IDB WORKING PAPER SERIES No. IDB-WP-364

Banking Crises and Financial Integration

Julián Caballero

December 2012

Inter-American Development Bank
Department of Research and Chief Economist

Banking Crises and Financial Integration

Julián Caballero

Inter-American Development Bank

Inter-American Development Bank

2012

Cataloging-in-Publication data provided by the
Inter-American Development Bank
Felipe Herrera Library

Caballero, Julián.
Banking Crises and Financial Integration / Julián Caballero.
p. cm. (IDB working paper series ; 364)
Includes bibliographical references.
1. Financial crises. 2. Capital movements. 3. Banks and banking—State supervision. I. Inter-American Development Bank. Research Dept. II. Title. III. Series.
IDB-WP-364

http://www.iadb.org

Abstract[1]

This paper explores whether the level of financial integration of banks in a country increases the incidence of systemic banking crises. The paper uses a *de facto* proxy for financial integration based on network statistics of banks participating in the global market of interbank syndicated loans. Specifically, the network statistics degree and betweenness are used to proxy for the *de facto* integration of the average bank in a country. The paper fits a count data model in the cross-section for the period 1980-2007 and finds that the level of integration of the average bank is a robust determinant of the incidence of banking crises. An increased level of *de facto* integration as measured by borrowing by banks is positively associated with the incidence of crises. A higher level of *de jure* integration (capital account openness) is also associated with a higher incidence of crises. However, the results also indicate that prudential banking regulation (supervision) plays a crucial and much larger role in reducing the incidence of crises. Interestingly, the results also show that the level of integration as measured by betweenness of the average bank has a negative effect on the incidence of crises. That is, the more important the average bank of a country is to the global bank network, the fewer the number of crises the country endures.

JEL Classification: E44, E51, F21, F32, F34, G01

Keywords: Banking crises; Financial crises; Capital flows; Financial Networks

[1] *E-mail:* julianc@iadb.org. Tel: +1(202)623.3556. 1300 New York Ave. NW, Washington DC, 20577. I would like to thank the Federal Reserve Bank of San Francisco for providing a stimulating environment while I was visiting as a PhD intern in the summer of 2009 and prepared the first draft of this paper. I would especially like to thank Galina Hale, not least for sharing her data. Michael Hutchison made useful comments on an early draft. All errors, of course, are mine.

1 Introduction

The recent global financial crisis has led to a revival of the literature on financial crises. Part of the recent discussion has emphasized the role of international financial integration, and the concomitant capital flows, as a factor exacerbating the vulnerability of the banking system. One strand of the literature has focused on the association between *de facto* financial integration and financial crises. However, it is not clear at all if countries with an increased level of financial integration are indeed more prone to financial crises.[2] On the other hand, a new breed of papers is increasingly successful in linking rapid inflow growth (a surge, bonanza or boom) with an increased probability of crises. This literature also finds that the type of inflows does matter, debt inflows being particularly problematic.[3]

The purpose of this paper is to study the effects of *de facto* financial integration of the banking system on the incidence of systemic banking crises. The paper focuses on the role of banks and uses as proxy for *de facto* financial integration a measure computed from bank-level data on borrowing and lending. Specifically, I use network statistics for the average bank in a country to proxy for a country's *de facto* financial integration. These network statistics are computed from lending and borrowing flows among banks in the interbank syndicated loan market and are averaged out at the country level to obtain proxies of *de facto* financial integration for over 100 countries. The data have been taken from Hale (2012).

Network analysis is popular in the social sciences, and it is now gaining popularity in the economic literature. The banking system lends itself to being represented by a network in which each bank is a node and the links between banks are the interbank borrowing and lending flows. By no means is this the first attempt to use network analysis in Finance or Economics. In recent years there has been an explosion of studies trying to understand the phenomena of contagion and systemic risk from non-conventional perspectives, including the use of a network approach.

However, the existing literature on financial networks has either of two limitations: (i) Most of the literature is theoretical in nature or use simulations to study the properties of the models.[4] (ii) All but three of the existing empirical studies characterizing a financial network are

[2] The literature tends to proxy *de facto* financial integration by the stock of foreign liabilities. For example, Bonfiglioli (2008) reports a positive link in developed countries between banking crises and the aggregate stock of foreign liabilities, but she finds no association in developing countries. Joyce (2010) and Ahrend and Goujard (2011) find a robust association between the likelihood of banking crises and the stock of foreign debt liabilities in emerging economies–with the latter study also reporting a greater probability of crises the larger the share of debt in foreign liabilities. However, Gourinchas and Obstfeld (2012) fail to find any association between the share of external debt in total external liabilities and the probability of banking crises in emerging markets–although they do find a robust association in high-income countries.

[3] See e.g., Reinhart and Reinhart (2009), Furceri et al. (2011), Caballero (2012), and Powell and Tavella (2012).

[4] For a recent review of the theoretical literature on financial networks see Allen and Babus (2009). Anand et al. (2011) and Zawadowski (2012) present models of contagion in financial markets; related models of cascading effects

domestic in nature: they try to characterize the network structure of banks in a country.[5] The lack of international bank-level data on lending is a huge obstacle in this line of research. Three of the four existing papers using a network approach to characterize a global bank network rely on country-level data (Hattori and Suda, 2007; Minoiu and Reyes, 2011; von Peter, 2007).[6]

Hale (2012) takes a different approach, using bank-level micro data to construct a global bank network. She uses data from eight thousand banks that participate in the market of syndicated loans and studies the evolution of the resulting network of interbank borrowing and lending. She compares the structure of the network and the formation of new bank relationships after recessions and financial crises, finding that crises have long-lasting negative effects on the formation of new bank relationships. Hale et al. (2011) use similar data and studies how the location of a country in the resulting global bank network, as described by network statistics, is associated with capital flows into and out of the country.

An advantage of a network approach is that it can capture different dimensions of how connected each node (bank or country) is to a network and allows us to think not only in terms of the size of the flows going into a node (*borrowing*), but also on how connected or important is a node to the network (as explained below, this is captured by the network statistic *betweenness*). These different network effects on the incidence of systemic banking crises are what I explore in this paper.

The different degrees of connectedness or the position relative to the network may be important for understanding how different shocks affect each node in a network. Intuitively, we can think that a more connected node would be more affected by a systemic shock. However, as em-

are studied by Acemoglu et al. (2012), Acemoglu et al. (2010) and Blume et al. (2011). For systemic risk simulations using a network approach see IMF (2009).

[5] Boss et al. (2004) is an early study on the network topology of an inter-bank market; they use data for the Austrian inter-bank market. Inaoka et al. (2004) use a network approach to study the inter-bank market in Japan. Söromaki and Beyeler (2006) study the network characteristics of the inter-bank payments transferred between commercial banks over the Fedwire Funds Service. Cajueiro and Tabak (2008) study the Brazilian inter-bank market network. Iori et al. (2008) explore the network topology of the Italian overnight money market. Bech and Atalay (2010) explore the network topology of the inter-bank money market in the United States (federal funds market). Bech and Bonde (2008) study the money market network and the network of customer driven transactions in Denmark. Pröpper et al. (2008) characterize the inter-bank payment flows in the Netherlands. Becher et al. (2008) study the network topology of inter-bank payment flows in the United Kingdom.

[6] von Peter (2007) uses data on assets and liabilities of 40 reporting banking systems in the locational banking statistics of the Bank of International Settlements (BIS). He constructs a network of international banking centers by country and uses network statistics to characterize each country. Hattori and Suda (2007) use the BIS consolidated banking statistics to construct a global bank network. They compute statistical measures of the network's topology and examine the changes in such statistics over time. More recently, Minoiu and Reyes (2011) have examined the topology of the network resulting from BIS banking statistics. Other country-level studies have looked at other dimensions of financial flows, not only bank flows. For example, Kubelec and Sá (2010) construct a dataset on cross-border assets and liabilities for a group of 18 countries in four asset classes: FDI, equity, debt, and foreign exchange reserves. They compare the geographical properties of these financial linkages, and compare it with the traditional trade linkages. Similarly, bilateral trade flows have been used by Kali and Reyes (2007), Fagiolo et al. (2008), Fagiolo et al. (2010b), and Fagiolo et al. (2010a) to construct network statistics to measure international economic integration.

phasized by Haldane (2009), the structure of the financial network can make it simultaneously fragile and robust. Thus, being well connected to the global banking network may allow a country easier access to the international capital markets when it needs it the most and thus enable that country to withstand different shocks that otherwise may trigger a financial crisis.[7] Similarly, a higher level of connectedness may be associated with an increased ability to dissipate economic shocks. For example, Kali and Reyes (2010) find that countries that are well integrated into the global trade network were able to cushion the impact of financial shocks, such as the Mexican and Asian crises, while Caballero et al. (2009) show that countries where banks were more connected to the global network of syndicated loans prior to the global financial crisis were less affected by the crisis.

I use the network statistics *betweenness*, *indegree* and *outdegree* to capture the connectedness of the average bank of a country to the global bank network. Betweenness measures the importance of a bank as intermediary in the international banking network. Indegree is a measure of the number of incoming links. Thus, in a bank network indegree is a measure of the number of borrowing relationships of a bank. Weighted indegree is just the borrowing by a bank. Outdegree captures the outgoing links, or lending, of a bank.

I use data from Hale (2012), who computes network statistics at the bank level for eight thousand banks active in the market of syndicated loans. I focus on banks that participate as lead arrangers in the syndicates. The statistics are averaged out at the country level to obtain statistics for the average bank in a country. The sample includes banks from 116 countries.[8] Throughout the text, I refer to these network statistics as the *de facto* financial integration of the average bank of a country.

The paper performs non-parametric and regression analyses of the relationship between the *de facto* financial integration of the average bank and the incidence of banking crises in the cross-section of the period 1980-2007. The analysis is done for the period before the Global Financial Crises of 2008 because this crisis is in a league of its own. As shown by Hale (2012) and Minoiu and Reyes (2011), this crisis had a deep impact on banking flows all around the globe and had unique characteristics, especially regarding the way it spread out to many developed countries.

[7] Bank lending, as well as much of economic activity, crucially depends on available information, trust, and relationships. One can expect that the higher the connectedness of a country in the global banking system, the stronger the relationships this country has, and, hence, the easier its access to international capital markets. One can also think in terms of the literature on financial crises (e.g., Chang and Velasco, 2001) and sudden stops (e.g. Calvo, 1998), emphasizing the inability to obtain short-term debt or that being starved of financial inflows can trigger a banking crisis or a sudden stop event that ends in a crisis.

[8] See detailed explanation of network statistics in section 2 and description of bank lending data in Section 3.

The analysis is done in the cross-section, and the regression analysis fits a count data model using a Generalized Linear Model technique, which is a novel approach to study financial crises.[9]

I find that the level of financial integration of the average bank in a country is a robust determinant of the incidence of banking crises. I find that increased *de facto* integration of banks as measured by total borrowing (sum of weighted indegree for all banks in a country) is positively associated with the incidence of banking crises. Using the proxy for *de jure* financial integration of Chinn and Ito (2008), I find that a higher level of *de jure* integration is associated with a higher incidence of crises.

However, the results also indicate that other factors are at work, and potentially can have a much bigger role as determinants of banking crises. In particular, prudential banking regulation (supervision) seems to play a crucial role in reducing the incidence of crises. Interestingly, the results also indicate that the level of integration into the international capital markets, as measured by betweenness of the average bank, has a negative effect on the incidence of banking crises. That is, the more important the average bank of a country is to the global bank network, the smaller the number of banking crises the country experiences, even after controlling for total borrowing and the degree of *de jure* capital account openness.

2 Network Approach to International Financial Integration

To define the network statistics, first I need to introduce some definitions and notation. In this network each bank is a node and is indexed by $i = 1, \ldots, N$. The link or edge between banks i and j is denoted by c_{ij}. It is not necessary to have each pair of banks (nodes) connected. We are characterizing a directional network, in which the direction of the link matters: thus, $c_{ij} \neq c_{ji}$, which captures the fact that not all banks flows are bidirectional. The link between banks i and j can also be characterized by the size or intensity of the connection, and we denote this weighted connection as w_{ij} (in this directional network we have $w_{ij} \neq w_{ji}$).

The length of the path between nodes i and j is the number of links that must be covered in the trajectory from i to j; this captures the reality that not all banks have direct relationships, but at the same time bank k is indirectly connected to banks i and j through the direct connection between them. A *geodesic* path is a path between two nodes that has the shortest possible length. The length of the geodesic path from bank i to bank j is denoted as g_{ij}. The number of geodesic paths from nodes i to j is denoted as p_{ij}, while the number of geodesic paths that go from bank i to bank j passing through bank k is denoted as p_{ikj}.

Network statistics that capture the connectedness of a given node can be divided into two main classes: centrality and degree measures. Centrality statistics such as closeness and

[9] After an extensive search, I was not able to find other papers that fit a count data model for the number of financial crises in a given country. The most similar paper I found is Eichengreen (2002). However, this paper fits a count data model on the number of crises for each year, not for the number of crises in a country.

the Bavelas-Leavitt index of centrality are constructed based on the length of geodesics between nodes. Thus, a large centrality measure for a given node can be the result of a relatively large network (geodesic paths of large length for the average node) or that the node is relatively isolated (relatively large geodesic paths for a particular node). For these reasons, my preferred proxy for financial integration of the average bank in a country is betweenness, also known as betweenness-centrality. This measure captures how important and central a node is to the network, disregarding the direction of the flows, and it is not affected by the size of the network (the number of nodes or of geodesic paths). It is constructed as the ratio of the paths in which node i is an intermediary between nodes k and l to the total number of paths between k and l. Formally, betweenness is computed as $betweenness_i = \sum_l \sum_k (\frac{p_{kil}}{pkl})$.

Degree measures (indegree, outdegree, degree) capture how connected is each node to the network, taking into account the direction of the flows. Indegree is simply the number of incoming relationships. Indegree can also be computed after weighting by the the size of flows, which captures the sum of all borrowing done by a bank. I will use both unweighted and weighted indegree measures, and I will refer to the former as indegree and to the latter as borrowing. Borrowing is computed as $borrowing_i = \frac{\sum_j w_{ji}}{N}$. I will also use a similar measure for outdegree, and the corresponding weighted statistic, which I will call lending.

One shortcoming of betweenness statistics is that they do not take into account the intensity of the flows. Thus, a node that serves as hub for banking flows in some region can have a very large measure of betweenness, even though it is not a world heavyweight in terms of the size of the flows. To overcome this problem, betweenness statistics are also weighted by the size of the share of the total flows in an out of bank i on the total global flows. Thus, weighted betweeness is computed after multiplying by $\frac{\sum_i w_{ij} + \sum_j w_{ji}}{\sum_j (\sum_i w_{ij} + \sum_j w_{ji})}$.

The idea is to use these network statistics to proxy for the *de facto* financial integration of the banking system of a given country. The original network statistics are computed at the bank level and for all banks that have participated as lead arrangers in the interbank syndicated loans market. To obtain a country-level measure, averages over all active lead banks in a country are taken. Thus, in effect I am proposing that the *de facto* financial integration of a country be proxied by the betweenness or degree statistic of the average lead bank in a country. Borrowing and lending will be also used as the sum for all lead banks in order to control for all borrowing or lending by banks in a country.[10]

3 Data

The analysis in this paper centers in the cross-section of the period 1980-2007. I compiled a database on financial crises with a set of macroeconomic and institutional variables, and, as de-

[10] Throughout the paper I use country-level betweenness statistics normalized so that the maximum is 1.

scribed before, I use measures of *de facto* financial integration based on network statistics computed from interbank syndicated loans.

3.1 Loan Data

I use data from Hale (2012), who employs data on international syndicated interbank loans to construct a global bank network and compute the network statistics described in Section 2. The database is constructed from syndicated loans between private banks reported by Dealogic Loan Analytics (these data are also known as Loanware).[11] With these data it is possible to create bank-to-bank links (lending or borrowing relationships) between participating banks. Each bank-to-bank link in a deal is replicated as many times as there are lenders in the syndicate, and equal loan amounts are assigned to each participating lender in the deal. The dataset used to compute network statistics has a total of 15,324 loans reported in the period from January 1980 to December 2009, with a total of 8,525 participating banks from 124 countries. See Hale (2012) for further details on these data.

The syndicated loan market is a good alternative for studying the international bank lending market. As shown by Gadanecz and von Kleist (2002), the lending flows of syndicated private loans are a good proxy for the flows implied by the BIS consolidated banking statistics. According to these authors "the proportional changes in both data sets seem to be closely linked, with the change factor significantly different from zero and virtually identical to one" (p. 71). Hale (2012) further documents that the total annual loan originations in the interbank market for syndicated loans on average have amounted to 20 percent of interbank claims reported to the BIS between 1980 and 2009–although during the late 1990s this ratio was as high as 34 percent.

Since the values of the network statistics are obtained as an average of the statistics of a country's banks participating in the market of syndicates loans, these statistics are affected by the inclusion of banks that rarely participate in the market. The majority of banks participate as lead arrangers and usually alternate roles in subsequent loans (Cai, 2010). However, there are a number of banks that never participate as lead arrangers. Including these banks may skew downwards the proxies of financial integration we are interested in exploring. Thus, the paper uses network

[11] A syndicated loan is one jointly funded by a group of banks. A bank establishes a lending relationship with the borrower and negotiates the terms of the loan agreement (this bank is called the lead arranger). Then, the lead arranger, for reasons such as exposure and risk management, looks for participant banks which fund a share of the loan; in return, the participant banks receive fees. Syndicated loans are a significant source of international financing, accounting for a third of all international financing, including bond, commercial paper and equity. For an explanation on syndicated loans and their rationale and determinants see, for example, Godlewski and Weill (2008), Gadanecz (2004), Pichler and Wilhelm (2002), and Gatev and Strahan (2009).

statistics computed from the network of banks that have participated in at least one deal as lead arrangers.[12]

As mentioned before, this paper focuses on the cross-section of the period 1980-2007, that is, before the unwinding of the subprime crisis in the United States and the subsequent Global Financial Crisis. Specifically, the network statistics used in this paper as proxies of *de facto* financial integration were computed using data for the period spanning January 1980 to June 2007.[13] The total number of banks that participated as lead arrangers during this period is 4,806. The network statistics betweenness, indegree and outdegree described in Section 2 were computed for the 116 countries in Table 1.

3.2 Banking Crises Data

To identify banking crises, I use the database on financial crises by Laeven and Valencia (2010). In this database a banking crisis is defined as a systemic banking crisis, in which a country's corporate and financial sectors experience a large number of defaults and financial institutions and corporations face great difficulties repaying contracts on time. Their definition does not include isolated banks in distress.

The database identifies the year of start of a banking crisis if that year coincides with deposit runs, the introduction of a deposit freeze or blanket guarantee, or extensive liquidity support or bank interventions. Bank runs are defined as a monthly percentage decline in deposits in excess of 5 percent, while extensive liquidity support is defined as claims from monetary authorities on deposit money banks to total deposits of at least 5 percent and at least double the ratio compared to the previous year. The definition also requires that it becomes apparent that the banking system has a large proportion of nonperforming loans and that most of its capital has been exhausted.

It is important to bear in mind the structure of the indicator for banking crises. The dummy identifies the start of a banking crisis, but assigns a value zero for other years, even if the banking crisis lasts for some time. Since the analysis is done in the cross-section, this structure is adequate for our purposes. A dummy for subsequent years would double count each crisis episode. Table 1 makes explicit the sample of crises used in the paper.

[12] Focusing on lead banks is usual in the literature using data on syndicated loans, as lead banks control the lion's share of the market. For example, Cai et al. (2011) document that in the United States the top 100 lead banks controlled an aggregated share of between 99.7 percent and 100 percent of the market during 1988-2010.

[13] The dating of the start of the subprime crisis is imprecise. June 30, 2007 is chosen as a cut-off for the loans data because it is just before the first clear signals of the start of the liquidity crunch in the United States. The events that precipitated the crash include the liquidation of two hedge funds by Bear Stearns in July 31 and the decision of BNP Paribas of suspending three hedge funds focused on US mortgages in August 9. For a timeline of events leading to the crisis see `http://timeline.stlouisfed.org/pdf/CrisisTimeline.pdf`.

3.3 Other Data

The set of macroeconomic variables to be used as controls was obtained from the World Development Indicators database of the World Bank, including GDP per capita, openness in trade, bank credit to private sector (as percentage of GDP), current account balance, and inflation. To account for *de jure* capital account openness I use the database by Chinn and Ito (2008). I use different databases to account for institutional variables, including data on financial reforms by Abiad et al. (2010), who construct indexes of financial reform and banking supervision. To proxy for quality of political institutions, I use the index of political risk from ICRG. Details on each variable used in the paper can be found in Table 11.

4 Financial Integration and Banking Crises: Non-Parametric Analysis

This section performs a non-parametric analysis based on Chi-Squared independence tests. These tests are performed using two-way tabulations in which banking crises are on the rows and the other variable is on the columns. Three independence tests are performed: Pearson Chi-squared, Likelihood-ratio, and Fisher's exact test. The null hypothesis in these tests has the general form: $H_o : P_{ij} = P_{i+} * P_{j+}$, that is, the probability that an observation selected at random will be classified in the *i*th row and the *j*th column is equal to the marginal probability that the observation is classified in the *i*th row times the marginal probability of being classified in the *j*th column. Thus the null hypothesis implies that the rows are statistically independent from the columns.[14]

The data for this analysis use a dummy that takes the value 1 for countries that have suffered a systemic banking crisis in the period 1980-2007, and zero otherwise. There are a total of 61 countries with at least one banking crisis in the period, out of a total of 116 in the sample with network statistics. The sample of countries and number of crises per country is reported in Table 1.

I compute the two-way tabulations and independence tests using quartiles of the network statistics described in Section 2. I use a total of 14 different network statistics: eight statistics for average bank betweenness, degree, indegree, and outdegree, and the corresponding unweighted and weighted measures; and six additional network statistics for the sum of all banks in a country, including degree, indegree, and outdegree, and the corresponding unweighted and weighted statistics (recall that throughout the text weighted indegree is referred to as borrowing, and weighted outdegree is referred to as lending).

The battery of network statistics captures different aspects of the *de facto* financial integration of the country. Average betweenness captures how important and central the average bank of a country is in the global bank network. The other average degree measures give us an idea of the

[14] A small *p*-value of the test, then, rejects the null, meaning that the test rejects the hypothesis of equality of incidence, or alternatively, a small *p*-value tells us that the rows and columns have a statistical association. Not rejecting the null (a large *p*-value) means that the incidence of the two phenomena is statistically independent.

financial integration of the average bank in terms of borrowing or lending relationships, and the average total borrowing of lending of the average bank. All banks borrowing is simply the same as the usual measure of flows into a country. It captures the size of borrowing by banks.

Table 2 reports summarized results of the independence tests for the network statistics and a set of institutional variables of interest.[15] The independence tests are performed on an indicator for a banking crises in the period against quartiles of network statistics for the average bank (unweighted and weighted betweenness, degree, indegree and outdegree).

The *p*-values of the independence tests indicate that an increased *de facto* financial integration of the average bank is statistically correlated with banking crises. The independence tests tell us that unweighted betweenness of the average bank is statistically associated with the incidence of banking crises over the period. The outdegree measures are also associated with the incidence of crises. The indegree or borrowing measures for the average bank seem not to be associated with crises, while total bank borrowing and lending are.

To gauge the association between banking crises and financial globalization, I use a proxy for *de jure* capital account openness. This index goes from 0 to 3 and is increasing in the level of openness of the capital account transactions. The index is taken from Abiad et al. (2010).[16] The tests point that there seems to be no statistical relationship between the incidence of banking crises and *de jure* capital account openness. One reason, as argued by Edwards (2007), who reports similar results, may be that countries often find ways to circumvent regulations and *de jure* capital controls. The *p*-values of the independence tests, however, do not suggest strong evidence of independence.

Employing the indexes elaborated by Abiad et al. (2010), I also perform this non-parametric analysis for some other variables of interest. In particular, I perform independence tests for the incidence of banking crises and an index of financial reform and for an index of banking supervision. The results indicate that there is a statistical association between the incidence of banking crises and both the index of financial reform and the level of regulation of the banking system.

In summary, the non-parametric analysis via independence tests suggests that the incidence of banking crises is associated with the level of *de facto* financial integration, as measured by betweenness and outdegree of the average bank. Total lending by banks in a country is also associated with the incidence of crises. The analysis also indicates that banking regulation is statistically associated with the occurrence of crises.

The analysis so far cannot answer questions of causality or direction of the relationship. The independence tests offer a simple but systematic way to study the statistical association or

[15] The underlying two-way tabulations of the results summarized in Table 2 are available upon request.

[16] There are several indexes in the literature, and I will use Chinn and Ito (2008)'s KAopen index in the regression analysis later on. However, for this non-parametric analysis based on two-way tabulations I use the discrete index by Abiad et al. (2010). This index has a correlation of 0.73 with the continuous, and more nuanced, KAopen index.

independence between the incidence of two categorical variables. However, one should not read more than that into these tests: the tests tell us if there is an association between the two variables, but not what the association is. Also, the tests cannot capture the interactions of the two variables once we control for other plausible determinants of the incidence of crises. To study this, in the next section I perform a regression analysis using a count data model.

5 Financial Integration and Banking Crises: Regression Analysis

The regression analysis in this section explores the hypothesis whether or not higher financial integration of banks increases the incidence of banking crises. The strategy is to fit an empirical count model in the cross-section of the data, using as controls the variables the literature has found relevant to influence the occurrence of banking crises and introducing different measures of the *de facto* financial integration based on network statistics.

5.1 Empirical Strategy

I fit a model for count data where the dependent variable is the *number* of banking crises over the period in a given country. The explanatory variables are a vector of averages of macroeconomic and institutional variables over the period, plus the proxies of financial integration of the banking system computed using the network statistics described before. The models used the most in the literature of count data are the Poisson and the Negative Binomial models. Both models are suited to analyzing non-negative count data. These techniques model the probability of occurrence of independent events in a given period of time and relate this probability to a vector of explanatory variables, plus a constant. Following the standard approach, I estimate the model:

$$bankcrises_i = \alpha + \beta FinInt_i + \psi X_i + \xi_i \tag{1}$$

where $bankcrises_i$ is the sum of banking crises over the period 1980-2007 in country i, α is a constant, $FinInt_i$ is a vector of *de facto* financial integration measures for country i based on network statistics, and X_i is a vector of macroeconomic and institutional variables, including a dummy for income,[17] openness in trade, an index of institutional quality (political risk), banking credit to private sector (as percentage of GDP), the current account balance (as percentage of GDP), and inflation. Controls for *de jure* financial integration are also included, as is an index of quality

[17] This dummy takes the value 1 if the country is a high-income OECD member and the value 0 otherwise.

of banking supervision. Details on each variable used in the paper can be found in Table 11.[18] Table 3 presents summary statistics of the variables.

This cross-sectional analysis should be viewed with caution. Since the end and start of the period are arbitrary, the averages of macro variables and institutional indexes should be considered carefully. On the other hand, since we are using averages, there are some relevant macroeconomic variables that must be omitted because they do not carry relevant information in a cross-section format or may present some endogeneity with banking crises.[19] The cross-section nature of the analysis also precludes a discussion about causality. Nonetheless, this approach offers a baseline from which we can evaluate the association between *de facto* financial integration and banking crises.

As explained in Cameron and Trivedi (1998), the model selection for count data depends on the dispersion characteristics of the data. The Poisson model assumes that the data exhibit equidispersion; that is, it assumes that the conditional variance of the dependent variable is equal to its conditional mean.[20] If the conditional mean is larger (smaller) than the variance, the data present overdispersion (underdispersion). In the case of equidispersion, the Poisson model yields consistent and efficient estimates. However, if the data are overdispersed, the Poisson regression loses efficiency. For this reason the Negative Binomial model is preferred in the case of overdispersion.[21]

Figure 1 shows a histogram of the distribution of banking crises. The figure shows that most of the countries did not suffer a crisis in the period 1980-2007, and only one country (Argentina) faced more than two crises, with a tally of four. The unconditional mean and variance reported in Table 3 do not suggest large differences in mean and variance, but we cannot be sure if the data are under or overdispersed when including all covariates in the analysis (i.e., we do not know how the conditional means will turn out).

[18] The literature on banking crises has found as determinants of banking system distress a set of macroeconomic and institutional variables which includes above-trend credit growth, financial (banking) system regulation, levels of corruption, exchange rate regime, and trade openness, among others. A rigorous study of the determinants of banking crises is beyond the scope of this paper. For a recent survey see Demirgüc-Kunt and Detragiache (2005). After experimenting with a large set of macroeconomic and institutional variables, I settled for the most parsimonious model that captures the main variables suggested in the literature and that are suited for a cross-sectional analysis.

[19] For example, interest rates have been found to be related to banking crises; however, once the crisis takes place the interest rate becomes an endogenous variable. The same can be said about ratio of reserves to broad money and money growth. Thus, I selected as controls variables that would be meaningful after taking averages over a quarter-century period.

[20] Formally, the Poisson model assumes that the number of occurrences of the event y over a fixed exposure period has the probability mass function $Pr(Y = y) = \frac{e^{-\mu}\mu^{\gamma}}{\gamma!}, y = 0, 1, 2, \ldots$ This model, then, assumes that $E(Y) = Var(Y) = \mu$. Also, when estimating a Poisson regression model it is usual to have an exponential mean parameterization, so that $\mu_i = exp[x_i'\beta]$, where i refers to each of the N observations and x is a vector of regressors. Cameron and Trivedi (1998) show how the Poisson is a limiting case of the Negative Binomial.

[21] However, a limitation of the Negative Binomial model is that its assumptions imply overdispersion in the data, making it unsuitable for underdispersed data.

An alternative when the assumption of equidispersion is violated in the data is to estimate the model using a Generalized Linear Model (GLM) technique. The GLM approach can take into account the over or underdispersion of the data and still yield consistent coefficients estimates. To achieve consistency, the GLM is estimated assuming a Poisson distribution and using a pseudo-maximum likelihood estimator (PMLE) and robust standard errors.[22] This estimator will produce consistent estimates provided that the conditional mean is well specified. This requires that the assumed density belongs to the Linear Exponential Family.[23] In the case of mis-specification of the conditional mean, however, the GLM PMLE loses efficiency.

Given the consistency in the coefficients under the GLM PMLE, even under mis-specification of the conditional mean, this regression framework is enough to evaluate our hypothesis on whether financial integration of the banking system is associated with an increase in the incidence of banking crisis. Furthermore, in the case of over or underdispersion the direction of the bias is known for the Poisson model (Winkelmann, 2008, p.91). In the case of underdispersion the variance is overestimated; thus, in this case the model tends to yield t-values too small and, as a result, the model will yield more than necessary stringent p-values. In the case of overdispersion, the variance is underestimated, resulting in excessivley large t-values and possibly spurious inference.

5.2 Results

Tables 4 and 5 present results of estimating equation 1 assuming a Poisson distribution for the conditional mean, and using the GLM PMLE and robust standard errors. Table 4 shows the results of estimating the model including degree network statistics for the average bank. The table presents results for the baseline specification of the model, which includes as controls trade openness, political risk, domestic credit as percentage of GDP, current account balance, inflation, banking supervision, capital account openness, and an indicator for high-income OECD country. The analysis uses data from 74 countries. The table reports coefficient estimates and some statistics of the fit of the model including estimated deviance, the Pearson deviance, the dispersion of these two measures (i.e., the variables scaled by the degrees of freedom),[24] and the Bayesian Information Criterion.

---

[22] The variance matrix can be consistently estimated using the "robust sandwich" estimator (Cameron and Trivedi, 1998, p.65).

[23] Cameron and Trivedi (1998, p.31) emphasize that consistency does not need the data generating process (DGP) to belong to the Linear Exponential Family, only the assumed distribution. Members of the Linear Exponential Family are the Poisson, Gamma, Normal, Negative Binomial, and Binomial.

[24] The deviance has an approximate chi-square distribution with $N-K$ degrees of freedom, where N is the number of observations and K is the number of predictor variables including the intercept. Since the expected value of a chi-square random variable is equal to the degrees of freedom, then if the model fits the data well the ratio of the deviance to degrees of freedom, or its dispersion, should be about one. Thus, the estimated dispersion can be used as a gauge of the assumption of equidispersion. Values greater than 1 indicate overdispersion, and values smaller than 1 indicate underdispersion. Section 5.2.2 discusses the fit of the model.

The results indicate that the incidence of crises is negatively correlated with the number of lending relationships that the average bank in a country has. The other degree measures for the average bank, including weighted statistics (mean borrowing and lending), are not statistically different from zero.

Given the literature on capital inflows and discussed in the introduction, it is also desirable to control for total borrowing of banks in a given country, as well as include both betweenness and weighted degree statistics for the average bank. Table 5 reports the results of including these variables together.[25]

Column 1 of Table 5 starts with unweighted betweenness of the average bank, as it is the betweenness variable that the non-parametric analysis suggested is correlated with crises. The estimates for unweighted betweenness appear significant with a negative sign, suggesting that the more connected the average bank in a country is to the global bank network, the smaller the number of banking crises the country experiences.[26] In this sense, countries that are intermediaries in the global bank network are less likely to experience banking crises. One way to rationalize this result is to see betweenness as a measure capturing how easy is for a country to tap international capital markets: a country that has relatively easy access to debt flows is able to avoid a liquidity crisis.

Columns 2 and 3 of Table 5 add mean borrowing and mean lending, and column 4 controls for total borrowing. The coefficient of mean betweenness is always negative and highly statistically significant. Interestingly, the coefficient for total borrowing is positive and highly significant, which is a result in line with the theoretical and empirical literatures linking debt flows and banking crises.

Column 5 of Table 5 puts these network statistics together. Betweenness keeps its negative and highly significant coefficient, as does total borrowing for its positive coefficient. This specification suggests that the the higher is the international lending of the average bank in a country, the lower the incidence of banking crises. Intuitively, a large betweenness measure captures the ability of a country to roll over or obtain short-term debt. Pushing this idea further, one can think in terms of the model proposed by Chang and Velasco (2001), in which large debt inflows make more likely the occurrence of a crisis, while at the same time the inability of obtaining either ongoing or short-term debt increases financial system fragility.

Finally, column 6 of Table 5 estimates the model with the variables that were found to be significant. This specification also drops mean lending for reasons that will be apparent when we analyze the fit of the model in Section 5.2.2. This is the preferred model, and we will use it to

[25] There is some degree of correlation between a few of the network statistics. In particular, betweenness is somewhat highly correlated with mean outdegree, and total borrowing and lending are highly correlated with mean borrowing and sum of all lending. Thus, we cannot include all variables in one specification. However, there is a low degree of correlation between betweenness and both mean borrowing and mean lending.

[26] In regressions not shown weighted betweenness does not result statistically different from zero.

gauge how economically significant are the effects of *de facto* financial integration in the incidence of banking crises. Again, similar results for betweenness of the average bank and total borrowing are obtained.

In all cases, the results of the model indicate that measures of *de jure* financial integration are positively correlated with the incidence of crises. The number of banking crises is increasing in *de jure* capital account openness. The other macroeconomic variables and institutional indexes show up with the expected sign, and in most cases are significant. The coefficient estimates suggest that the incidence of banking crises is decreasing in the degree of trade openness of a country, as also found by Rose and Spiegel (2009). The coefficient of inflation shows up positive and significant a few times. Since in this cross-sectional analysis we are considering averages, we can think of this coefficient as a proxy for macroeconomic instability. Also as expected, the larger the political risk in a country, the larger the number of banking crises (a coefficient with a strong statistical significance). Not surprisingly, with data up to 2007, the indicator for high income countries is negatively correlated with the incidence of banking crises.

The estimated coefficient for the index of banking supervision is always significant and with a negative sign, suggesting that the existence of prudential banking supervision is an important factor in reducing the incidence of banking crises. The intuition is straightforward: better regulation and better political institutions prevent moral hazard in the banking industry, reducing the likelihood of a systemic crisis.

5.2.1 Marginal Effects

To gauge the economic significance of the estimated coefficients, I estimate both Incidence Rate Ratios (IRR) and Average Marginal Effects (AME) for the preferred specification in column 6 of Table 5. IRRs in the Poisson model are calculated as the rate of change in the outcome (incidence) of the dependent variable as a response of a one-unit change in an independent variable. In the Poisson model the IRR are simply exponentiated coefficients (Hardin and Hilbe, 2007, p.197). With two covariates and a constant, the calculation of the incidence rate ratio for variable 1 reduces to: $IRR_1 = \frac{exp[\beta_0+(x_1+1)\beta_0+x_2\beta_2]}{exp[\beta_0+x_1\beta_0]} = exp[\beta_1]$. Thus, the IRR is positive and constant – it does not depend on the particular values of the regressors. However, a limitation of IRRs is that the scale (the units in which the regressors are measured) affects the estimation.

Marginal effects in the Poisson model are calculated as elasticities and semi-elasticities. Cameron and Trivedi (1998) suggest that the best way to gauge the average response across observations of a change in regressor j is to compute $AME_j = \frac{1}{N}\sum_i \frac{\partial E[y_i|x_i]}{\partial x_i} = \frac{1}{N}\beta_j exp[x_i'\beta]$. In the Poisson model with intercept this simplifies to $AME_j = \beta_j \bar{y}$. This measure gives the change in y, given a unit change in x. Like IRRs, this measure will be affected by the scale. Thus, it is preferable to compute average elasticity: $\frac{ey}{ex} = AME_j \times \frac{x}{y}$, which gives the average proportionate change in y associated with a proportionate change in x. Alternatively, we can estimate the semi-elasticity $\frac{dy}{ex} = AME_j \times \frac{1}{y}$, which gives the average change in y associated with a proportionate change in x. These elasticities and semi-elasticities, along with IRRs, are reported in Table 6 for specification 6 of Table 5.

The results suggest that the negative effects in the incidence of banking crises coming from *de facto* and *de jure* financial integration are not large when compared with other covariates, and it may be the case that other factors play a more crucial role as determinants of banking crises, in particular prudential regulation of the banking sector, political risk and trade openness. Surprisingly, the results suggest that the beneficial effects of *de facto* financial integration coming from a higher connectedness, rationalized here as ease of access to international lending, are an order of magnitude larger than the negative effects.

As Table 6 reports, the estimated elasticity $\frac{ey}{ex}$ suggests that a 10 percent increase in the borrowing of all banks in a country increases the occurrence of crises by 1.1 percent. Also, a 10 percent increase in the *de jure* openness of the current account would have an increase in the occurrence of crises of 0.5 percent. These effects are relatevely small when compared with the negative effects from increased political risk, reduced banking supervision or reduced trade openness. For example, the elasticity $\frac{ey}{ex}$ calculates that a 10 percent increase in the index of prudential bank regulation reduces the occurrence of banking crises by 7.7 percent. Also, the estimated elasticity suggests that a 10 percent increase in the measured betweenness of the average bank will reduce the occurrence of banking crises by 2.9 percent.

Alternatively, the semi-elasticity $\frac{dy}{ex}$ indicates that a 10 percent improvement in the banking supervision index will be associated with 0.04 fewer banking crises. In comparison, an increase of 10 percent in the current account openness index will be associated with 0.003 more banking crises, while the same proportionate increase in total borrowing of banks will be associated with 0.006 more banking crises. On the other hand, a 10 percent increase in the measured betweenness of the average bank will be associated with 0.016 fewer banking crises.

IRR estimates are also reported. However, as stated before, a limitation of this measure is that it is not scale-free. This is particularly problematic for interpreting the coefficient of borrowing by all banks, as it is expressed in billions in the data used in the estimation. The results suggest that an increase in 1 unit in the current account openness index would increase the occurrence of banking crises by 13 percent. On the other hand, a one-unit increase in the banking supervision index would decrease the occurrence of banking crises by (1-0.48)$\times$100 = 52 percent.

5.2.2 *Goodness of Fit of the Model*

The bottom rows of Tables 4 and 5 report goodness of fit statistics of the model. The deviance and the Pearson deviance (P) are to be compared with $N - K$, where N is the number of observations and N is the number of regressors. Obtaining $P < N - K$ implies underdispersion of the data if the conditional mean has been well specified. Scaled deviance statistics of less than one also indicate undersdisplersion. It is evident from the computed statistics that the data exhibit some degree of underdispersion. This implies that the Poisson model is a better fit than the Negative Binomial, and it is the reason why I followed this strategy.

However, we must bear in mind that $P \neq N - K$ can also indicate that the conditional mean has been mis-specified. This does not imply, however, that the results from the model are not consistent. As discussed before, the consistency of the Poisson estimator is obtained by the use of the GLM PMLE estimator (although it loses efficiency if data are underdispersed). Nonetheless, with underdispersion the direction of the bias is known for the Poisson model. Since the variance is overestimated in this case and we obtain greater than necessary stringent *p*-values, we can be confident about the statistical inference from the the results reported above.

An overall test of adequacy of the model is to evaluate how close the residuals are to normality (Cameron and Trivedi, 1998, p.145). Figure 2 plots the kernel density of the estimated residuals of the model in specification 6 of Table 5 against a normal distribution. Table 7 presents results for normality tests for the estimated residuals. The null hypothesis in these tests is that the variable is normal. From the plot and the results of the tests it seems to be the case that the specification in column 6 provides a fair representation of the data.

Table 5 also reports the deviance and the Pearson deviance, which are measures of aggregate goodness of fit. The deviance is the counterpart of the sum of residuals in the linear regression framework. The results also report Bayesian Information Criterion (BIC) statistics. These measures suggests that the model including mean borrowing and mean lending (column 5 of Table 5) is the one that best fits the data. However, this specification performs poorly when we evaluate the goodness of fit of the residuals of the model. We cannot reject the hypothesis of normality of the residuals, but at somewhat low confidence levels. Thus, the preferred specification is column 6 of Table 5, which drops the variables that were not found to be significant and the mean lending network statistic.

5.2.3 Robustness Checks

The results are robust to estimating the model including only countries with five or more active banks. The sample size reduces to 67 countries, but the point estimates are basically the same as before. Table 8 reports the results of estimating the model in this sample and including the full set of network statistics (replication of Table 5).[27] The results are also robust to the inclusion of different macroeconomic variables, including the exchange rate regime, the coefficient of variation of the nominal and real exchange rates, and to the use of a different proxy for quality of political institutions (Polity2 variable of the Politiy IV project).

[27] Similar results are also obtained for the non-parametric analysis. Results available upon request.

A concern with this cross-section analysis is that the network statistics may be unstable over time and hence, may not be suitable for a cross-section approach. Even though Hale (2012) shows that there is little year-on-year variation in the computed network statistics based on the syndicated loans market, the cross-section used in this paper is over a quarter century, and it is possible to have important changes in the network statistics if they were computed in a different cross-section.

To address this concern, I estimate the model using network statistics computed on the subsample spanning the period from January 2001 to June 2007.[28] Table 9 documents the correlation between network statistics computed in the two different subsamples. The table reports the correlations at both the bank and country levels. The table shows quite high correlations for the degree network statistics, and for both bank and country levels.[29] Table 10 presents the results of replicating Table 5 with network statistics computed in the 2001-2007 subsample. All the results are qualitatively similar to the ones obtained with the full sample.

6 Concluding Remarks

This paper explores the hypothesis of whether increased financial integration is associated with an increased incidence of systemic banking crises. The paper uses a measured of *de facto* financial integration based on the connectedness of the average bank in the global network of interbank syndicated loans. The paper performs a non-parametric analysis of the null hypothesis that banking crises are statistically independent from these proxies of financial integration, and it also performs a regression analysis of the incidence of banking crises over the period 1980-2007 using a Generalized Linear Model approach.

The results of both the non-parametric tests and the regression analysis support the hypothesis that financial integration is positively associated with the incidence of banking crises. The larger the borrowing by banks in a country, the more prone the country is to financial distress. Interestingly, the results indicate that betweenness of the average bank, which can be viewed as a proxy for how readily a country can access international capital markets, plays an important role in reducing the incidence of banking crises, even after controlling for the size of borrowing and the capital account openness. The results also suggest that other factors are at work, and potentially can have a much bigger role as determinants of banking crises. In particular, prudential banking supervision seems to play a crucial role in reducing the occurrence of banking crises.

[28] The number of lead arrangers falls to 470 banks from 4,806, while the number of countries goes from 116 to 70.

[29] Network statistics are computed at the bank level, and then average out at the country level. For both subsamples and for bank and country levels, betweenness is normalized to have a maximum of 1. To further document the stability of the network statistics in the two subsamples, the table also reports the network statistic centrality, which is computed as $centrality_i = \frac{\sum_i \sum_j g_{ij}}{\sum_j (g_{ij} + g_{ji})}$, and is also normalized to have a maximum of 1 at both bank and country levels.

References

Abiad, A., Detragiache, E., and Tressel, T. (2010). A New Database of Financial Reforms. *IMF Staff Papers*, 57(2):281–302.

Acemoglu, D., Carvalho, V., Ozdaglar, A., and Tahbaz-Salehi, A. (2012). The network origins of aggregate fluctuations. *Econometrica*, 80(5):1977–2016.

Acemoglu, D., Ozdaglar, A., and Tahbaz-Salehi, A. (2010). Cascades in networks and aggregate volatility. Working Paper 16516, NBER.

Ahrend, R. and Goujard, A. (2011). Drivers of Systemic Banking Crises: The Role of Bank-Balance-Sheet Contagion and Financial Account Structure.

Allen, F. and Babus, A. (2009). Networks in Finance. In Kleindorfer, P., Wind, Y., and Gunther, R., editors, *The Network Challenge: Strategy, Profit, and Risk in an Interlinked World*, pages 367–382. Wharton School Publishing.

Anand, K., Brennan, S., Gai, P., Kapadia, S., and Willison, M. (2011). A Network Model of Financial System Resilience. SFB 649 Discussion Paper 2011-051, Humboldt University, Berlin.

Bech, M. and Atalay, E. (2010). The Topology of the Federal Funds Market. *Physica A: Statistical Mechanics and its Applications*, 389(22):5223–5246.

Bech, M. and Bonde, K. (2008). The Topology of Danish Interbank Money Flows. Workiing Paper No. 59, December, Danmark National Bank.

Becher, C., Millard, S., and Söromaki, K. (2008). The Network Topology of CHAPS Sterling. Working Paper No. 355, Bank of England.

Blume, L., Easley, D., Kleinberg, J., Kleinberg, R., and Tardos, É. (2011). Which Networks are Least Susceptible to Cascading Failures? In *2011 IEEE 52nd Annual Symposium on Foundations of Computer Science*, pages 393–402. IEEE.

Bonfiglioli, A. (2008). Financial Integration, Productivity and Capital Accumulation. *Journal of International Economics*, 76(2):337–355.

Boss, M., Elsinger, H., Summer, M., and Thurner, S. (2004). Network Topology of the Interbank Market. *Quantitative Finance*, 4(6):677–684.

Caballero, J. (2012). Do Surges in International Capital Flows Influence the Likelihood of Banking Crises. IDB Working Paper No. 305, Inter-American Development Bank, Washington DC.

Caballero, J., Candelaria, C., and Hale, G. (2009). Bank Relationships and the Depth of the Current Economic Crisis. *FRBSF Economic Letter*, 2009:38.

Cai, J. (2010). Competition or Collaboration? The Reciprocity Effect in Loan Syndication. Technical report, FRB of Cleveland Policy Discussion Paper No. 09-09R.

Cai, J., Saunders, A., and Steffen, S. (2011). Syndication, Interconnectedness, and Systemic Risk. Technical report, NYU Working Paper No. FIN-11-040.

Cajueiro, D. and Tabak, B. (2008). The Role of Banks in the Brazilian Interbank Market: Does Bank Type Matter? *Physica A: Statistical Mechanics and its Applications*, 387(27):6825–6836.

Calvo, G. (1998). Capital Flows and Capital-Market Crises: The Simple Economics of Sudden Stops. *Journal of Applied Economics*, 1(1):35–54.

Cameron, A. and Trivedi, P. (1998). Regression Analysis of Count Data. *Cambridge Books*.

Chang, R. and Velasco, A. (2001). A Model of Financial Crises in Emerging Markets. *The Quarterly Journal of Economics*, 116(2):489–517.

Chinn, M. and Ito, H. (2008). A New Measure of Financial Openness. *Journal of Comparative Policy Analysis: Research and Practice*, 10(3):309–322.

Demirgüc-Kunt, A. and Detragiache, E. (2005). Cross-Country Empirical Studies of Systemic Bank Distress: A Survey. *National Institute Economic Review*, 192(1):68.

Edwards, S. (2007). Capital Controls, Sudden Stops, and Current Account Reversals.

Eichengreen, B. (2002). International Financial Crises: Is the Problem Growing? *Jahrbuch für Wirtschaftsgeschichte*, 1:89–104.

Fagiolo, G., Reyes, J., and Schiavo, S. (2008). On the Topological Properties of the World Trade Web: A Weighted Network Analysis. *Physica A: Statistical Mechanics and its Applications*, 387(15):3868–3873.

Fagiolo, G., Reyes, J., and Schiavo, S. (2010a). International Trade and Financial Integration: A Weighted Network Analysis. *Quantitative Finance*, 10(4):389–399.

Fagiolo, G., Reyes, J., and Schiavo, S. (2010b). The Evolution of the World Trade Web: A Weighted-Network Analysis. *Journal of Evolutionary Economics*, 20(4):479–514.

Furceri, D., Guichard, S., and Rusticelli, E. (2011). Episodes of Large Capital Inflows and the Likelihood of Banking and Currency Crises and Sudden Stops. *OECD Economics Department Working Papers*.

Gadanecz, B. (2004). The Syndicated Loan Market: Structure, Development and Implications. *BIS Quarterly Review*, pages 75–89.

Gadanecz, B. and von Kleist, K. (2002). Do Syndicated Credits Anticipate BIS Consolidated Banking Data? *BIS Quarterly Review*, pages 65–74.

Gatev, E. and Strahan, P. (2009). Liquidity Risk and Syndicate Structure. *Journal of Financial Economics*, 93(3):490–504.

Godlewski, C. and Weill, L. (2008). Syndicated Loans in Emerging Markets. *Emerging Markets Review*, 9(3):206–219.

Gourinchas, P. and Obstfeld, M. (2012). Stories of the Twentieth Century for the Twenty-First. *American Economic Journal: Macroeconomics*, 4(1):226–65.

Haldane, A. (2009). Rethinking the Financial Network. Speech delivered at the Financial Student Association, Amsterdam, April. http://http://www.bankofengland.co.uk/publications/Documents/speeches/2009/speech386.pdf.

Hale, G. (2012). Bank Relationships, Business Cycles, and Financial Crises. *Journal of International Economics*, (In press).

Hale, G., Candelaria, C., Caballero, J., and Borisov, S. (2011). Global Banking Network and Cross-Border Capital Flows. Mimeo. Federal Reserve Bank of San Francisco, and University of California, Santa Cruz.

Hardin, J. and Hilbe, J. (2007). *Generalized Linear Models and Extensions*. Stata Corp.

Hattori, M. and Suda, Y. (2007). Developments in a Cross-Border Bank Exposure Network. CGFS Papers Chapters, Bank for International Settlements.

IMF (2009). Assessing the Systemic Implications of Financial Linkages. In *Global Financial Stability Report: Responding to the Financial Crisis and Measuring Systemic Risks*. International Monetary Fund, April.

Inaoka, H., Ninomiya, T., Taniguchi, K., Shimizu, T., and Takayasu, H. (2004). Fractal Network Derived from Banking Transaction–An Analysis of Network Structures Formed by Financial Institutions. Working Papers, No. 4, Bank of Japan.

Iori, G., De Masi, G., Precup, O., Gabbi, G., and Caldarelli, G. (2008). A Network Analysis of the Italian Overnight Money Market. *Journal of Economic Dynamics and Control*, 32(1):259–278.

Joyce, J. (2010). Financial Globalization and Banking Crises In Emerging Markets. *Open Economies Review*, pages 1–21.

Kali, R. and Reyes, J. (2007). The Architecture of Globalization: A Network Approach to International Economic Integration. *Journal of International Business Studies*, 38(4):595–620.

Kali, R. and Reyes, J. (2010). Financial Contagion on the International Trade Network. *Economic Inquiry*, 48(4):1072–1101.

Kubelec, C. and Sá, F. (2010). The Geographical Composition of National External Balance Sheets: 1980-200. Working Paper No. 384.

Laeven, L. and Valencia, F. (2010). Resolution of Banking Crises: The Good, the Bad, and the Ugly. Working Paper 10/146, International Monetary Fund.

Minoiu, C. and Reyes, J. (2011). A Network Analysis of Global Banking: 1978-2009. Working Paper 11/74.

Pichler, P. and Wilhelm, W. (2002). A Theory of the Syndicate: Form Follows Function. *The Journal of Finance*, 56(6):2237–2264.

Powell, A. and Tavella, M. (2012). Capital Inflow Surges in Emerging Economies: How Worried Should LAC Be? IDB Working Paper No. 326, Inter-American Development Bank, Washington DC.

Pröpper, M., van Lelyveld, I., and Heijmans, R. (2008). Towards a Network Description of Interbank Payment Flows. Dnb working papers no. 177, Netherlands Central Bank, Research Department.

Reinhart, C. and Reinhart, V. (2009). Capital Flow Bonanzas: An Encompassing View of the Past and Present. In *NBER Macroeconomics Annual*. University of Chicago Press.

Rose, A. and Spiegel, M. (2009). International Financial Remoteness and Macroeconomic Volatility. *Journal of Development Economics*, 89(2):250–257.

Söromaki, K., B. M. A. J. G. R. and Beyeler, W. (2006). The Topology of Interbank Payment Flows. Federal Reserve Bank of New York, Staff Report. No. 243.

von Peter, G. (2007). International Banking Centres: a Network Perspective. *BIS Quarterly Review*, pages 33–45.

Winkelmann, R. (2008). *Econometric Analysis of Count Data*. Springer Verlag.

Zawadowski, A. (2012). Entangled Financial Systems. Manuscript. http://people.bu.edu/zawa/.

Figure 1. Histogram: Number of Banking Crises

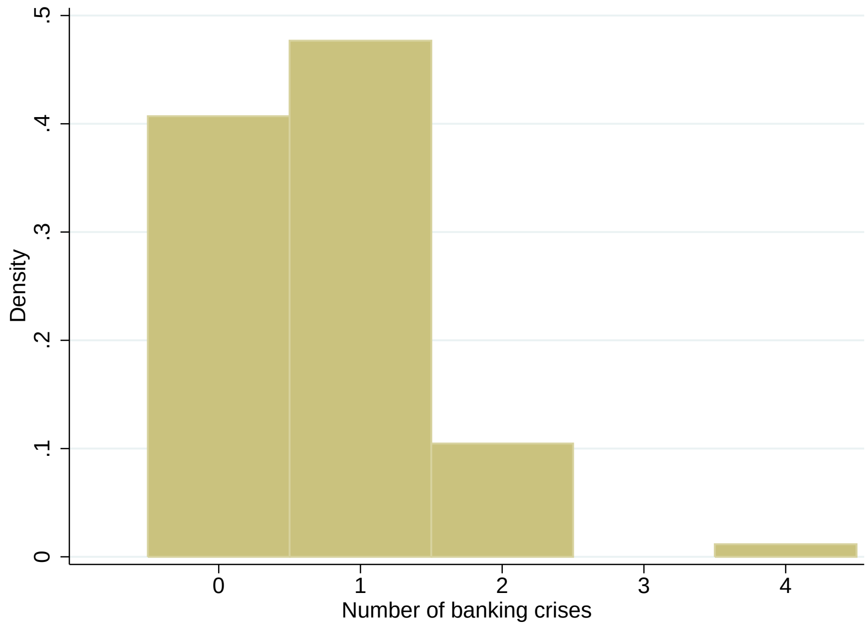
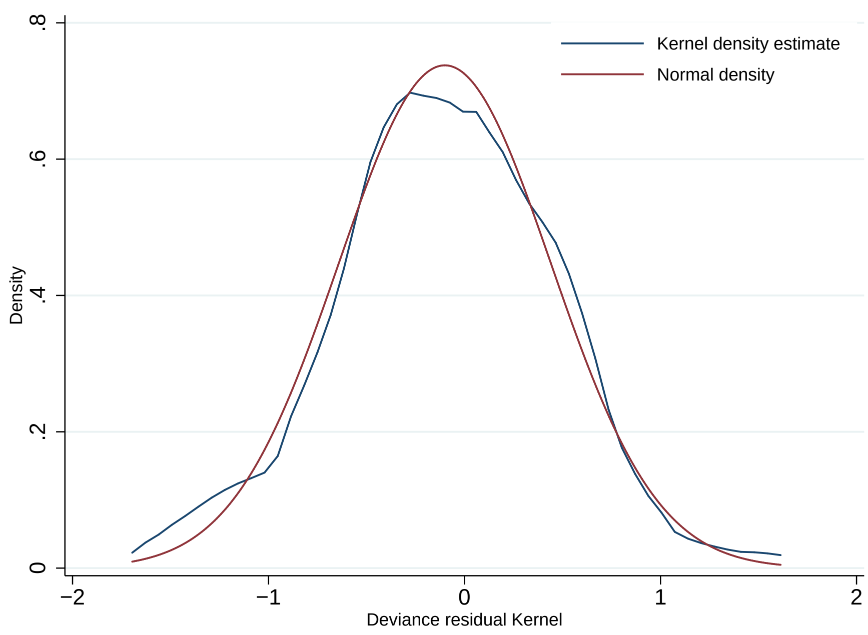


Figure 2. Estimated Residuals (Deviance)



Note: Figure compares the estimated residuals, or deviance, with a normal distribution, using the Epanechnikov kernel for the estimation of the kernel density (bandwidth of 0.2092). Residuals are for specification of column 6 in Table 5.

Table 1. Sample. Number of Systemic Banking Crises in Parentheses

High income countries			
Australia (0)	Finland (1)	Korea (1)	Qatar (0)
Austria (0)	France (0)	Kuwait (1)	Singapore (0)
Bahamas (0)	Germany (0)	Luxembourg (0)	Slovenia (1)
Bahrain (0)	Greece (0)	Macao (0)	Spain (0)
Belgium (0)	Hong Kong (0)	Malta (0)	Sweden (1)
Bermuda (0)	Iceland (0)	Netherlands (0)	Switzerland (0)
Brunei Darussalam (0)	Ireland (0)	Netherlands Antilles (0)	United Arab Emirates (0)
Canada (0)	Israel (0)	New Zealand (0)	United Kingdom (0)
Cyprus (0)	Italy (0)	Norway (1)	United States (1)
Denmark (0)	Japan (1)	Portugal (0)	
Developing countries			
Algeria (1)	Egypt (1)	Lithuania (1)	Serbia (0)
Angola (0)	El Salvador (1)	Macedonia (1)	Slovakia (1)
Argentina (4)	Estonia (1)	Malaysia (1)	South Africa (0)
Armenia (1)	Ethiopia (0)	Mauritius (0)	Sri Lanka (1)
Azerbaijan (1)	Georgia (1)	Mexico (2)	Tajikistan (0)
Belarus (1)	Ghana (1)	Moldova (0)	Tanzania (1)
Bolivia (2)	Guatemala (0)	Mongolia (0)	Thailand (2)
Bosnia and Herzegovina (1)	Honduras (0)	Morocco (1)	Trinidad and Tobago (0)
Brazil (2)	Hungary (1)	Namibia (0)	Tunisia (1)
Bulgaria (1)	India (1)	Nigeria (1)	Turkey (2)
Cayman Islands (0)	Indonesia (1)	Oman (0)	Ukraine (1)
Chile (1)	Iran (0)	Pakistan (0)	Uruguay (2)
China (1)	Iraq (0)	Panama (1)	Uzbekistan (0)
Colombia (2)	Jamaica (1)	Peru (1)	Venezuela (1)
Costa Rica (2)	Jordan (1)	Philippines (2)	Yemen (1)
Croatia (0)	Kazakhstan (0)	Poland (1)	Zambia (1)
Cuba (0)	Kenya (2)	Romania (1)	Zimbabwe (1)
Czech Republic (1)	Latvia (1)	Russia (1)	
Dominican Republic (1)	Lebanon (1)	Rwanda (0)	
Ecuador (2)	Libya (0)	Saudi Arabia (0)	

Note: Source: Laeven and Valencia (2010).

Table 2. Results of Two-Way Tabulations and Independence Tests of Indicator for a Banking Crisis in 1980-2007 and Network Statistics

	Obs	Pearson	LR	Fishers	Stat Assoc
Mean Betweenness	116	0.071	0.069	0.074	Yes
Mean Betweenness (weighted)	116	0.142	0.140	0.152	No
Mean Indegree	116	0.331	0.329	0.359	No
Mean Outdegree	116	0.001	0.001	0.001	Yes
Mean Degree	116	0.131	0.125	0.138	No
Mean Borrowing	116	0.147	0.144	0.160	No
Mean Lending	116	0.006	0.005	0.005	Yes
Mean Borrowing+Lending	116	0.116	0.112	0.124	No
Sum Indegree	116	0.460	0.456	0.471	No
Sum Outdegree	116	0.020	0.018	0.019	Yes
Sum Degree	116	0.071	0.068	0.074	Yes
Sum Borrowing	116	0.081	0.074	0.082	Yes
Sum Lending	116	0.039	0.037	0.040	Yes
Sum Borrowing+Lending	116	0.016	0.013	0.016	Yes
Cap. Acc. liberaliz index	76	0.177	0.171	0.198	No
Fin. Reform index	76	0.075	0.073	0.083	Yes
Banking supervision index	76	0.000	0.000	0.000	Yes

Table 3. Summary Statistics, Full Sample

	mean	sd	min	max	sum	count
Number of banking crises	0.647	0.725	0.000	4.000	75.000	116
Trade openness	0.838	0.521	0.198	4.117	92.990	111
Political risk	66.719	12.588	32.904	92.617	6938.801	104
Domestic credit	0.649	0.415	0.081	2.667	71.390	110
Current account balance	-1.127	7.219	-17.018	36.235	-121.736	108
Inflation	0.549	1.244	0.006	6.794	59.346	108
Mean Betweenness	0.083	0.200	0.000	1.000	9.672	116
Mean Betweenness (weighted)	0.000	0.000	0.000	0.000	0.000	116
Mean Indegree	3.559	3.166	0.571	18.909	412.819	116
Mean Outdegree	1.283	2.347	0.000	11.669	148.848	116
Mean Degree	4.842	3.729	1.000	19.318	561.668	116
Mean Borrowing	0.260	0.341	0.002	1.755	30.159	116
Mean Lending	0.101	0.309	0.000	2.001	11.658	116
Mean Borrowing+Lending	0.360	0.558	0.002	3.343	41.817	116
Sum Indegree	0.137	0.270	0.001	1.351	15.915	116
Sum Outdegree	0.138	0.463	0.000	3.250	16.011	116
Sum Degree	0.275	0.654	0.001	4.120	31.926	116
Sum Borrowing	0.020	0.067	0.000	0.571	2.355	116
Sum Lending	0.020	0.109	0.000	1.040	2.360	116
Sum Borrowing+Lending	0.041	0.167	0.000	1.374	4.715	116

Table 4. Results of GLM Regressions, Degree Network Statistics for Average Bank

	(1)	(2)	(3)	(4)	(5)	(6)
Trade openness	-0.921***	-0.911***	-0.833***	-0.960***	-0.929***	-0.919***
	[0.232]	[0.235]	[0.252]	[0.233]	[0.234]	[0.239]
Political risk	0.046***	0.045***	0.044***	0.048***	0.046***	0.044***
	[0.012]	[0.012]	[0.012]	[0.013]	[0.012]	[0.012]
Domestic credit	0.009	-0.011	0.233	0.003	-0.015	0.078
	[0.306]	[0.301]	[0.319]	[0.278]	[0.297]	[0.284]
Current account balance	-0.002	-0.006	0.003	0.002	-0.003	-0.001
	[0.022]	[0.021]	[0.022]	[0.023]	[0.023]	[0.021]
Inflation	0.091*	0.099**	0.095*	0.091*	0.094**	0.096**
	[0.049]	[0.048]	[0.051]	[0.048]	[0.048]	[0.048]
High income-OECD country	-2.306***	-2.277***	-1.944***	-2.042***	-2.247***	-1.980***
	[0.414]	[0.423]	[0.445]	[0.528]	[0.485]	[0.469]
Bank supervision	-0.674***	-0.698***	-0.692***	-0.660***	-0.687***	-0.648***
	[0.224]	[0.229]	[0.209]	[0.215]	[0.216]	[0.220]
Capital account openness	0.146**	0.157**	0.160**	0.141**	0.148**	0.163**
	[0.067]	[0.067]	[0.070]	[0.067]	[0.069]	[0.066]
Mean Degree	-0.009					
	[0.030]					
Mean Indegree		0.004				
		[0.028]				
Mean Outdegree			-0.155*			
			[0.093]			
Mean Borrowing+Lending				-0.386		
				[0.383]		
Mean Borrowing					-0.127	
					[0.440]	
Mean Lending						-1.229
						[0.879]
Constant	-1.591**	-1.602**	-1.611**	-1.658**	-1.621**	-1.560**
	[0.730]	[0.738]	[0.713]	[0.724]	[0.713]	[0.716]
Deviance	28.649	28.709	27.262	28.288	28.690	27.791
Deviance_df	0.448	0.449	0.426	0.442	0.448	0.434
Pearson	25.701	25.989	23.206	24.899	25.822	24.354
Pearson_df	0.402	0.406	0.363	0.389	0.403	0.381
BIC	-246.811	-246.751	-248.199	-247.172	-246.770	-247.669
Obs	74	74	74	74	74	74

Note: Standard errors in brackets; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5. Results of GLM Regressions, Betweenness and Degree Network Statistics for Average Bank, Controlling for All Borrowing

	(1)	(2)	(3)	(4)	(5)	(6)
Trade openness	-0.872***	-0.845***	-0.883***	-0.741***	-0.701***	-0.763***
	[0.236]	[0.236]	[0.239]	[0.222]	[0.234]	[0.209]
Political risk	0.048***	0.046***	0.046***	0.050***	0.048***	0.050***
	[0.012]	[0.012]	[0.012]	[0.011]	[0.011]	[0.012]
Domestic credit	0.017	0.029	0.075	-0.059	0.013	
	[0.266]	[0.278]	[0.262]	[0.291]	[0.322]	
Current account balance	0.014	0.012	0.015	0.020	0.022	
	[0.024]	[0.026]	[0.024]	[0.025]	[0.026]	
Inflation	0.080	0.083*	0.081	0.079	0.080	0.080
	[0.049]	[0.050]	[0.049]	[0.053]	[0.055]	[0.050]
High income-OECD country	-2.145***	-2.228***	-1.951***	-2.357***	-1.995***	-2.340***
	[0.407]	[0.454]	[0.435]	[0.465]	[0.526]	[0.451]
Bank supervision	-0.611***	-0.612***	-0.589***	-0.734***	-0.731***	-0.745***
	[0.216]	[0.220]	[0.219]	[0.201]	[0.195]	[0.194]
Capital account openness	0.127*	0.135*	0.136**	0.119*	0.135*	0.120*
	[0.070]	[0.071]	[0.068]	[0.072]	[0.071]	[0.070]
Mean Betweenness	-2.417***	-2.565***	-2.185***	-3.121***	-3.023***	-2.866***
	[0.718]	[0.720]	[0.629]	[0.746]	[0.666]	[0.595]
Mean Borrowing		0.247			0.078	
		[0.376]			[0.387]	
Mean Lending			-0.830		-1.931*	
			[0.688]		[1.122]	
Sum Borrowing				3.929**	5.467***	3.750**
				[1.715]	[1.398]	[1.643]
Constant	-1.721**	-1.691**	-1.685**	-1.821***	-1.764**	-1.861***
	[0.697]	[0.690]	[0.700]	[0.695]	[0.690]	[0.704]
Deviance	26.410	26.304	25.940	24.584	22.898	24.797
Deviance_df	0.413	0.418	0.412	0.390	0.375	0.381
Pearson	22.945	22.930	22.503	19.890	17.615	20.810
Pearson_df	0.359	0.364	0.357	0.316	0.289	0.320
BIC	-249.050	-244.852	-245.216	-246.572	-239.649	-254.967
Obs	74	74	74	74	74	74

Note: Standard errors in brackets; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6. Incidence Rate Ratios and Average Marginal Effects

	IRR	$\frac{ey}{ex}$	$\frac{dy}{ex}$
Trade openness	0.4665	-0.5706	-0.3172
Political risk	1.0509	3.3643	1.8699
Inflation	1.0829	0.0455	0.0253
Banking supervision	0.4746	-0.7739	-0.4302
KA open	1.1272	0.0534	0.0297
Betweenness	0.0569	-0.2959	-0.1643
Sum Borrowing	42.5385	0.1144	0.0636

Note: Elasticities from specification 6 of Table 5.

Table 7. Results of Normality Tests of Residuals

Test	W or W'	V or V'	Z	Prob>z
Shapiro-Wilk W	0.98567	0.923	-0.176	0.56977
Shapiro-Francia W'	0.98447	1.106	0.195	0.42283
	Pr(Skewness)	Pr(Kurtosis)	Adj chi2(2)	Prob>chi2
Skewness/Kurtosis	0.3294	0.5009	1.45	0.4846

Note: Tests are for residuals obtained from specification in column 6 of Table 5.

Table 8. Robustness Check Excluding Countries with fewer than five Banks, Results of GLM Regressions; Betweenness and Degree Network Statistics for Average Bank, Controlling for All Borrowing

	(1)	(2)	(3)	(4)	(5)	(6)
Trade openness	-0.924***	-0.907***	-0.935***	-0.783***	-0.749***	-0.809***
	[0.253]	[0.253]	[0.256]	[0.227]	[0.239]	[0.217]
Political risk	0.042***	0.041***	0.041***	0.045***	0.044***	0.044***
	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]	[0.010]
Domestic credit	-0.024	-0.017	0.032	-0.101	-0.034	
	[0.274]	[0.284]	[0.270]	[0.302]	[0.331]	
Current account balance	0.012	0.011	0.013	0.019	0.021	
	[0.027]	[0.028]	[0.026]	[0.027]	[0.028]	
Inflation	0.042	0.045	0.045	0.038	0.040	0.039
	[0.053]	[0.054]	[0.055]	[0.054]	[0.058]	[0.055]
High income-OECD country	-2.043***	-2.099***	-1.860***	-2.261***	-1.881***	-2.266***
	[0.403]	[0.447]	[0.433]	[0.458]	[0.517]	[0.448]
Bank supervision	-0.606***	-0.605***	-0.586***	-0.731***	-0.730***	-0.742***
	[0.215]	[0.217]	[0.218]	[0.198]	[0.190]	[0.192]
Capital account openness	0.126*	0.132*	0.136*	0.114	0.127	0.118
	[0.074]	[0.076]	[0.074]	[0.077]	[0.078]	[0.074]
Mean Betweenness	-2.461***	-2.559***	-2.237***	-3.183***	-3.059***	-2.984***
	[0.739]	[0.740]	[0.649]	[0.762]	[0.678]	[0.600]
Mean Borrowing		0.161			-0.011	
		[0.371]			[0.381]	
Mean Lending			-0.791		-1.915*	
			[0.675]		[1.122]	
Sum Borrowing				3.936**	5.523***	3.725**
				[1.701]	[1.482]	[1.626]
Constant	-1.267**	-1.260**	-1.234*	-1.407**	-1.370**	-1.404**
	[0.638]	[0.642]	[0.647]	[0.623]	[0.635]	[0.625]
Deviance	21.628	21.582	21.193	19.801	18.159	19.981
Deviance_df	0.379	0.385	0.378	0.354	0.336	0.345
Pearson	19.663	19.649	19.232	16.648	14.408	17.528
Pearson_df	0.345	0.351	0.343	0.297	0.267	0.302
BIC	-218.040	-213.881	-214.269	-215.662	-208.895	-223.891
Obs	67	67	67	67	67	67

Note: Standard errors in brackets; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9. Correlation of Network Statistics 1980-2007 and 2001-2007

	Bank level	Country level
Indegreee	0.6130	0.6841
Outdegree	0.8167	0.8154
Degree	0.7137	0.6892
Betweenness	0.0493	0.0786
Centrality	0.7573	0.7673
Obs	470	70

Table 10. Robustness Check Sub-Sample 2001-2007, Results of GLM Regressions; Betweenness and Degree Network Statistics for Average Bank, Controlling for All Borrowing

	(1)	(2)	(3)	(4)	(5)	(6)
Trade openness	-1.038***	-1.036***	-1.008***	-0.886***	-0.825***	-0.887***
	[0.329]	[0.333]	[0.313]	[0.283]	[0.288]	[0.268]
Political risk	0.011	0.011	0.014	0.021	0.028	0.016
	[0.020]	[0.021]	[0.019]	[0.019]	[0.019]	[0.016]
Domestic credit	-0.029	-0.033	-0.145	-0.118	-0.195	
	[0.371]	[0.375]	[0.400]	[0.377]	[0.382]	
Current account balance	-0.011	-0.010	-0.011	-0.011	-0.020	
	[0.025]	[0.024]	[0.025]	[0.026]	[0.028]	
Inflation	0.049	0.054	0.041	0.024	-0.033	0.039
	[0.077]	[0.088]	[0.068]	[0.072]	[0.061]	[0.074]
High income-OECD country	-1.697***	-1.712***	-1.863**	-1.788***	-1.838**	-1.867***
	[0.541]	[0.576]	[0.750]	[0.627]	[0.809]	[0.558]
Bank supervision	-0.725**	-0.758**	-0.735**	-1.000***	-0.904***	-0.964***
	[0.353]	[0.301]	[0.348]	[0.322]	[0.322]	[0.281]
Capital account openness	0.257*	0.272	0.233	0.231	0.103	0.248
	[0.152]	[0.184]	[0.146]	[0.159]	[0.155]	[0.153]
Mean Betweenness	-4.066*	-4.160**	-4.151*	-5.781**	-6.066**	-5.643**
	[2.140]	[2.019]	[2.135]	[2.345]	[2.420]	[2.191]
Mean Borrowing		0.509			-3.825	
		[2.708]			[2.507]	
Mean Lending			1.299		0.881	
			[2.241]		[2.469]	
Sum Borrowing				125.840**	222.233***	121.794**
				[60.606]	[77.879]	[60.456]
Constant	0.828	0.843	0.675	0.371	-0.023	0.558
	[0.988]	[1.045]	[0.937]	[0.994]	[0.984]	[0.924]
Deviance	17.273	17.236	17.118	15.416	14.367	15.576
Deviance_df	0.443	0.454	0.450	0.406	0.399	0.389
Pearson	17.451	17.027	17.999	15.249	14.326	15.525
Pearson_df	0.447	0.448	0.474	0.401	0.398	0.388
BIC	-134.508	-130.654	-130.771	-132.473	-125.739	-140.096
Obs	49	49	49	49	49	49

Note: Standard errors in brackets; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 11. Data Description

Variable	Definition	Source
Banking crises	Discrete variable equal to the total number of systemic banking crises in 1980-2007. Definition of a systemic banking crisis is found in the text in Section 3.2.	Laeven and Valencia (2010)
Trade Openness	Total trade (sum of exports and imports of goods and services) as a percentage of GDP. Variable NE.TRD.GNFS.ZS in WDI.	WDI database, World Bank
Political Risk	Political risk index designed by the Political Risk Group, and known as International Country Risk Guide (ICRG). The index goes from 0 to100 and is decreasing in the level of risk.	Political Risk Group. International Country Risk Guide (ICRG)
Domestic credit to private sector	Domestic credit provided by the banking sector as percentage of GDP. Includes all credit to various sectors on a gross basis, with the exception of credit to the central government, which is net. Variable FS.AST.DOMS.GD.ZS in WDI database.	WDI database, World Bank.
Current Account Balance	Current account balance as percentage of GDP. Variable BN.CAB.XOKA.GD.ZS in WDI database.	WDI database, World Bank
Inflation	Annual percentage change in consumer price index. Variable FP.CPI.TOTL.ZG in WDI database.	WDI database, World Bank
Capital Account Openness (KA open)	Index that measures the extent of openness in capital account transactions (it tries to capture the extent and intensity of capital controls). It is built based on the binary dummy variables that codify the tabulation of restrictions on cross-border financial transactions reported in the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER). The index is continuous and increasing in the openness of the capital account transactions. For the available sample it ranges in the interval [-1.8, 2.5].	Chinn and Ito (2008)
Banking supervision Index	Banking supervision index. It is increasing in the level of regulation of the banking system. The index is built using four dimensions: (i) adoption of Basel standards on capital adequacy, (ii) independence of banking supervisory agency from executive's influence, (iii) existence and effectiveness of on-site and off-site examinations by the supervisory agency, and (iv) spectrum of financial institutions covered by the supervisory agency. Index goes from 0 to 6 and is increasing in the level of regulation (however, the highest index awarded in the database is 3).	Abiad et al. (2010)
Financial reform Index	Index is increasing in the level of financial reform achieved. The index is built using seven dimensions: (i) credit controls and excessively high reserve requirements, (ii) interest rate controls, (iii) entry barriers, (iv) state ownership of the banking sector, (v) capital account restrictions, (vi) banking supervision, and (vii) security markets policy. Index goes from 0 to 21. To use the index in the non-parametric analysis the scores were adjusted to fit 3 categories as follows: value 1 for index values from 0 to 6; value 2 for index values from 7 to 14; and value 3 for index values from 15 to 21.	Abiad et al. (2010)
Capital account transactions index	Index is increasing in the liberalization of the CA transactions. The index is built using three dimensions: (i) existence of a unified exchange rate system, (ii) extent of restrictions on capital inflows, (iii) extent of restrictions on capital inflows. Index goes from 0 to 3.	Abiad et al. (2010)
Income Dummy	Dummy variable that takes value 1 if country is high income country. Income group is that of World Bank. High income countries include all OECD countries, plus Hong Kong, Israel, Kuwait and Slovenia. However, some OECD members are classified as developing countries: Chile, Czech Republic, Hungary, Korea, Mexico, Poland, Slovak Republic, and Turkey.	World Bank, OECD
GNI per capita	GNI per capita, Atlas method (current US$)Variable NY.GNP.PCAP.CD in WDI.	WDI database, World Bank