD	InF	OutF	Betw	InD	OutD	InF	OutF	Betw
FDI Out	0.003	-0.003	0.0001	-0.003	-0.00	-0.00	-0.002	-0.001	-0.001	0.0001***
	0.31	0.31	0.31	0.31	0.31	0.15	0.17	0.15	0.17	0.16
	0.31	0.31	0.31	0.31	0.31	0.15	0.17	0.15	0.17	0.16
FDI In	0.002	-0.003	0.0003	-0.006*	-0.00	-0.001	-0.001	0.002	-0.002	-0.001
	0.21	0.21	0.21	0.21	0.21	0.087	0.093	0.087	0.093	0.092
	0.21	0.21	0.21	0.21	0.21	0.088	0.095	0.088	0.095	0.089
Equity Out	0.003*	0.004	0.002	0.004**	0.00	-0.001	-0.002	-0.001	-0.002	-0.00
	0.42	0.42	0.42	0.42	0.43	0.075	0.079	0.078	0.079	0.080
	0.42	0.42	0.42	0.42	0.43	0.075	0.075	0.075	0.075	0.081
Equity In	0.002	-0.003*	0.0008	-0.002	-0.00	-0.0003	-0.001	-0.001	-0.004*	0.00
	0.12	0.12	0.11	0.12	0.12	0.062	0.064	0.063	0.074	0.064
	0.12	0.12	0.12	0.12	0.12	0.065	0.066	0.065	0.066	0.066
Debt Out	-0.0004	-0.0004	-0.002	-0.001	0.00	-0.00	0.0002	-0.0003	0.002	-0.00
	0.54	0.54	0.54	0.54	0.54	0.065	0.064	0.065	0.068	0.066
	0.54	0.54	0.54	0.54	0.54	0.067	0.066	0.067	0.066	0.068
Debt In	-0.002	0.004	-0.003	-0.0018	-0.00	-0.009**	-0.008**	-0.005**	-0.01***	-0.0004
	0.34	0.34	0.34	0.34	0.34	0.10	0.11	0.095	0.11	0.095
	0.34	0.34	0.34	0.34	0.34	0.089	0.091	0.089	0.091	0.094

Dependent variables in rows, measured as a share of GDP. Signs of coefficients for outflows are reversed.

Reported in each cell are coefficient on changes in network statistic in column, R^2 of the regression with network statistic, and R^2 of the regression without network statistic. Ireland, Iceland, and Hong Kong are dropped.

Controls are changes in total borrowing and total lending as well as GDP growth rate, trade/GDP, geographical distance, inflation, ICRG government score, GDP per capital, real GDP in USD, all in logs and lagged by one year.

5 Appendix 1. Network statistics

Table 6: Network statistics for G-20

Early sample			medians					weighted means					
country	lending	borrowing	banks	indegree	outdegree	infarness	outfarness	betw	indegree	outdegree	infarness	outfarness	betw (%)
Argentina	971	23,744	53	2	0	1.0	0.0	0	1.22	0.16	0.07	0.07	0.0012
Australia	61,351	271,437	181	2	0	1.5	0.0	0	0.27	0.41	0.02	0.02	0.0009
Brazil	1,338	32,629	99	2	0	1.5	0.0	0	0.30	0.04	0.04	0.03	0.0002
Canada	44,859	55,326	70	0	1	0.0	1.0	0	0.08	1.05	0.05	0.04	0.0001
China	2,127	39,655	77	0	1	0.0	1.0	0	3.64	0.30	0.04	0.05	0.0154
France	192,136	186,263	195	0	2	0.0	2.2	0	0.21	0.79	0.02	0.01	0.0022
Germany	521,777	318,435	244	0	3	0.0	3.3	0	0.04	0.50	0.01	0.01	0.0000
India	1,011	9,121	20	7	1	3.3	1.0	0	7.36	1.13	0.17	0.20	0.0022
Indonesia	318	14,126	79	12	0	4.1	0.0	0	0.95	0.08	0.05	0.04	0.0001
Italy	56,144	140,231	252	0	1	0.0	1.0	0	0.40	0.37	0.01	0.01	0.0006
Japan	135,439	71,052	276	0	3	0.0	3.5	0	0.03	0.54	0.01	0.01	0.0002
Mexico	753	26,652	33	6	0	3.7	0.0	0	2.34	0.25	0.11	0.13	0.0016
Russia	1,357	52,569	42	14.5	0	3.6	0.0	0	5.78	0.66	0.07	0.09	0.0069
Saudi Arabia	3,487	0	15	0	7	0.0	3.6	0	0.00	2.17	0.00	0.23	0.0000
South Africa	87	7,974	18	20	0	3.9	0.0	0	5.73	0.18	0.21	0.07	0.0002
South Korea	7,491	101,336	142	0	2	0.0	4.0	0	1.84	0.13	0.02	0.03	0.0042
Turkey	1,031	31,419	71	12	1	3.2	1.0	0	2.82	0.13	0.04	0.04	0.0000
United Kingdom	1,625,961	527,443	747	0	2	0.0	2.7	0	0.03	0.13	0.00	0.00	0.0001
United States	466,023	783,442	1150	0	1	0.0	1.0	0	0.04	0.09	0.00	0.00	0.0001
Unweighed mean				7.9	7.9	1.4	2.3						0.0001
Late sample			medians					weighted means					
country	lending	borrowing	banks	indegree	outdegree	infarness	outfarness	betw	indegree	outdegree	infarness	outfarness	betw (%)
Argentina	7	2,508	7	7	0	1.4	0.0	0	6.58	0.14	0.56	0.14	0.0000
Australia	15,913	16,729	36	1.5	1	1.5	1.0	0	0.27	0.52	0.23	0.10	0.0016
Brazil	166	6,746	28	4	0	1.5	0.0	0	0.96	0.08	0.18	0.04	0.0000
Canada	15,822	223	33	0	1	0.0	1.0	0	0.48	1.18	0.23	0.14	0.0000
China	2,994	2,821	25	1	2	1.0	4.1	0	0.45	0.84	0.27	0.17	0.0014
France	39,731	14,218	70	0	2	0.0	2.8	0	0.69	1.28	0.10	0.05	0.0018
Germany	86,672	3,351	112	0	6	0.0	3.0	0	0.44	1.24	0.06	0.03	0.0002
India	872	9,282	29	18	0	4.7	0.0	0	2.02	0.94	0.21	0.20	0.0047
Indonesia	23	306	6	1.5	0.5	1.3	0.5	0	2.02	0.26	0.67	1.12	0.0033
Italy	20,851	3,755	105	0	1	0.0	1.0	0	0.49	0.49	0.04	0.04	0.0000
Japan	42,424	15,436	146	0	1	0.0	1.0	0	0.18	0.44	0.04	0.02	0.0000
Mexico	0	2,159	8	7	0	2.9	0.0	0	4.28	0.00	0.81	0.00	0.0000
Russia	1,460	23,761	107	10	1	2.8	1.0	0	0.70	0.17	0.03	0.02	0.0002
Saudi Arabia	1,378	2,231	18	0	4	0.0	6.3	0	1.52	1.27	0.25	0.32	0.0011
South Africa	543	7,171	21	0	1	0.0	1.0	0	2.34	0.95	0.32	0.22	0.0001
South Korea	715	18,870	43	1	1	1.0	1.0	0	1.88	0.07	0.11	0.10	0.0006
Turkey	516	35,787	31	34	1	2.8	1.8	0	5.08	0.29	0.09	0.13	0.0092
United Kingdom	83,052	40,098	213	0	2	0.0	2.2	0	0.16	0.51	0.03	0.02	0.0001
United States	121,683	192,808	280	0	1	0.0	1.0	0	0.24	0.31	0.02	0.01	0.0003
Unweighed mean				7.5	7.5	1.6	2.5						0.0001

6 Appendix 2. Potential determinants of bank relationships.

GDP growth: the geometric rate of growth of real GDP, between the earliest data in the sample and 2000, in constant 2000 USD. Source: WDI database, World Bank.

Trade/GDP: the sum of total exports and imports of goods and services as a percentage of GDP. Source: WDI database, World Bank.

FDI/total investment: the ratio of FDI net inflows to total investment, i.e., gross fixed capital formation. Source: WDI database, World Bank.

Lending interest rate: the rate charged by banks on loans to prime customers, in percent. Source: WDI database, World Bank.

Growth of Monetary aggregates: the average annual growth rate in M2, in percent. Source: WDI database, World Bank.

Coefficient of variation of nominal exchange rate: the ratio of the standard deviation to the mean of the official exchange rate, computed from annual frequency data. Source: WDI database, World Bank.

Coefficient of variation of real exchange rate: the ratio of the standard deviation to the mean of the real effective exchange rate (index 2000=100), computed from annual frequency data. Source: WDI database, World Bank.

Exchange rate regime: *coarse* index. Source: Ilzetzki, Reinhart, and Rogoff (2008).

Polity2: an index of democracy strength constructed by the Polity IV project, which higher values indicated more democratic systems. Source: http://www.systemicpeace.org/polity/polity4.htm.

Political risk: an index of political risk constructed by ICRG, with higher values associated with lower risk.

Government: an index of government stability constructed by ICRG, with higher values associated with more stability.

Corruption: an index of corruption and transparency within the political system constructed by ICRG, with higher values associated with less corruption.

Financial risk: an index of financial risk (ability to pay foreign official and private debt) constructed by ICRG, with higher values associated with lower risk.

Domestic credit provided by banking sector: bank lending to domestic private sector as a percentage of GDP.

Stocks traded: the total value of shares traded during a year as percentage of GDP. Source: WDI database, World Bank.

Financial Reform Index: an index of financial sector reform, with higher values corresponding to more reforms. Source: Abiad, Detragiache, and Tressel (2008).

Capital account openness: an index of legal restrictions on international financial transactions constructed by Chinn and Ito (2008), with higher values indicating a country is more open to cross-border capital transactions.

Government debt: the ratio of central government debt to GDP. Source: WDI database, World Bank.

Fiscal balance: cash surplus or deficit as percentage of GDP. Source: WDI database, World Bank.

Inflation: average annual inflation in a country's consumer price index. Source: WDI database, World Bank.

Current account balance: the current account balance as percentage of GDP. Source: WDI database, World Bank.

Banking crises: the number of *systemic* banking crises during the period. Source: Laeven and Valencia (2008).

Gross National Income: GNI calculated by the Atlas method (using current US dollars). Source: WDI database, World Bank.

GDP per capita: the ratio of GDP at constant prices of 2005 international dollars to total population. Source: WDI database, World Bank.

Weighted average distance: a remoteness measure computed as the average distance to other countries, weighted by GDP in constant 2000 US dollars.

Foreign currency rating: Standard and Poor's rating of sovereign external debt (short and long term)