Global Banking Network and Cross-Border Capital Flows

Galina Hale*
Federal Reserve Bank of San Francisco

Christopher Candelaria
Federal Reserve Bank of San Francisco

Julian Caballero
UC Santa Cruz

Sergey Borisov
AT&T Interactive

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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. The importance of relationships, especially between financial institutions, is frequently emphasized in finance and economics literature, but is still little understood. This paper addresses both the determinants and the effects of bank relationships, with the main focus on understanding the influence of banks' positions in the global banking network on aggregate international capital flows. We identify factors that help explain banks' network characteristics. 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 20 percent of the cross-country variation in international capital flows between 2001 and 2006 are explained by network characteristics for developed countries, and up to 50 percent for developing countries. One of the paper contributions is a novel data set, a bank-level global network, constructed from individual interbank loan data (Loanware) and associated bank-level and country-level banking network statistics that measure the strength of bank relationships.

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1 Introduction

Recent literature on international and domestic finance emphasizes the role of information flows and relationships between financial institutions. For example, Veldcamp and Van Nieuwerburgh (2010, forthcoming) show that information acquisition by investors can be endogenous and may affect investment patterns. The global liquidity crisis also demonstrated the importance of the relationships between financial institutions, not only within a country but also across national borders. This paper takes a step towards empirically understanding the 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 facilitating payments, it is natural to expect that bank relationships will be important for both capital markets and bank lending.

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 an international 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 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

[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.

use loan-level data to construct our network with banks as nodes. For each bank we then compute a set of statistics that would describe its role in the network, network statistics. We rely on four main statistics: farness, ineccentricity, and outeccentricity, which measure the reach of the bank in the network, and betweenness, which measures the importance of the bank in intermediation.

Before addressing our main question, we first analyze the determinants of bank relationships. In particular, we examine which macroeconomic and institutional variables help understand bank relationships. We investigate this question at bank- and country-levels, while our main question is analyzed at a cross-country level.

The empirical analysis in this paper is cross-country rather than country panel because we are interested in long-term determinants and effects of bank relationships, which we also define as long-term. Specifically, we define our macroeconomic variables as 20-year averages for developed and 10-year averages for developing countries, for the sample period ending in 2000. We construct two global banking networks—one based on lending in 1980-2000 and another one based on lending in 2001-2007:H1.[3] This approach reflects our belief that relationships between banks are formed over extended period of time and have lasting effects.

We find that for the rich countries, bank relationships in 2001-2007:H1 are affected by government quality, inflation rate, banking crises, and country size, while for poor countries, they are determined by the level of democracy and government quality, GDP growth, trade, inflation, banking crises, as well as the size and the remoteness of the country. All of these explanatory variables are computed as long term averages prior to year 2000.

In terms of our main question, 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, the reach seems to be particularly important — farness and outeccentricity explain, respectively, 14 and 19 percent of cross-country variation in international capital flows in this sample. For developing countries, betweenness is more important — it explains 50 percent of the variation in international capital flows, while outeccentricity explains 38 percent. We further

[3] Our second networks sample ends before the global financial crisis.

find that for developed countries the aggregate results are driven by debt flows with farness and betweenness together explaining 13 percent of the cross-country variance. For developing countries, we find that bank relationships were important for both portfolio equity and portfolio debt flows, with farness and betweenness together explaining 38 and 23 percent in cross-border equity and debt flows, respectively. These results are robust to including a set of control variables.

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

We obtain deal–level data on syndicated international and domestic 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.[4] 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 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.[5]

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

[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.

[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.

amount (in millions of US dollars).[6] 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. 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]

Further summarizing this data set, there are 8,138 unique institutions that appear. 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 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.

[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.

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 additional samples are generated exactly like the main sample described above. Using our three samples, we create three directed bank networks that take into account the loan amounts and computer network statistics that are described in the next section.

After computing the network statistics, we link each bank to a country. In order to do this, 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.[9] 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 nationality , 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);[10] (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

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

[10] 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.

(4) we assign bank i the nationality in $C3$ if $C1$ and $C2$ is missing.

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: $ie_i = \max_j g_{ji}$
- **MeanFarness** (f_i) is the length of an average geodesic path originating or terminating in node i: $mf_i = \sum_j (g_{ij} + g_{ji}) / \sum_j (p_{ij} + p_{ji})$
- **Betweenness** 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 of all edges incident *from* node i divided by the total number of nodes in the network: $EMISSION_i = \sum_j w_{ij}/I$

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

For some of our analysis, we aggregate network statistics by country. To do this, we construct average networks statistics for each country, as both simple and 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 size of the share of the total flows in and out of bank i on the total global flows; thus, we multiply network statistics by

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

Appendix Tables 1 and 2 list these statistics (weighted and unweighed) for all countries in our sample. As mentioned above, we base these statistics on three separate samples of the loan data: 1980-June 2007 (full sample), 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.[11] We repeat this for two main subcategories of assets and liabilities: portfolio equity and portfolio debt.

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

[11] 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.

World Bank, including measures of income (GDP per capita), size (GNI), openness (ratios of trade to GPD and FDI to investment), financial indicators (bank credit to private sector and real interest rate), fiscal indicators (fiscal balance and public debt), 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, 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, whether 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. The shorter sample for developing countries is driven by 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.

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 trade of financial assets (and goods). 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, Rey, and Oh, 2001). These information costs and asymmetries are further explained by factors such as common borders and cultural affinity (e.g., common language and colonial and legal origins). In the case of banks, one would expect a large effect of these information asymmetries, since a bank's ability to acquire information on potential borrowers is a key determinant on their lending.

Portes and Rey (2005) and Buch (2005) discuss the literature of gravity models used in international finance. 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 Buch's estimates show a robust and negative coefficient for distance[12].

The role of distance may reflect not a direct influence of information asymmetries in international

[12] Wei (2000) and Wei and Wu (2001) also estimates a gravity-type model and finds significant coefficients for size and distance in a small sample using data on international lending 1994-1996.

capital flows, however. It may also be picking up the effect of trade in goods or economic ties due to investment. The idea that international trade in financial assets follows trade in goods was first established by Jain (1986), which 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 BIS (2002) in the case of bank's aggregate lending flows, and by Rose and Spiegel (2002) for sovereign lending. More recently, Aviat and Coeurdacier (2007) argue that the influence of distance in bilateral asset holdings is not direct but works mainly through its impact on trade in goods. Using data on international bank asset holdings, they present evidence that, once controlling for bilateral trade in goods, the negative coefficient of distance is reduced. Their results show that, even though the role of distance is greatly reduced after controlling for bilateral trade in goods, it still remains negative and significant, as it is the case for other variables that proxy for institutional and cultural affinity.

Institutional variables have also been found to be determinants of international capital flows and bank lending. Alfaro, Kalemli-Ozcan, and Volosovych (2008) show instrumental variables evidence of a positive effect of institutional quality on capital inflows. However, their basic measure of capital inflows excludes debt flows. Using data on cross-border bank holdings, Aviat and Courdacier (2007) and Elias (2009) report a positive and significant coefficient for a measure of institutional quality and international lending. Moreover, Papaioannou presents instrumental variables evidence that institutional quality is a robust driver of international bank lending. In his estimations, rule of law, risk of expropriation, and risk of contract repudiation are found to be the most important institutional factors hindering international bank lending. Results in the same vein are reported by Buch (2001) for measures of protection of property rights and by Daude and Fratzscher (2007) for proxys of investor protection and corruption –both studies using international bank lending.

However, there seems to be evidence that the quality of institutions does not have the same effect on all types of capital inflows, and some of the results for corruption are conflicting with the view that better institutions promote international lending. Wei BPEA (20003) 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 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 (2007).

It is usually thought that macroeconomic variables such as GDP growth, interest rate, and measures of macroeconomic stability (i.e. inflation, fiscal balance) should be associated with higher capital inflows, since high-growth and stable economies should attract more capital than underperforming countries. However, most empirical studies don't find a robust association between bank lending and these macro variables once proper controls for institutional quality and information asymmetries are introduced in the analysis (Papaioannou (2009); BIS (2002), Buch (2001))[13]. One explanation for this may be that the effect of higher economic growth in recipient countries (borrowers) may not be the same in industrialized and developing economies and may be subject to macroeconomic conditions not in the borrowing country but in the lending country. Evidence of this is presented by Goldberg (2002), who shows that international lending by US banks is uncorrelated with foreign demand conditions, while lending to Latin American countries is positively associated with economic expansion and tighter monetary policy in the US, while lending to other industrialized economies shows the opposite pattern.

Financial indicators are also found to be important drivers of international capital flows. BIS (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. BIS (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

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

of capital controls and high corporate-tax rates reduce cross-border bank lending[14]. Aviat and Courdacier (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 the following list of potential explanatory variables, where each variable is a simple average between the first year in our sample and 2000 unless otherwise specified:

GDP growth: the geometric rate of growth of real GDP, between the earliest data in the sample and 2000, in constant 2000 USD.

Trade/GDP: the sum of total exports and imports of goods and services as a percentage of GDP.

FDI/total investment: the ratio of FDI net inflows to total investment, i.e., gross fixed capital formation.

Lending interest rate: the rate charged by banks on loans to prime customers, in percent.

Growth of Monetary aggregates: the average annual growth rate in M2, in percent.

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.

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.

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

Polity2: an index of democracy strength constructed by the Polity IV project, which higher values indicated more democratic systems.

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.

[14] 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.

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.

Financial Reform Index: an index of financial sector reform constructed by Abiad, Detragiache, and Tressel (2008), increasing in reform achieved.

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.

Fiscal balance: cash surplus or deficit as percentage of GDP.

Inflation: average annual inflation in a country's consumer price index.

Current account balance: the current account balance as percentage of GDP.

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

Gross National Income: GNI calculated by the Atlas method (using current US dollars).

GDP per capita: the ratio of GDP at constant prices of 2005 international dollars to total population

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)

3.2 Empirical methodology and results

We begin by analyzing correlations 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 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 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 (which includes all countries), 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). 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 Tables 1 and 3 for developed and developing countries, respectively, at the bank level, with standard errors clustered by country. Tables 2 and 4 repeat the same analysis at country level, using aggregated network statistics with the same weights as in the bank-level regressions. In all tables firsts three columns present regressions of network statistics that measure the reach of the bank within the network, while the last column presents regression of betweenness, which measures the importance of the bank in intermediation. All measures could be thought of measuring the strength of a bank's relationships in the network.

We find that for developed countries, as one would expect, better quality of the government as measured by ICRG index is associated with higher betweenness — large financial intermediaries tend to locate in politically stable countries. We also find as one would expect that banking crises destroy relationships between banks. Finally, banks in larger countries are better connected to the global network. Higher inflation is associated with less reach of the banks in terms of lending (again, lenders like to locate in low–inflation countries), and with more reach in terms of borrowing (it takes a longer chain of banks to lend to banks in higher inflation countries).

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, are less prone to banking crises, and those that are less remote, have banks with stronger relationships within the network (see Table 3). Size also appears to be positively correlated with bank relationships. Surprisingly, our measures of bank relationships are negatively correlated with trade to GDP ratio, although this results goes away when we estimate regressions at the country level (Table 4). With the exception of inflation rate, which looses significance in country-level regressions, the results are qualitatively the same whether we estimate the regression at the bank- or country-level.

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 is based on the early sample of bank loans (1980-2000) and aggregate international capital flow data for 2001-2006. Thus, 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.

Again, we begin with simple correlations between the international capital flows since 2000 and our network statistics from the network that was formed prior to 2000. 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 5 reports the results of the regressions of a change in total foreign assets and liabilities (in constant U.S. dollars) between 2001 and 2006. We find that all network statistics have positive and significant effects on cross-border capital flows with three exceptions: ineccentricity does not have a significant effect, betweenness becomes insignificant for developed countries sample when it is included together with farness, and farness becomes insignificant for 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, the reach seems to be particularly important — farness and outeccentricity explain, respectively, 14 and 19 percent of cross-country variation in international capital flows in this sample.[15] For developing countries, betweenness is more important — it explains 50 percent of the variation in international capital flows, while outeccentricity explains 38 percent.

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.[16] The results are reported in Tables 6 and 7, respectively. We find that for developed countries the aggregate results are driven by debt flows: while some coefficients are statistically significant in Table 6 for developed countries, the network statistics hardly explain any variance in cross-border equity flows; from Table 7, however, we can see that further reach and higher betweenness are associated with more portfolio debt flows, with farness and betweenness together explaining 13 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, with farness and betweenness together explaining 38 and 23 percent in cross-border equity and debt flows, respectively, in this sample.

One concern with interpreting these regressions as causal effects 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 2000 and higher capital flows after 2000 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,

[15] As measured by adjusted R-squared.

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

Polity 2 index, and remoteness for both developed and developing countries. In addition, we control for size, as measured by atlas method GNP for developing countries.

The results are reported in Tables 8, 9, and 10 for total flows, portfolio equity and portfolio debt flows, respectively. Table 8 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, when included by itself, is no longer significant for the sample of developing countries.

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.

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.

[To be completed]

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[To be completed]

Table 1: Macro 80 to 00 multivariate regs: HAT measures, RICH, bank

	(1) outeccentricity	(2) ineccentricity	(3) farness1	(4) betweenness
Avg. GDP Growth 80 to 00	-0.0018	-0.017	-0.0022	-1.36
	(0.0032)	(0.012)	(0.0015)	(0.98)
Trade/GDP	-0.00015	0.00069	0.000085	-0.0042
	(0.00011)	(0.00053)	(0.000070)	(0.042)
ICRG government score	0.62	-0.24	-0.033	186.6*
	(0.53)	(1.06)	(0.15)	(100.5)
Inflation	-0.19**	0.22*	0.012	-2.63
	(0.075)	(0.11)	(0.015)	(20.6)
Banking crisis	-2.97**	-0.98	-0.26	-377.9
	(1.19)	(1.28)	(0.19)	(220.6)
GNI (nominal)	0.00075***	0.0017**	0.00026***	0.12**
	(0.00024)	(0.00062)	(0.000084)	(0.050)
Average distance	-0.00073	0.0054	0.00070	-0.23
	(0.0023)	(0.0045)	(0.00066)	(0.51)
Constant	0.83	-2.32	0.031	-665.0
	(4.00)	(7.52)	(1.05)	(865.7)
Observations	1416	1416	1416	1416
Adjusted R^2	0.0021	0.0049	0.0065	-0.0034

Dep Var Varies

Robust standard errors, clustered by country, in parentheses

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

Table 2: Macro 80 to 00 multivariate regs: HAT measures, RICH, CTY

	(1) outeccentricity	(2) ineccentricity	(3) farness1	(4) betweenness
Avg. GDP Growth 80 to 00	-0.00038	-0.015	-0.0017	-1.29
	(0.0042)	(0.011)	(0.0015)	(1.03)
Trade/GDP	-0.00022	0.00062	0.000069	-0.015
	(0.00013)	(0.00052)	(0.000072)	(0.045)
ICRG government score	0.20	-1.31	-0.18	-8.18
	(0.49)	(1.33)	(0.18)	(162.0)
Inflation	-0.24***	-0.021	-0.021	-31.2
	(0.049)	(0.15)	(0.019)	(26.4)
Banking crisis	-1.93	-0.68	-0.14	-474.9**
	(1.13)	(0.90)	(0.097)	(227.6)
GNI (nominal)	-0.000029	0.00014	0.000026	-0.12
	(0.00052)	(0.00077)	(0.000093)	(0.19)
Average distance	-0.0023	0.0014	0.000026	-0.54
	(0.0020)	(0.0042)	(0.00067)	(0.44)
Constant	6.15	11.2	1.99	1575.5
	(3.81)	(10.8)	(1.46)	(1736.4)
Observations	22	22	22	22
Adjusted R^2	0.22	0.048	0.012	-0.17

Dep Var Varies

Robust standard errors in parentheses

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

Table 3: Macro 90 to 00 multivariate regs: HAT measures, Poor, Bank

	(1) outeccentricity	(2) ineccentricity	(3) farness1	(4) betweenness
Avg. GDP Growth 90 to 00	0.11***	0.014	0.0077	3.83
	(0.026)	(0.095)	(0.0050)	(4.66)
Trade/GDP	-0.0041	-0.022*	-0.0014**	-1.54**
	(0.0033)	(0.013)	(0.00062)	(0.60)
Polity score	0.013	0.16***	0.013***	7.24*
	(0.024)	(0.050)	(0.0031)	(4.21)
ICRG government score	0.23**	0.91***	0.069***	61.5***
	(0.11)	(0.22)	(0.012)	(20.9)
Inflation	-0.00049	-0.0018**	-0.00014***	-0.23***
	(0.00036)	(0.00077)	(0.000050)	(0.081)
Banking crisis	-0.14	-0.57	-0.087***	20.1
	(0.19)	(0.46)	(0.028)	(37.2)
GNI (nominal)	0.00048	0.0032**	0.00033***	0.079
	(0.00056)	(0.0015)	(0.000083)	(0.13)
Average distance	-0.0020***	-0.0023	-0.00016	-0.32***
	(0.00069)	(0.0023)	(0.00013)	(0.099)
Constant	0.58	-2.39	-0.16	-28.7
	(1.07)	(2.57)	(0.16)	(169.7)
Observations	696	696	696	696
Adjusted R^2	0.018	0.039	0.042	0.0088

Dep Var Varies

Robust standard errors, clustered by country, in parentheses

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

Table 4: Macro 90 to 00 multivariate regs: HAT measures, Poor, CTY

	(1) outeccentricity	(2) ineccentricity	(3) farness1	(4) betweenness
Avg. GDP Growth 90 to 00	0.10***	0.027	0.0098*	6.60
	(0.034)	(0.073)	(0.0058)	(5.05)
Trade/GDP	-0.0013	-0.012*	-0.00073*	-0.79*
	(0.0023)	(0.0069)	(0.00043)	(0.42)
Polity score	0.017	0.081**	0.0084***	5.28*
	(0.020)	(0.034)	(0.0030)	(2.95)
ICRG government score	0.23**	0.63***	0.058***	47.3**
	(0.10)	(0.20)	(0.016)	(19.4)
Inflation	-0.00012	-0.00035	-0.000042	-0.059
	(0.00030)	(0.00069)	(0.000058)	(0.076)
Banking crisis	-0.29*	-0.44	-0.075***	-2.40
	(0.16)	(0.31)	(0.026)	(25.0)
GNI (nominal)	0.0015***	0.0038**	0.00044***	0.16
	(0.00053)	(0.0015)	(0.00012)	(0.10)
Average distance	-0.0018***	-0.00093	-0.00014	-0.23***
	(0.00061)	(0.0016)	(0.00013)	(0.083)
Constant	-0.029	-2.60	-0.20	-84.8
	(0.86)	(1.96)	(0.16)	(135.2)
Observations	60	60	60	60
Adjusted R^2	0.31	0.23	0.41	0.19

Dep Var Varies

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	65.4***					30.1***				
	(21.4)					(9.82)				
ineccentricity		0.48					0.047			
		(0.37)					(0.031)			
farness1			895.5**		781.6*			94.5*		0.51
			(345.7)		(395.5)			(56.1)		(34.6)
betweenness				0.057***	0.028				0.14***	0.14***
				(0.014)	(0.020)				(0.038)	(0.041)
Constant	93.8	149.7**	57.6	202.2***	56.2	3.25***	6.31**	5.51**	3.76**	3.74**
	(70.5)	(69.2)	(77.6)	(65.5)	(79.9)	(1.22)	(2.61)	(2.37)	(1.57)	(1.59)
Observations	23	23	23	23	23	81	81	81	81	81
Adjusted R^2	0.19	0.022	0.14	0.038	0.12	0.38	0.066	0.060	0.50	0.50

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	6.18*					7.28***				
	(3.32)					(1.66)				
ineccentricity		0.061					0.011			
		(0.072)					(0.0070)			
farness1			92.3		81.5			23.5*		3.66
			(56.0)		(58.3)			(13.9)		(7.89)
betweenness				0.0057*	0.0027				0.031***	0.030***
				(0.0032)	(0.0029)				(0.0046)	(0.0048)
Constant	37.8*	39.5*	32.7	47.8***	32.6	0.64*	1.44**	1.15*	0.93**	0.77
	(18.8)	(19.4)	(20.3)	(16.4)	(20.8)	(0.35)	(0.71)	(0.66)	(0.41)	(0.49)
Observations	23	23	23	23	23	81	81	81	81	81
Adjusted R^2	-0.0071	-0.025	-0.0080	-0.031	-0.055	0.37	0.055	0.062	0.39	0.38

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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Rich	Rich	Rich	Rich	Rich	Poor	Poor	Poor	Poor	Poor
outeccentricity	14.8***					2.12***				
	(2.67)					(0.53)				
ineccentricity		0.16					0.0048**			
		(0.11)					(0.0022)			
farness1			225.1***		175.8***			13.9**		-0.19
			(55.1)		(59.3)			(6.22)		(5.73)
betweenness				0.019***	0.012**				0.0092***	0.0093***
				(0.0036)	(0.0045)				(0.0021)	(0.0024)
Constant	31.9*	34.0*	18.8	51.1***	18.2	0.55***	0.77**	0.49	0.65***	0.66**
	(18.0)	(18.9)	(17.3)	(17.3)	(18.1)	(0.20)	(0.35)	(0.33)	(0.22)	(0.32)
Observations	23	23	23	23	23	49	49	49	49	49
Adjusted R^2	0.12	0.056	0.12	0.080	0.13	0.29	0.043	0.084	0.25	0.23

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: 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	57.5*					5.77				
	(27.3)					(5.84)				
ineccentricity		0.51					0.00043			
		(0.45)					(0.015)			
farness1			776.3*		729.7			-17.7		-29.6
			(373.7)		(494.2)			(28.1)		(25.3)
betweenness				0.077*	0.012				0.065*	0.068**
				(0.041)	(0.049)				(0.033)	(0.033)
Avg. GDP Growth 90 to 00	137.2	84.2	109.3	104.5	107.2	-0.020	0.12	0.12	-0.46	-0.48
	(81.2)	(85.5)	(84.1)	(77.8)	(86.9)	(0.57)	(0.59)	(0.62)	(0.43)	(0.45)
Trade/GDP	-3.46	-4.33	-3.86	-4.20	-3.84	0.052*	0.056**	0.051**	0.046**	0.038*
	(3.92)	(3.41)	(3.74)	(3.43)	(3.85)	(0.027)	(0.024)	(0.022)	(0.021)	(0.019)
Polity score	-157.2	-16.8	-128.7	201.1	-75.9	-0.39	-0.40	-0.43	-0.42*	-0.47*
	(107.8)	(189.7)	(105.0)	(227.4)	(237.8)	(0.28)	(0.29)	(0.30)	(0.23)	(0.24)
Average distance	-0.35	-0.60*	-0.46	-0.57*	-0.47	-0.012	-0.016*	-0.017*	-0.0052	-0.0074
	(0.31)	(0.33)	(0.29)	(0.32)	(0.32)	(0.0079)	(0.0088)	(0.0092)	(0.0060)	(0.0063)
GNI (nominal)						1.2e-10***	1.3e-10***	1.4e-10***	9.5e-11***	9.9e-11***
						(4.2e-11)	(4.0e-11)	(3.9e-11)	(3.0e-11)	(3.1e-11)
Constant	1771.6*	787.2	1638.4*	-1416.0	1126.3	6.61	9.35	12.0	1.85	5.76
	(861.3)	(1670.7)	(873.0)	(2100.6)	(2224.5)	(6.10)	(7.20)	(7.67)	(5.85)	(5.97)
Observations	21	21	21	21	21	72	72	72	72	72
Adjusted R^2	0.24	0.12	0.22	0.11	0.16	0.71	0.70	0.70	0.77	0.77

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 9: 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	4.24					1.91^{*}				
	(4.68)					(0.96)				
ineccentricity		0.072					0.0023			
		(0.073)					(0.0024)			
farness1			72.4		53.4			3.05		1.08
			(63.1)		(77.1)			(3.85)		(3.51)
betweenness				0.0098	0.0051				0.011^{***}	0.011^{***}
				(0.0079)	(0.0089)				(0.0037)	(0.0037)
Avg. GDP Growth 90 to 00	38.1^{*}	31.7	35.8^{*}	34.8^{*}	35.0^{*}	-0.075	-0.020	-0.030	-0.13^{*}	-0.13^{*}
	(18.0)	(18.3)	(19.1)	(18.7)	(19.6)	(0.058)	(0.068)	(0.073)	(0.074)	(0.072)
Trade/GDP	-1.05	-1.10	-1.06	-1.08	-1.06	0.010^{***}	0.013^{***}	0.013^{***}	0.010^{***}	0.010^{***}
	(0.89)	(0.80)	(0.85)	(0.81)	(0.87)	(0.0035)	(0.0043)	(0.0041)	(0.0032)	(0.0033)
Polity score	-5.55	12.2	-3.50	38.3	18.1	0.023	0.026	0.026	0.017	0.019
	(23.9)	(30.2)	(22.0)	(38.7)	(46.7)	(0.033)	(0.031)	(0.033)	(0.027)	(0.030)
Average distance	-0.090	-0.11	-0.097	-0.11	-0.10	0.0019	0.0012	0.0010	0.0026^{*}	0.0027^{*}
	(0.070)	(0.067)	(0.064)	(0.065)	(0.070)	(0.0015)	(0.0015)	(0.0016)	(0.0014)	(0.0015)
GNI (nominal)						$2.6\text{e-}11^{***}$	$3.0\text{e-}11^{***}$	$3.0\text{e-}11^{***}$	$2.4\text{e-}11^{***}$	$2.4\text{e-}11^{***}$
						(2.3e-12)	(3.0e-12)	(3.1e-12)	(2.9e-12)	(2.7e-12)
Constant	123.7	-20.0	109.9	-285.1	-99.2	-3.01^{**}	-2.69^{*}	-2.50^{*}	-3.39^{***}	-3.54^{**}
	(181.6)	(261.7)	(172.5)	(372.5)	(429.5)	(1.31)	(1.40)	(1.48)	(1.18)	(1.39)
Observations	21	21	21	21	21	72	72	72	72	72
Adjusted R^2	0.17	0.18	0.18	0.17	0.13	0.86	0.84	0.83	0.88	0.88

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 10: 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	11.5**					1.69***				
	(4.65)					(0.59)				
ineccentricity		0.12					0.0064***			
		(0.11)					(0.0023)			
farness1			168.6**		150.1*			11.4		3.24
			(64.0)		(83.0)			(6.83)		(5.89)
betweenness				0.018*	0.0049				0.0079***	0.0074***
				(0.010)	(0.011)				(0.0021)	(0.0022)
Avg. GDP Growth 90 to 00	47.7**	36.1	41.9*	40.5*	41.0*	0.012	0.11	0.080	-0.025	-0.021
	(21.2)	(22.4)	(22.2)	(21.2)	(22.8)	(0.066)	(0.081)	(0.078)	(0.077)	(0.075)
Trade/GDP	-1.20	-1.37	-1.27	-1.34	-1.26	-0.00092	0.0016	0.0011	0.0013	0.0012
	(1.04)	(0.92)	(1.00)	(0.93)	(1.02)	(0.0052)	(0.0046)	(0.0049)	(0.0049)	(0.0050)
Polity score	-62.5*	-31.5	-56.8*	21.2	-35.8	0.038	0.029	0.029	0.0055	0.0055
	(29.4)	(45.5)	(27.1)	(53.8)	(60.2)	(0.031)	(0.030)	(0.031)	(0.029)	(0.030)
Average distance	-0.11	-0.16*	-0.13	-0.15*	-0.13	-0.00091	-0.0023*	-0.0023	-0.00056	-0.00060
	(0.085)	(0.086)	(0.080)	(0.084)	(0.087)	(0.0015)	(0.0014)	(0.0014)	(0.0016)	(0.0016)
GNI (nominal)						-7.8e-13	-2.1e-13	5.6e-13	2.3e-13	-4.1e-13
						(2.2e-12)	(2.7e-12)	(3.3e-12)	(2.1e-12)	(2.3e-12)
Constant	688.2**	463.6	658.0***	-68.8	454.0	1.06	1.79	1.84	0.78	0.73
	(234.1)	(403.4)	(222.6)	(502.6)	(560.2)	(1.47)	(1.26)	(1.33)	(1.54)	(1.58)
Observations	21	21	21	21	21	46	46	46	46	46
Adjusted R^2	0.29	0.24	0.30	0.24	0.25	0.41	0.29	0.22	0.44	0.44

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

Robust standard errors in parentheses

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

6 Appendix

Table 11: Country Network Statistics. Sample: 1 January 1980 to 31 December 2000

Country	Banks	Emission	Reception	Farness1	Betweenness	Outeccentricity	Ineccentricity
OECD Countries							
Australia	181	6.3	37	0.36	2600	2.8	5.9
Austria	70	2.1	6.1	0.13	1700	1.9	1.4
Belgium	93	3.2	0.76	0.058	410	0.87	0.41
Canada	70	6.5	8.1	0.28	490	3.2	2.1
Denmark	55	1.5	5.5	0.18	73	1.3	1.6
Finland	28	0.84	3.8	0.25	320	3.8	1.6
France	196	25	24	0.34	7300	3.9	5.4
Germany	244	73	43	0.59	1200	8.5	2.7
Greece	16	0.1	0.58	0.07	200	0.88	1.2
Iceland	15	0.0021	0.84	0.11	26	0.0018	1.7
Ireland	73	0.7	11	0.24	350	1.4	3.7
Italy	252	7.8	20	0.15	710	1.7	2.3
Japan	276	20	10	0.15	1100	2	0.9
Luxembourg	147	5.8	7.6	0.13	370	1.6	0.81
Netherlands	109	11	30	0.33	790	3.1	3
New Zealand	30	0.22	3.5	0.14	93	0.47	2
Norway	75	0.37	6	0.15	210	1.2	1.6
Portugal	36	0.51	1.6	0.058	110	0.59	0.56
Spain	101	1.7	1.2	0.038	41	0.44	0.16
Sweden	44	1.2	8	0.36	1600	3.6	5.6
Switzerland	109	12	2.2	0.19	25	2.8	0.24
United Kingdom	747	230	72	0.54	1100	8.6	3.2
United States	1150	67	110	0.23	820	2.3	3.1
Developing Countries							
Algeria	8	0.0084	2.3	0.41	81	0.0003	9.1
Angola	1	0.0011	0	0.0023	0.19	0.028	0
Argentina	53	0.14	3.5	0.11	81	0.65	1.8
Bangladesh	1	0	0.017	0.029	4.6	0	0.51
Belarus	2	0.0015	0.0044	0.00034	0.00093	0.000071	0.00043
Bolivia	4	0	0.023	0.0066	0.95	0	0.11
Bosnia & Herzegovina	1	0	0.13	0.18	36	0	3.9
Brazil	99	0.19	4.8	0.067	26	0.22	1.1
Brunei Darussalam	1	0	0.0069	0.00066	0.00066	0	0.00066
Bulgaria	6	0.0043	0.36	0.083	16	0.000068	1.8

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Country	Banks	Emission	Reception	Farness1	Betweenness	Outeccentricity	Ineccentricity
Burundi	1	0.00044	0	0.000042	0.000042	0.000042	0
Channel Islands	1	0.00088	0	0.000085	0.000085	0.000085	0
Chile	19	0.014	1	0.099	58	0.13	1.7
China	77	0.31	5.8	0.11	720	1.6	2.3
Colombia	20	0.017	0.53	0.051	22	0.27	0.7
Congo, Dem. Rep.	1	0	0.0013	0.0027	0.36	0	0.039
Cook Islands	1	0	0.052	0.075	14	0	1.6
Ivory Coast	1	0	0.0045	0.011	1.2	0	0.14
Croatia	8	0.00059	0.19	0.035	12	0.0018	0.72
Cuba	1	0	0.027	0.048	7.5	0	0.85
Czech Republic	22	0.13	0.96	0.081	280	0.99	1.4
Dominican Republic	1	0	0.0032	0.0062	0.86	0	0.094
Ecuador	9	0.00036	0.11	0.014	1.7	0.0000039	0.19
Egypt	17	0.2	0.3	0.045	69	0.54	0.6
El Salvador	2	0	0.0045	0.00026	0.00051	0	0.00036
Estonia	7	0.0017	0.16	0.032	7.2	0.00076	0.57
Fiji	1	0	0.00006	0.0000058	0.0000058	0	0.0000058
Ghana	6	0.38	0.087	0.19	15	1.6	0.42
Guyana	1	0	0.0014	0.00013	0.00013	0	0.00013
Honduras	2	0	0.025	0.0023	0.17	0	0.02
Hong Kong	508	16	11	0.09	190	1.2	0.81
Hungary	30	0.093	0.44	0.028	81	0.22	0.52
India	20	0.15	1.3	0.12	210	0.58	2.2
Indonesia	79	0.046	2.1	0.044	11	0.037	0.77
Iran	6	0.0092	0.65	0.18	30	0.035	3.3
Iraq	1	0	0.44	0.62	120	0	14
Israel	8	0.31	0.069	0.078	360	0.96	0.97
Jamaica	2	0	0.016	0.013	2.2	0	0.24
Jordan	5	0.22	0.0012	0.07	7.5	1.1	0.0074
Kazakhstan	8	0.00076	0.12	0.015	3.1	0.0000092	0.35
Kenya	1	0	0.00095	0.0019	0.26	0	0.029
Latvia	7	0.0021	0.058	0.0098	3	0.0003	0.15
Lebanon	12	0.033	0.28	0.033	10	0.0086	0.45
Libya	2	0.033	0.031	0.054	7.1	0.41	0.48
Lithuania	6	0.0038	0.038	0.013	2.5	0.00027	0.2
Macedonia	5	0.0012	0.31	0.11	25	0.0007	1.9
Madagascar	1	0	0.0044	0.0076	1.2	0	0.13
Malaysia	94	0.56	1.2	0.027	17	0.11	0.4
Mexico	33	0.11	3.9	0.19	200	1.4	3.4
Mongolia	1	0	0.0018	0.0034	0.5	0	0.056
Namibia	1	0	0.0055	0.0095	1.5	0	0.17

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Country	Banks	Emission	Reception	Farness1	Betweenness	Outeccentricity	Ineccentricity
Niger	2	0	0.0058	0.0046	0.79	0	0.088
Nigeria	1	0	0.0008	0.000077	0.000077	0	0.000077
Pakistan	7	0.014	0.04	0.0099	6.9	0.004	0.15
Panama	25	0.19	0.14	0.019	7.2	0.17	0.15
Peru	11	0.00064	0.18	0.029	4.9	0.042	0.46
Philippines	31	0.042	1	0.056	17	0.17	1
Poland	24	0.09	0.73	0.049	110	0.61	1
Puerto Rico	11	0.019	0.88	0.15	23	0.00027	2.4
Qatar	4	0.033	0.03	0.025	22	0.34	0.27
Romania	11	0.019	0.37	0.049	9.6	0.00067	1
Russia	42	0.2	7.7	0.21	130	1.7	5.8
San Marino	1	0.01	0	0.0015	0.008	0.002	0
Saudi Arabia	15	0.51	0	0.053	5.5	0.79	0
Serbia	1	0	0.027	0.046	7.4	0	0.82
Singapore	290	5.1	0.95	0.035	86	0.46	0.15
Slovakia	6	0.018	0.046	0.013	46	0.19	0.27
Slovenia	9	0.0056	0.28	0.056	31	0.0025	0.97
South Africa	18	0.013	1.2	0.1	48	0.0072	2
South Korea	142	1.1	15	0.16	630	2.6	3.2
Sri Lanka	4	0	0.046	0.01	1.9	0	0.23
Syria	1	0	0.043	0.091	12	0	1.3
Taiwan	87	0.58	0.6	0.022	12	0.2	0.17
Tanzania	2	0	0.054	0.046	7.3	0	0.8
Thailand	72	0.089	2.5	0.058	12	0.14	1
Tunisia	8	0.021	0.068	0.018	2.7	0.045	0.25
Turkey	71	0.14	4.6	0.083	55	0.031	2
Turkmenistan	2	0	0.16	0.15	17	0	1.9
Uganda	2	0	0.008	0.0047	0.72	0	0.08
Ukraine	2	0	0.011	0.0088	1.5	0	0.17
Uruguay	8	0.0013	0.059	0.013	1.9	0.000016	0.21
Uzbekistan	1	0	0.1	0.16	28	0	3.1
Venezuela	24	0.059	0.93	0.065	22	0.26	1.1
Vietnam	6	0	0.026	0.0078	1.2	0	0.13
Yemen	3	0.0034	0.045	0.024	4.1	0.00011	0.47
Zambia	1	0	0.0004	0.000038	0.000038	0	0.000038
Zimbabwe	5	0	0.073	0.026	4	0	0.44
Offshore Financial Centers							
Andorra	1	0.0012	0	0.00012	0.00023	0.00012	0
Bahamas	18	0.054	0.49	0.022	2.7	0.044	0.23
Bahrain	14	0.024	0	0.0015	0.15	0.022	0
Cayman Islands	51	0.15	2.2	0.063	10	0.03	1.1

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Country	Banks	Emission	Reception	Farness1	Betweenness	Outeccentricity	Ineccentricity
Cyprus	2	0.003	0	0.00026	0.0025	0.00084	0
Gibraltar	2	0.00029	0.065	0.0055	0.012	0.000014	0.0062
Guernsey	2	0.0037	0	0.0019	0.18	0.025	0
Jersey	9	0.024	0	0.0038	0.44	0.064	0
Macao	9	0.021	0.026	0.009	2.3	0.12	0.078
Malta	1	0.013	0	0.027	2.2	0.32	0
Netherlands Antilles	4	0.015	0	0.00035	0.00035	0.00035	0
Oman	1	0.0087	0	0.016	1.5	0.22	0
United Arab Emirates	3	0.0079	0	0.0022	0.27	0.037	0
Virgin Islands (British)	1	0	0.073	0.13	20	0	2.2

Notes: Emission and Reception are sums; other measures are weighted country means.
Farness, Betweenness, Ineccentricity, and Outeccentricity are measures multiplied by 100

Table 12: Country Network Statistics. Sample: 1 January 2001 to 30 June 2007

Country	Banks	Emission	Reception	Farness1	Betweenness	Outeccentricity	Ineccentricity
OECD Countries							
Australia	36	5.9	6.2	0.79	250	4.4	3.5
Austria	47	6.1	1.3	0.26	100	2.8	0.68
Belgium	32	4.6	21	2	130	2.5	13
Canada	33	6.1	0.086	0.51	23	3.9	0.055
Denmark	32	4.6	2.4	0.43	2000	2.5	4
Finland	9	0.59	0	0.14	7.2	1.1	0
France	70	15	5.5	0.7	1400	4.2	2.9
Germany	112	33	1.3	0.46	180	6.1	0.45
Greece	14	0.99	0.087	0.17	690	1.7	0.96
Iceland	18	0.057	2.6	0.34	81	0.14	3
Ireland	45	2.1	3.4	0.32	290	1.4	1.7
Italy	105	8	1.4	0.19	11	1.5	0.19
Japan	146	16	5.9	0.25	16	2	0.43
Luxembourg	44	3.7	0.093	0.18	11	1.5	0.048
Netherlands	39	10	1.7	0.67	1100	5.4	1.9
New Zealand	1	0	0.0045	0.00095	0.0019	0	0.00095
Norway	30	1.1	2.3	0.22	37	0.63	1.3
Portugal	25	1.5	1.1	0.28	170	1.3	0.97
Spain	27	6.5	0.2	0.42	38	5.3	0.037
Sweden	20	3.7	0.17	0.49	25	4.1	0.18
Switzerland	38	3	4.1	0.44	720	3.1	2.6
United Kingdom	213	32	15	0.42	85	3.2	1.5
United States	280	47	74	1	690	5.6	5.5
Developing Countries							

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Country	Banks	Emission	Reception	Farness1	Betweenness	Outeccentricity	Ineccentricity
Angola	1	0	0.045	0.0095	0.057	0	0.0095
Argentina	7	0.0027	0.97	0.17	21	0.000082	2.5
Armenia	3	0	0.0041	0.00029	0.00029	0	0.00029
Azerbaijan	9	0.0024	0.15	0.039	7.4	0.0057	0.35
Bangladesh	1	0	0.0007	0.00015	0.00015	0	0.00015
Belarus	7	0	0.16	0.035	4.4	0	0.56
Bosnia and Herzegovina	4	0	0.054	0.025	1.4	0	0.18
Brazil	28	0.064	2.6	0.15	21	0.01	1.5
Bulgaria	17	0.029	0.45	0.058	4.1	0.038	0.5
Burundi	1	0.0023	0	0.0005	0.0005	0.0005	0
Chile	10	0.048	0.78	0.11	24	0.035	0.66
China	25	1.2	1.1	0.26	230	1.9	1.5
Colombia	10	0.017	0.24	0.067	3.1	0.026	0.39
Croatia	7	0.027	0.86	0.24	49	0.49	2.6
Cuba	4	0.005	0.047	0.0033	0.0092	0.00026	0.0036
Czech Republic	13	0.06	0.025	0.01	0.36	0.065	0.00042
Egypt	17	0.75	0.81	0.2	320	1.8	1.4
El Salvador	6	0.0052	0.18	0.076	9.3	0.0059	0.62
Estonia	1	0	0.011	0.0036	0.021	0	0.0093
Ethiopia	1	0	0.014	0.0034	0.021	0	0.0059
Faroe Islands	1	0	0.067	0.14	11	0	1.4
Gambia	1	0.0026	0	0.00055	0.00055	0.00055	0
Georgia	3	0	0.016	0.009	0.5	0	0.066
Ghana	1	0.0047	0	0.0026	0.072	0.013	0
Guatemala	2	0	0.036	0.038	2.2	0	0.28
Honduras	2	0.001	0.042	0.0046	0.023	0.00011	0.0045
Hong Kong	133	5.5	10	0.3	140	2.1	1.5
Hungary	26	0.41	2	0.21	270	1.2	1.6
India	29	0.34	3.6	0.34	370	1.6	2.7
Indonesia	6	0.0088	0.12	0.04	8.2	0.28	0.35
Iran	7	0.029	1	0.32	57	0.94	2.9
Iraq	2	0	0.39	0.11	3.2	0	0.48
Israel	6	0.75	0.035	0.4	26	2.8	0.18
Jordan	8	0.59	0.035	0.2	10	1.5	0.093
Kazakhstan	19	0.062	4.2	0.24	280	0.14	5
Kenya	1	0	0.0032	0.00091	0.002	0	0.0014
Kyrgyzstan	1	0	0.00098	0.00021	0.00021	0	0.00021
Latvia	10	0.1	1.1	0.21	570	0.17	2.6
Lebanon	5	0.011	0.055	0.0039	0.025	0.0021	0.0051
Libya	1	0.016	0	0.039	2	0.35	0
Lithuania	4	0.00072	0.056	0.037	3.2	0.0035	0.28

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Country	Banks	Emission	Reception	Farness1	Betweenness	Outeccentricity	Ineccentricity
Macedonia	1	0	0.031	0.0081	0.17	0	0.033
Malaysia	25	0.32	1.2	0.13	61	0.99	0.9
Maldives	1	0	0.00091	0.00019	0.00019	0	0.00019
Mexico	8	0	0.83	0.27	14	0	1.9
Moldova	5	0	0.018	0.00076	0.0012	0	0.00076
Mongolia	3	0.031	0.002	0.0031	0.07	0.013	0.00014
Namibia	2	0	0.046	0.056	3.8	0	0.49
Nigeria	5	0.0047	0.087	0.0091	0.25	0.001	0.035
Pakistan	4	0.085	0	0.04	1.5	0.27	0
Panama	12	0.15	0.45	0.11	11	0.019	0.83
Peru	4	0.011	0.11	0.062	3.7	0.00058	0.48
Philippines	8	0.0021	0.18	0.048	2.3	0.000055	0.31
Poland	24	0.39	0.84	0.11	190	0.38	0.85
Puerto Rico	3	0.012	0.97	0.89	53	0.00082	7.1
Qatar	9	0.44	0.43	0.2	310	2.1	1.5
Romania	12	0.08	0.76	0.12	79	0.22	1.4
Russian Federation	107	0.56	9.1	0.15	120	0.095	2
Rwanda	2	0	0.0042	0.00045	0.00045	0	0.00045
Saudi Arabia	18	0.53	0.86	0.21	62	1.5	1.1
Serbia	6	0	0.059	0.0022	0.012	0	0.0033
Seychelles	1	0	0.0082	0.0023	0.0052	0	0.0035
Singapore	76	2.6	0.58	0.1	8.1	0.67	0.15
Slovak Republic	4	0.012	0.029	0.0049	0.051	0.013	0.0038
Slovenia	12	0.071	2.3	0.46	470	2.6	4
South Africa	21	0.2	2.7	0.37	39	0.15	2.7
South Korea	43	0.28	7.3	0.32	58	0.66	3.4
Sri Lanka	3	0.0029	0.2	0.17	11	0.0002	1.4
Sudan	1	0.0014	0	0.0003	0.0003	0.0003	0
Taiwan	68	2.5	0.25	0.092	3.8	0.63	0.0016
Tajikistan	4	0	0.0043	0.00023	0.00023	0	0.00023
Thailand	11	0.043	0.44	0.031	1.4	0.00092	0.18
Trinidad and Tobago	4	0.019	0.19	0.11	19	0.0053	1
Tunisia	8	0.14	0.11	0.073	4.3	0.33	0.29
Turkey	31	0.19	14	0.54	370	2.2	9
Turkmenistan	1	0	0.17	0.036	0.036	0	0.036
Uganda	1	0	0.011	0.0022	0.0022	0	0.0022
Ukraine	26	0.0049	1.2	0.082	8.5	0.0013	1
Uzbekistan	4	0	0.029	0.0015	0.0069	0	0.0015
Venezuela	5	0	0.04	0.002	0.0042	0	0.0025
Vietnam	2	0	0.0066	0.00098	0.0019	0	0.0014
Yemen	1	0.0044	0	0.00093	0.0019	0.00093	0

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Country	Banks	Emission	Reception	Farness1	Betweenness	Outeccentricity	Ineccentricity
Offshore Financial Centers							
Bahamas	2	0.014	0	0.0027	0.02	0.0049	0
Bahrain	12	0.096	0.1	0.043	5.6	0.094	0.19
Cayman Islands	10	0.22	0	0.014	0.46	0.076	0
Cyprus	2	0.0021	0.042	0.06	3.4	0.0016	0.44
Guernsey	1	0.003	0	0.00064	0.00064	0.00064	0
Macao	2	0.0059	0	0.008	0.33	0.058	0
Malta	1	0.13	0	0.2	16	2.8	0
Mauritius	1	0	0.026	0.1	4.2	0	0.56
Oman	1	0.2	0	0.57	25	3.9	0
United Arab Emirates	4	0.18	0	0.013	0.15	0.035	0

Notes: Emission and Reception are sums; other measures are weighted country means.
Farness, Betweenness, Ineccentricity, and Outeccentricity are measures multiplied by 100