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A network analysis of global banking: 1978–2009

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A network analysis of global banking: 1978–2009

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Abstract

In this paper we explore the properties of the global banking network using cross-border bank lending data for 184 countries over 1978–2009. Specifically, we analyze financial interconnectedness using network metrics of centrality, connectivity, and clustering. We document a relatively unstable global banking network, with structural breaks in network indicators identifying several waves of capital flows. Interconnectedness rankings, especially for borrowers, are relatively volatile over the period. Connectivity tends to fall during and after systemic banking crises and sovereign debt crises. The 2008–09 global financial crisis stands out as an unusually large perturbation to the cross-border banking network.

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We need to spend much more time modeling and understanding the topology of linkages among agents, markets, institutions, and countries. (Caballero, 2010, pp. 92)

I. Introduction

Network analysis is increasingly recognized as a powerful methodological tool for modeling interactions between economic agents and assessing the resilience of financial systems to systemic risk.[2] Financial interconnectedness is also becoming an important concern in macro-financial surveillance and has taken center-stage in discussions on prudential regulation policies.[3] Network techniques have been used, among others, to describe the global architecture of cross-border financial flows,[4] to analyze financial contagion,[5] and to examine the dynamics of payment systems and interbank markets.[6] Renewed interest in the application of network analysis tools to analyze economic interconnectedness was spurred by the 2008–09 global financial crisis, which due to its voracity and wide reach, provides a fertile experiment in the evolution of financial networks during times of stress.

In this paper, we explore the properties of the global banking network (henceforth 'GBN') using network analysis techniques. Using bilateral data on cross-border bank lending for 184 countries, we describe the topology of the network using different metrics of interconnectedness (such as country centrality and network clustering) and assess its dynamics over 1978–2009. We also document changes in the network around periods of financial stress such as systemic banking crises and sovereign debt crises. Our main findings are as follows. First, network metrics for the GBN tend to be volatile, with a number of structural breaks identifying waves of capital flows. Second, interconnectedness rankings of countries, especially for borrowers, are relatively unstable. Third, connectivity tends to diminish during and after financial crises, with the 2008–09 crisis standing out as an unusually large perturbation to the network.

Our analysis contributes to the literature in several ways. To our knowledge, this is the first study that analyzes geographical patterns in the GBN using *network* techniques. Second, unlike earlier studies we focus on *flows* rather than exposures. While stocks of cross-border claims that capture inter-country exposures can be useful indicators of the potential for contagion, cross-border flows of financial capital reflect liquidity conditions in international markets. As such, they are a potentially informative source of variation during times of financial stress than slowly-evolving stocks of cross-border claims. Third, we focus not only on the presence or absence of bilateral relationships (i.e., the binary network), but extend the analysis to a weighted approach by

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[2] For recent contributions, see, Nier et al. (2007), Alessandri et al. (2009), and Cechetti et al. (2010). Goyal (2007) provides an excellent introduction to network theory. For reviews of its applications in economics and finance, see Nagurney (2003) and Allen and Babus (2009).
[3] Haldane (2009), ECB (2010a, 2010b), and IMF (2009, 2010a, 2010b).
[4] Hattori and Suda (2007), Sa (2010), and Kubelec and Sa (2010).
[5] See, e.g., Soramaki et al. (2007) and Iori et al. (2008) for toplogical descriptions of interbank markets.
[6] Allen and Gale (2000), Degryse et al. (2010), Gai and Kapadia (2010), and Kali and Reyes (2010).

adjusting the network statistics to reflect the intensity of financial flows across countries. This allows us to better capture the heterogeneity in cross-border financial links.[7]

The international bank lending market has expanded significantly in recent years.[8] Net cross-border bank lending (new loans minus repayments) reached a high of $4.3 trillion in 2007 and plummeted to a negative of almost $1 trillion as the subprime crisis unfolded in 2008. Figures 1–2 show cross-border bank loans relative to other financial flows (FDI and portfolio investment) over 1980–2008. The figures underscore the importance of cross-border lending as a key source of finance for emerging and developing economies, having reached levels comparable to FDI prior to the 2008–09 crisis. Advanced economies are the main players in the GBN, with flows circulating among them that are roughly ten times higher than those to emerging and developing economies.[9] We refer to these economies as the "core" of the network, while emerging and developing countries receiving liquidity from the core form the "periphery."

Why does the network of banking relationships among countries matter above and beyond the actual cross-country bilateral flows? In the wake of the recent crisis it has been argued that network theories can enrich our understanding of the functioning of financial systems by helping model complexity, systemic risk, and the factors that cause seizures in financial markets (Haldane, 2009; Caballero, 2010). For instance, higher interconnectedness in the financial system is believed to improve risk sharing and reduce the risk of contagion (through better ability to absorb shocks) but to also increase it (through a wider outreach of reverberations). Financial systems have been shown to display *robust-yet-fragile* tendencies (Gai and Kapadia, 2010) and to react differently to shocks depending on the pattern of interconnectedness (Allen and Gale, 2000).[10] A thorough knowledge of topological structures of real world financial markets could therefore be useful in developing models that can predict the observed patterns and forecast the reaction of the financial system to shocks.

Network graphs offer a unique perspective on the evolution of interconnectedness in the global banking market between 1980 and 2007 (Figure 3). Both the core-periphery and the core-core network have changed substantially over the last three decades, with the web of cross-border bank relationships expanding markedly as new links were born and cross-border flows increased in magnitude. More banking activity took place with the periphery in 2007 than in 1980, with ECA and MENA being the most integrated regions into the global market in 2007 (Panel A). The

[7] The importance of analyzing topological features of real-world networks in both binary and weighted terms has been highlighted, e.g., in Fagiolo et al. (2010) who show that in the binary international trade network countries with many trade partners typically trade with countries with few partners. However, in the weighted trade network where trade intensity is taken into account, countries that exchange large trade volumes have many trade partners, but only trade intensively with few well-connected partners.

[8] We use interchangeably the terms global, international, or cross-border lending to mean cross-border (external) loans extended by banks in a given country to institutions in other countries.

[9] Through the paper we assume that the cross-border banking statistics we use (further discussed in Section III.A) are a good first-order approximation for actual cross-border banking flows among countries. Nevertheless, the coverage is incomplete because only banks from some 15 advanced economies have submitted data to the BIS since the early 1980s. Currently, 43 countries report their locational statistics to the BIS.

[10] See also Georg (2010) and Fujii and Takaoka (2010) for analyses of how network topology influences contagion in interbank markets and a hypothetical financial market, respectively.

network links have been expanding outwards since 1980 particularly towards emerging Europe and international banking centers such as Bahrain, Cyprus, and Mauritius.[11] Link proliferation is apparent in the core-core network as cross-border lending activity among advanced economies intensified, too (Panel B). Although Figure 3 clearly depicts the expansion of the GBN, more could be said about the characteristics and dynamics of the network through a thorough analysis of its topology. In what follows, we use network metrics to explore the features of the GBN, while paying special attention to waves of capital flows that took place in recent decades.

The remainder of this paper is structured as follows. In Section II we review previous studies that have borrowed analytical tools from network theory to analyze cross-border financial flows. Section III contains a description of our data and network metrics of interest. The topological properties of the GBN are discussed in Section IV, where we focus on both static and dynamic features of the network and analyze the distributional stability of network statistics, country rankings and ranking dynamics, and within-sample and out-of-sample dynamics. In Section V we document the behavior of the network around financial crises. Conclusions are presented in Section VI.

II. RELATED STUDIES

Our work relates to a rapidly expanding line of research applying network analysis tools to analyze financial linkages in global markets and their implications for the emergence and management of systemic risk.[12] This literature draws on the seminal work of Allen and Gale (2000), who use network theory to model financial interconnectedness and draw implications for system stability. Allen and Gale (2000) relate banking system resilience to shocks to its underlying structure in a stylized four-bank network that is either “complete” (i.e., every bank is connected to every other banks) or “incomplete” (i.e., every bank is connected with fewer than all banks). They find that complete networks are more resilient to shocks due to risk sharing and individual banks bearing a smaller share of the shock, while incomplete networks are more fragile since banks with fewer counter-parties have difficulty diffusing the shock. Using Allen and Gale’s setup, Leitner (2005) shows that interlinkages can be desirable even if they act as conduits for contagion, because they can motivate banks to bail out one another provided that they can coordinate to do so when the threat of contagion arises.

In response to concerns that the network structure considered in Allen and Gale (2000) was too stylized to reflect real-world financial systems, Nier et al. (2007) model a more complex network of banks with interlinked balance sheets to examine financial contagion as a function the bank capitalization, size of cross-exposures, and interconnectedness. They find that bank connectivity has a non-monotonic effect on contagious defaults: at small levels of connectivity, a small

[11] This mostly reflects activities by internationally active foreign banks (see, e.g., McGuire and Tarashev, 2006).
[12] A recent foray into network models of systemic risk include Martinez-Jaramillo et al. (2010) who simulate contagion in a banking system and derive measures of system fragility based on the topological features of the interbank exposures network. Furthermore, network structures have been incorporated into stress tests of financial systems to monitor the first- and second-round effects of macroeconomic shocks (see, e.g., Espinosa-Vega and Sole, 2010).

increase raises the likelihood of contagion, but in more interconnected networks, higher connectivity improves the ability of the financial system to absorb shocks.

The trade-off between shock absorption and shock diffusion in financial networks is a recurring theme in the economics literature, with complex network structures being seen as both better able to diversify away idiosyncratic risk and more capable of propagating financial distress. Battiston et al. (2010) assess how network density (measured as the number of connecting links) relates to systemic risk in a model of the economy as a credit network, arguing that while higher connectivity allows for improved risk sharing of distress propagation, it also leads to a mechanism of trend reinforcement: when an economic agent suffers a negative shock, her trade partners react by making her conditions even harder. Thus, financial fragility feeds on itself. With higher connectivity and trend reinforcement going hand in hand, a highly interconnected system will be at risk of experiencing avalanches of bankruptcies when negative shocks occur.

Macroeconomic complexity due to network relationships has been recently captured in models of panic during financial crises. Although not directly modeling the structure of the financial network, Caballero and Simsek (2009) bring to the fore the relevance of the complexity of a bank's web of relationship by developing a model in which banks assess the health of their trading partners by collecting information about them. When financial stress affects the system, banks find it necessary to collect information not only about their immediate trading partners, but also about the trading partners of those trading partners, and so on. In a complex and highly interconnected network, there comes a point when the information gathering process becomes too costly and is abandoned, with banks withdrawing from loan commitments and illiquid positions, hence spreading the financial crisis. This complexity is endogenized in the model of Caballero and Simsek (2010) where banks facing plummeting asset prices and liquidity positions during severe financial crises, must understand a complex web of inter-connections when making financial decisions. The model thus displays a "complexity externality" in which market seizures occur because banks are increasingly reluctant to buy assets in a confusing and uncertain environment.

These theoretical contributions underscore the importance of documenting the topological properties of real-world economic and financial networks. The most extensively analyzed cross-border network is that of international trade flows (Fagiolo et al., 2009, 2010; Schiavo et al., 2010; Schweitzer et al., 2009). This line of research has documented a trade network with a core-periphery structure and an emerging "rich club" of countries that share high trade intensities and are highly-interconnected (with one another and the periphery) thus bridging different parts of the network. The trade network also appears to be stationary. Financial contagion through the trade network is analyzed in Kali and Reyes (2010), who use network-based measures of connectedness to explain abnormal stock market returns during recent crises, and find that contagion is more likely to occur when the epicenter country is better integrated into the trade network, while more interconnected downstream countries are better able to dissipate the impact.

Our study most closely relates to topological descriptions of global financial networks. Hattori and Suda (2007) analyze the core-periphery network of international bank exposures (stocks of claims) for 215 countries over 1985–2006. They find that the network has become more tightly connected and more clustered over time, displaying higher connectivity and shorter average path length[13] in the recent period. Against the backdrop of an increasingly dense network, the authors posit that systemic risk is building up while risk and capital are also being allocated more efficiently.[14] A key finding is that network features remain largely unperturbed during major events such as the LTCM near-collapse or the 1997–98 Asian crisis. In contrast, we will document a network of financial flows that is more turbulent than that of financial exposures—one that behaves differently during times of financial stress compared to tranquil periods.

In a similar vein, Kubelec and Sa (2010) and Sa (2010) assemble a large dataset of bilateral cross-border exposures by asset class (FDI, portfolio equity, debt, and foreign exchange reserves) for 18 advanced and emerging market economies, documenting a marked increase in financial interconnectedness over 1980–2005. The financial network has become more clustered with a lower average path length over time, and its central hubs are the United States and the United Kingdom. Comparisons with the international trade network reveal that both networks have experienced increased connectivity over time, despite the fact that trade openness (total trade over GDP) has risen less than financial openness (total assets and liabilities over GDP). Both trade and financial exposures distributions are long tailed,[15] with a few countries exchanging large flows while most countries exchange much smaller flows—a pattern that hints at a core-periphery structure.

III. Data and definitions

A. BIS locational statistics

Our data are the BIS locational statistics on exchange-rate adjusted cross-border bank credit over 1978–2009 (on a quarterly basis: 1978Q1–2009Q3) for 184 countries. Locational statistics are compiled on the basis of residence of BIS reporting banks (in a number of countries)[16] and cover "the cross-border positions of all banks domiciled in the reporting area, including positions vis-à-vis their foreign affiliates" (Wooldridge, 2002, p. 80). These positions include loans, deposits, debt securities, and other assets provided by banks. Cross-border flows are then estimated as changes in cross-border exposures (stocks). Since locational cross-border exposures are also reported by currency, changes in stocks are estimated after accounting for exchange rate changes. Thus, exchange-rate adjusted estimates of cross-border flows, which we use in this paper, are considered a better approximation of true flows than unadjusted changes in stocks (Wooldridge, 2002).

[13] Average path length is defined as average of the shortest path between all pairs of nodes in the network. It measures the "degrees of separation" among nodes.
[14] Using similar data on cross-border financial exposures, Degryse et al. (2010) use simulations to examine the risk and speed of potential contagion in the global financial network over 1999–2006. They find that a shock that affects the liabilities of one country may have rippling effects through the system. Furthermore, the network topology in 2006 suggests that a shock affecting emerging Europe, Turkey or Russia would affect most countries in the world.
[15] Using data from the Coordinated Portfolio Investment Survey (CPIS) for 2001-06, Song et al. (2009) show that the distribution of global financial exposures are well approximated by a Weibull distribution.
[16] In contrast, another often-used source of cross-border financial data are the BIS *consolidated* statistics, which are based on the nationality of the reporting bank, and net out intragroup positions. For a comparison between consolidated and locational banking statistics, see, e.g., Waysand, Ross, and Guzman (2010).

Since, the BIS locational banking statistics capture "net flows of financial capital between any two regions channeled through the banking system" (McGuire and Tarashev, 2006, p. 34), they are best suited for analyzing geographical interlinkages, but less so for analyzing the global balance sheets of banks or funding risk (Fender and McGuire, 2010). These location-based data capture activities of *all* banks (domestic and foreign) operating in a particular location. Thus, to the extent that foreign banks are more active than domestic ones in any given location, the data will reflect that. The BIS locational banking statistics are thus well-suited for studying temporal patterns in financial linkages across countries, the subject of our study, but will have little to say about the drivers of such patterns (Fender and McGuire, 2010).

B. The network

Each of the 184 countries in our dataset is a *node* within the network. We model the financial flows as a directed network, with nodes being linked through cross-border lending. Banking flows between countries are the *links*. We work both with quarterly data and annual data (obtained by adding up flows across quarters), and model each quarter or year over the sample period (1978–2009) as a separate network.

The sample comprises 15 lenders (BIS reporting countries) and 169 borrowers. Thus, our full network has a core-periphery structure, with the "core" comprising the economies that act as lenders (and represent a sample of BIS reporting countries), and the "periphery" comprising countries that act as borrowers (non-BIS reporting countries). Since intra-core lending activity dwarfs in magnitude exchanges between the core and the periphery, in the remainder of the paper we focus on the core-periphery network (in which core countries act as lenders only) as opposed to the full network (in which core countries are borrowers as well). We also analyze the core-core network made up solely of "core" countries that are both lenders and borrowers (see the appendix for the list of countries).

From the dataset of bilateral banking flows, we construct our network of interest as follows. We retain all positive flows (corresponding to net increases in cross-border exposure or "net investments") and replace the negative flows with zeros.[17] The resulting matrix—one of net financial investments—thus comprises positive values (i.e., net investments) and zeros (i.e., net repayments or no flows).

C. Network indicators

The network metrics we use to study interconnectedness in the GBN include measures of country centrality (degree and strength) and network density (connectivity and clustering). We describe the network focusing not only on binary country-pair lending relationships, but also through a weighted approach to take into account the magnitude of flows across countries.[18]

[17] The analysis of the "net repayments" network is left for future research.
[18] See Barrat et al. (2004).

We use bilateral (net) bank lending flows (adjusted for inflation using the US CPI) to build matrices M^t where rows represent lenders and columns represent borrowers. Each entry m_{ij}^t is the value of the flow from lender *i* to borrower *j* at time *t*. These matrices can be transformed into their binary counterparts (A^t) where each cell a_{ij}^t takes value 1 if the flow from country *i* to country *j* at time *t* is positive and 0 otherwise. The dimensions of these matrices ($15 \times N^t$ for 15 lenders and N^t borrowers) change through the sample period as new countries enter the network.

Country centrality

Node degree counts the number of connections (links) for each country (node). Since we work with a directed network, we have in-coming links for borrowers and out-going links for lenders. Therefore, we compute the *out-degree* (the number of outgoing links) for each country by counting the countries to which it lends (its debtors) and *in-degree* (the number of incoming links) for each country by counting the countries from which it borrows (its creditors), as follows:

$$ND_{it}^{out} = A_{(i)}^t 1$$

$$ND_{it}^{in} = (A_{(i)}^t)'1$$

where $A_{(i)}^t$ denotes the i^{th} row of matrix A^t, ($A_{(i)}^t$)' denotes the i^{th} row of the transpose of matrix A^t and 1 is a unitary vector with N^t elements. The maximum value for in-degree is 15 as the sample of lenders does not change over time. The maximum number for out-degree (N^t) varies by year as countries enter the network. Note that node degree only uses information from the binary representation of the network.[19]

Node strength is the total value of flows originating or terminating in a given node. In our case, in-strength for country *i* (NS_{it}^{in}) is the total amount of cross-border credit it receives, whereas out-strength for country *i* (NS_{it}^{out}) is the total amount of cross-border credit it lends. Out-strength and in-strength are computed by substituting matrix A^t for matrix M^t in the node degree formulas presented above. Node strength is the simplest weighted network indicator that captures the intensity of financial relationships among countries.

Relative node strength focuses on the relative importance of lenders as providers of financial capital, and respectively, that of borrowers as destinations for financial investment in the network. Borrower *j*'s dependence on lender *i* is the share of inflows it receives from *i* in her total borrowing. Hence, relative node out-strength increases with the lender's relative importance

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[19] Node degree captures the extent to which a country is well connected or "in the thick of things." A high node degree simply means that the node has a large neighborhood of local contacts, be it lenders or borrowers, and it relatively prominent in its neighborhood. Thus, node degree is an indicator of "local centrality." More sophisticated indicators (such as shortest path length) measure the node's strategic significance in the overall network, or its "global centrality" (see Scott, 2009, pp. 82–93.) We are limited in undertaking such an analysis, however, by the core-periphery structure of the dataset, with countries in the periphery not being interlinked except via the core.

as a creditor in the network. Defining a new matrix ($\tilde{M}^t$) where each cell $\tilde{m}_{ij}^t$ represents the ratio of inflows received by borrower *j* from lender *i* to *j*'s total inflows, relative node out-strength is given by:

$$RNS_{it}^{out} = \tilde{M}_{(i)}^t 1$$

Similarly, lender *i*'s dependence on borrower *j* as a destination for its financial capital is determined by the share of lending to *j* in her total lending. Defining matrix ($\hat{M}^t$) where each cell $\hat{m}_{ij}^t$ is the ratio of the inflow received by *j* from lender *i* to *i*'s total lending, relative node in-strength is given by:

$$RNS_{it}^{in} = (\hat{M}_{(i)}^t)'1$$

Note that the maximum relative out-strength is equal the total number of borrowers (in a network where one lender provides all the credit) while the maximum relative in-strength is the total number of lenders (in a network in which a borrower receives all the loans).[20]

Network density

Connectivity. Network connectivity is the number of links that exist between countries (or total node degree) expressed as a share of the total possible number of links. It represents the likelihood of connection between two countries in the GBN. Let m_t be the observed number of links (corresponding to positive flows $m_{ij}^t > 0$ in the matrix M^t or 1's in the matrix A^t). With 15 lenders and N^t borrowers in the core-periphery network, the degree of connectivity is given by $\left(\frac{m_t}{15 \times N^t}\right)$.

Unweighted/binary clustering. We consider two clustering coefficients—a binary and a weighted clustering coefficient. The binary measure is the ratio between the total number of complete triangles (in which every country lends to every other country) and the total possible number of such triangles (see Text figure 1). For the core-core network, we take complete triangles to mean bi-directional lending among three countries *i*, *j*, and *k* from the core. For the core-periphery network, complete triangles are those where countries *i* and *j* from the core lend to one another and they both lend to periphery country *k*. (Complete triangles for the two networks are shown in Panel A.) The binary clustering coefficient ranges between 0 and 1, with higher values representing a more clustered network—one that displays a greater share of tripartite relationships. This particular definition also enables us to compute *regional* clustering coefficients for the core-periphery network by restricting *k* to belong to a certain region.

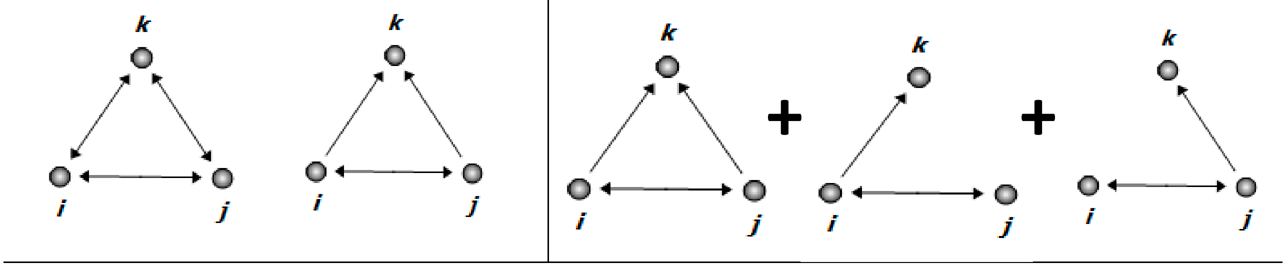
Weighted clustering. Our weighted clustering coefficient is inspired by the generalized node clustering coefficient proposed by Opsahl and Panzarasa (2009), which counts complete triangles as defined above and calculates their total value as the geometric mean of their weights (i.e., cross-country flows). The weighted clustering coefficient is obtained by dividing the total value

[20] By construction, average RNS^{out} (across borrowers) is the average number of borrowers per lender, while average RNS^{in} (across lenders) is the average number of lenders per borrower.

of complete triangles by the total value of complete (three-sided) and incomplete (two-sided) triangles (as shown in Panel B).

Text figure 1. Triangles for clustering coefficients

Panel A. Complete triangles		Panel B. Complete and incomplete triangles
Core-core	Core-periphery	



Notes: Panel A shows complete triangles used to compute binary clustering coefficients. For the core-core network, all countries belong to the core and there are bi-directional links among all three. For the core-periphery network, countries *i* and *j* are in the core, while country *k* is in the periphery. Panel B shows the three types of triangles used in the denominator of the weighted clustering coefficient for both networks.

IV. Results

Here we describe the topology of the network using the measures of connectivity defined above, focusing on the time-evolution of their empirical distributions. The aim is to determine how the web of bilateral bank lending relationships has changed over 1978–2009. Occasionally we also draw comparisons between the GBN and the international trade network (henceforth 'ITN'), thus contrasting two key channels of financial contagion—financial and trade linkages (Van Rijckeghem and Weder, 2001).

A. Network connectivity

Table 1 gives the summary statistics of our key network indicators for the full, core-periphery, and core-core networks. In the full GNB, countries borrow on average from 4.4 lenders up to a maximum of 15 (that is, all lenders), while the core countries lend to 48 borrowers, of which 8 are in the core and 40 in the periphery. Some \$293 million are lent out on average across borders each quarter—\$81 million to periphery countries and \$212 to the core. The likelihood that two countries are connected through cross-border flows ranges between 26 and 44 percent in the full network, reaching 79 percent within the core before the current crisis. Similarly, the binary clustering coefficient in the full network—the probability that two countries are connected with one another if they both have a relationship with a third country—is about 11 percent. In the core, where clustering is defined more restrictively by requiring that relationships be bi-directional, the probability is 13 percent and has reached 27 percent before the 2008–09 crisis.

The time-evolution of summary statistics for network indicator confirms that the last three decades have experienced several waves of financial globalization (Figure 4). The average number of outgoing links for each lender steadily increased from about 40 to a peak of 60 countries in 2007 before sharply dropping in 2008. Node strength (the total flows per country) has followed a similarly steep increase during the 2000s, followed by a drop in 2008 that is of historically unprecedented magnitude. Connectivity and clustering indicators for the network as a whole have been volatile, too.[21] These features stand in contrast with the ITN, for which network metrics have remarkably stable empirical moments over the past decades (Fagiolo et al., 2010).

Looking closer at the fluctuations in network metrics, we can identify three global waves of cross-border bank lending. First, the build-up of financial interlinkages between the early 2000s upto to the current crisis stands out for all indicators. Second, a smaller surge in connectivity is evident prior to the 1997–98 Asian crisis. Third, the charts depict part of the build-up of cross-border lending that came to an end with the debt crisis of the early 1980s. The shifts in the topology of the GBN confirm our prior knowledge about the global waves of private capital flows as documented, for instance, in the IMF's World Economic Outlook (2007).[22]

Another way to detect shifts in network connectivity over time is by analyzing the shape of the distributions of network metrics. Nonparametric kernel density estimates for degree and relative strength in 1980 and 2007 are shown in Figure 5. On the lender side, the density estimate for out-degree (the number of outgoing links) has preserved its shape over time, but has shifted to the right as lenders have provided financial capital to an increasing number of countries. Similarly, the distribution of in-degree (the number of incoming links) has shifted to the right as borrowers tap into a larger pool of lenders. The bimodality of the 2007 distribution of in-degree suggests that a large group of borrowers are emerging as particularly well-connected, i.e., borrowing from about 10 of the available lenders. The distribution of relative out-strength suggests that most lenders in 1980 provided about 5 percent of flows to any given borrower; by 2007, that number had shifted to about 10 percent, as relative importance has been shared more equitably among lenders. In contrast, the density of relative in-strength reveals a great degree of heterogeneity in terms of the importance of borrowers as destinations for liquidity. Inequality in terms of relative strength among borrowers has risen between 1980 and 2007, hinting at a more polarized periphery. As further documented in the next section, highly-connected borrowers share the periphery with a plethora of less relevant nodes.

We wrap up the analysis of the evolution of the empirical distributions through two-sample Kolmogorov-Smirnov tests. The null hypothesis is that the observed empirical distributions (at two points in time) are close enough to conclude that they are drawn from the same data generating process. We undertake the test for each indicator by comparing its empirical distribution function at the beginning of each decade with that in subsequent decades. We summarize the results in Table 2, where we report the proportion of years each decade with empirical distributions of network metrics that are unlike those at the beginning of the decade. Interestingly, the empirical distributions of lender centrality metrics are more stable than those of borrower centrality. Borrower connectivity, strength, and relative strength show much turbulence, with the distributions in 1980 being poor predictors of future ones. For instance, the landscape for borrowers through the 2000s is unlike that in previous decades, but seems

[21] Interestingly, network connectivity for the GBN based on cross-border flows appears less persistent than that for the GBN based on cross-border exposures. The reason is that the likelihood of links dying in the network of cross-border exposures is substantially lower than in our network (see Hattori and Suda, 2007).

[22] The concept of "private" capital flows refers to changes in foreign assets and liabilities of the recipient domestic private sector (IMF, 2007, pp. 3).

unchanged since the year 2000, which suggests that periphery countries have been consolidating their relative positions in the GBN over the last decade.

B. Country rankings, dynamics, and regional heterogeneity

Two questions arise from the patterns discussed in the previous section. The first is which countries and regions have been or currently are the most interconnected in the GBN. The second is whether the relatively stable shapes of the empirical distributions conceal turbulence of country rankings, which may be possible if countries swap places in terms of connectivity from one year to another.

We begin by reporting the top ten lenders in terms of node degree and strength (Table 3) for 1980, 1995, and 2007. The most globally connected lenders are Belgium, France, Germany, Switzerland, and the United Kingdom, with Japan, Switzerland, and the United States joining the top ranks in terms of absolute and relative volumes (Panel A). The rankings are relatively stable for lenders, but less so for borrowers, with liquidity appearing to follow different geographical patterns (Panel B).[23] Before the debt crisis of the early 1980s, LAC countries (Argentina, Brazil, Chile, Mexico, and Venezuela) were the most central borrowers in the network. In 1995 they gave way to the fast-growing East Asian countries, while the BRICs began their own ascending path. By the end of the period, the BRICs had become the most interconnected borrowers alongside emerging Europe (e.g., the Baltics, Poland, Romania, and Ukraine).

To obtain a broader view of ranking dynamics for all counties, we also calculate pair-wise Spearman rank-correlation coefficients for consecutive years $\rho_{t,t-1}(X)$ and define a Ranking Stability Index (RSI) for each network indicator X as the time-average of the Spearman coefficients, as follows:

$$RSI(X) = \frac{1}{T-1}\sum_{t=2}^{T}\rho_{t,t-1}(X)$$

The RSI, which has the usual properties of a correlation coefficient, is useful in detecting shape-preserving ranking turbulence, which occurs when the empirical distributions of network indicators do not change but countries swap places in terms of centrality in the network.

The RSIs for degree and strength are depicted in Figure 6. Lender rankings seem more stable than borrower rankings, becoming less volatile after the debt crisis of the early 1980s and stabilizing at about 0.8. In contrast, borrower rankings based on the number incoming links are more volatile (0.2 on average over the full period), and even negative in the late 1970s. This suggests that the relatively stable empirical distributions of node in-degree (seen in Figure 5) conceal degree great deal of rankings turbulence. In contrast, rankings based on strength have become more stable since the early 1990s, leveling off at about 0.7 during the 2000s. This pattern suggests that a group of strong borrowers has emerged and is consolidating its place as a

[23] In constructing borrower rankings we exclude high-income countries. Including them brings to the top of interconnectedness countries such as Australia, Finland, Greece, Portugal, and Spain.

central destination for cross-border lending in the recent years. Closer inspection of borrower rankings reveals that this strong group comprises primarily the BRICs and emerging European countries (Figure 7). Reyes et al. (2008) show that through the 1990s the BRICs have moved from the periphery into the core of the ITN as well, reaching the top in terms of network centrality (Reyes et al., 2008).). Nevertheless, the ITN has relatively less volatile country rankings than the GBN.

Global averages of network metrics conceal interesting regional heterogeneity (Figure 8). During the 2000s, the ECA region (including emerging Europe) has been the most integrated region into the GBN, with the highest level of connectivity (in-degree), average inflows per country (in-strength), and clustering (complete triangles with countries in the core). Average and total flows for EAP display a strong cyclicality, with a peak in cross-border lending to this region occurring prior to the Japanese crisis in the early 1990s. For other regions, network metrics tell a different story compared to total flows. The MENA region comes fourth based on total lending, but ranks higher up in terms of in-degree and binary clustering. Although during the 2000s, SA (driven by India) has become more interconnected by tapping into a larger pool of lenders, cross-border lending volumes remain relatively low. Further, total lending to LAC falls markedly in the wake of the early-1980s debt crisis but surges prior to the 2001 Argentine crisis and the recent downturn. However, prior to the end of the sample period, the LAC region never attains the degree of connectivity it enjoyed prior to the debt crisis of the early 1980s. Similarly, EAP experienced three surges in cross-border lending, but these are relatively muted in network connectivity terms. In all charts, the downturn in network connectivity and clustering during the 2008–09 crisis stands out as an unusually large perturbation to the network.

C. In-sample dynamics and out-of-sample evolution

We now turn to characterizing the distributional dynamics of the GBN over 1978–2009. We have found the fluctuations in network features roughly coincide with previously documented global waves of private capital flows. To formalize the dates of the waves, we carry out unit root tests with one and two structural breaks in the mean (Clemente, Montanes, and Reyes, 1998) for all four indicators (average degree, average strength, network connectivity and network clustering). The results (Table 4) show that one-break tests identify a break in 2001 or 2003, while two-break tests find the first mean shift either in 1980 (before the debt crisis) or mid-1990s (before the Asian crisis) and the second one in 2002–03. In what follows we ignore the first break in the early 1980s since our data is insufficient to gauge the build-up of that wave, and restrict our attention to the behavior of the GBN during the more recent windows 1987–98 and 2002–08 (dated as in IMF, 2007).

These two windows provide an interesting setting for an exercise about out-of-sample dynamics. Over the past three decades the global financial architecture has been constantly reshaped by financial and debt crises, and different regulatory and macroeconomic policy regimes. Here we seek to map the in-sample dynamics of the GBN observed within the two waves into long-term dynamics. We wish to determine how the global financial architecture would have looked in the long run if in-sample dynamics were the same as in 1987–98 and 2002–08, respectively. We proceed in two steps. First, we analyze the within-window transitional dynamics using stochastic kernel estimates and a network-wide statistic. We then estimate long-run, limiting distributions for the network indicators.

Transitional dynamics can be visualized using stochastic kernel estimates, which we present in contour plots. These depict the conditional density estimate for a random variable that governs the transition of countries from one quantile of a network statistic distribution to another quantile. For illustration, we compute the 1-year stochastic kernel estimates for in-degree and relative in-strength (Figure 9). For the number of incoming links, most of the probability mass is concentrated around the 45-degree line in the middle range, meaning that countries in the middle quantiles of the distribution tend to stay in the same quantile from one year to another. In contrast, countries in the upper quantiles tend to ascend towards higher quantiles, which means that once a country establishes borrowing relationships with many lenders, in the next period chances are that it will borrow from even more lenders. This pattern is clearer still during the second wave of capital flows. For relative in-strength a "middle-class" of globally-interconnected countries seems to be emerging in the second wave.

Another measure of the persistence of distributional dynamics is the empirical M-statistic, which aggregates country-level probabilities of moving across quantiles (of network statistic *X*) from one year to the next. Assuming that the distributional dynamics of our network statistics can be approximated well by 10 quantiles (or deciles), we construct a Markov transition matrix by estimating 1-step transition probabilities using the maximum likelihood estimator for the probability of migrating from one decile to another:[24]

$$\hat{p}_{ijt} = \frac{n_{ij}^{t-1,t}}{n_i^t}$$

where $n_{ij}^{t-1,t}$ is the number of countries transitioning from the i^{th} to the j^{th} decile (of each network metric *X*) between *t–1* and *t* and n_i^t is the number of countries in decile *i* at time *t*. Since the network indicators considered present structural breaks which identify distinct waves of capital flows (1987–98 and 2002–08), we compute our measure of distributional dynamics—the M-statistic—within each window as the time-average of:

$$M_{\varpi,t}(X) = \frac{1}{10}\sum_{i=1}^{10}\sum_{j:|j-i|\le\varpi}^{10}\hat{p}_{ijt}$$

where parameter $\varpi=0$ corresponds to countries staying in the same quantile and $\varpi=1$ corresponds to countries moving one quantile up or down.[25] The M-statistic is bounded between 0 and 1, with higher values indicating a higher probability that countries stay in the same or adjacent quantile in consecutive years.

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[24] Note that we are not assuming time-homogeneity of the transition probabilities.

[25] For $\varpi=0$, the M statistic is the trace of the 1-step transition matrix(divided by 10 while for $\varpi=1$, the M statistic is the average of all the entries in the main diagonal and those lying one entry to the right and one entry to the left of the main diagonal.

Distributional dynamics display little persistence as our empirical M-statistics are relatively low (Table 5), ranging between 0.2 and 0.5 for parameter value ϖ=0 (staying in the same quantile). For the second window (2002–08) the M statistics are higher, which is consistent with the emergence of a group of borrowers that have been consolidating their position in the network. We also report 95 percent confidence intervals for the M-statistics corresponding to a "random" network.[26] The M-statistics for the GBN always fall to the right of the confidence interval upper bounds for the random network, suggesting that the GBN is more stable than a random network. Nevertheless, they are lower than the values of 0.8 and 0.9 documented for the trade network (Fagiolo et al., 2010), hinting at in-sample dynamics of financial flows that are more turbulent than trade links.

Finally, we investigate the implications of these transitional dynamics for the out-of-sample evolution of the GBN by estimating the ergodic distributions for in-degree, taking the first year of each window as the base year.[27] Figure 10 depicts the long-run stabilizing tendency of the in-degree distribution arising from the transitional dynamics observed within each wave of capital flows (and taking the mid-year as the base). The limiting distribution of country connectivity is unimodal in the first wave and bimodal in the second wave. A more "diversified" long-run financial landscape emerges based on second wave transitional dynamics—in which there are more highly-connected borrowers than previously. This is consistent with the 1990s being dominated by a single region—East Asia—as the leading destination of cross-border bank lending, while the 2000s witnessed the emergence of a number of economies (such as the BRICs and emerging Europe) as key borrowers of financial capital.[28]

V. THE GLOBAL BANKING NETWORK DURING FINANCIAL CRISES

We close our exploration of the topological features of the GBN by describing its behavior before, during, and after financial crises. Cetorelli and Goldberg (2010) have identified cross-border bank linkages as a key transmission channel of the 2007–08 US subprime crisis to emerging market countries, arguing that domestic loan supply in afflicted economies contracted due to the collapse of direct cross-border lending by foreign banks and a general weakening of balance sheets of both foreign affiliates and domestic banks caused by shortages of interbank and cross-border liquidity. To provide evidence of cross-border lending acting as a potential conduit of the negative shock both inside the core and towards the periphery, we present network visualizations for 2007Q4 and 2008Q4—just before and after the crisis (Figure 11). There is markedly lower intra-core and core-periphery connectivity at end-2008, with links disappearing as cross-border banking flows dried up (Hoggarth et al., 2009; Milesi-Ferretti and Tille, 2011).

[26] The "random" network is obtained by keeping the distribution of flows unchanged and reshuffling the links across countries.

[27] The conclusions are qualitatively the same if we consider alternative years as the base years for the ergodic distributions.

[28] How the 2008–09 crisis has affected this trend is an interesting question to explore as more recent data becomes available.

To determine how periods of financial distress correlate with features of the GBN, we plot network connectivity and clustering against synchronized recession dates (Figure 12). These include the 1987 stock market crash, the 1991–92 Scandinavian banking crises and 1992–93 ERM crisis, the 1998Q3 LTCM near-collapse, the 2000Q2 Internet bubble collapse, and the 2008Q3 Lehman Brothers bankruptcy. Many links die and network clustering diminishes during episodes of financial stress. This pattern is even clearer when we move to the regional level to consider regional network density during the crises of Latin America and East Asia (Figure 13).

How country connectivity in the GBN behaves during financial crises is depicted in Figures 14–15, where we plot average degree and strength (across countries) around systemic banking and sovereign debt crisis episodes.[29] The averages are shown for 5 years before and after the onset of the crisis. Without exception, network indicators of borrower connectedness in the GBN fall during crises, although the decline generally begins before the event.[30] The pattern holds up for lenders despite the paucity of systemic banking crises in the core prior to 2007. For sovereign debt crises, we only show the evolution of connectedness for borrowers, and document the same deleterious impact. Borrowers afflicted by debt crises do not attain pre-crisis connectedness levels within the following five years. When incorporating 2007–08 crises into the sample and restricting the window to –5/+1 years around the episode (Figure 15), all connectedness measures for lenders sharply decline one year after the crisis, reflecting the unusually large impact of the 2008–09 episode on the GBN.

We formalize the analysis by estimating a simple panel specification that traces the evolution of network measures around crisis dates. Specifically we regress country-level indicators of network centrality (degree, strength, and relative strength) on a set of dummies for crisis and post-crisis years while controlling for country fixed effects. The results (Table 6) indicate that banking and debt crises are associated with reduced borrower access to capital markets as measured by network degree (number of links) and strength (total flows). Cross-border inflows to the afflicted country decrease by $24 million at the onset of the crisis, and $30 million on average over the subsequent five years (columns 1–3). On the lending side, the F tests of joint significance of coefficient estimates on the lags cannot reject a nil effect of banking crises on lender connectedness (columns 4–6), which may be explained by the lack of variation in the sample. The negative effects of sovereign debt crises are also evident for borrowers (columns 7–9), but are smaller in magnitude. These results complement the literature on access to capital markets in the aftermath of debt crises (e.g., Ozler, 1993; Arteta and Hale, 2008; Fuentes and Saravia, 2009). Furthermore, by looking beyond lending volumes, they represent a deeper characterization of access to global financial markets in the aftermath of crises.

[29] See Laeven and Valencia (2008, 2010) for definitions.
[30] The analysis of network measures' capacity to act as leading indicators of crises is left for future research.

VI. Conclusions

The potential usefulness of network techniques in analyzing systemic risk has taken center-stage in academic and policy debates in the aftermath of the 2008–09 global crisis. Nevertheless, little is known about the structural properties and time-evolution of the network of cross-country financial linkages, which are key to understanding how the global financial system reacts to shocks, and whether and where systemic risk may emerge. In this paper we have analyzed the properties of the global cross-border bank lending market (for 184 countries over 1978–2009) using network metrics of interconnectedness such as centrality, connectivity, and clustering. We have also sought to determine how geographical linkages changes around financial crises.

We found that the global banking network is relatively unstable; we have identified structural breaks in network connectivity and centrality, and documented volatile interconnectedness rankings for countries, especially borrowers. In the 2002–08 wave of global capital flows, the BRIC countries and high-growth Europe emerge and consolidate their position as highly-interconnected borrowers. Network density expands and contracts, following the cycle of capital flows. Furthermore, country centrality falls at the onset and in the aftermath of banking and sovereign debt crises. While the global banking network appeared more stable in the second half of the 2000s than in earlier periods, the 2008–09 global financial crisis stands out as an unusually large perturbation.

A number of questions emerge from our analysis. While it has been established that cross-border bank lending is a key channel of transmission of financial crises, how the topology of financial networks relate to the emergence of systemic risk remains underexplored. How do the properties of the different networks— banking, FDI, trade, and remittances—compare and how do countries' degrees of connectedness interact in different webs of relationships? What is the empirical relationship between connectedness and the way in which shocks get amplified or diffused? These and related questions remain interesting avenues to explore in future work.

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APPENDIX

Figure 1. Cross-border financial flows to advanced economies

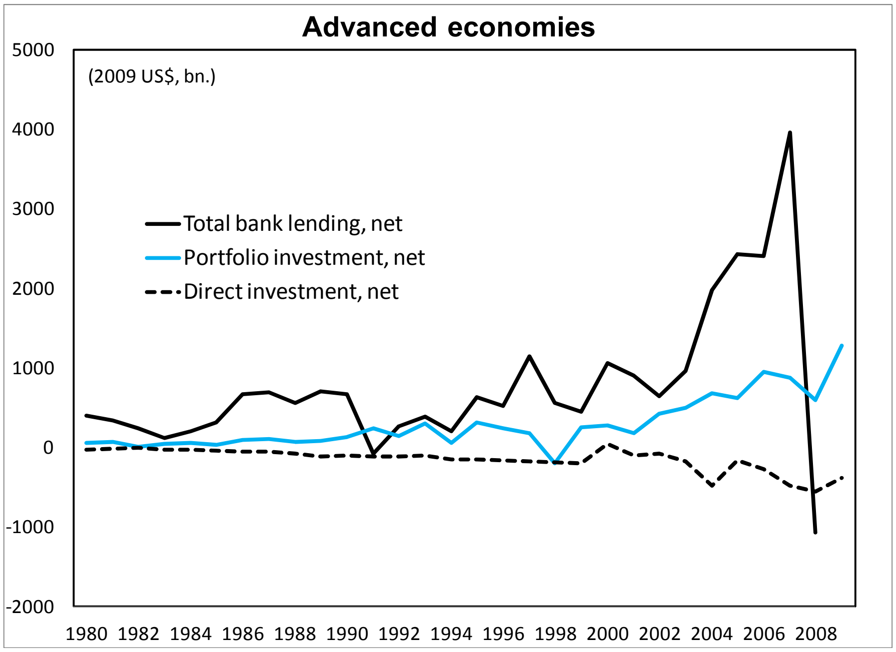
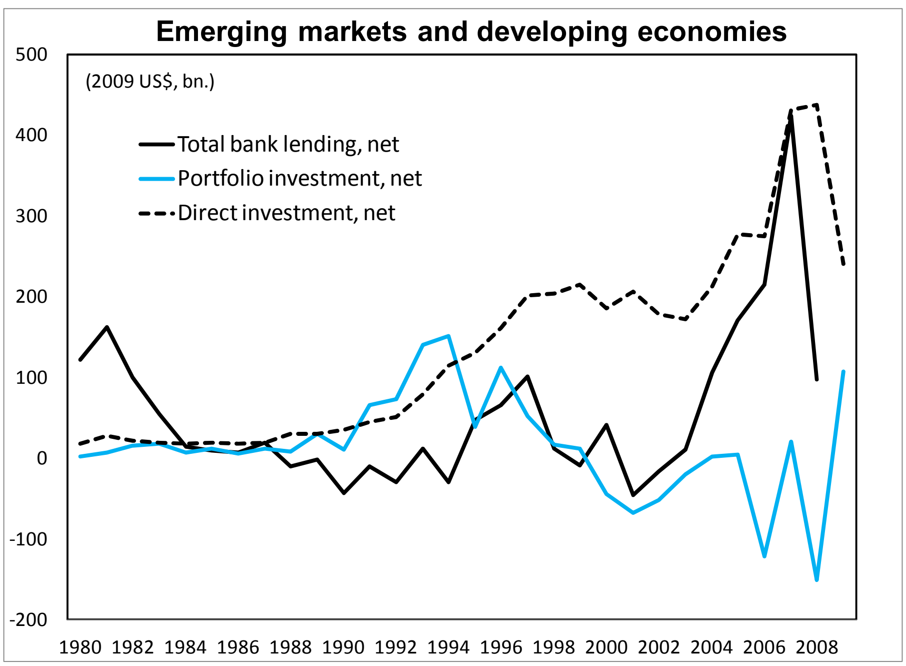


Figure 2. Cross-border financial flows to emerging markets and developing economies



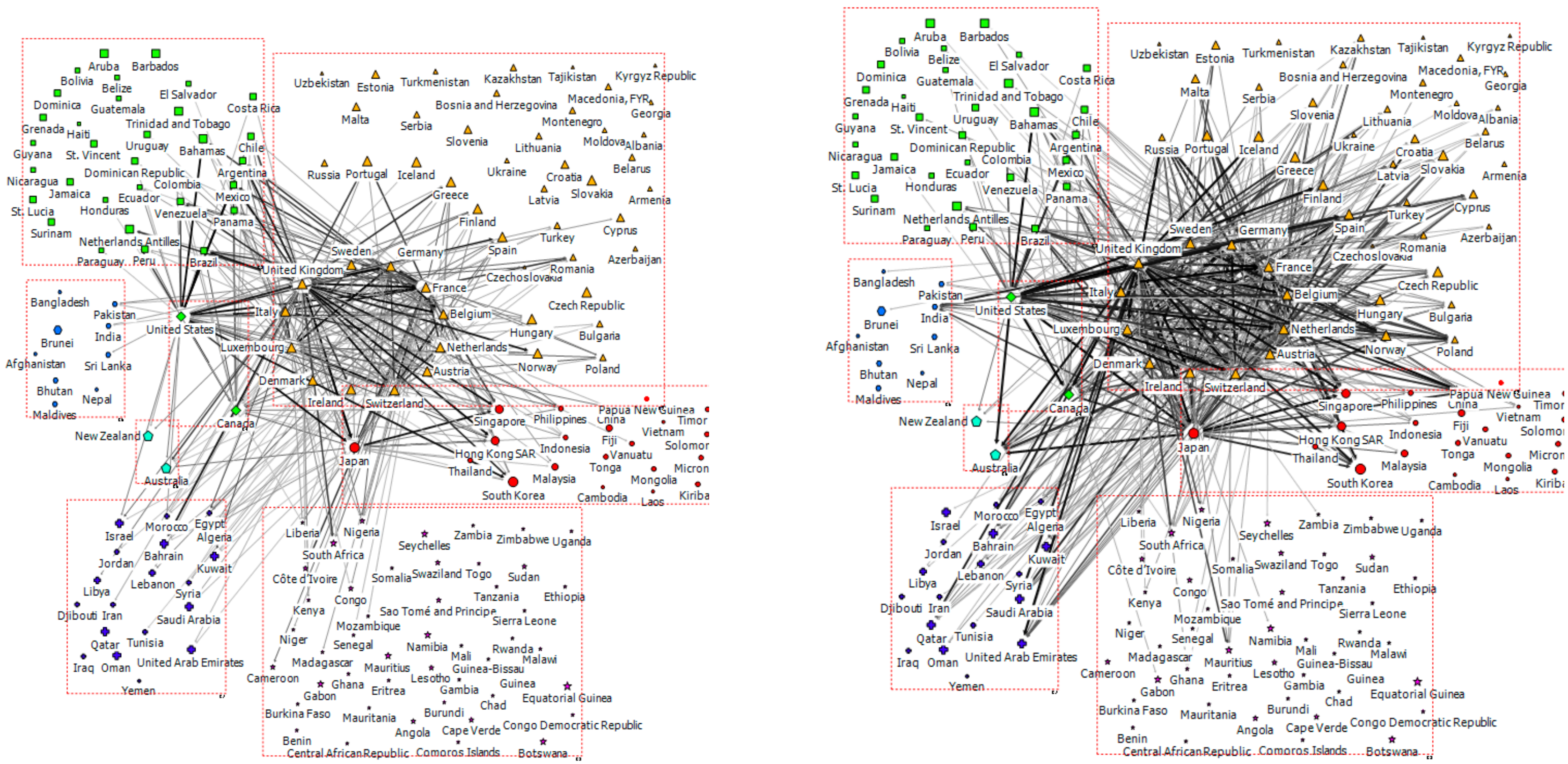
Source: Authors' calculations based on World Economic Outlook (December 2010) and BIS locational banking statistics.

Note: Total bank lending flows (net) are from BIS reporting countries (with with complete data over 1978Q4–2009Q3) and are calculated by summing up flows across borrowers in each country group. Note that there is some degree of overlap between bank lending flows and portfolio investment, with cross-border investments by banks in debt securities showing up in both variables.

Figure 3. Network view of cross-border banking, 1980 and 2007

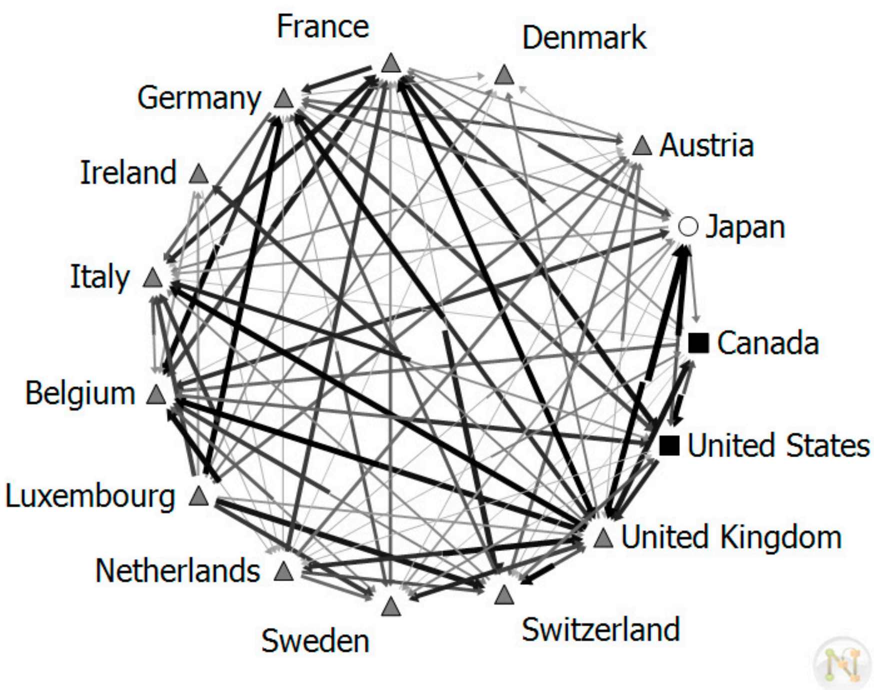
Panel A. Core-periphery

1980 **2007**

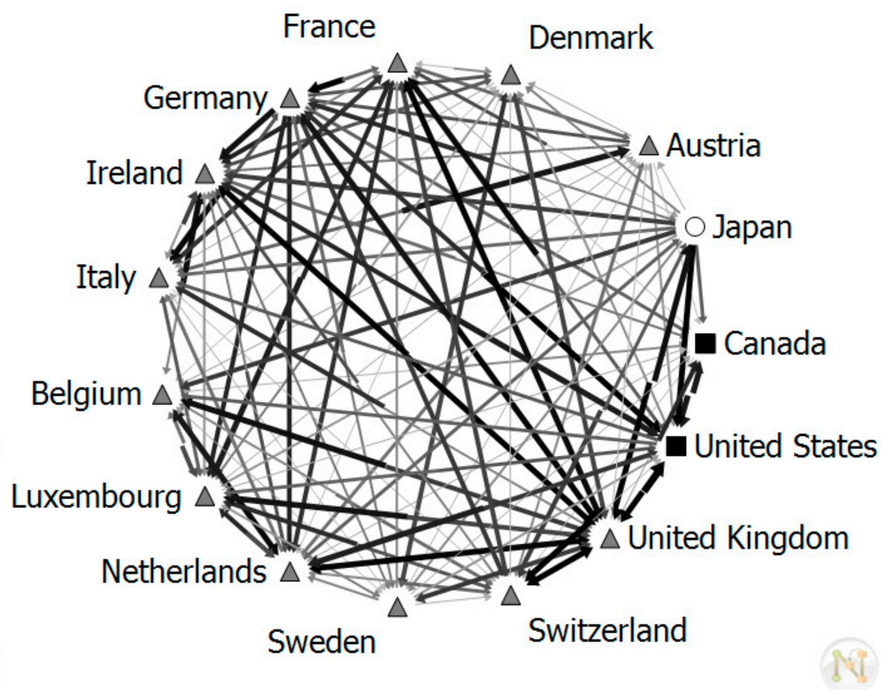


Panel B. Core-core

1980



2007



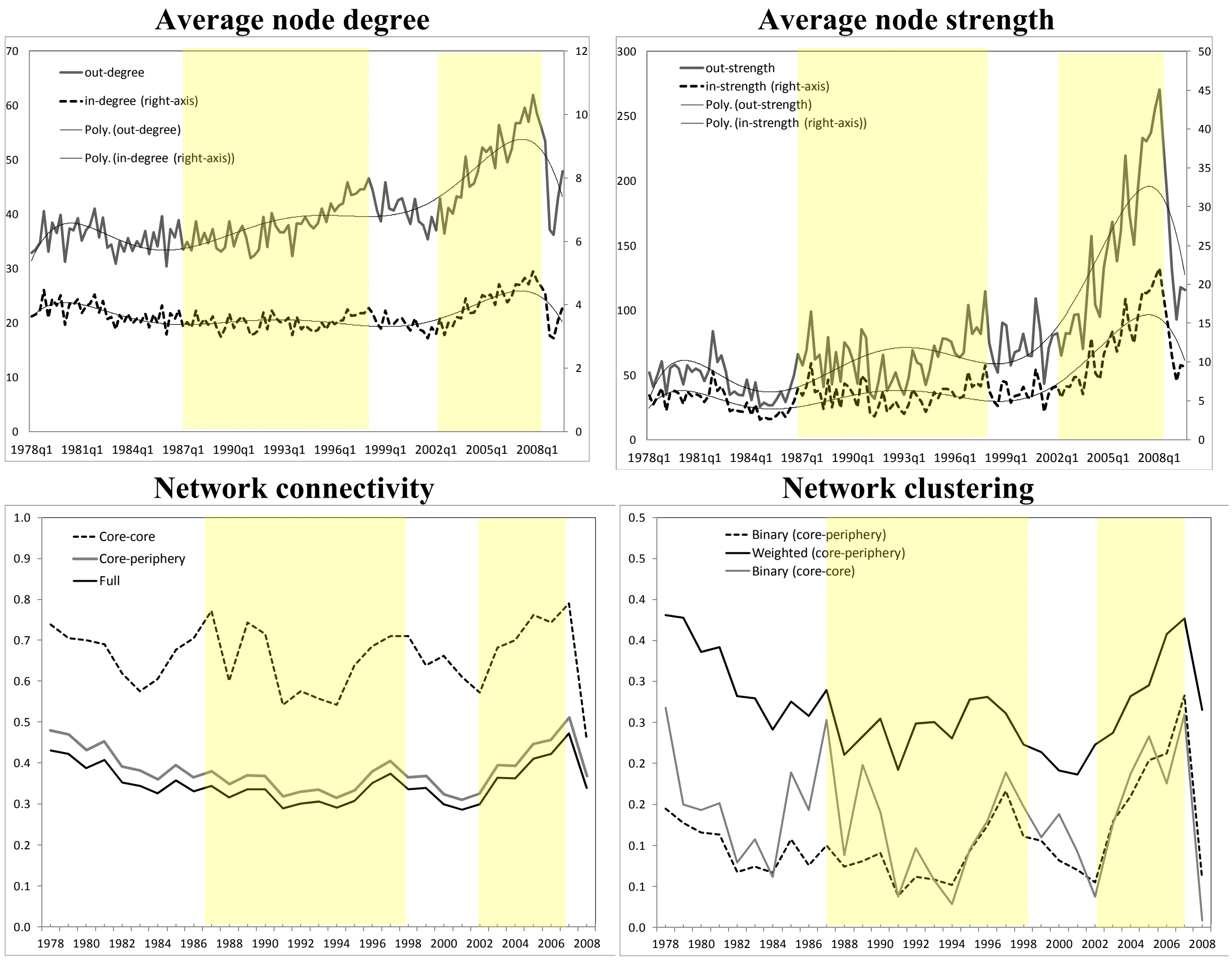
Source: Authors' calculations using BIS locational banking statistics (yearly).
Note: The countries represent nodes, while the links between countries represent cross-border bank loans. Thicker and darker colored links indicate larger flows. In Panel B arrows indicate the direction of the flows. When bi-directional flows occur, the connecting links is split into two, each half-link reflecting the magnitude of one flow (hence may have a different color).

Table 1. Summary statistics of network indicators

	Obs.	Mean	St. Dev.	Min	Max
Measures of country centrality					
Full network					
In-degree	20,903	4.4	3.2	0	15
In-strength	20,903	26.7	122	0	5907
Relative in-strength	20,903	0.1	0.3	0	5
Out-degree	1,904	48.1	17.4	0	149
Out-strength	1,904	293	446	0	6646
Relative out-strength	1,904	9.9	8.4	0	55
Core-periphery					
In-degree	20,903	3.7	3.2	0	15
In-strength	20,903	7.3	30.9	0	859
Relative in-strength	20,903	0.1	0.3	0	4
Out-degree	1,904	40.3	16.7	0	135
Out-strength	1,904	80.5	122.5	0	1156
Relative out-strength	1,904	8.9	7.7	0	51
Core-core					
Degree	1,905	7.8	2.5	0	14
Strength	1,905	212.2	355.2	0	6012
Relative strength	1,905	1.0	0.9	0	6
Measures of network density					
Full network					
Connectivity	31	0.33	0.05	0.26	0.47
Binary clustering	31	0.11	0.05	0.04	0.29
Weighted clustering	31	0.37	0.06	0.25	0.49
Core-periphery					
Connectivity	31	0.36	0.05	0.28	0.51
Binary clustering	31	0.11	0.05	0.04	0.28
Weighted clustering	31	0.27	0.05	0.19	0.38
Core-core					
Connectivity	31	0.66	0.08	0.46	0.79
Binary clustering	31	0.13	0.07	0.01	0.27
Weighted clustering	31	0.57	0.12	0.23	0.81

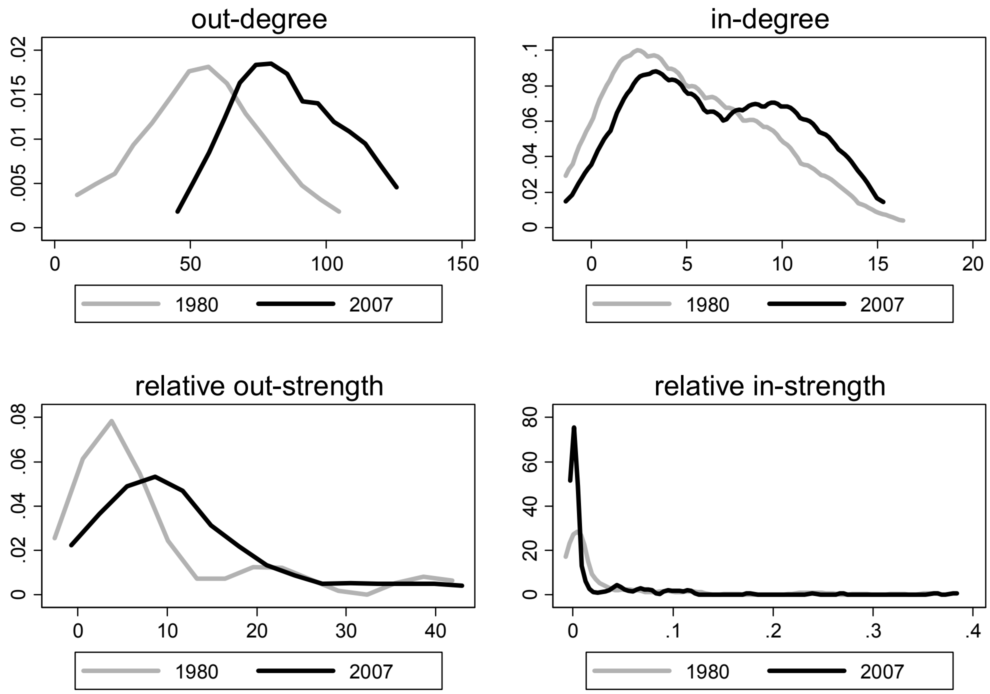
Source: Authors’ calculations using BIS locational banking statistics (quarterly).
Notes: Node strength is expressed in 2009 US$ million.

Figure 4. Trends in network indicators, 1978–2009



Source: Authors' calculations using BIS locational banking statistics (quarterly and annual).
Notes: Results are shown for the core-periphery network. In the upper panels the smooth curves are nonparametric local polynomial smoothed estimates. In all panels we superimpose the dates of the two global waves of capital flows discussed in the text: 1987–98 and 2002–08 (as dated in IMF, 2007).

Figure 5. Empirical distributions of network indicators



Source: Authors' calculations using BIS locational banking statistics (annual).
Notes: Results are shown for the core-periphery network. The kernel density estimates use the Epanechnikov kernel and optimal bandwidth (Silverman, 1986).

Table 2. Kolmogorov-Smirnov tests

Lenders				**Borrowers**			
Out-degree				In-degree			
	1980	**1990**	**2000**		**1980**	**1990**	**2000**
1980s	0			**1980s**	11		
1990s	0	11		**1990s**	100	0	
2000s	25	50	38	**2000s**	100	75	0
Out-strength				In-strength			
	1980	**1990**	**2000**		**1980**	**1990**	**2000**
1980s	0			**1980s**	56		
1990s	22	0		**1990s**	100	22	
2000s	63	50	25	**2000s**	63	50	50
Relative out-strength	**1980**	**1990**	**2000**	Relative out-strength	**1980**	**1990**	**2000**
1980s	0			**1980s**	11		
1990s	0	0		**1990s**	100	0	
2000s	38	0	0	**2000s**	100	75	0

Source: Authors' calculations using BIS locational banking statistics (annual).
Notes: The table reports the proportion of years that display "statistically different" empirical distribution of the network indicators in each decade compared to the year indicated as column head. For instance, the figure 25 in the out-degree panel says that in 25 percent of years (i.e., 2 years) through the 2000s, the empirical distribution of out-degree was different than that in 1980. The statistical closeness of empirical distributions is assessed using Kolmogorov-Smirnov tests at the 5 percent level of significance.

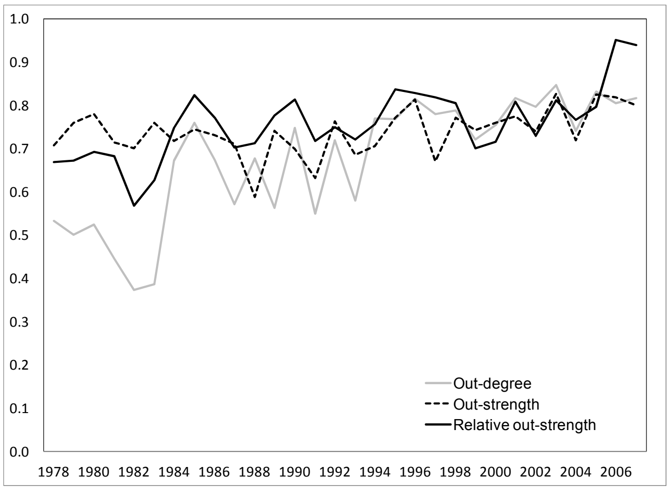
Table 3. Country rankings by degree of interconnectedness

Panel A	Lenders			Panel B	Borrowers		
	1980	1995	2007		1980	1995	2007
Out-degree	UK	Switzerland	Switzerland	**In-degree**	Argentina	Indonesia	Brazil
	France	Germany	UK		Venezuela	China	China
	Belgium	Netherlands	France		Egypt	Thailand	Russian Fed.
	US	France	Germany		Chile	Philippines	India
	Luxembourg	UK	Belgium		Brazil	India	Poland
	Germany	Luxembourg	Luxembourg		Colombia	Malaysia	Chile
	Austria	Belgium	Netherlands		Mexico	Iran	Ukraine
	Netherlands	Austria	Denmark		Ecuador	Chile	Latvia
	Canada	US	Austria		Nigeria	Argentina	Lithuania
	Italy	Italy	Japan		Syria	Pakistan	Panama
Out-strength	UK	Japan	UK	**In-strength**	Mexico	Thailand	Russian Fed.
	US	UK	France		Brazil	Brazil	China
	France	US	US		Argentina	Indonesia	Brazil
	Japan	Germany	Japan		Venezuela	Panama	Poland
	Belgium	France	Germany		Chile	China	India
	Luxembourg	Luxembourg	Austria		Romania	South Africa	Turkey
	Germany	Netherlands	Netherlands		Philippines	Turkey	Romania
	Canada	Belgium	Belgium		Panama	Chile	Ukraine
	Netherlands	Austria	Luxembourg		Poland	Argentina	Panama
	Austria	Italy	Switzerland		Egypt	India	Mexico
Relative	UK	UK	UK	**Relative**	Mexico	Thailand	Russian Fed.
out-strength	France	France	France	**in-strength**	Brazil	Brazil	Romania
	US	Germany	Germany		Argentina	Indonesia	Poland
	Belgium	US	Switzerland		Poland	China	Brazil
	Germany	Switzerland	US		Venezuela	Russian Fed.	China
	Luxembourg	Japan	Austria		Romania	Argentina	Turkey
	Netherlands	Netherlands	Japan		Panama	Turkey	Ukraine
	Japan	Belgium	Netherlands		Nigeria	Chile	Lithuania
	Austria	Austria	Belgium		Algeria	South Africa	India
	Canada	Luxembourg	Canada		Chile	Iran	Latvia

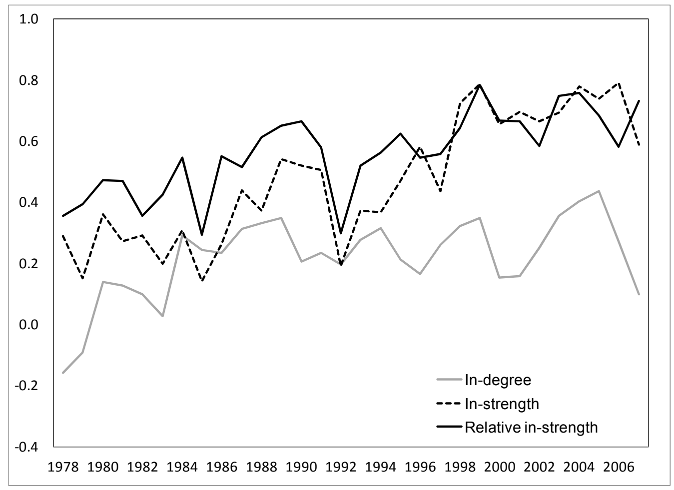
Source: Authors' calculations using BIS locational banking statistics (annual).
Notes: Panel A refers to our sample of BIS reporting countries only. Panel B refers to non BIS-reporting, middle-income countries.

Figure 6. Ranking stability indices

Lenders



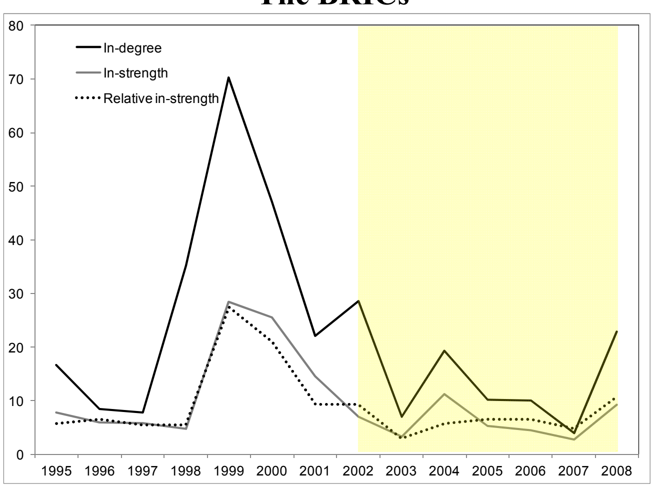
Borrowers



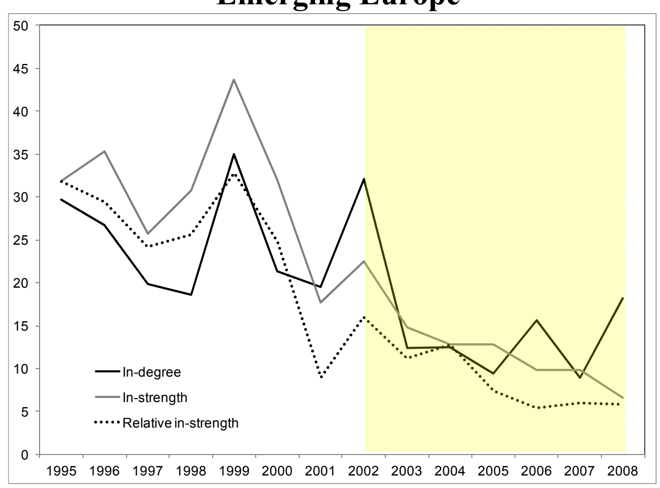
Source: Authors’ calculations using BIS locational banking statistics (annual).
Notes. The results are based on the sub-sample of borrowers present throughout the sample period.

Figure 7. Average rankings for the BRICs and emerging Europe

The BRICs



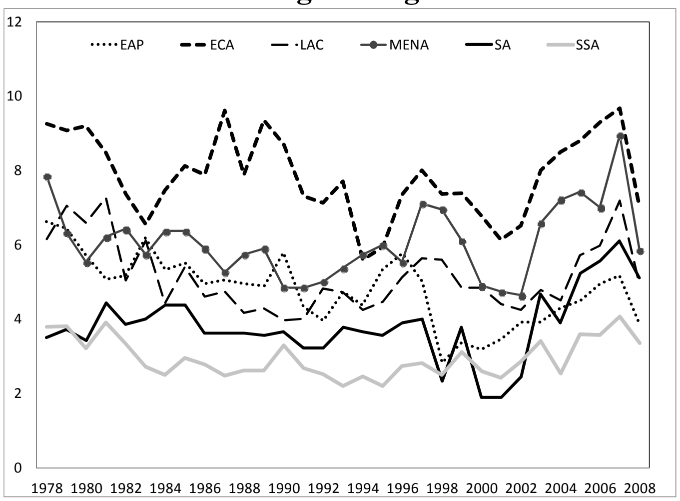
Emerging Europe



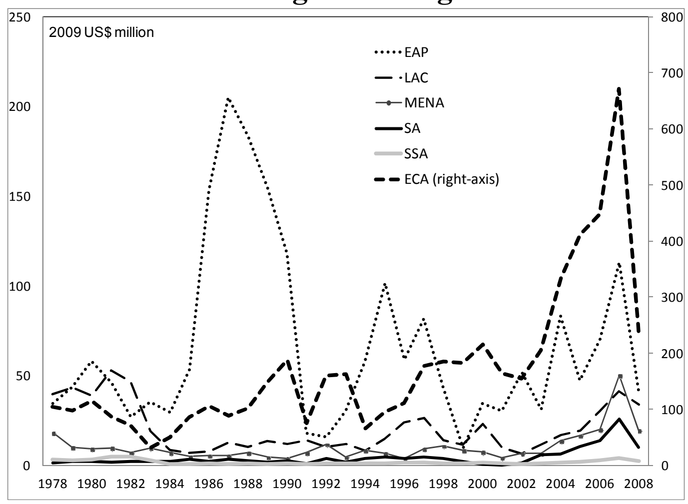
Source: Authors’ calculations using BIS locational banking statistics (annual).
Notes. The countries grouped under ‘emerging Europe’ comprise Latvia, Lithuania, Poland, Romania, and Ukraine.
In both panels we superimpose the dates of the second global wave of capital flows discussed in the text: 2002–08.

Figure 8. Regional heterogeneity: degree, strength, and clustering

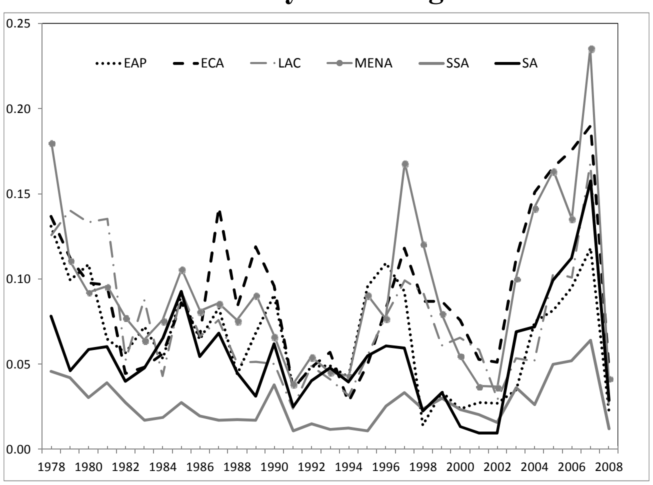
Average in-degree



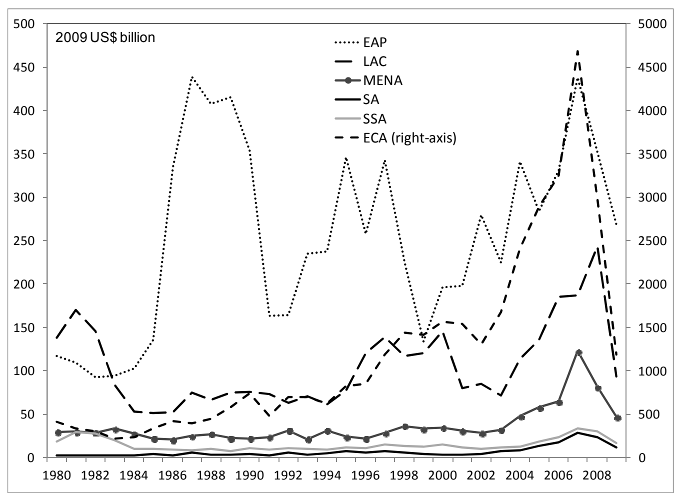
Average in-strength



Binary clustering



Total flows



Source: Authors' calculations using BIS locational banking statistics (annual).
Notes: Results for North America/Oceania are omitted from all charts for visual tractability. In the bottom right panel, the figures for 2009 are upto Q3 inclusive.

Table 4. Unit root tests for empirical moments of network indicators

	1 break	p-value	2 breaks		p-value first break	p-value second break
Out-degree	**2001**	0.001	**1994**	**2003**	0.002	0.006
In-degree	**2003**	0.044	**1980**	**2003**	0.042	0.003
Out-strength	**2002**	0.000	**1993**	**2002**	0.017	0.000
In-strength	**2003**	0.000	1980	**2003**	0.411	0.000
Connectivity	**2003**	0.034	1996	**2003**	0.679	0.010
Binary clustering	**2003**	0.016	1996	**2003**	0.679	0.010
Weighted clustering	2004	0.142	1996	**2002**	0.121	0.031

Source: Authors' calculations using BIS locational banking statistics (annual).
Notes: The results pertain to the core-periphery network. Years in boldface identify the structural breaks that are statistically significant at the 5 percent level.

Table 5. Empirical M-statistics

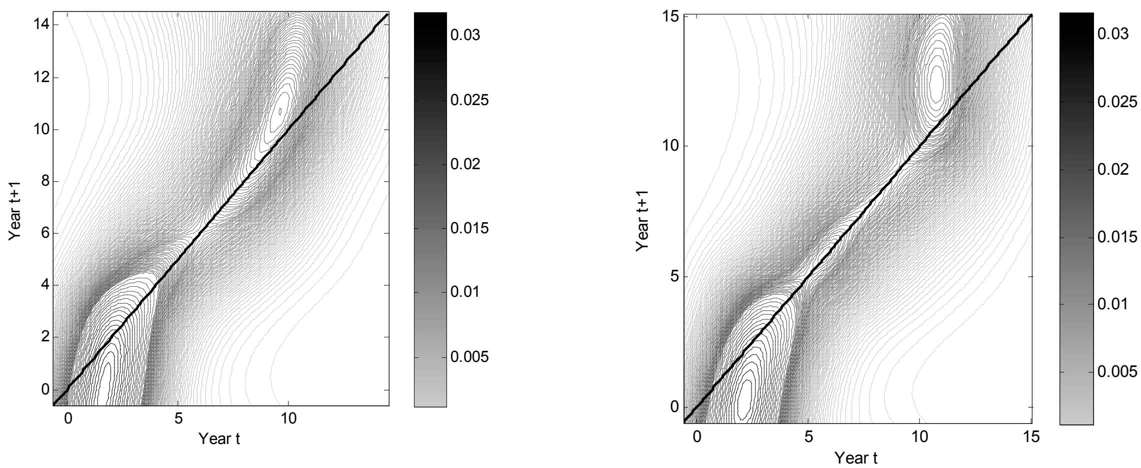
First window: 1987–98	$\omega = 0$	$\omega = 1$
Node degree	0.2134 (0.0872, 0.1185)	0.5335 (0.2534, 0.2991)
Node strength	0.3583 (0.0836, 0.1159)	0.7204 (0.2561, 0.3065)
Relative node strength	0.3539 (0.0845,0.1159)	0.7460 (0.2569,0.3026)
Second window: 2002–08	$\omega = 0$	$\omega = 1$
Node degree	0.2536 (0.0774, 0.1177)	0.5996 (0.2496, 0.3150)
Node strength	0.4363 (0.0780, 0.1200)	0.8270 (0.2486, 0.3117)
Relative node strength	0.4556 (0.0780, 0.1223)	0.8449 (0.2478, 0.3117)

Source: Authors' calculations using BIS locational banking statistics (annual).
Notes: 95 percent confidence intervals for the M statistics for a "random" network are shown in parentheses (see text for explanations).

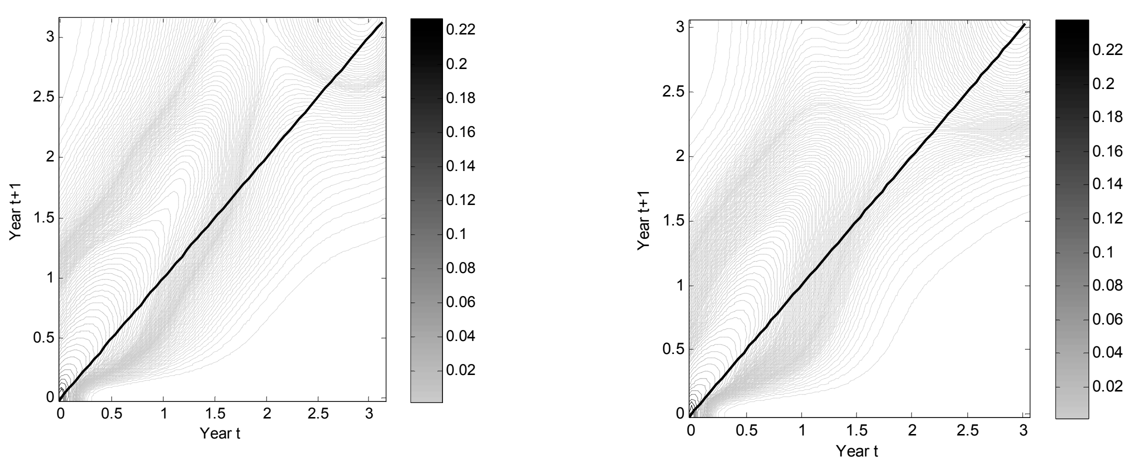
Figure 9. Stochastic kernel density estimates

First window: 1987–98 **Second window: 2002–08**

Panel A. In-degree



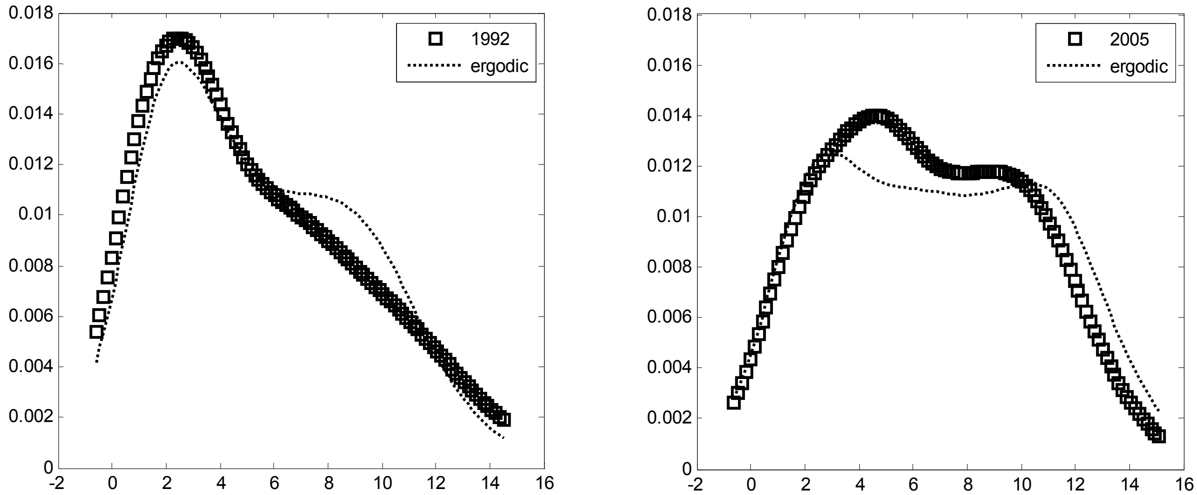
Panel B. Relative in-strength



Source: Authors' calculations using BIS locational banking statistics (annual).
Notes: The results are based on the sub-sample of countries present through the sample period.

Figure 10. Ergodic distributions for node degree

First window **Second window**

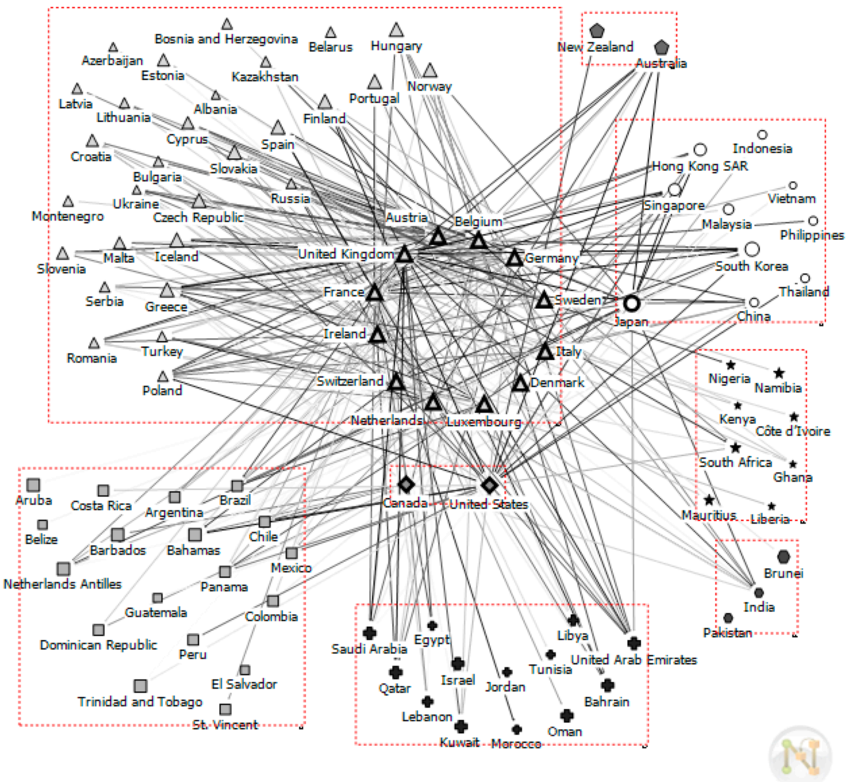


Source: Authors' calculations using BIS locational banking statistics (annual).
Note: The ergodic distributions are computed based on transitional dynamics in each window, after restricting the sample to the countries present in the dataset throughout the full period. The base year is 1992 for the first window and 2005 for the second window.

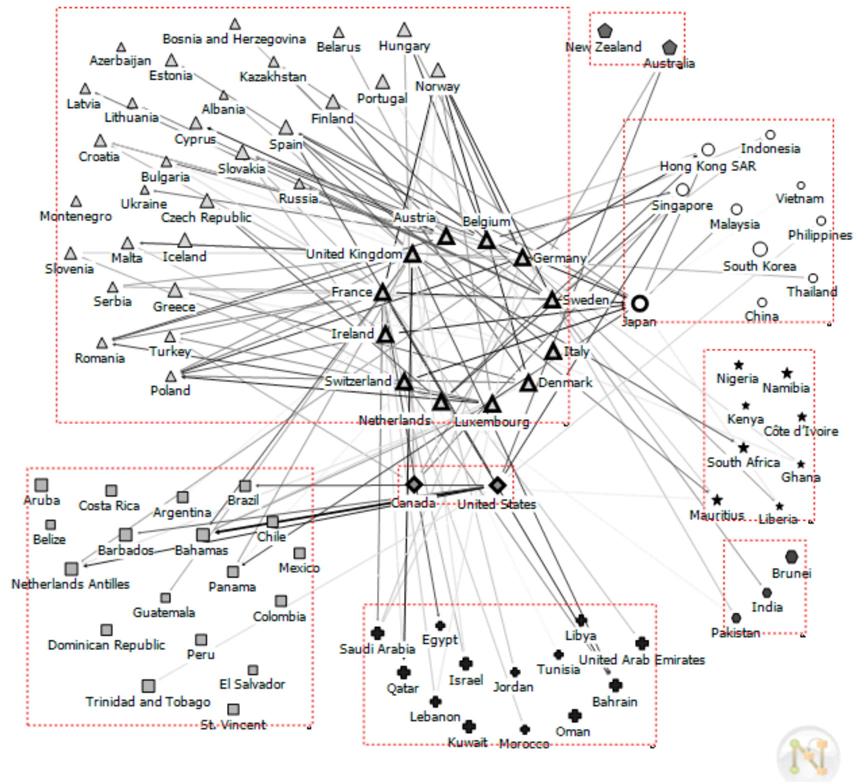
Figure 11. Global banking network before and during the 2008-09 crisis

Panel A. Core-periphery

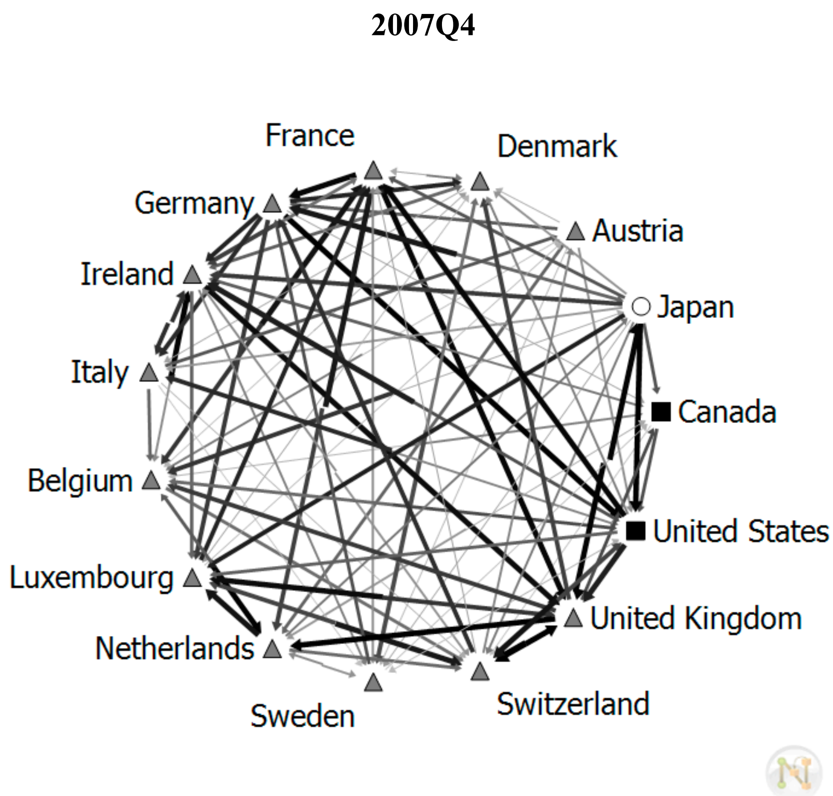
2007Q4

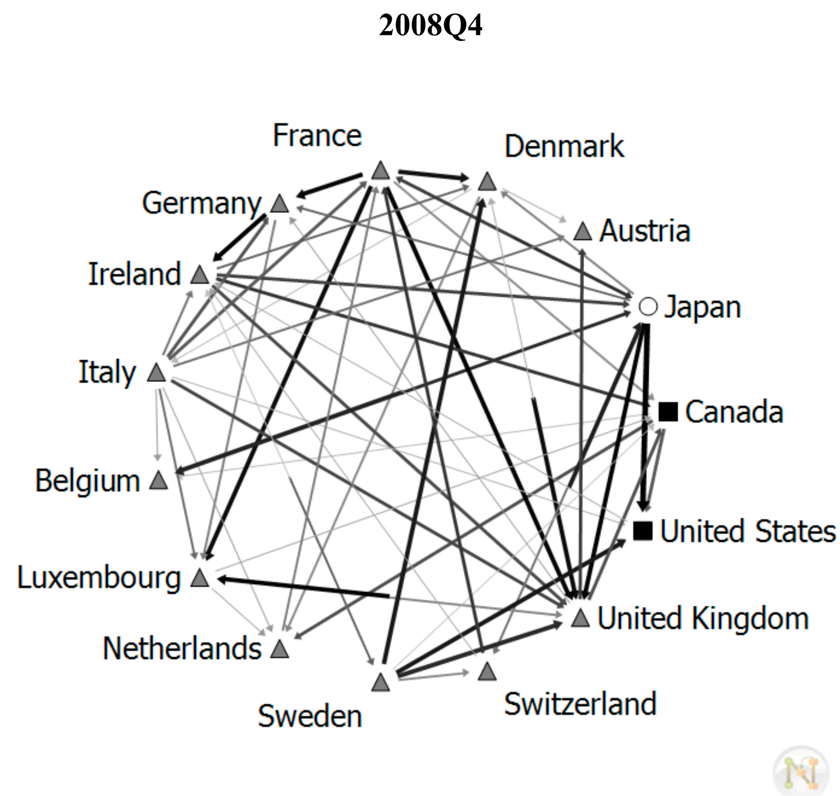


2008Q4



Panel B. Core-core

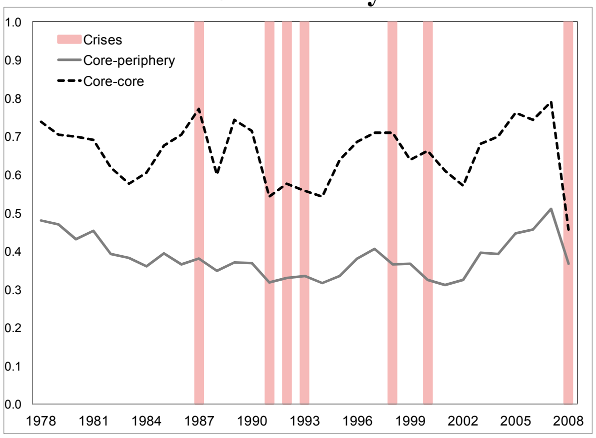




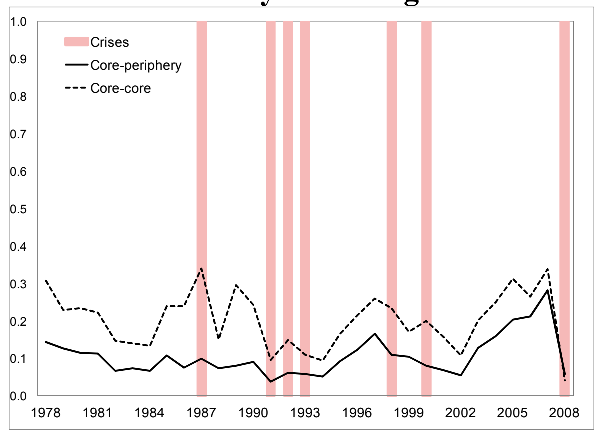
Source: Authors' calculations using BIS locational banking statistics (quarterly).
Notes: The countries represent nodes, while the links between countries represent cross-border bank loans. Thicker and darker colored links indicate larger flows. In Panel B arrows indicate the direction of the flows. When bidirectional flows occur, the connecting links is split into two, each half-link reflecting the magnitude of one flow (hence may have a different color).

Figure 12. Network density during financial crises

Connectivity



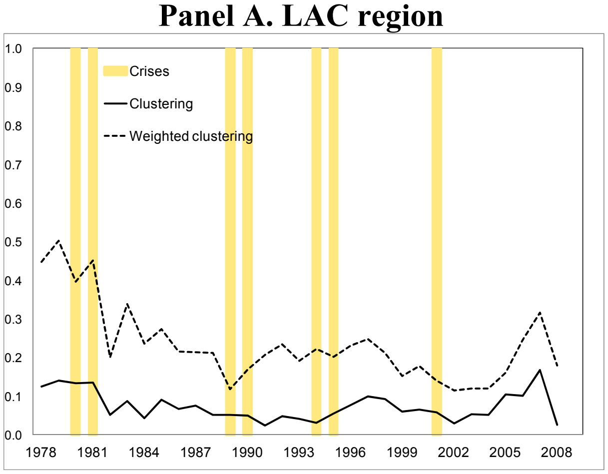
Binary clustering



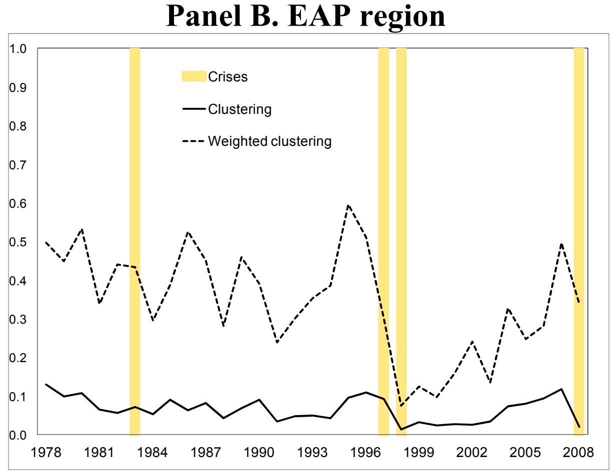
Source: Authors' calculations using BIS locational banking statistics (annual).
Notes: Highlighted areas represent synchronized recession dates (IMF, 2007), namely the 1987Q3 stock market crash, 1991–92 Scandinavian banking crises, 1992 ERM crisis, 1998Q3 LTCM near-collapse, 2000Q2 Internet bubble collapse, and 2008Q3 Lehman Brothers bankruptcy.

Figure 13. Regional clustering for LAC and EAP regions during financial crises

Panel A. LAC region

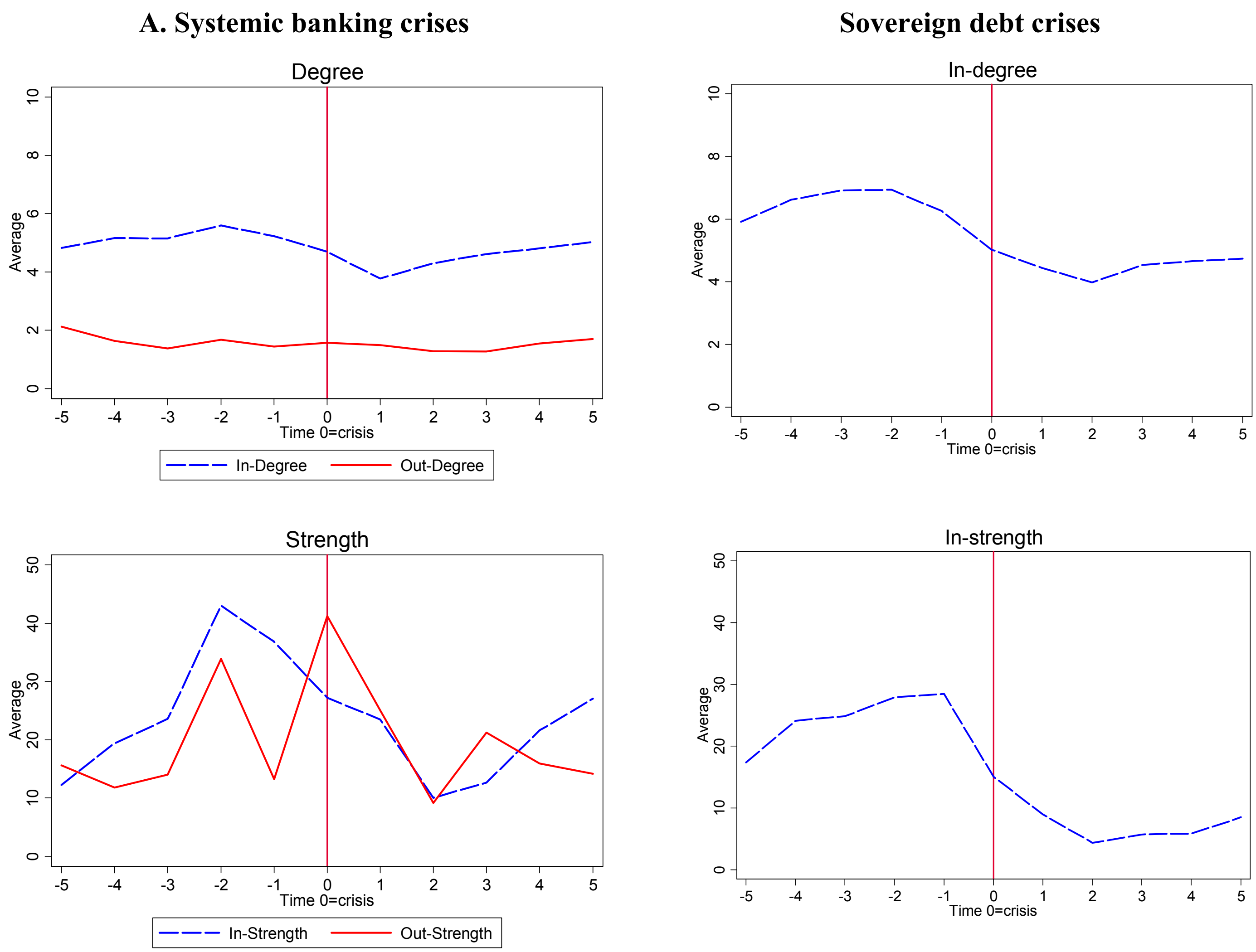


Panel B. EAP region



Source: Authors' calculations using BIS locational banking statistics (annual).
Notes: For LAC we superimpose dates for the onset of systemic banking crises for Argentina, Brazil, and Mexico. For EAP we superimpose dates for the onset of systemic banking crises for Japan, Indonesia, Korea (Republic of), Malaysia, Philippines, Thailand, Vietnam, and Mongolia. Crisis dates have been taken from Laeven and Valencia (2010).

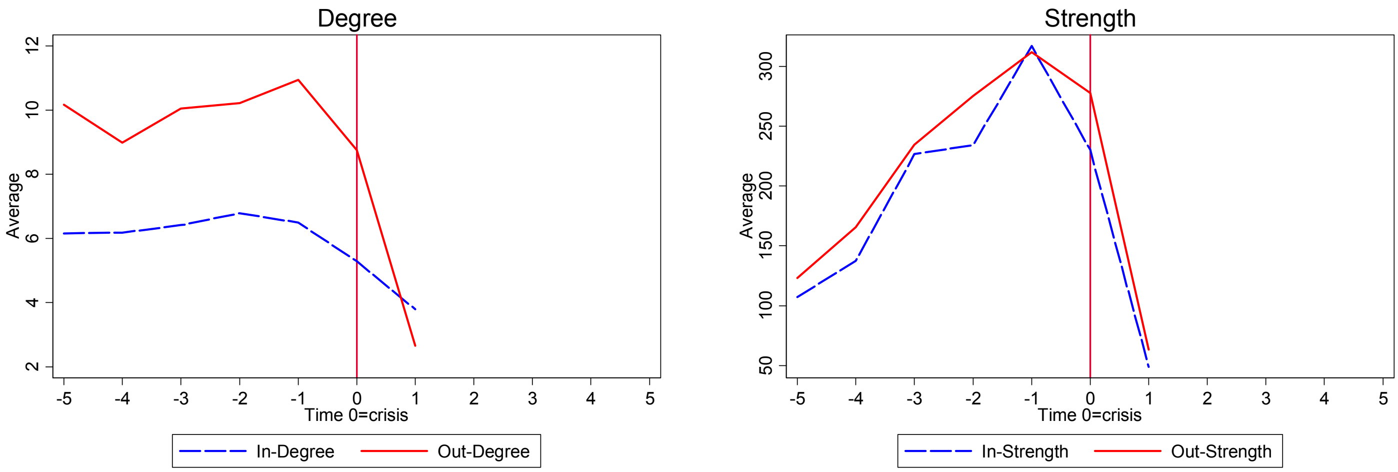
Figure 14. Interconnectedness before and after financial crises



Source: Authors' calculations using BIS locational banking statistics (annual) and Laeven and Valencia (2010) database for systemic banking and sovereign debt crises dates.
Notes: Results are based on the full network. The left panels include systemic banking and sovereign debt crises that occurred between 1985 and 2003 and are at least 10 years apart, which allows for a 5-year non-overlapping window around them. (Countries with two crises within 10 years are dropped, but the results are robust to retaining either crisis.)

Figure 15. Interconnectedness before and after systemic banking crises (including 2007–08 episodes)

–5/+1 years around crises



Source: Authors' calculations using BIS locational banking statistics (annual) and Laeven and Valencia (2008) database for systemic banking crises.
Notes: Results are based on the full network. Data for 2009 is upto Q3 inclusive.

Table 6. Interconnectedness during financial crises: Regression estimates

	Systemic banking crises						Sovereign debt crises		
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
	In-degree	In-strength	Relative in-strength	Out-degree	Out-strength	Relative out-strength	In-degree	In-strength	Relative in-strength
Year of crisis	-0.75***	-24.25*	-0.02*	-0.11	3.38	-0.02	-0.23	-5.22	0.02*
	(0.26)	(12.88)	(0.01)	(0.10)	(12.47)	(0.06)	(0.45)	(3.78)	(0.01)
1 year later	-1.66***	-26.91**	-0.02***	-0.16	-12.95	0.01	-0.90**	-4.72	0.01*
	(0.26)	(12.37)	(0.01)	(0.21)	(8.33)	(0.04)	(0.37)	(4.15)	(0.01)
2 years later	-1.19***	-39.32**	-0.03***	-0.32*	-27.80*	-0.12	-1.36***	-9.30***	-0.00
	(0.25)	(15.54)	(0.01)	(0.19)	(16.42)	(0.07)	(0.33)	(3.50)	(0.00)
3 years later	-0.86***	-36.23**	-0.02**	-0.32*	-15.39	-0.08	-0.81**	-7.97***	-0.01*
	(0.22)	(17.97)	(0.01)	(0.19)	(12.13)	(0.06)	(0.34)	(2.87)	(0.00)
4 years later	-0.67***	-27.29**	-0.00	-0.03	-20.64	-0.04	-0.68*	-7.84***	-0.00
	(0.22)	(10.78)	(0.01)	(0.18)	(12.87)	(0.07)	(0.37)	(2.78)	(0.00)
5 years later	-0.45*	-21.84*	-0.01***	0.12	-22.43*	0.00	-0.67*	-5.45***	0.01
	(0.25)	(13.26)	(0.00)	(0.17)	(13.57)	(0.06)	(0.38)	(1.89)	(0.01)
F test joint significance:	14.86	3.11	4.13	1.36	1.43	0.96	5.82	3.30	0.92
test statistic and p-value	0.00	0.01	0.00	0.24	0.21	0.44	0.00	0.01	0.47
Obs.	4398	4398	4398	4398	4398	4398	4398	4398	4398
Number of countries	86	86	86	86	86	86	41	41	41
R-squared	0.63	0.49	0.79	0.94	0.54	0.90	0.63	0.49	0.79

Source: Authors' estimations using BIS locational banking statistics (annual).
Notes: Robust standard errors in parentheses (*** p<0.01; ** p<0.05; * p<0.1). The F-test of joint significance is for all coefficient estimates on lagged variables.

List of countries used in the analysis

Core (Sample of BIS reporting countries)[1/]	Periphery (Other countries)[2/]				
Austria	Afghanistan	Czech Republic	Kuwait	Paraguay	Turkey
Belgium	Albania	Côte d'Ivoire	Kyrgyz Republic	Peru	Turkmenistan
Canada	Algeria	Djibouti	Laos	Philippines	Uganda
Denmark	Angola	Dominica	Latvia	Poland	Ukraine
France	Argentina	Dominican Republic	Lebanon	Portugal	United Arab Emirates
Germany	Armenia	Ecuador	Lesotho	Qatar	Uruguay
Ireland	Aruba	Egypt	Liberia	Romania	Uzbekistan
Italy	Australia	El Salvador	Libya	Russia	Vanuatu
Japan	Azerbaijan	Equatorial Guinea	Lithuania	Rwanda	Venezuela
Luxembourg	Bahamas	Eritrea	Macau SAR	Samoa	Vietnam
Netherlands	Bahrain	Estonia	Macedonia, FYR	Sao Tomé and Princip	Yemen
Sweden	Bangladesh	Ethiopia	Madagascar	Saudi Arabia	Zambia
Switzerland	Barbados	Fiji	Malawi	Senegal	Zimbabwe
United Kingdom	Belarus	Finland	Malaysia	Serbia	
United States	Belize	Gabon	Maldives	Seychelles	
	Benin	Gambia	Mali	Sierra Leone	
	Bhutan	Georgia	Malta	Singapore	
	Bolivia	Ghana	Mauritania	Slovakia	
	Bosnia and Herzegovina	Greece	Mauritius	Slovenia	
	Botswana	Grenada	Mexico	Solomon Islands	
	Brazil	Guatemala	Micronesia	Somalia	
	Brunei	Guinea	Moldova	South Africa	
	Bulgaria	Guinea-Bissau	Mongolia	South Korea	
	Burkina Faso	Guyana	Montenegro	Spain	
	Burundi	Haiti	Morocco	Sri Lanka	
	Cambodia	Honduras	Mozambique	St. Lucia	
	Cameroon	Hong Kong, SAR	Myanmar	St. Vincent	
	Cape Verde	Hungary	Namibia	Sudan	
	Central African Republic	Iceland	Nepal	Surinam	
	Chad	India	Netherlands Antilles	Swaziland	
	Chile	Indonesia	New Zealand	Syria	
	China	Iran	Nicaragua	Tajikistan	
	Colombia	Iraq	Niger	Tanzania	
	Comoros Islands	Israel	Nigeria	Thailand	
	Congo, Rep.	Jamaica	Norway	Timor Leste	
	Congo, DRC	Jordan	Oman	Togo	
	Costa Rica	Kazakhstan	Pakistan	Tonga	
	Croatia	Kenya	Panama	Trinidad and Tobago	
	Cyprus	Kiribati	Papua New Guinea	Tunisia	

1/ Includes BIS reporting countries with complete data from 1978Q4 onwards.
2/ Includes all countries for which the sample BIS reporting countries provide data.