Global Banking Network and Cross-Border Capital Flows

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Abstract

Introducing a novel data set that uses a network approach to measure relationships between banks built through lending, we find that these relationships explain a substantial portion of cross-country differences in gross international capital flows between 2001 and 2006. This paper's focus is on understanding the influence of banks' positions in the global banking network on aggregate international capital flows. First, we identify macroeconomic and institutional factors that help explain banks' network characteristics. Then, controlling for these factors, we find that bank relationships, as measured by their network characteristics, affect cross-border portfolio debt flows to and from developed countries, while they affect cross-border portfolio debt and equity flows to and from developing countries. Up to 15 percent of the cross-country variation in international capital flows between 2001 and 2006 are explained by network characteristics for developed and up to 57 percent for developing countries. We find that network characteristics are less useful in explaining year-to-year changes in international capital flows.

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1 Introduction

The importance of information flows and relationships between financial institutions, is frequently emphasized in finance and economics literature, but is still little understood. 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 of 2007-09 also demonstrated the importance of the relationships between financial institutions, not only within a country but also across national borders. This paper takes a step towards empirically understanding the macroeconomic and institutional determinants of banking relationships and their role in international capital flows.

Our main question is: How important are bank relationships in determining international capital flows at the aggregate level? Because banks are important in intermediating asset purchases and facilitating payments, it is natural to expect that bank relationships will be important not only for bank lending, but also for portfolio capital flows.

There is a rich literature in both finance and international finance on the importance of relationships and information flows between institutions, especially financial institutions. 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 the social interactions and firm theory literature,[1] to international banking. Unlike some recent analysis of banking networks that builds on aggregate bilateral bank lending from the BIS data (von Peter, 2007), this paper creates a global banking network at the bank level, 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

[1]Karlan, 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.

[2]Cocco, 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.

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 vertices, or nodes. For each bank we then compute a set of statistics that would describe its role in the network, network statistics. We rely on four main statistics: farness, ineccentricity, and outeccentricity, which measure the reach of the bank in the network or its proximity to the network center, and betweenness, which measures the importance of a given bank in intermediating bank loan flows.

Before addressing our main question, we analyze the determinants of bank relationships. In particular, we examine which macroeconomic and institutional variables help understand bank relationships. We investigate this question at the bank level. We find that for developed countries, bank relationships in 2001-2007:H1 are affected by government quality, inflation rate, banking crises, and country size, while for developing countries, they are determined by the level of democracy and government quality, GDP growth, foreign trade, inflation rate, frequency of banking crises, as well as the size and the geographical remoteness of the country. All of these 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 network statistics are based on lending in 2001-07:H1, so that our results are not affected by the global financial crisis.

We begin the analysis of our main question in a cross-country setting rather than in country panel because we are interested in long-term determinants and effects of bank relationships, which we also define as long-term. This approach reflects our belief that relationships between banks are formed over extended periods of time and have lasting effects. For this part we use network statistics that are based on loans extended between 1980 and 2000 and international capital flow data for 2001-2006. We find that countries in which banks were more connected in a sense of further reach (outeccentricity and farness) and had a more important role in intermediation (betweenness) before year 2000 experienced larger international capital flows afterwards. For developed countries, network statistics explain up to 15 percent of the cross-country variation in international capital flows, while for developing countries they explain up to 57 percent. We further find that for developed countries the aggregate results are driven by debt flows, while for developing countries bank relationships were important for both portfolio equity and portfolio debt flows. These results are robust to including as control variables macroeconomic and institutional variables that we found to be important in determining bank relationships in the first part of our analysis.

Next we study the effect of bank relationship on short-term changes in international capital flows by constructing country-year panel data of changes in bank relationship and estimating a model with country and year fixed effects. We find that for developing countries short-term effects of bank relationship on international capital flows (both equity and debt) are similar to the cross-country long-term effects. For developed countries, however, the effects are different. We continue to find that for developed countries bank relationships are not related to equity flows, but only to portfolio debt flows. For both developed and developing countries, however, bank relationship explain only small portion of year-to-year variation in international capital flows.

The paper is organized as follows. Part 2 describes our data, mainly focusing on the construction of global banking networks. Part 3 analyzes the effects of macroeconomic, institutional and financial factors on bank relationships. Part 4 estimates the effect of these relationships on international capital flows. Part 5 concludes.

2 Data description

We construct a novel data set of bank relationships, based on loan–level data from Dealogic's Loan Analytics data base, and country–level data from conventional sources. 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. As our goal is to capture interbank lending activity, we download all loans extended to public and private sector banks between 1 January 1980 and 30 June 2007.[3] There are 13,506 loans of this type in our data sample. Ideally, we would like to ensure that each of the loans in our sample is an interbank loan, but the Dealogic database only allows us to constrain

[3] 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.

borrowers' type (which we constrain to be either public or private sector bank); it does not allow us to place the same constraints on lenders.[4]

While a variety of loan characteristic variables are available for each of the 13,506 loan deals in our sample, we focus on three: name of borrower (or borrowers), names of lenders, and total loan amount (in millions of US dollars).[5] Ultimately, these variables will enable us to calculate network statistics, but we first make adjustments to the data set, as it consists of syndicated loans with an average of 8 lenders per loan deal. In particular, 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.[6] 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.[7]

There are 8,138 unique institutions that appear in this data set. Again, we cannot say that all of 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 8,1398 unique institutions, 2,354 appear only as borrowers in the data set and 1,028 appear as both borrowers

[4]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.

[5]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.

[6]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.

[7]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.

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 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 to 31 December 2000 and (2) a subsample with loan deals between 1 January 2001 to 30 June 2007. 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 computer 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. We check our computations, when possible, against MatlabBGL version 4.0 (Gleich, 2008) which makes use of the Boost Graph Library (Siek, Lee, and Lumsdaine, 2001). After computing the network statistics, we link each bank to a country as described in Appendix 1.

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.

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. 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 node we calculate the following measures:

- **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: $ie_i = \max_j g_{ji}$;

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

- **Emission** is a sum of values or weights of all edges incident *from* node i divided by the total loan value in the network, denoted by L: $EMISSION_i = \sum_j w_{ij}/L$;

- **Reception** is a sum of values or weights of all edges incident *to* node i divided by the total loan value in the network, denoted by L: $RECEPTION_i = \sum_j w_{ji}/L$.

For the second part of our analysis, we aggregate network statistics by country. To do this, we construct average networks statistics for each country as weighted averages, using each bank's sum of emission and reception as weights. Specifically, before computing country averages we multiply each bank-level statistic by the share s_i of the total flows in and out of bank i on the total global flows; thus, we multiply network statistics by

$$s_i = \frac{\sum_j w_{ij} + \sum_j w_{ji}}{\sum_i \left(\sum_j w_{ij} + \sum_j w_{ji} \right)}.$$

Appendix 2 tables list these statistics for all countries in our sample. As mentioned above, we base these statistics on two separate samples of the loan data: 1980-2000 (early sample), and 2001-June 2007 (late sample).

2.3 International capital flows

Our main goal is to see whether bank relationships help us understand international capital flows.

We use the Lane and Milesi-Ferretti (2001) External Wealth of Nations II updated data set to calculate capital flows from 2001 to 2006. The set provides us with stocks of foreign asset holdings and foreign liabilities for each country, measured in U.S. dollars. After deflating these using U.S. CPI, we subtract 2001 stocks from 2006 stocks to get a lower-bound estimate of gross flows between 2001 and 2006.[8] We repeat this for two main subcategories of assets and liabilities: portfolio equity and portfolio debt.

To test whether our results are sensitive to the source of data used, we also use capital flows data from the *Balance of Payments Statistics* from the IMF. After deflating the individual flows data by the US annual consumer price index (2000=100), we compute gross flows for each category of interest (portfolio securities, debt securities and total flows). Gross portfolio equity securities are computed subtracting line *78bkd* (for assets) from line *78bmd* (for liabilities). Debt securities are computed using lines *78bld* and *78bnd*. We compute a measure of total gross flows adding the computed portfolio and debt gross flows and adding flows of FDI (*78bdd* and *78bed*), financial derivatives, when available, (*78bwd* and *78bxd*), and other investments (*78bhd* and *78bid*).

2.4 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 and 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, Detragiache, and Tressel (2008), data on private credit rights from Djankov, McLiesh,

[8] It is a lower bound because some of the flows could have been reversed during this time period and did not contribute to 2006 stocks.

and Shleifer (2007), and data on exchange rate regimes from Ilzetzki, Carmen, and Rogoff (2008). In the analysis we also control for banking and currency crises, using the database on financial crises by Laeven and 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 Macro determinants of bank relationships

Before addressing the main question of this paper, to what extent do bank relationships help us understand international financial flows, we need to understand the determinants of bank relationship measures 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.[9]

3.1 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 trade in financial assets into five broad categories: (i) information asymmetries (ii) international trade in goods and FDI links; (iii) regulation and institutional characteristics; (iv) macroeconomic variables; and (v) financial sector indicators.

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

[9] 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.

information costs and information asymmetries that agents face (Portes, Rey, and Oh, 2001; Portes and 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 and Wolf (2000) and by Daude and 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.[10]

Geographical distance, however, may be picking up the effect of trade in goods or economic ties due to direct investment. Aviat and 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 and Nigh (1989) report a positive and significant coefficient of trade in the international lending of US banks, while Goldberg and Johnson (1990) and Dahl and 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 and Micu (2002) in the case of bank's aggregate lending flows, and by Rose and Spiegel (2002) for sovereign lending.

Institutional variables have also been found to be determinants of international capital flows and bank lending. Alfaro, Kalemli-Ozcan, and Volosovych (2008), Aviat and Coeurdacier (2007), and Elias (2009) find a positive and significant effect of institutional quality on international bank lending. Similar results are reported by Buch (2003) for measures of protection of property rights and by Daude and Fratzscher (2008) for proxies of investor protection and corruption — both studies using international bank lending. In contrast to these findings, Wei (2000) and Wei and Wu (2001) report a positive coefficient for corruption in a gravity-type model of bilateral international lending. Thus, in contrast with other studies, they find that a lower quality of institutions is

[10] Wei (2000) and Wei and 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.

associated with larger lending flows. Similarly, Wei (2006) and Faria and 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 and Fratzscher (2008).

Most empirical studies don't find a robust association between bank lending and macroeconomic variables once proper controls for institutional quality and information asymmetries are introduced in the analysis (Elias, 2009; Jeanneau and Micu, 2002; Buch, 2003).[11] 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 and Tarashev (2008) reports that the spread of interest rate between countries i and j increases lending to j. Similar results are reported by Moshirian and Bishop (1997) for a small sample of industrial countries. McGuire and 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.[12] Aviat and Coeurdacier (2007) also report negative and significant coefficients for tax rates on dividends and interest.

Guided by this literature and constrained by data availability, we put together a list of potential explanatory variables presented in Appendix 3, each variable calculated as a simple average over the years between the first year in our sample and 2000, unless otherwise specified.

3.2 Empirical methodology and results

We begin by analyzing the relationship between our network statistics, at bank level, and our potential explanatory variables. Because the level of financial development is very different in developed and developing countries, we split our sample into high income OECD countries and

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

[12] 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.

the rest. As described above, we use 1980-2000 averages for developed and 1990-2000 averages for developing countries. We conduct all our analysis for these two samples separately.

After inspecting correlations between 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).[13] 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 in Table 1 for both developed and developing countries' regressions. Columns (1)-(3) and (5)-(7) present regressions of network statistics that measure the reach of the bank within the network, while columns (4) and (8) presents regression of betweenness, which measures the importance of the bank in intermediation. All four of these network statistics could be thought of as measuring the strength of a bank's relationships with the global network.

We find that for developed countries, as one would expect, better quality of the government as measured by ICRG index is associated with stronger bank relationships in terms of outeccentricity. We also find as one would expect that banking crises destroy relationships between banks, both in terms of outeccentricity and in terms of betweenness. Finally, banks in larger countries are better connected to the global network in terms of all four measures. Higher inflation is associated with less reach of the banks in terms of lending, outeccentricity, (lenders like to locate in low–inflation countries), and with more reach in terms of borrowing, ineccentricity, (it takes a longer chain of banks to lend to banks in countries with higher inflation).

For developing countries we find, as one would expect, that countries that are more stable politically (as measured by ICRG government and Polity2 indexes), that grow faster, have lower inflation,

[13] 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.

are less prone to banking crises, and those that are less remote geographically, have banks with stronger relationships within the network (see Table 1). Size also appears to be positively correlated with bank relationship measures. Surprisingly, our measures of bank relationships are negatively correlated with trade to GDP ratio, significantly so for ineccentricity and farness measures.

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-squared. 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.

4 Bank relationships and international capital flows

We now turn to the analysis of our main question: the impact of bank relationships 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. That is, we are trying to understand how bank relationships that were formed during two decades prior to 2000 affected international capital flows in the last decade, prior to the liquidity crisis. In addition, we use a panel version of the data to test for any impact of newly formed bank relationships on international capital flows in the following year, controlling for country fixed effects. We use Lane and Milesi-Ferretti data in our benchmark analysis and then test whether our results change if we use balance of payments data instead.

4.1 Cross-country analysis

We begin with simple correlations between the international capital flows since 2001 and our network statistics from the network that was formed prior to 2001. Because left-hand side variables are at a country level, we use country averages of weighted network statistics as explanatory variables. We continue to conduct our analysis separately for developed and developing countries.

Network statistics are highly correlated, especially farness and in- and out- eccentricity. Thus, we include them one at a time and then we include both farness and betweenness together. Table 2 reports the results of the regressions of a change in total foreign assets and liabilities (in constant U.S. dollars) between 2001 and 2006 for both developed and developing countries samples. We find that all network statistics have positive and significant effects on cross-border capital flows with two exceptions: ineccentricity does not have a significant effect and farness becomes insignificant for the developing countries sample when it is included together with betweenness.

These results show that countries in which banks were more connected in a sense of further reach (outeccentricity and farness) and more important role in intermediation (betweenness) before year 2001 experienced larger international capital flows afterwards. For developed countries, outeccentricity, farness, and betweenness explain 14, 7, and 15 percent, respectively, of the cross-country variation in the international capital flows.[14] For developing countries, betweenness is most important — it explains 57 percent of the variation in international capital flows, while outeccentricity explains 36 percent, and farness explains 6 percent. The effect of farness weakens and becomes insignificant when we include it in the regressions at the same time as betweenness.

Next, we look at components of international capital flows — in particular, we look at changes in cross-border portfolio equity holdings and changes in cross-border portfolio debt holdings.[15] The results are reported in Tables 3 and 4, respectively. We find that for developed countries the aggregate results are driven by debt flows: while some coefficients are statistically significant in Table 3 for developed countries, the network statistics hardly explain any variance in cross-border equity flows; from Table 4, however, we can see that further reach and higher betweenness are associated with more portfolio debt flows, with farness and betweenness together explaining 17 percent of the variance for the developed country sample.

For developing countries, we find that bank relationships were important for both portfolio equity and portfolio debt flows. Outeccentricity seems to be almost equally important in explaining both

[14] As measured by adjusted R-squared.

[15] We are not considering FDI due to valuation difficulties, and we are not considering derivatives due to many missing values.

equity and debt flows, explaining 37 and 26 percent of the variance, respectively. Farness also enters significantly in both tables, but has less explanatory power, while betweenness explains 33 and 15 percent in the cross-country variation in equity and debt portfolio flows, respectively. Interestingly, the only regression in which ineccentricity enters significantly is in explaining debt flows for developing countries — larger ineccentricity, which means that the country's banks are on average far from the center of the network when it comes to borrowing, is associated with larger portfolio debt flows. While this result appears to be counterintuitive at first, it is possible that if country's banks find it hard to borrow from the global banking system in terms of bank loans, firms in this country substitute foreign portfolio debt for bank lending.

One concern with interpreting these effects as causal is that, although we use network information from the time prior to the capital flow sample period, we may have a simultaneity problem. It may arise if stronger bank relationships prior to 2001 and higher capital flows after 2001 are driven by the same factors. To alleviate the problem, we include on the right-hand side of the above regressions macroeconomic and institutional variables that we found important in explaining bank relationships. In particular, we control for real GDP growth, trade to GDP ratio, Polity 2 index, and remoteness for both developed and developing countries. In addition, we control for size, as measured by atlas method GNI for developing countries.[16]

The results are reported in Tables 5, 6, and 7 for total flows, portfolio equity and portfolio debt flows, respectively. Table 5 shows that adding control variables does not affect the results for developed countries, but does take away the effects of network reach for developing countries — only the effect of betweenness remains positive and significant, whether or not farness is also included. Decomposing capital flows into equity and debt, however, we find that network reach (outeccentricity) still explains portfolio equity flows for developing countries, while the effects of network characteristics on portfolio debt flows are not affected much when we include controls: the only exception is that farness no longer has a statistically significant effect for the sample of developing countries.

Next, we repeat the analysis using a different measure of international capital flows — a sum of

[16]For developed countries sample, GNI is highly correlated with other control variables and is, therefore, excluded.

asset and liability flows from the IMF's *Balance of Payments Statistics data*, from 2001 to 2006. The results are reported in Tables 8-10, which correspond to Tables 5-7 discussed above and are very similar to the ones discussed above, both qualitatively and in terms of the share of variance in the international capital flows explained by our network statistics.

One interesting difference is that we find a statistically significant effect of farness for the sample of developing countries, when we control for macroeconomic fundamentals and betweenness. In the regressions of total asset flows (Table 8) and portfolio debt asset flows (Table 10) we find that higher measure of farness is associated with less capital flows. This result makes intuitive sense: since developing countries' banks are mostly the recipients of international bank flows (Appendix Table 2 shows that for most developing countries reception far exceeds emission), farness is expressing average remoteness rather than the reach of country's banks. Thus, more remote, in terms of bank relationships, countries are less engaged in international capital markets.[17]

Thus, we find that even controlling for macroeconomic and institutional variables, bank relationships play an important role in determining international capital flows, especially portfolio debt flows, for developed and both portfolio equity and debt flows for developing countries. As always in cross-country regressions, however, a concern remains that our findings reflect, somehow, inherent difference between the countries and not a causal relationship between the variables in question. To address this concern we need to get away from the cross-country nature of the data so that we can include country fixed effects that would absorb all inherent time-invariant differences between countries. We do this in two ways: first by constructing the "cumulative panel" from our data, second, by using data on bilateral capital flows and constructing bilateral bank relationships in order to conduct our analysis at the country pair level.

4.2 Cumulative panel analysis

In this section we attempt to detect short-term relationship between network statistics and international capital flows in the panel data setting. 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,

[17] It is important to note that the additional explanatory power of this variable is rather small — adjusted R^2 only increases marginally from the addition of farness (from column (9) to column (10).)

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 were network statistics represent the relationships between banks accumulated since year 1980. We use first differences in these network statistics which measure new relationships formed in year t, lagged one year, as our explanatory variables.

On the left-hand side, we use the change in stocks of assets and liabilities from Lane and Milesi-Ferretti or flows from balance of payments data. We include, in addition to our macroeconomic control variables, country and year fixed effects. The results are presented in Tables 11-16, with all regressions including country and year fixed effects. Note that we can 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 newly formed bank relationships on international capital flows in the following year, absorbing all long-term cross-country differences by country fixed effects and all common trends by year fixed effects.

For developed countries the only significant pattern we find is negative effect of betweenness on total assets and liabilities flows that is driven by the effect on debt assets and liabilities. That is, when a country's importance in intermediation of international capital flows increases, it tends to have fewer portfolio debt in- and outflows in the year that follows. We observe this pattern whether we use Lane and Milesi-Ferretti data or balance of payments data. One possible explanation for this finding is that increased importance in international bank intermediation means that banks substitute bank loans for portfolio debt flows.

For developing countries our findings are mostly consistent with those in the cross-country analysis — we find that when a given country's banks become more connected to the global banking network, this country experiences larger portfolio equity and debt flows in the following year. As before, the effect of farness is less straightforward — an increase in farness is associated with larger portfolio debt flows but smaller portfolio equity flows in the following year.

It is important to note that in all of these regressions the addition of network statistics to the set of explanatory variables only makes a marginal contribution to the explanatory power. That is, bank relationships, as measured by network statistics, are much less useful in explaining year-to-year changes in international capital flows than in explaining long-term cross-country differences. This is consistent with our priors: Relationships are persistent and while, as we show above, they matter for the long-run patterns of international capital flows, they don't vary enough from year to year in order to explain much of the changes in international capital flows that are driven by many short-term factors.

4.3 Country-pair analysis

[To be completed]

5 Conclusion

Introducing a novel data set that uses network approach to measure relationships between banks built through lending, we find that these relationships explain a substantial portion of cross-country differences in gross international capital flows between 2001 and 2006, even when we control for the macroeconomic and institutional variables that are likely to affect both bank relationships and international capital flows. This finding is not surprising — banks' intermediation is important not only for bank flows, but also for portfolio debt and equity flows.

This finding is important in a number of ways. First, 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. Moreover, 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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Table 1: Macro multivariate regs: Weighted NetStats, Bank Level

	(1) outeccentricity Rich	(2) ineccentricity Rich	(3) farness1 Rich	(4) betweenness Rich	(5) outeccentricity Poor	(6) ineccentricity Poor	(7) farness1 Poor	(8) betweenness Poor
Avg. GDP Growth	-490.2	-1811.6	-408.0	-0.049	164.4***	86.0	43.0***	0.038
	(293.9)	(1288.4)	(295.1)	(0.086)	(53.5)	(69.1)	(14.3)	(0.032)
Trade/GDP	-9.72	68.0	14.4	-0.0014	-9.73	-20.9**	-4.75**	-0.0058
	(11.4)	(57.4)	(14.2)	(0.0032)	(7.19)	(9.24)	(1.90)	(0.0046)
ICRG government score	874.6*	68.0	38.2	0.15	468.0***	942.5***	203.9***	0.090*
	(491.6)	(1206.6)	(335.0)	(0.11)	(152.1)	(165.8)	(32.5)	(0.052)
Inflation	-192.2**	241.4*	21.8	0.0024	-0.95*	-1.70**	-0.22	-0.00019
	(71.0)	(139.8)	(37.2)	(0.022)	(0.51)	(0.72)	(0.14)	(0.00018)
Banking crisis	-3134.1**	-1837.0	-783.5	-0.35*	-244.1	-600.2	-245.8***	0.080
	(1206.3)	(1738.7)	(549.4)	(0.19)	(296.7)	(420.5)	(84.8)	(0.11)
GNI (nominal)	0.86***	1.65**	0.52***	0.00013**	0.67	3.37***	0.89***	-0.00038
	(0.25)	(0.59)	(0.16)	(0.000048)	(0.96)	(1.05)	(0.27)	(0.00047)
Average distance	-165.3	1362.8	313.0	-0.026	-547.6**	-305.6	-90.2	-0.16
	(408.4)	(880.9)	(262.8)	(0.085)	(235.2)	(290.5)	(59.7)	(0.14)
Polity score					53.7	188.2***	46.9***	0.024
					(39.3)	(39.1)	(8.51)	(0.017)
Constant	-21.6	-5793.2	-671.2	-0.65	466.2	-3366.4*	-486.1	0.56
	(3824.1)	(8715.9)	(2430.5)	(1.14)	(1781.2)	(1955.5)	(408.6)	(0.83)
Observations	1416	1416	1416	1416	696	696	696	696
Adjusted R^2	0.0016	0.0046	0.0062	-0.0031	0.019	0.051	0.056	-0.0053

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Robust standard errors, clustered by country, in parentheses

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

Table 2: Change in Total Assets and Liabilities with Weighted NetStats

	(1) Rich	(2) Rich	(3) Rich	(4) Rich	(5) Rich	(6) Poor	(7) Poor	(8) Poor	(9) Poor	(10) Poor
outeccentricity	2.28**					0.93***				
	(0.91)					(0.30)				
ineccentricity		1.33					0.14			
		(0.95)					(0.095)			
farness1			8.56**		5.08*			1.32*		0.13
			(3.77)		(2.92)			(0.74)		(0.21)
betweenness				5788.1**	4783.2**				1336.7***	1321.4***
				(2332.3)	(2117.2)				(221.4)	(232.8)
Constant	960.7	1453.2*	1064.7	1969.2***	1184.3	29.3**	64.8**	52.1**	66.9***	62.1***
	(769.1)	(720.7)	(773.6)	(530.2)	(745.5)	(12.1)	(26.2)	(24.5)	(16.6)	(17.0)
Observations	23	23	23	23	23	81	81	81	81	81
Adjusted R^2	0.14	0.016	0.073	0.15	0.15	0.36	0.055	0.062	0.57	0.56

Dependent variable: '01 to '06 Change in total assets and liabilities, in BN of Constant USD

Robust standard errors in parentheses

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

Table 3: Change in Portfolio Equity Assets and Liabilities with Weighted NetStats

	(1) Rich	(2) Rich	(3) Rich	(4) Rich	(5) Rich	(6) Poor	(7) Poor	(8) Poor	(9) Poor	(10) Poor
outeccentricity	0.20					0.23***				
	(0.14)					(0.047)				
ineccentricity		0.16					0.033			
		(0.19)					(0.022)			
farness1			0.75		0.31			0.33*		0.11
			(0.67)		(0.62)			(0.17)		(0.091)
betweenness				671.8*	610.3				251.9***	238.8***
				(376.6)	(377.2)				(22.7)	(22.7)
Constant	390.7*	400.6*	399.6*	462.9***	414.8*	5.00	14.5**	10.8	16.8***	12.6**
	(199.1)	(206.9)	(222.1)	(143.7)	(224.6)	(3.36)	(7.16)	(6.71)	(5.34)	(5.50)
Observations	23	23	23	23	23	81	81	81	81	81
Adjusted R^2	-0.019	-0.030	-0.029	0.0053	-0.042	0.37	0.048	0.063	0.33	0.33

Dependent variable: '01 to '06 Change in portfolio equity assets and liabilities, in BN of Constant USD

Robust standard errors in parentheses

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

Table 4: Change in Portfolio Debt Assets and Liabilities with Weighted NetStats

	(1) Rich	(2) Rich	(3) Rich	(4) Rich	(5) Rich	(6) Poor	(7) Poor	(8) Poor	(9) Poor	(10) Poor
outeccentricity	0.53***					0.063***				
	(0.13)					(0.016)				
ineccentricity		0.45					0.017**			
		(0.28)					(0.0080)			
farness1			2.48***		1.53*			0.14*		-0.020
			(0.78)		(0.88)			(0.069)		(0.061)
betweenness				1600.2***	1296.9***				72.0***	76.1***
				(417.2)	(432.8)				(13.4)	(15.8)
Constant	316.3	312.2	254.6	523.9***	287.0	5.16**	7.20**	6.63*	9.77***	10.4***
	(192.0)	(197.1)	(202.1)	(149.6)	(207.0)	(2.07)	(3.49)	(3.32)	(2.77)	(3.31)
Observations	23	23	23	23	23	49	49	49	49	49
Adjusted R^2	0.095	0.054	0.093	0.17	0.17	0.26	0.048	0.041	0.15	0.13

Dependent variable: '01 to '06 Change in portfolio debt assets and liabilities, in BN of Constant USD

Robust standard errors in parentheses

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

Table 5: Change in Total Assets and Liabilities with Weighted NetStats

	(1) Rich	(2) Rich	(3) Rich	(4) Rich	(5) Rich	(6) Poor	(7) Poor	(8) Poor	(9) Poor	(10) Poor
outeccentricity	2.27*					0.12				
	(1.08)					(0.21)				
ineccentricity		1.21					-0.0066			
		(1.16)					(0.046)			
farness1			8.28*		2.88			-0.30		-0.30
			(4.18)		(3.63)			(0.46)		(0.22)
betweenness				10897.6**	9612.4*				915.6***	915.2***
				(4043.3)	(4597.2)				(239.1)	(235.0)
Avg. GDP Growth 90 to 00	1349.5	957.4	1106.5	726.9	745.4	0.37	1.13	0.96	-0.28	-0.51
	(852.7)	(861.6)	(866.8)	(744.7)	(788.7)	(6.03)	(5.91)	(6.02)	(2.19)	(2.27)
Trade/GDP	-29.9	-43.4	-43.2	-31.1	-32.4	0.54*	0.55**	0.51**	0.13	0.081
	(38.4)	(37.1)	(39.0)	(30.9)	(33.2)	(0.28)	(0.24)	(0.22)	(0.14)	(0.14)
Polity score	-1794.5	-497.2	-1018.2	5769.2*	5054.3	-4.11	-4.05	-4.36	-1.38	-1.74
	(1032.2)	(1806.1)	(1174.8)	(3274.6)	(3580.2)	(2.79)	(2.93)	(2.99)	(1.76)	(1.86)
Average distance	-134.4	-589.1	-448.8	-650.8	-618.1	-22.8	-27.1*	-29.6*	-14.9*	-18.0*
	(392.9)	(446.3)	(400.3)	(445.8)	(462.9)	(13.9)	(14.8)	(15.6)	(8.61)	(9.93)
GNI (nominal)						1.3e-09***	1.4e-09***	1.4e-09***	6.2e-10***	6.7e-10***
						(4.6e-10)	(3.9e-10)	(4.0e-10)	(1.4e-10)	(1.6e-10)
Constant	17573.2*	9270.6	12925.5	-52837.1	-46255.6	75.4	99.7	125.0	85.5*	115.7*
	(9323.9)	(16508.9)	(10494.8)	(32557.5)	(35423.2)	(62.5)	(71.9)	(79.7)	(46.9)	(58.7)
Observations	21	21	21	21	21	72	72	72	72	72
Adjusted R^2	0.12	-0.025	0.060	0.22	0.18	0.71	0.70	0.70	0.88	0.88

Dependent variable: '01 to '06 Change in total assets and liabilities, in BN of Constant USD

Robust standard errors in parentheses

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

Table 6: Change in Portfolio Equity Assets and Liabilities with Weighted NetStats

	(1) Rich	(2) Rich	(3) Rich	(4) Rich	(5) Rich	(6) Poor	(7) Poor	(8) Poor	(9) Poor	(10) Poor
outeccentricity	0.20					0.058*				
	(0.17)					(0.032)				
ineccentricity		0.15					0.0074			
		(0.21)					(0.0076)			
farness1			0.89		0.20			0.043		0.044
			(0.75)		(0.81)			(0.058)		(0.044)
betweenness				1325.6**	1238.4				115.1***	115.1***
				(597.5)	(714.8)				(32.9)	(31.7)
Avg. GDP Growth 90 to 00	373.7*	329.6	350.1*	302.3	303.5	-0.70	-0.22	-0.26	-0.48	-0.44
	(190.8)	(193.3)	(197.9)	(181.2)	(187.4)	(0.60)	(0.69)	(0.72)	(0.48)	(0.44)
Trade/GDP	-9.14	-10.3	-10.3	-8.83	-8.92	0.11***	0.13***	0.12***	0.064**	0.071**
	(8.69)	(8.20)	(8.36)	(7.57)	(7.79)	(0.036)	(0.042)	(0.041)	(0.028)	(0.027)
Polity score	-109.9	36.7	-34.3	796.5	748.1	0.15	0.26	0.25	0.53**	0.58**
	(220.3)	(270.2)	(204.7)	(486.2)	(570.5)	(0.33)	(0.31)	(0.33)	(0.26)	(0.29)
Average distance	-39.7	-83.3	-66.6	-90.6	-88.4	3.07	1.96	1.72	2.72	3.18
	(96.2)	(82.5)	(87.7)	(86.5)	(91.6)	(2.69)	(2.59)	(2.72)	(2.17)	(2.44)
GNI (nominal)						2.6e-10***	3.0e-10***	3.0e-10***	2.2e-10***	2.1e-10***
						(2.4e-11)	(3.0e-11)	(3.0e-11)	(2.4e-11)	(2.4e-11)
Constant	1204.4	154.9	694.9	-7376.0	-6929.9	-29.7**	-26.8*	-24.8	-21.5*	-26.0*
	(1902.7)	(2635.2)	(1866.1)	(5021.8)	(5729.3)	(13.7)	(14.1)	(15.2)	(10.8)	(13.5)
Observations	21	21	21	21	21	72	72	72	72	72
Adjusted R^2	0.060	0.043	0.061	0.13	0.065	0.86	0.84	0.83	0.90	0.90

Dependent variable: '01 to '06 Change in portfolio equity assets and liabilities, in BN of Constant USD

Robust standard errors in parentheses

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

Table 7: Change in Portfolio Debt Assets and Liabilities with Weighted NetStats

	(1) Rich	(2) Rich	(3) Rich	(4) Rich	(5) Rich	(6) Poor	(7) Poor	(8) Poor	(9) Poor	(10) Poor
outeccentricity	0.48**					0.055***				
	(0.17)					(0.018)				
ineccentricity		0.29					0.022**			
		(0.30)					(0.0082)			
farness1			2.12**		1.28			0.11		-0.023
			(0.86)		(1.30)			(0.096)		(0.055)
betweenness				2074.4***	1502.9				76.5***	79.1***
				(636.8)	(938.5)				(13.7)	(11.6)
Avg. GDP Growth 90 to 00	473.4*	383.5	416.6*	351.9	360.1	0.073	1.05	0.95	0.99	0.99
	(225.6)	(232.6)	(232.8)	(204.7)	(221.0)	(0.66)	(0.80)	(0.81)	(0.67)	(0.67)
Trade/GDP	-10.7	-13.6	-13.6	-11.3	-11.9	-0.0065	0.018	0.012	-0.013	-0.014
	(10.3)	(9.76)	(10.2)	(8.77)	(9.66)	(0.052)	(0.045)	(0.048)	(0.049)	(0.050)
Polity score	-684.6**	-386.8	-502.8*	764.5	446.6	0.32	0.26	0.31	0.46	0.48
	(278.9)	(437.6)	(262.0)	(516.1)	(644.0)	(0.32)	(0.30)	(0.31)	(0.31)	(0.31)
Average distance	-56.3	-155.9	-121.9	-162.9	-148.3	-1.47	-3.79*	-4.17*	-3.39	-3.42
	(111.0)	(109.2)	(105.6)	(108.3)	(111.7)	(2.46)	(2.24)	(2.37)	(2.32)	(2.36)
GNI (nominal)						-1.2e-11	-1.9e-12	1.2e-11	-6.2e-12	-2.7e-12
						(2.0e-11)	(2.7e-11)	(3.9e-11)	(1.6e-11)	(2.3e-11)
Constant	6819.0**	4842.0	5606.6**	-6572.8	-3646.1	10.1	16.7	19.9	20.6	21.2
	(2462.6)	(4101.9)	(2384.9)	(5308.3)	(6543.0)	(14.6)	(12.5)	(13.2)	(13.9)	(14.4)
Observations	21	21	21	21	21	46	46	46	46	46
Adjusted R^2	0.19	0.11	0.19	0.21	0.19	0.42	0.29	0.19	0.50	0.49

Dependent variable: '01 to '06 Change in portfolio debt assets and liabilities, in BN of Constant USD

Robust standard errors in parentheses

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

Table 8: Sum of Gross Total Assets and Liabilities (BOP flows), 2001-2006 with Weighted NetStats

	(1) Rich	(2) Rich	(3) Rich	(4) Rich	(5) Rich	(6) Poor	(7) Poor	(8) Poor	(9) Poor	(10) Poor
outeccentricity	1.93*					0.046				
	(1.06)					(0.10)				
ineccentricity		0.81					-0.014			
		(1.01)					(0.022)			
farness1			5.99		1.35			-0.24		-0.24*
			(3.98)		(3.17)			(0.23)		(0.12)
betweenness				8864.4*	8261.7*				392.4***	393.1***
				(4239.3)	(4689.8)				(137.7)	(133.5)
Avg. GDP Growth 90 to 00	1262.1*	976.3	1070.1	751.1	759.7	0.49	0.67	0.61	-0.049	-0.30
	(703.9)	(712.5)	(710.6)	(633.1)	(662.6)	(3.23)	(3.17)	(3.14)	(1.72)	(1.63)
Trade/GDP	-26.7	-38.2	-38.1	-28.2	-28.8	0.25	0.24*	0.23*	0.075	0.038
	(32.3)	(31.4)	(33.1)	(26.2)	(27.8)	(0.15)	(0.13)	(0.12)	(0.097)	(0.095)
Polity score	-1210.9	-269.3	-598.5	4956.0	4620.7	-1.32	-1.37	-1.48	-0.18	-0.38
	(783.1)	(1515.4)	(991.5)	(3412.8)	(3680.3)	(1.44)	(1.48)	(1.49)	(0.97)	(0.98)
Average distance	-162.7	-530.7	-434.5	-595.4	-580.0	-14.3*	-16.9**	-17.9**	-10.4**	-12.5**
	(326.4)	(394.8)	(342.1)	(410.9)	(424.5)	(7.43)	(7.54)	(7.82)	(4.60)	(5.09)
GNI (nominal)						6.5e-10***	7.0e-10***	7.2e-10***	3.7e-10***	4.1e-10***
						(2.2e-10)	(1.9e-10)	(2.0e-10)	(6.5e-11)	(8.2e-11)
Constant	11497.0	6016.8	8191.8	-45760.0	-42673.3	57.7*	76.2**	86.6**	60.2**	82.2**
	(6914.8)	(13451.8)	(8597.1)	(33600.1)	(36128.2)	(33.9)	(35.8)	(38.8)	(27.4)	(31.6)
Observations	21	21	21	21	21	70	70	70	70	70
Adjusted R^2	0.14	-0.032	0.034	0.21	0.16	0.72	0.72	0.73	0.85	0.86

Dependent variable: Sum of gross BOP flows, 2001-2006, in total assets and liabilities, in BN of Constant USD

Robust standard errors in parentheses

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

Table 9: Sum of Gross Portfolio Equity Assets and Liabilities (BOP flows), 2001-2006 with Weighted NetStats

	(1) Rich	(2) Rich	(3) Rich	(4) Rich	(5) Rich	(6) Poor	(7) Poor	(8) Poor	(9) Poor	(10) Poor
outeccentricity	0.098					0.0043				
	(0.061)					(0.014)				
ineccentricity		0.049					-0.00015			
		(0.093)					(0.0025)			
farness1			0.38		0.21			-0.017		-0.017
			(0.29)		(0.32)			(0.026)		(0.024)
betweenness				395.8	300.9				38.6***	38.7***
				(253.0)	(275.8)				(14.2)	(13.8)
Avg. GDP Growth 90 to 00	232.7***	216.5**	221.9***	209.2**	210.6**	0.59	0.62*	0.61*	0.53	0.52
	(69.7)	(73.5)	(73.4)	(71.3)	(74.4)	(0.37)	(0.36)	(0.35)	(0.41)	(0.38)
Trade/GDP	-2.47	-3.06	-3.04	-2.61	-2.71	0.032*	0.032*	0.030*	0.014	0.011
	(3.04)	(2.83)	(2.92)	(2.67)	(2.84)	(0.018)	(0.018)	(0.017)	(0.013)	(0.013)
Polity score	-190.8**	-137.4	-156.2**	86.7	33.9	0.085	0.088	0.075	0.20*	0.18
	(77.5)	(100.6)	(69.6)	(188.4)	(207.8)	(0.16)	(0.17)	(0.17)	(0.11)	(0.13)
Average distance	-12.6	-32.0	-26.1	-33.8	-31.4	0.50	0.34	0.21	0.89	0.74
	(43.2)	(34.8)	(38.6)	(37.0)	(39.1)	(1.11)	(1.18)	(1.22)	(1.01)	(1.14)
GNI (nominal)						7.0e-11***	7.3e-11***	7.6e-11***	4.2e-11***	4.5e-11***
						(2.0e-11)	(1.7e-11)	(1.8e-11)	(1.2e-11)	(1.2e-11)
Constant	1629.8**	1297.2	1414.3**	-924.4	-438.2	-7.23	-6.40	-5.01	-7.01	-5.44
	(639.9)	(1012.0)	(630.9)	(1969.8)	(2128.0)	(5.45)	(6.14)	(6.45)	(4.81)	(6.03)
Observations	21	21	21	21	21	70	70	70	70	70
Adjusted R^2	0.26	0.23	0.25	0.27	0.22	0.64	0.64	0.64	0.73	0.73

Dependent variable: Sum of gross BOP flows, 2001-2006, in portfolio equity assets and liabilities, in BN of Constant USD

Robust standard errors in parentheses

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

Table 10: Sum of Gross Portfolio Debt Assets and Liabilities with Weighted NetStats

	(1) Rich	(2) Rich	(3) Rich	(4) Rich	(5) Rich	(6) Poor	(7) Poor	(8) Poor	(9) Poor	(10) Poor
outeccentricity	0.36**					0.027				
	(0.17)					(0.029)				
ineccentricity		0.19					-0.0054			
		(0.28)					(0.0054)			
farness1			1.61*		0.85			-0.085		-0.087*
			(0.84)		(1.23)			(0.057)		(0.047)
betweenness				1727.7**	1347.7				112.8***	113.0***
				(672.1)	(946.3)				(28.2)	(25.4)
Avg. GDP Growth 90 to 00	495.9*	433.0*	453.2*	397.1*	402.5	1.28	1.43*	1.41*	1.24	1.15*
	(242.2)	(245.1)	(249.1)	(223.6)	(237.3)	(0.84)	(0.80)	(0.77)	(0.80)	(0.68)
Trade/GDP	-13.3	-15.5	-15.4	-13.5	-13.9	0.044	0.041	0.036	-0.0052	-0.018
	(11.1)	(10.5)	(10.8)	(9.65)	(10.3)	(0.041)	(0.036)	(0.035)	(0.024)	(0.024)
Polity score	-438.8	-230.7	-302.0	760.8	549.4	-0.40	-0.40	-0.44	-0.054	-0.13
	(272.6)	(397.7)	(253.2)	(553.0)	(687.2)	(0.38)	(0.39)	(0.39)	(0.28)	(0.28)
Average distance	-58.7	-131.4	-107.6	-141.0	-131.3	-4.36**	-5.68**	-5.99***	-3.69**	-4.45**
	(116.9)	(107.1)	(110.0)	(109.8)	(114.5)	(2.15)	(2.14)	(2.19)	(1.57)	(1.72)
GNI (nominal)						7.0e-11	9.7e-11*	1.0e-10**	5.6e-13	1.4e-11
						(5.7e-11)	(4.9e-11)	(5.0e-11)	(1.8e-11)	(2.3e-11)
Constant	4529.3*	3193.9	3610.4	-6632.9	-4686.9	17.9*	26.6**	30.1**	20.9**	28.8***
	(2365.7)	(3767.5)	(2296.8)	(5695.6)	(6931.1)	(10.2)	(10.7)	(11.4)	(8.76)	(10.4)
Observations	21	21	21	21	21	70	70	70	70	70
Adjusted R^2	0.16	0.11	0.16	0.19	0.14	0.43	0.42	0.44	0.69	0.71

Dependent variable: Sum of Gross BOP flows, 2001-2006, in portfolio debt assets and liabilities, in BN of Constant USD

Robust standard errors in parentheses

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

Table 11: Change in Total Assets and Liabilities (LMF data) FE(CTY YR) with Weighted NetStats

	(1) Rich	(2) Rich	(3) Rich	(4) Rich	(5) Rich	(6) Poor	(7) Poor	(8) Poor	(9) Poor	(10) Poor
LD.outeccentricity	-0.022					0.0032***				
	(0.014)					(0.00046)				
LD.ineccentricity		-0.030					0.0013*			
		(0.018)					(0.00071)			
LD.farness1			-0.023		-0.015			0.0043**		0.0043**
			(0.034)		(0.035)			(0.0016)		(0.0019)
LD.betweenness				-57.7*	-55.3*				0.78	-0.013
				(28.9)	(27.7)				(0.48)	(0.38)
L.GDP growth	5.47	4.58	4.95	5.08	5.07	-0.15	-0.15	-0.14	-0.14	-0.14
	(10.2)	(9.91)	(10.0)	(10.0)	(10.0)	(0.30)	(0.29)	(0.30)	(0.30)	(0.30)
L.Trade/GDP	-5.49	-5.45	-5.42	-5.44	-5.43	0.050	0.054	0.056	0.049	0.056
	(6.77)	(6.78)	(6.77)	(6.76)	(6.77)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
L.Polity score	-74.9	-71.6	-70.4	-83.0	-81.9	-0.47	-0.50	-0.48	-0.50	-0.48
	(74.3)	(71.9)	(73.4)	(70.4)	(70.2)	(0.50)	(0.54)	(0.50)	(0.53)	(0.50)
L.Average distance	2361.0*	2370.6*	2357.4*	2361.4*	2362.2*	-21.4	-24.5	-21.1	-24.8	-21.0
	(1169.1)	(1167.4)	(1167.4)	(1168.4)	(1168.4)	(24.0)	(24.2)	(23.2)	(24.5)	(23.3)
Constant	-9320.1*	-9403.9**	-9367.7**	-9247.9*	-9273.8*	107.5	123.1	111.2	124.4	111.1
	(4473.5)	(4453.4)	(4462.1)	(4450.6)	(4446.7)	(130.5)	(131.2)	(127.6)	(131.8)	(128.1)
Observations	544	544	544	544	544	1444	1444	1444	1444	1444
Adjusted R^2	0.38	0.38	0.38	0.38	0.38	0.15	0.14	0.14	0.14	0.14

Dependent variable:Change in total assets and liabilities, in BN of Constant USD

Robust standard errors in parentheses

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

Table 12: Change in Portfolio Equity Assets and Liabilities (LMF Data) FE(CTY YR) with Weighted NetStats

	(1) Rich	(2) Rich	(3) Rich	(4) Rich	(5) Rich	(6) Poor	(7) Poor	(8) Poor	(9) Poor	(10) Poor
LD.outeccentricity	-0.0017					-0.00035***				
	(0.0022)					(0.00011)				
LD.ineccentricity		-0.00097					0.00014			
		(0.0027)					(0.00013)			
LD.farness1			-0.0031		-0.0025			-0.00056**		-0.00070*
			(0.0065)		(0.0061)			(0.00025)		(0.00037)
LD.betweenness				-3.94	-3.36				0.031	0.16**
				(7.04)	(6.69)				(0.064)	(0.073)
L.GDP growth	-0.53	-0.58	-0.57	-0.57	-0.57	-0.0010	-0.0077	-0.0020	-0.0056	-0.0039
	(2.70)	(2.67)	(2.68)	(2.68)	(2.68)	(0.061)	(0.059)	(0.061)	(0.061)	(0.060)
L.Trade/GDP	-0.23	-0.22	-0.22	-0.22	-0.22	0.018	0.019	0.017	0.018	0.017
	(1.31)	(1.31)	(1.31)	(1.31)	(1.31)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
L.Polity score	-12.9	-12.6	-11.8	-15.9	-14.7	0.044	0.049	0.045	0.049	0.047
	(32.0)	(31.6)	(30.7)	(36.6)	(35.4)	(0.065)	(0.067)	(0.064)	(0.066)	(0.064)
L.Average distance	316.2	316.2	315.8	316.7	316.6	0.47	0.58	0.38	0.63	0.088
	(317.7)	(317.8)	(317.5)	(318.6)	(318.8)	(4.51)	(4.64)	(4.46)	(4.64)	(4.42)
L.GNI (nominal)						5.4e-11***	5.3e-11***	5.4e-11***	5.3e-11***	5.4e-11***
						(4.8e-12)	(4.9e-12)	(4.9e-12)	(4.9e-12)	(4.9e-12)
Constant	-1249.9	-1253.5	-1262.0	-1223.6	-1236.6	-5.16	-5.38	-5.43	-5.74	-3.92
	(1126.6)	(1126.4)	(1132.7)	(1099.4)	(1106.8)	(24.1)	(24.7)	(23.9)	(24.7)	(23.7)
Observations	539	539	539	539	539	1422	1422	1422	1422	1422
Adjusted R^2	0.28	0.28	0.28	0.28	0.28	0.42	0.42	0.42	0.42	0.42

Dependent variable: Change in portfolio equity assets and liabilities, in BN of Constant USD

Robust standard errors in parentheses

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

Table 13: Change in Portfolio Debt Assets and Liabilities (LMF data) FE(CTY YR) with Weighted NetStats

	(1) Rich	(2) Rich	(3) Rich	(4) Rich	(5) Rich	(6) Poor	(7) Poor	(8) Poor	(9) Poor	(10) Poor
LD.outeccentricity	0.0021					0.00022				
	(0.0049)					(0.00038)				
LD.ineccentricity		-0.0012					0.00076**			
		(0.0036)					(0.00031)			
LD.farness1			0.021**		0.023**			0.0017		0.0016
			(0.0091)		(0.010)			(0.0011)		(0.0012)
LD.betweenness				-5.31	-9.15**				0.11***	0.067
				(4.70)	(3.69)				(0.034)	(0.042)
L.GDP growth	-1.02	-0.97	-1.09	-0.96	-1.11	0.090	0.080	0.085	0.090	0.085
	(2.40)	(2.31)	(2.29)	(2.31)	(2.28)	(0.098)	(0.096)	(0.097)	(0.098)	(0.097)
L.Trade/GDP	-2.65	-2.65	-2.64	-2.65	-2.63	0.025*	0.026*	0.028*	0.025*	0.028*
	(2.05)	(2.05)	(2.04)	(2.05)	(2.04)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
L.Polity score	-5.54	-5.98	-5.28	-6.87	-7.00	0.096	0.098	0.086	0.10	0.090
	(20.1)	(20.3)	(19.8)	(19.7)	(18.5)	(0.060)	(0.062)	(0.059)	(0.062)	(0.060)
L.Average distance	600.2*	600.8*	602.4*	600.7*	602.7*	0.79	0.47	1.68	0.53	1.45
	(332.1)	(332.8)	(333.7)	(332.8)	(334.1)	(5.37)	(5.35)	(5.23)	(5.41)	(5.27)
L.GNI (nominal)						1.9e-11	1.8e-11	1.8e-11	1.9e-11	1.8e-11
						(1.3e-11)	(1.3e-11)	(1.4e-11)	(1.3e-11)	(1.4e-11)
Constant	-2384.6*	-2382.5*	-2387.5*	-2374.2*	-2371.8*	-7.46	-5.08	-10.3	-5.81	-9.25
	(1313.4)	(1311.7)	(1315.6)	(1312.3)	(1313.7)	(29.2)	(29.3)	(28.7)	(29.5)	(28.9)
Observations	481	481	481	481	481	676	676	676	676	676
Adjusted R^2	0.40	0.40	0.40	0.40	0.40	0.0076	0.010	0.0094	0.0079	0.0080

Dependent variable: '01 to '06 Change in portfolio debt assets and liabilities, in BN of Constant USD

Robust standard errors in parentheses

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

Table 14: Total Assets and Liabilities gross flow (BP data) FE(CTY YR) with Weighted NetStats

	(1) Rich	(2) Rich	(3) Rich	(4) Rich	(5) Rich	(6) Poor	(7) Poor	(8) Poor	(9) Poor	(10) Poor
LD.outeccentricity	0.00017					0.00051*				
	(0.011)					(0.00030)				
LD.ineccentricity		-0.011					0.00037			
		(0.010)					(0.00031)			
LD.farness1			0.012		0.018			0.00041**		0.00023
			(0.029)		(0.030)			(0.00016)		(0.00021)
LD.betweenness				-36.7**	-39.4**				0.26***	0.21**
				(15.8)	(14.0)				(0.059)	(0.086)
L.GDP growth	3.99	3.85	4.00	4.05	4.06	0.31**	0.31**	0.32**	0.32**	0.32**
	(5.92)	(5.79)	(5.79)	(5.80)	(5.77)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
L.Trade/GDP	-3.32	-3.32	-3.33	-3.31	-3.33	0.025	0.026	0.026	0.025	0.026
	(4.16)	(4.16)	(4.15)	(4.15)	(4.15)	(0.051)	(0.050)	(0.051)	(0.051)	(0.051)
L.Polity score	-53.9	-54.1	-54.4	-60.3	-61.4	0.037	0.036	0.035	0.036	0.037
	(56.6)	(55.8)	(55.8)	(54.5)	(53.7)	(0.13)	(0.14)	(0.13)	(0.13)	(0.13)
L.Average distance	1547.4**	1552.9**	1546.5**	1550.6**	1549.5**	8.90	8.45	8.88	8.30	8.49
	(715.5)	(714.8)	(716.9)	(714.9)	(717.1)	(7.95)	(8.15)	(8.11)	(8.06)	(8.11)
L.GNI (nominal)						9.7e-11***	9.8e-11***	9.8e-11***	9.8e-11***	9.8e-11***
						(9.3e-12)	(9.2e-12)	(9.3e-12)	(9.2e-12)	(9.3e-12)
Constant	-6069.9**	-6095.9**	-6051.7**	-6024.9**	-5995.2**	-46.3	-43.8	-45.8	-43.0	-43.7
	(2694.5)	(2684.3)	(2696.9)	(2680.4)	(2686.7)	(43.5)	(44.5)	(44.1)	(44.0)	(44.2)
Observations	538	538	538	538	538	1423	1423	1423	1423	1423
Adjusted R^2	0.29	0.29	0.29	0.29	0.29	0.54	0.54	0.54	0.54	0.54

Dependent variable: Total assets and liabilities gross flow, in BN of Constant USD

Robust standard errors in parentheses

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

Table 15: Portfolio Equity Assets and Liabilities gross flow (BP Data) FE(CTY YR) with Weighted NetStats

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Rich	Rich	Rich	Rich	Rich	Poor	Poor	Poor	Poor	Poor
LD.outeccentricity	0.00078					-0.0000031				
	(0.0011)					(0.000032)				
LD.ineccentricity		-0.00091					0.000017			
		(0.0014)					(0.000011)			
LD.farness1			0.00064		0.0010			0.0000028		-0.0000073
			(0.0033)		(0.0034)			(0.000065)		(0.000083)
LD.betweenness				-2.78***	-2.94***				0.010**	0.012
				(0.83)	(0.96)				(0.0050)	(0.018)
L.GDP growth	-0.70	-0.70	-0.68	-0.68	-0.68	0.015	0.014	0.015	0.014	0.014
	(0.72)	(0.70)	(0.72)	(0.71)	(0.71)	(0.0094)	(0.0095)	(0.0094)	(0.0094)	(0.0094)
L.Trade/GDP	0.078	0.076	0.075	0.077	0.076	0.0041	0.0042	0.0041	0.0041	0.0041
	(0.80)	(0.80)	(0.80)	(0.80)	(0.80)	(0.0078)	(0.0078)	(0.0077)	(0.0078)	(0.0077)
L.Polity score	-6.68	-6.80	-6.81	-7.34	-7.40	0.0017	0.0019	0.0017	0.0019	0.0019
	(6.33)	(6.34)	(6.31)	(6.11)	(6.00)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
L.Average distance	56.0	56.7	56.2	56.4	56.3	-0.0091	-0.014	-0.0055	-0.022	-0.029
	(134.8)	(135.2)	(134.9)	(134.8)	(135.1)	(1.37)	(1.37)	(1.37)	(1.37)	(1.37)
L.GNI (nominal)						7.0e-12***	7.0e-12***	7.0e-12***	7.0e-12***	7.0e-12***
						(1.7e-12)	(1.7e-12)	(1.7e-12)	(1.7e-12)	(1.8e-12)
Constant	-181.6	-183.3	-180.2	-176.8	-174.9	-0.66	-0.61	-0.67	-0.58	-0.55
	(533.3)	(535.7)	(536.5)	(533.5)	(537.3)	(7.33)	(7.34)	(7.33)	(7.36)	(7.32)
Observations	523	523	523	523	523	1306	1306	1306	1306	1306
Adjusted R^2	0.26	0.26	0.26	0.26	0.26	0.19	0.19	0.19	0.19	0.19

Dependent variable: Portfolio equity assets and liabilities gross flow, in BN of Constant USD

Robust standard errors in parentheses

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

Table 16: Portfolio Debt Assets and Liabilities gross flow (BP data) FE(CTY YR) with Weighted NetStats

	(1) Rich	(2) Rich	(3) Rich	(4) Rich	(5) Rich	(6) Poor	(7) Poor	(8) Poor	(9) Poor	(10) Poor
LD.outeccentricity	0.00020					0.000052				
	(0.0033)					(0.000048)				
LD.ineccentricity		-0.0032					0.000082**			
		(0.0039)					(0.000040)			
LD.farness1			0.0054		0.0067			0.00019***		0.00014**
			(0.010)		(0.010)			(0.000067)		(0.000054)
LD.betweenness				-8.03	-9.08*				0.083***	0.057**
				(5.58)	(4.95)				(0.028)	(0.025)
L.GDP growth	-0.29	-0.33	-0.28	-0.27	-0.26	0.026	0.025	0.025	0.025	0.025
	(2.07)	(2.02)	(2.03)	(2.04)	(2.02)	(0.042)	(0.041)	(0.042)	(0.041)	(0.041)
L.Trade/GDP	-1.19	-1.19	-1.19	-1.19	-1.19	-0.014*	-0.014*	-0.014*	-0.014*	-0.014*
	(1.59)	(1.59)	(1.59)	(1.59)	(1.59)	(0.0077)	(0.0076)	(0.0077)	(0.0078)	(0.0077)
L.Polity score	-18.7	-18.8	-18.9	-20.1	-20.5	-0.0055	-0.0051	-0.0047	-0.0045	-0.0040
	(18.3)	(18.1)	(18.1)	(18.1)	(17.8)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
L.Average distance	467.6	469.3	467.2	468.4	467.9	0.47	0.39	0.57	0.32	0.45
	(315.0)	(315.7)	(315.8)	(315.3)	(316.1)	(2.76)	(2.73)	(2.71)	(2.79)	(2.77)
L.GNI (nominal)						5.7e-12***	5.7e-12***	5.6e-12***	5.7e-12***	5.6e-12***
						(1.8e-12)	(1.7e-12)	(1.8e-12)	(1.8e-12)	(1.8e-12)
Constant	-1774.8	-1782.3	-1766.3	-1764.9	-1753.2	-1.21	-0.74	-1.45	-0.33	-0.84
	(1216.3)	(1216.7)	(1218.7)	(1212.6)	(1216.7)	(15.3)	(15.3)	(15.1)	(15.6)	(15.5)
Observations	527	527	527	527	527	1326	1326	1326	1326	1326
Adjusted R^2	0.33	0.33	0.33	0.33	0.33	0.057	0.058	0.058	0.058	0.058

Portfolio debt assets and liabilities gross flow, in BN of Constant USD

Robust standard errors in parentheses

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

6 Appendix 1. Procedure used to match banks to countries

To link banks to countries, we create three country lists—$C1$, $C2$, $C3$—that are used to assign nationalities to the banks in our samples. To create the first country list, we download all variables in Dealogic's *Loan Analytics* and *DCM Analytics* databases 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. We dropped institutions that were not unique in our list. That is, if a given institution was associated with country X in one observation and country Y in another, we eliminate it. We merge the list to our networks samples and call it $C1$.

To create country list two, we take advantage of the fact that some 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). Given that the country name may serve as an identifier of location , we merge the list to our networks samples and call it $C2$.

We create $C3$ after lists $C1$ and $C2$ are generated. We create it by manually searching for bank nationalities for those banks with missing data in $C1$ or $C2$. We used online data provided by Alacra, Inc. and Mergent, Inc. to help us identify the nationality of a majority of banks; remaining bank nationalities were found using search engines.

Given the three country lists, we assign a nationality to a bank, denoted by i, using the following methodology: (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);[18] (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 $C1$ and $C2$ is missing.

[18] We base our list of OFCs on Rose and Spiegel (2007) but exclude large financial centers from this list. As a result, the 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.

7 Appendix 2. Network statistics

Table 17: Country Network Statistics. Sample: 1 January 1980 to 31 December 2000

Country	Banks	Emission	Reception	Farness1	Betweenness	Outeccentricity	Ineccentricity
OECD Countries							
Australia	181	12000	71000	260	0.32	710	2000
Austria	70	4100	12000	110	0.015	640	560
Belgium	92	6200	1500	45	0.0083	260	150
Canada	70	13000	16000	230	0.0088	880	860
Denmark	55	2800	11000	150	0.001	380	630
Finland	28	1600	7300	200	0.016	1200	780
France	195	48000	47000	320	1.1	1100	2000
Germany	244	140000	84000	470	0.023	2300	1200
Greece	16	200	1100	49	0.02	330	410
Iceland	15	4.1	1600	56	0.00056	18	600
Ireland	73	1300	21000	200	0.014	430	1300
Italy	252	15000	39000	110	0.16	490	770
Japan	276	38000	20000	100	0.064	520	380
Luxembourg	147	11000	15000	86	0.011	480	310
Netherlands	109	20000	58000	410	0.032	850	1300
New Zealand	30	420	6800	140	0.0048	160	780
Norway	75	720	12000	83	0.011	450	620
Portugal	36	980	3100	63	0.003	190	230
Spain	101	3400	2400	33	0.00066	140	71
Sweden	44	2200	15000	260	0.028	1100	1900
Switzerland	109	22000	4300	120	0.0021	770	210
United Kingdom	747	450000	140000	340	0.36	2100	1100
United States	1150	130000	220000	160	0.17	620	1100
Developing Countries							
Algeria	8	16	4500	270	0	2	2800
Angola	1	2.2	0	1.2	0	7.7	0
Argentina	53	270	6700	86	0.042	260	510
Bangladesh	1	0	33	25	0	0	200
Belarus	2	2.8	8.6	3.4	0	0.71	4.3
Bolivia	4	0	44	5.7	0	0	45
Bosnia and Herzegovina	1	0	250	170	0	0	1300
Brazil	99	380	9200	67	0.0073	99	360
Brunei Darussalam	1	0	13	6.6	0	0	6.6
Bulgaria	6	8.2	690	82	0	0.68	570
Burundi	1	0.85	0	0.42	0	0.42	0

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Country	Banks	Emission	Reception	Farness1	Betweenness	Outeccentricity	Ineccentricity
Channel Islands	1	1.7	0	0.85	0	0.85	0
Chile	19	27	2000	63	0.014	79	490
China	77	590	11000	82	0.9	460	680
Colombia	20	33	1000	43	0.0035	130	220
Congo, Democratic Republic of the	1	0	2.5	3.5	0	0	18
Cook Islands	1	0	100	42	0	0	450
Cote D'Ivoire (Ivory Coast)	1	0	8.7	6.1	0	0	56
Croatia	8	1.1	360	28	0.000072	18	210
Cuba	1	0	53	29	0	0	260
Czech Republic	22	250	1800	51	0.049	360	470
Dominican Republic	1	0	6.1	7.3	0	0	39
Ecuador	9	0.7	220	16	0	0.039	62
Egypt	17	380	580	27	0.0093	180	200
El Salvador	2	0	8.6	2.6	0	0	3.6
Estonia	7	3.3	300	28	0.00014	7.6	190
Fiji	1	0	0.12	0.059	0	0	0.059
Ghana	6	730	170	87	0.000000033	430	140
Guyana	1	0	2.7	1.3	0	0	1.3
Honduras	2	0	49	13	0	0	18
Hong Kong	508	32000	21000	51	0.028	330	280
Hungary	30	180	850	18	0.013	78	170
India	20	280	2600	87	0.031	190	700
Indonesia	79	89	4000	26	0.0026	16	220
Iran	6	18	1300	130	0	12	1100
Iraq	1	0	840	490	0	0	4200
Israel	8	590	130	53	0.0062	290	380
Jamaica	2	0	31	15	0	0	86
Jordan	5	430	2.4	44	0	300	3.4
Kazakhstan	8	1.5	230	11	0	0.092	100
Kenya	1	0	1.8	1.5	0	0	10
Latvia	7	4	110	7.7	0.000006	3	56
Lebanon	12	64	540	43	0.000038	15	200
Libya	2	64	60	28	0	110	180
Lithuania	6	7.3	73	9.5	0.00000081	2.7	65
Macedonia	5	2.4	600	72	0.00014	7	620
Madagascar	1	0	8.5	6.3	0	0	43
Malaysia	94	1100	2300	22	0.0007	40	140
Mexico	33	210	7500	150	0.062	520	1100
Mongolia	1	0	3.5	3.6	0	0	19
Namibia	1	0	11	6.6	0	0	53
Niger	2	0	11	4.1	0	0	33

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Country	Banks	Emission	Reception	Farness1	Betweenness	Outeccentricity	Ineccentricity
Nigeria	1	0	1.5	0.77	0	0	0.77
Pakistan	7	27	76	14	0.0000026	15	58
Panama	25	370	260	20	0.00032	68	47
Peru	11	1.2	350	25	0.000011	21	150
Philippines	31	82	2000	40	0.002	79	310
Poland	24	170	1400	38	0.014	190	340
Puerto Rico	11	36	1700	110	0.0000036	2.7	850
Qatar	4	63	58	15	0.0022	110	100
Romania	11	37	720	46	0.0000012	4	330
Russian Federation	42	380	15000	180	0.52	530	1600
San Marino	1	20	0	15	0	20	0
Saudi Arabia	15	980	0	36	0	240	0
Serbia	1	0	52	35	0	0	290
Singapore	290	9900	1800	24	0.0024	160	54
Slovak Republic	6	36	88	15	0.0053	70	83
Slovenia	9	11	540	36	0.00072	25	320
South Africa	18	24	2200	73	0.002	37	640
South Korea	142	2100	28000	110	0.63	840	1000
Sri Lanka	4	0	89	13	0	0	72
Syria	1	0	83	61	0	0	460
Taiwan	87	1100	1100	17	0.00028	65	66
Tanzania	2	0	100	42	0	0	260
Thailand	72	170	4900	40	0.0051	59	310
Tunisia	8	41	130	13	0	16	85
Turkey	71	260	8800	62	0.0017	100	590
Turkmenistan	2	0	310	120	0	0	790
Uganda	2	0	15	8	0	0	32
Ukraine	2	0	21	6.1	0	0	59
Uruguay	8	2.5	110	10	0	0.16	76
Uzbekistan	1	0	190	140	0	0	970
Venezuela	24	110	1800	54	0.0085	110	300
Vietnam	6	0	49	4.5	0	0	41
Yemen	3	6.5	87	18	0	1.1	160
Zambia	1	0	0.77	0.38	0	0	0.38
Zimbabwe	5	0	140	20	0	0	140
Offshore Financial Centers							
Andorra	1	2.3	0	1.2	0	1.2	0
Bahamas	18	100	950	55	0.0000045	19	130
Bahrain	14	46	0	1.9	0	8.7	0
Cayman Islands	51	300	4300	61	0	13	350
Cyprus	2	5.8	0	2.3	0	4.5	0

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Country	Banks	Emission	Reception	Farness1	Betweenness	Outeccentricity	Ineccentricity
Gibraltar	2	0.56	120	55	0	0.14	62
Guernsey	2	7.2	0	2.3	0	8.6	0
Jersey	9	46	0	3.4	0	22	0
Macao	9	41	50	5.7	0.0049	37	26
Malta	1	25	0	7.6	0	110	0
Netherlands Antilles	4	28	0	3.5	0	3.5	0
Oman	1	17	0	14	0	76	0
United Arab Emirates	3	15	0	3.5	0	16	0
Virgin Islands (British)	1	0	140	61	0	0	780

Notes: Emission and Reception are sums; other measures are weighted country means.
All measures are multiplied by 10^6 for display purposes.

Table 18: Country Network Statistics. Sample: 1 January 2001 to 30 June 2007

Country	Banks	Emission	Reception	Farness1	Betweenness	Outeccentricity	Ineccentricity
OECD Countries							
Australia	36	25000	26000	2500	0.43	4600	6600
Austria	47	26000	5600	860	0.12	4400	880
Belgium	32	19000	91000	4000	0.0089	3400	14000
Canada	33	26000	370	1100	0	4400	83
Denmark	32	20000	10000	1500	3.6	3500	5600
Finland	9	2500	0	370	0	1900	0
France	70	65000	23000	2200	0.8	5000	4700
Germany	112	140000	5500	1200	0.15	6400	670
Greece	14	4200	370	440	0.6	2200	1200
Iceland	18	240	11000	910	0.034	690	3600
Ireland	45	9000	15000	860	0.37	1800	2400
Italy	105	34000	6100	490	0.0028	2000	310
Japan	146	69000	25000	800	0.00048	2100	840
Luxembourg	44	16000	390	500	0.0082	2300	54
Netherlands	39	45000	7200	1800	0.2	6700	3200
New Zealand	1	0	19	9.5	0	0	9.5
Norway	30	4500	9700	800	0.014	930	2000
Portugal	25	6200	4700	800	0.016	2000	1400
Spain	27	28000	840	800	0.0043	4700	230
Sweden	20	16000	730	1300	0	4600	260
Switzerland	38	13000	17000	1100	0.64	4500	3700
United Kingdom	213	140000	65000	1200	0.12	3600	2200
United States	280	200000	320000	2900	0.84	6100	7400
Developing Countries							
Algeria	3	0	320	53	0	0	53

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Country	Banks	Emission	Reception	Farness1	Betweenness	Outeccentricity	Ineccentricity
Angola	1	0	190	95	0	0	95
Argentina	7	11	4100	650	0	0.82	2400
Armenia	3	0	17	2.9	0	0	2.9
Azerbaijan	9	10	660	51	0.002	57	320
Bangladesh	1	0	3	1.5	0	0	1.5
Belarus	7	0	660	53	0	0	280
Bosnia and Herzegovina	4	0	230	120	0	0	300
Brazil	28	270	11000	660	0.00045	100	1900
Bulgaria	17	120	1900	110	0	61	600
Burundi	1	9.9	0	5	0	5	0
Chile	10	200	3300	600	0.00073	170	1300
China	25	4900	4600	710	0.067	2000	2400
Colombia	10	71	1000	230	0	43	590
Croatia	7	110	3700	550	0.12	990	3300
Cuba	4	21	200	33	0	2.6	36
Czech Republic	13	250	110	40	0	120	4.2
Egypt	17	3200	3500	550	0.28	2700	1400
El Salvador	6	22	750	290	0.0067	59	870
Estonia	1	0	46	36	0	0	70
Ethiopia	1	0	59	34	0	0	59
Faroe Islands	1	0	280	660	0	0	2000
Gambia	1	11	0	5.5	0	5.5	0
Georgia	3	0	67	15	0	0	73
Ghana	1	20	0	24	0	50	0
Guatemala	2	0	150	160	0	0	430
Honduras	2	4.3	180	46	0	1.1	45
Hong Kong	133	23000	44000	770	0.91	2100	2200
Hungary	26	1800	8300	680	0.15	1700	2400
India	29	1400	15000	1000	0.39	2500	3600
Indonesia	6	37	500	120	0.0088	470	360
Iran	7	120	4300	1400	0.28	1500	3700
Iraq	2	0	1700	760	0	0	1500
Israel	6	3200	150	1200	0.00029	4400	270
Jordan	8	2500	150	390	0.000022	2400	87
Kazakhstan	19	260	18000	670	0.12	930	3100
Kenya	1	0	14	9.1	0	0	14
Kyrgyzstan	1	0	4.2	2.1	0	0	2.1
Latvia	10	440	4800	600	0.23	710	2200
Lebanon	5	48	240	39	0.0000079	19	51
Libya	1	68	0	89	0	510	0
Lithuania	4	3.1	240	95	0.00027	35	350

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Country	Banks	Emission	Reception	Farness1	Betweenness	Outeccentricity	Ineccentricity
Macedonia	1	0	130	81	0	0	200
Malaysia	25	1400	5100	370	0.15	1600	1000
Maldives	1	0	3.9	1.9	0	0	1.9
Mexico	8	0	3500	970	0	0	2700
Moldova	5	0	76	7.6	0	0	7.6
Mongolia	3	130	8.3	31	0	46	1.4
Namibia	2	0	200	110	0	0	730
Nigeria	5	20	370	64	0	6	97
Pakistan	4	360	0	140	0	470	0
Panama	12	650	1900	530	0.0072	110	1300
Peru	4	47	470	300	0	5.8	770
Philippines	8	8.8	780	240	0	0.55	560
Poland	24	1700	3600	450	0.011	700	1300
Puerto Rico	3	49	4100	1700	0	8.2	10000
Qatar	9	1900	1800	500	0.33	3200	1400
Romania	12	340	3200	270	0.13	350	1300
Russian Federation	107	2400	39000	330	0.044	300	1400
Rwanda	2	0	18	4.5	0	0	4.5
Saudi Arabia	18	2300	3700	510	0.033	2300	1100
Serbia	6	0	250	22	0	0	33
Seychelles	1	0	35	23	0	0	35
Singapore	76	11000	2500	210	0.0052	990	210
Slovak Republic	4	50	120	46	0.000043	54	38
Slovenia	12	300	9900	1200	0.4	4400	5600
South Africa	21	840	12000	950	0.0086	400	3800
South Korea	43	1200	31000	1100	0.096	1500	3900
Sri Lanka	3	12	860	200	0	2	1400
Sudan	1	6	0	3	0	3	0
Taiwan	68	11000	1100	240	0.0000025	1000	16
Tajikistan	4	0	18	2.3	0	0	2.3
Thailand	11	180	1900	160	0	9.2	370
Trinidad and Tobago	4	81	820	300	0.011	53	1300
Tunisia	8	580	490	180	0	490	280
Turkey	31	830	59000	1700	2.7	4800	7200
Turkmenistan	1	0	710	360	0	0	360
Uganda	1	0	45	22	0	0	22
Ukraine	26	21	5100	190	0.0001	13	830
Uzbekistan	4	0	120	15	0	0	15
Venezuela	5	0	170	20	0	0	25
Vietnam	2	0	28	9.8	0	0	14
Yemen	1	19	0	9.3	0	9.3	0

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Country	Banks	Emission	Reception	Farness1	Betweenness	Outeccentricity	Ineccentricity
Offshore Financial Centers							
Bahamas	2	59	0	26	0	38	0
Bahrain	12	410	430	120	0.000043	190	250
Cayman Islands	10	930	0	76	0	170	0
Cyprus	2	9	180	300	0	9	750
Guernsey	1	13	0	6.4	0	6.4	0
Macao	2	25	0	12	0	100	0
Malta	1	540	0	640	0	3500	0
Mauritius	1	0	110	550	0	0	1200
Oman	1	840	0	1500	0	6300	0
United Arab Emirates	4	750	0	100	0	130	0

Notes: Emission and Reception are sums; other measures are weighted country means.
All measures are multiplied by 10^6

8 Appendix 3. 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)