A Network Analysis of Global Banking: 1978–2010[±]

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First draft: April 1, 2011
This draft: December 30, 2011

Abstract

We explore the properties of the global banking network using data on cross-border banking flows for 184 countries over 1978–2010. The global banking network is unstable and the empirical distributions of network indicators change markedly over time, especially for borrowers. Structural breaks in network indicators identify two waves of global capital flows leading up respectively to the 1997–98 East Asian crisis and the 2008–09 global financial crisis. While network density tends to expand and contract with the global cycle of capital flows, network indicators provide incremental information compared to aggregate flows. For example, network density before the global financial crisis was comparable to earlier peaks despite the historically unique build-up in aggregate flows. We also find that country-level financial interconnectedness falls in the aftermath of systemic banking crises and sovereign default episodes. The aftermath of the global financial crisis stands out as an unusual perturbation to the global banking network.

Keywords: cross-border banking, network analysis, financial interconnectedness, financial crises

JEL classification: F3, F4, G1

[±] Part of this work was undertaken while Javier A. Reyes was a Visiting Scholar at the IMF Institute (October 2010). We are grateful to Eugen Tereanu for his contribution in the early stages of this project. We thank the Bank of International Settlements (BIS) for providing us with data on BIS locational banking statistics on a bilateral basis. We thank Alina Carare, Mario Eboli, Patrick Imam, Tümer Kapan, Swapan-Kumar Pradhan, Marc Quintyn, Stefano Schiavo, and participants at the Joint DNB-EBC Conference on Banking and the Globalization of Finance (Amsterdam, May 2011), the 9th INFINITI Conference on International Finance Institutions, Actors and International Finance" (Dublin, June 2011), the 17th International Conference on Computing in Economics and Finance organized by the Society for Computational Economics (San Francisco, June 2011), and IMF seminars for useful comments and discussions. We are grateful to Ian Cooper, Patrick McGuire, and Mahvash S. Qureshi for extensive comments on previous versions of the paper. The views expressed in this paper are those of the authors and do not necessarily reflect those of the IMF or IMF policy. All remaining errors are our own.

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1. Introduction

Following the seminal work of Allen and Gale (2000), a growing literature argues that the structure of financial networks—notably, the pattern of interconnectedness—matters for how financial systems react to shocks. Higher levels of financial interconnectedness improve risk-sharing hence reduce the risk of contagion. But they can also increase it if negative shocks can reach further out through a complex web of relationships. Our aim is to contribute to this literature by taking the first step in assessing how the global banking system would react to negative shocks—that is, by describing its structure. To this end we rely on network analysis, a powerful methodological toolkit for modeling interactions between economic agents.[1] Network techniques have previously been used, for instance, to describe the global architecture of cross-border financial flows, assess the resilience of financial systems to shocks, and describe the dynamics of interbank markets.[2]

In this paper, we explore the properties of the global banking network (henceforth 'GBN') over the 1978–2010 period and assess its dynamics during financial crises. To describe the structure (or topology) of the GBN we use network indicators that capture the importance of countries in the network and the interconnectedness of the network as a whole. Our data represent changes in cross-border financial claims held by banks, provided by the Bank of International Settlements (BIS). In contrast to earlier studies, we describe geographical patterns in the GBN using cross-border flows rather than cross-border exposures. Unlike slowly-moving stocks of cross-border financial claims, flows are more likely to reflect liquidity conditions in international markets. Furthermore, they provide variation that is particularly informative of how the GBN changes during periods of economic stress.

Our main findings are as follows. First, the GBN is relatively unstable. Network indicators are volatile and have structural breaks which identify waves of capital flows such as the ones leading up to the 1997–98 East Asian crisis and the 2008–09 global financial crisis. In addition, the empirical distributions of network indicators change shape over time, especially for borrowers. Second, while network density tends to expand and contract with the global cycle of capital flows, network indicators do provide incremental information compared to aggregate flows. For example, network density before the global financial crisis was comparable to the levels attained before previous crises, while total banking flows had experienced an unprecedented build-up. Third, we find that financial interconnectedness falls in the aftermath of country-specific systemic banking crises and sovereign default episodes—a result that complements the literature on post-crisis access to international capital markets. Fourth, the aftermath of the 2008–09 global financial crisis stands out as an unusually large perturbation to the GBN, with several network indicators reaching historically low levels in 2008.

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[1] See Goyal (2007) for an introduction to network theory. For reviews of network theory applications in economics and finance, see Nagurney (2003) and Allen and Babus (2009).

[2] Recent contributions include, e.g., Garratt et al. (2011), Hale (2011), Sa (2010), Kubelec and Sa (2010), Hattori and Suda (2007), von Peter (2007) on the global financial architecture; Gai et al. (2011), Degryse et al. (2010), Gai and Kapadia (2010) on resilience to shocks; and Iori et al. (2008) and Soramaki et al. (2007) on interbank markets.

An important concern in using network techniques to analyze cross-country banking relationships is whether they provide incremental information compared to aggregate flows. Network analysis helps describe the profile of economic agents, institutions, or countries with so-called "network characteristics." These include concepts such as centrality, connectivity, and clustering—all of which describe in novel ways the web of relationships in which economic agents make decisions. Both academics and policy-makers believe that the complexity of this web of relationship, often referred to as "financial linkages," is partly responsible for the severity and wide reach of the 2008–09 US subprime crisis (Caballero, 2010; Haldane, 2009). As a result, they argue that network theories can be useful in modeling macroeconomic complexity, systemic risk, and the factors that cause seizures in financial markets (Tumpel-Gugerell, 2009). Researchers have been encouraged "to spend much more time modeling and understanding the topology of linkages among agents markets, institutions, and countries" (Caballero, 2010, p. 92). As we will show, network measures of financial linkages sometimes tell a different story than aggregate flows.

The focus of our paper is on the lending activity of international banks, which suffered a sharp drop during the global financial crisis. Cross-border bank loans (net of repayments) to advanced economies had reached almost US$ 4 trillion in 2007 and plummeted to less than negative US$ 1 trillion in 2008. Figure 1 shows cross-border bank loans relative to other capital flows (foreign direct investment and portfolio investment) over 1980–2010. Panels A and B, for advanced and developing economies respectively, show that the "great retrenchment" of capital flows in the wake of the US subprime crisis was heterogeneous across asset classes, but banking flows suffered the most (Milesi-Ferretti and Tille, 2011; Hoggarth et al., 2009). Notably, banking flows to emerging and developing nations had reached unprecedented levels of almost US$ 500 billion prior to the crisis, rivaling foreign direct investment as a source of private capital.

Our GBN refers to cross-border asset-side movements of financial capital held by banks, and comprises advanced economies that report bilateral positions to the BIS (reporting countries) as well as countries vis-à-vis which positions are reported (non-reporting countries). The former represent the *core* of the network, while the latter make up the *periphery*. Figure 2 depicts the core-periphery and the core-core networks in 1980 and 2007 (Panels A, B). The figure shows that the networks changed substantially during the last three decades. Connecting lines are more numerous, suggesting that bank relationships have expanded. They are also thicker, showing that flows have increased. Eastern Europe and the Middle East were the most integrated regions in 2007. The rise of international banking centers such as Bahrain, Cyprus, and Mauritius is also evident.[3] Although Figure 2 clearly depicts the expansion of the GBN, more could be said about the characteristics and dynamics of the network by analyzing its topology. In what follows, we use network indicators to explore the features of the GBN while paying special attention to the global waves of capital flows that took place in recent decades.

The remainder of this paper is structured as follows. In Section 2 we review studies that use a networks approach to analyze the architecture of cross-border financial flows, financial system resilience to shocks, and macroeconomic complexity. Section 3 describes the data and network

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[3] This mostly reflects activities by internationally active foreign banks (see, e.g., McGuire and Tarashev, 2006).

indicators. The properties of the GBN over the past three decades are described in Section 4. In Section 5 we document the behavior of financial interconnectedness during financial crises. Conclusions are presented in Section 6.

2. Related Studies

Our paper relates to three strands of literature which we briefly review here. The first uses network analysis tools to describe real-world financial networks. Work on topology of financial networks often provides ingredients for studies of financial linkages and systemic risk, in a theoretical or simulations-based framework (the second group).[4] The third group of studies refers to the problem of macroeconomic complexity and its role during financial panics.

Our work is closely related to Hale (2011), who defines the global network of bank relationships using data on banks' participation in lending syndicates during 1980–2010. The network has become more tightly connected over time and more asymmetric (that is, the skewness of network indicator distributions has increased), hence potentially more fragile (Sachs, 2010). Similarly, Hattori and Suda (2007) analyze the network of cross-border banking exposures over 1985–2006 and also report that the network became more interconnected over time, a finding echoed by Kubelec and Sa (2010) who analyze the global network of cross-country exposures for asset classes such as foreign direct investment and portfolio investment. Hattori and Suda (2007) also show that the network of bank exposures hardly changes during major events such as the Long Term Capital Management near-collapse or the East Asian crisis. Similar to Hale (2011) but unlike studies that focus on cross-border exposures, we find that the GBN changes markedly during times of financial stress, with the 2008–09 crisis standing out as an unusually large perturbation.

The theoretical literature on financial networks provides a rationale for analyzing real-world network topologies. Allen and Gale (2000) were the first to explore the link between a stylized four-bank network and its resilience to shocks. The authors consider two extreme cases: a "complete" network in which every bank is connected to every other bank and an "incomplete" network in which every bank is connected with fewer than all banks. Allen and Gale (2000) find that complete networks are more resilient to shocks due to risk sharing, while incomplete networks are more fragile as banks with fewer counterparties have difficulty diffusing shocks. Using Allen and Gale's setup, Leitner (2005) shows that financial linkages are desirable even if they act as conduits for contagion because they can motivate banks to bail each other out if they can coordinate to do so when contagion arises.

Focusing on more complex networks of banks, Nier et al. (2007) examine financial contagion through simulations.[5] The authors document a non-monotonic effect of bank connectivity on contagious defaults: at small levels of connectivity, a small increase in connectivity raises the

[4] Other network theory applications in finance have focused, for instance, on the ability of network-based measures to predict default (Marco and Varetto, 1994) or capture systemic risk (Tabak et al., 2011; Billio et al., 2010).
[5] The simulations-based literature on resilience of financial systems to shocks is large and fast-growing. Recent contributions include Gai et al. (2011), Gai and Kapadia (2010), Degryse et al. (2010), Georg (2010), Martinez-Jaramillo et al. (2010), and Alessandri et al. (2009).

likelihood of contagion, but in more interconnected networks, higher connectivity improves the ability of the financial system to absorb shocks. Similarly, Battiston et al. (2010) assess the link between network density, measured as the number of connecting links, and systemic risk in a model of the economy as a credit network. They argue that while higher connectivity allows for improved risk sharing, 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.

Networks have also been prominent in recent models of panic during financial crises. In this line of research, the focus is on the complexity of the environment in which economic agents operate. Recent contributions stress the importance of modeling the web of relationships and documenting how it changes during crises. Caballero and Simsek (2010) develop a model in which banks assess the health of their trading partners by collecting information about them. When financial distress hits the system, banks must collect information not only about their immediate trading partners, but also about the trading partners of those trading partners, and so on. At high levels of interconnectedness there comes a point when the information gathering process becomes too costly and is abandoned. As a consequence, banks withdraw from loan commitments and illiquid positions, and the financial crisis spreads. The model displays a "complexity externality" whereby market seizures occur because banks are increasingly reluctant to buy assets in a confusing and uncertain environment.

3. Data and Definitions

3.1. The BIS Locational Statistics

Our data are the BIS locational statistics on exchange-rate adjusted changes in cross-border bank claims. The data capture flows of financial capital channeled through the banking system in every country, and are well-suited for an analysis of geographical patterns in financial linkages across countries.[6] The sample period is 1978 to 2010 (up to 2010Q3 inclusive) and the sample contains 184 countries, of which 15 reporting countries and 169 countries vis-à-vis which bilateral positions are reported.[7] BIS locational statistics are compiled on the basis of *residence* of BIS reporting banks 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). The data are only available at the country level, after bank-level positions have been aggregated up. These positions include loans, deposits, debt securities, and other bank assets.[8] The cross-border flows are estimated as changes in cross-border stocks, and are adjusted for exchange rate

[6] By contrast, the locational statistics are unfit for analyzing the global balance sheets of banks, for which the BIS consolidated banking statistics are more appropriate (BIS, 2009).
[7] See Appendix Table A1 for the full country list.
[8] Although bank lending takes the lion's share total assets, as shown in Appendix Figure A1, banks' reliance on debt securities has increased over time (Fender and McGuire, 2010; McGuire and Tarashev, 2006).

changes, which makes them a better approximation of true flows than unadjusted changes in stocks (Wooldridge, 2002).[9]

3.2. The Network

Each of the 184 countries in our dataset is a *node* within the network, with nodes being linked through cross-border banking. Flows between countries are the *links*. A link exists if there is a *strictly positive* flow—corresponding to a net increase in cross-border bank assets of a reporting country vis-à-vis another country.[10] Positive flows are "net investments" of financial capital channeled through the banking system between the source and the destination country. All negative flows—"net repayments"—are replaced with zeros and are ignored in the analysis.[11] The resulting network is thus based on positive values (net investments) and zeros (net repayments or no flow).

The sample comprises 15 lenders (BIS reporting countries) and 169 borrowers (countries vis-à-vis which the lenders report bilateral positions). We work with annual data and model each year over the sample period (1978–2010) as a separate network. Three networks are of interest: (i) the core-core network, which refers solely to the 15 reporting countries; (ii) the core-periphery network, which refers to exchanges between the core (lenders) and the periphery (borrowers); and (iii) the full network, which considers simultaneously the core-core and core-periphery networks, and is closest to the "true" web of cross-border banking flows.

The limited coverage of our data calls for some caution in interpreting the results. The analysis is performed on the 15 economies that have submitted banking statistics continuously to the BIS since end-1977. Although the sample BIS reporting countries has expanded over time (to some 45 currently), we limit the analysis to the original reporting countries in order not to confound changes in the network with changes in sample composition.[12] Relatedly, since only a small number of countries report data to the BIS, we can only partly capture the "true" GBN. If all 184 countries in our sample reported data since late 1970s, there would be 184*183=33,672 possible links in the network. Our data captures 15*14=210 possible links in the core-core network, and 15*169=2,535 possible links in the core-periphery network, for a total of 2,745 links. This only represents 8.15 percent of the "true" GBN. It follows that we perform the analysis and interpret the results conditional on the set of reporting countries.[13]

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[9] It is unclear to what extent the BIS locational statistics reflect changes in market valuations and write-downs, as large parts of bank assets are not marked to market. It is therefore unlikely that many of the flows are due simply to such changes rather than new credit. For a discussion of this and related issues, see Gourinchas et al. (2011).
[10] The data are adjusted for inflation using the US Consumer Price Index for urban areas.
[11] The analysis of the network of negative flows, while potentially informative of patterns in capital reversals, is left for future research.
[12] See BIS (2009) for detailed information regarding the international banking statistics and the list of countries that report locational banking statistics (BIS, 2009, p. 5.).
[13] The data incompleteness described here is inherent in exercises of this kind, and is common to studies on global financial networks. Cerutti et al. (2011) provide for a detailed account of data limitations that hamper the analysis of interconnectedness in the global financial system.

3.3. Network Indicators

The network indicators we consider include measures of country centrality (degree and strength) and of network density (connectivity and clustering). To compute them, we build matrices M^t in every time period *t* where rows represent lenders and columns represent borrowers. Each entry m_{ij}^t is the value of the flow from country *i* to country *j* at time *t*. These matrices are 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.

3.3.1. Measures of Country Centrality

Node degree counts the number of connections (links) for each country (node). Since we work with a directed network, we have incoming links for borrowers and outgoing links for lenders. Therefore, we compute the *out-degree*, the number of outgoing links, for each lender by counting the countries to which it lends, and *in-degree*, the number of incoming links, for each borrower by counting the countries from which it borrows. Out-degree is given by $ND_{it}^{out} = A_{(i)}^t 1$ whereas in-degree is given by $ND_{it}^{in} = \left(A_{(i)}^t\right)'1$, 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 and the maximum number for out-degree is N^t.

Node degree captures the extent to which a country is well connected or "in the thick of things." A high node degree means that the node has a large neighborhood of local contacts, be it lenders or borrowers, and it is relatively prominent in its neighborhood. Node degree is thus an indicator of "local centrality." More sophisticated indicators measure the node's strategic significance in the overall network, or its "global centrality" (Scott, 2009). However, we are limited in undertaking such an analysis by the core-periphery structure of the dataset, with (non-reporting) countries in the periphery not being linked with each other except through the core.

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

Relative node strength goes one step further by identifying important nodes in the network not based on the total flows they originate or receive, but on the extent to which other countries in the network are dependent on these flows. According to this indicator, a lender is more important as a source of banking flows if it accounts for a larger (average) share of borrowers' inflows. Similarly, a borrower is more important as a destination for banking flows if it accounts for a larger (average) share of lenders' outflows. Relative node strength is thus an alternative way of assessing node importance which rescales size, captured by flows passing through each node (or node strength), by the total flows of either the lender or the borrower.[14]

To calculate *relative node out-strength* we define a borrower dependency matrix ($\tilde{M}^t$) where each cell $\tilde{m}_{ij}^t$ represents the ratio of inflows received by borrower *j* from each lender to *j*'s total inflows, further divided by the total number of borrowers for ease of interpretation. The indicator is given by $RNS_{it}^{out} = \tilde{M}_{(i)}^t 1$ and captures how dependent borrowers are on each lender. Similarly, *relative node in-strength* is defined by computing the lender dependency 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 outflows, divided by the total number of lenders. The indicator is given by $RNS_{it}^{in} = (\hat{M}_{(i)}^t)'1$ and captures how dependent lenders are on each borrower. This indicator takes values between 0 and 1, and also refers to the weighted network.

3.3.2. Measures of Network Density

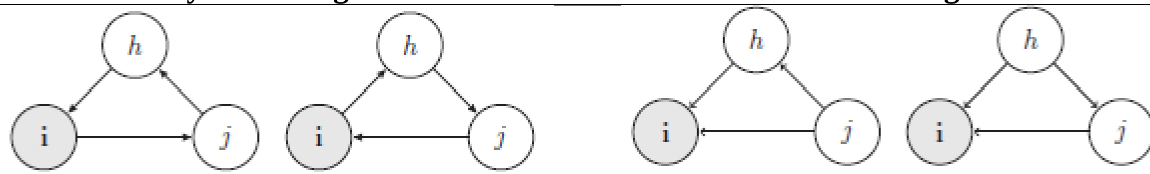
Network connectivity is the number of links that exist between countries expressed as a share of the total possible number of links.[15] Network connectivity represents the probability of a connection between two countries in the GBN. Let m_t be the observed number of links (corresponding to entries m_{ij}^t in the matrix M^t or 1's in the binary matrix A^t). Connectivity in the core-periphery network is given by $\left(m_t / 15 \times N^t\right)$.

Network clustering, measured with a clustering coefficient, is computed on the binary network and exploits its directed nature. The clustering coefficient represents the total number of triangles with a given flow pattern, divided by the total possible number of such triangles. For the core-core network we focus on the cycle triangle representation proposed by Fagiolo (2007), whereby every node has a cyclical relation with its two neighbors.[16] For the core-periphery network, we focus on the "in" representation, whereby flows from two lenders terminate into a periphery node. The triangles are depicted in Text figure 1 (Panels A, B). For the core-periphery network we also compute *regional* clustering coefficients by restricting the periphery node to belong to a certain region. The clustering coefficient ranges between 0 and 1, with higher values representing a more clustered network—one that has a greater share of trilateral relationships.[17]

[14] For a similar weighting scheme using GDP instead of total flows, see Fagiolo et al., 2009.
[15] As noted earlier, the total possible number of link is computed conditional on the structure of the dataset (210 links in the core-core network, 2,535 links in the core-periphery network, and 2,745 links in the full network).
[16] Tabak et al. (2011) used this and other triangle patterns to analyze systemic risk in the Brazilian interbank market.
[17] We are not considering weighted clustering coefficients because they can be sensitive to extremely large flows among nodes. Also not considered among our list of indicators is the average path length, which represents the average of the shortest distance between all pairs of countries. This indicator would be artificially large given our data structure, as non-reporting countries are only linked through the core (as opposed to directly).

Text figure 1. Complete triangles for clustering coefficients

Panel A. Core-core network "cycle" triangles	**Panel B. Core-periphery network "in" triangles**



Source: Fagiolo (2007).

4. Results

In this section we describe the properties of the GBN using the measures defined above. The aim is to determine how the web of country-pair banking relationships has changed over the past three decades, especially around periods of economic stress.

4.1. Network Connectivity during 1978–2010

Table 1 summarizes our key network indicators for the full, core-periphery, and core-core networks. In the full GNB, focusing on Panel A, we note that countries borrow on average from 5.1 lenders up to a maximum of 15, while the core countries lend to 56.8 borrowers, of which 9 are in the core and 47.8 in the periphery. Some US$ 75 billion are lent out on average across borders each year, of which two thirds to the core. The average borrower accounts for 0.7 percent of lenders' total outflows, whereas the average lender accounts for 6.2 percent of borrowers' total inflows.[18] In the core-periphery network, maximum relative in-strength is 23.6 percent (Hong Kong, 1994), whereas maximum relative out-strength is 29 percent (United Kingdom, 1997).

With regard to the density of the full network (Table 1, Panel B), the connectivity indicator, representing the likelihood that two countries are connected, ranges from 28.5 to 47.2 percent. In the core-core network, connectivity reached 79 percent before the 2008–09 crisis.[19] The average clustering coefficient in the full network—the probability of a trilateral relationship in which two countries lend to each other and also lend to a third country—is 8.1 percent. In the core-core network, where clustering is defined more restrictively by requiring that all relationships be reciprocal, the average probability is 12.6 percent, while clustering reached 26.8 percent before the global financial crisis.

The evolution of network indicators over time, depicted in Figure 3, suggests that that the GBN, like aggregate flows, follows a boom-bust cycle. The average number of outgoing links has

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[18] Relative in-strength distributions are highly skewed, as reflected in the discrepancy between means and medians, and the high standard deviation.

[19] To get a sense of these magnitudes, we take as a comparator the international trade network, which was analyzed for 159 countries over 1980–2001 by Fagiolo et al. (2009, 2010). To make the two networks comparable, we treat the GBN as an undirected network, set borrower outflows to zero, and re-scale connectivity using the true number of possible links (see Section 3.2). We find that connectivity in our GBN of flows ranges up to a maximum of 6.4 percent over the period compared to the 64.4 percent in the trade network (Fagiolo et al., 2009, p. 5).

steadily increased over time from about 40 to a peak of 60 countries before sharply dropping in 2008. In the run-up to major events such as the 1997–98 East Asian crisis and the 2008–09 global financial crisis, there was a noticeable build-up of connections between the core and the periphery (Panels A, C). In contrast, the long-term trend in the same indicators within the core has been relatively flat. However, they experienced declines to historically low levels in 2008 (Panels B, D). We explore how connectivity in the core-core network changed around major events in advanced economies such as the 1987 stock market crash, the 1991–92 Scandinavian banking crises, the 1992 Exchange Rate Mechanism (ERM) crisis, and the 2000 Internet bubble collapse by marking the dates of these major events in Panels B and D. Average degree, connectivity and clustering fell sharply in the aftermath of these episodes. This pattern is unique to the GBN of cross-border banking flows and has not been detected in earlier studies that examine cross-border exposures (e.g., Hattori and Suda, 2007).

4.2. Network Connectivity and the Global Cycles of Capital Flows

In analyzing the fluctuations in network indicators over 1978–2010, we mentioned two global waves of capital flows, respectively leading up to the 1997–98 Asian crisis and the 2008–09 crisis.[20] Changes in the topology of the GBN around these events are consistent with the dating of the global cycle of total private capital flows (IMF, 2007). We reinforce that dating with a series of unit root tests of one or two structural breaks in the mean developed by Clemente et al. (1998), which we apply to average degree, strength, connectivity, and clustering. The results (shown in Table 2) overwhelmingly identify a single break around 2001–03; or two breaks, the first in the mid-1990s, before the East Asian crisis, and the second at the start of the most recent wave. The core-core network seems once again more stable than the core-periphery network, having no breaks in any indicator except node strength, which captures the magnitude of flows across countries.

4.3. Network Indicators vs. Aggregate Flows

We explore whether network indicators offer supplementary information relative to aggregate flows by plotting average flows (per country) on the one hand, and measures of network density on the other (Figure 4). As expected, the density of the core-periphery network picked up visibly before the East Asian crisis and the global financial crisis, in line with the build-up of aggregate flows (Panel A). However, network clustering and connectivity increased less compared to aggregate flows in the build-up to these crises. Furthermore, network connectivity was roughly the same before the 1980s debt crisis, the East Asian crisis, and the global financial crisis, despite a five-fold increase in total flows over the period.

That aggregate flows do not tell the whole story is also evident in the core-core network (Figure 4, Panel B). On the one hand, average flows (per country) within the core have increased four-fold since 1980. On the other hand, network connectivity showed no apparent long-term trend and in 2007 was almost the same as in 1980. There were no unusual developments in the density

[20] Changes in the GNB in an earlier wave preceding the 1980s debt crisis are not analyzed as our sample starts in 1978.

of this network before the 2008–09 crisis apart from the standard boom-bust cycle. However, when the global financial crisis hit, connectivity in the core dropped by half, while clustering in the core all but vanished; in fact, both indicators attained their lowest levels ever in 2008. In contrast, in the same year aggregate flows "only" fell to their 1994 levels.

What could explain the virulence of the global financial crisis, especially the high death rate of links within the core, given that pre-crisis network density appears "normal" by historical standards? The literature on financial networks posits that more interconnected networks are more able to absorb shocks due to international risk diversification, but they also potentially harbor more systemic risk. We hypothesize that the severity of the global financial crisis cannot entirely be attributed to the network structure *per se*—that is, on increased financial interconnectedness worldwide—but rather on the *location* of the initial shock in the network. While the debt and the East Asian crises primarily afflicted countries in the GBN periphery, the global financial crisis started with a shock to its core nodes. As shown in Gai and Kapadia (2010) similar shocks can have different consequences for a financial system depending on the particular point in the network structure where the shock hits.

4.4. Stability of Network Indicator Distributions

A complementary way to assess changes in network connectivity is to look at the distributions of country-specific centrality measures and explore how they changed over time. First, we focus on two snapshots at the beginning and end of the sample period, and show nonparametric density estimates for degree and relative strength in 1980 and 2007 (Figure 5).[21] In the core-periphery network lender out-degree (the number of outgoing links) preserved its shape between 1980 and 2007, but shifted rightwards as lenders provided cross-border financial capital to a larger number of peripheral countries (Panel A). The distribution of in-degree (the number of incoming links) shifted rightwards as well with borrowers tapping into a larger pool of lenders by 2007 (Panel C). The density of in-degree became bimodal, which suggests that a large group of better-connected borrowers (with about 10 incoming links out of 15 possible) co-existed in 2007 with a large group of less connected borrowers (with half the number of incoming links).

The distributions of relative strength, or 'importance' in the core-periphery network, hint at dynamics suggesting greater homogeneity among lenders but greater heterogeneity among borrowers. The plot for relative out-strength (Panel B) shows that most lenders in 1980 provided about 5 percent of flows to any given borrower; that number had become about 10 percent by 2007. Put differently, relative importance has been shared more equally among lenders. In contrast, the distribution of relative in-strength (Panel D) depicts an increasing inequality of flow volumes among borrowers between 1980 and 2007, hinting at a more polarized periphery. In the core-core network (Panels E, F), while there is almost no change in the relative strength distribution, the variance of the degree distribution shrank. Taken together, these patterns suggest that the core has become more homogenous while the periphery has become more heterogeneous over the period.

[21] We chose 1980 and 2007 because they were tranquil years at the beginning and end of our sample period.

In addition to analyzing snapshots of the network indicator distributions, we also develop a global measure of how the distributions changed over time. For that, we undertake a series of two-sample Kolmogorov-Smirnov tests. The null hypothesis is that the observed empirical distributions at two points in time are close enough to not reject that they are drawn from the same data generating process. We run the test for each indicator by comparing its empirical distribution in the first year of each decade with subsequent years, within the same decade and in later decades. In Table 3 we report the proportion of years in each decade when empirical distributions of network indicators were statistically *different* than at the beginning of the decade at the 5 percent level of significance.

On the borrower side, we find that network indicator distributions at the beginning of each decade were poor 'predictors' of future ones (Table 3, Panel B). Further out distributions are more likely to be statistically different from the original distribution. For instance, the distribution of relative in-strength was statistically "the same" throughout the 1980s as at the beginning of the decade in all but one year. Throughout the 1990s the distribution of relative in-strength was different than in 1980 half of the time. Throughout the 2000s the distributions were statistically different from the 1980 distribution in all but one year. Put differently, the likelihood of encountering the initial distribution of relative in-strength drops over time from 90 percent in the 1980s to 50 percent in the 1990s and to 10 percent in the 2000s. By contrast, the distributions of lender centrality measures have been relatively more stable within and across decades (Panel A). For example, the out-degree distribution in 1980 is frequently found to be statistically "the same" as in subsequent years. Thus, in the core-periphery network, relatively unstable borrower centrality distributions have co-existed over time with relatively stable lender distributions.

4.5. Country Rankings: Top Players in the GBN

Two questions arise from the patterns discussed in the previous section. The first is whether the empirical distributions of network indicators underpin stable or turbulent country rankings. A network can have unstable indicator distributions but stable rankings if over time nodes retain their relative places in terms of centrality but bundle up to generate distributional mass in diverse ways. Similarly, a network can have stable indicator distributions and unstable rankings if countries swap places in terms of centrality in the network. A second question concerns which countries and regions are most interconnected. Identifying the top players in the GBN, especially on the lender side, is informative as they likely host systemically important financial institutions.

To answer the first question, we calculate 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 rankings turbulence, or conversely, shape-altering rankings stability. The RSI for degree and relative strength for countries in the core-periphery network is depicted in Figure 6.[22]

[22] To avoid sample composition effects, we restrict the analysis to borrowers that have been present in the sample during the full period.

On the lender side, the RSI for relative out-strength rankings has been relatively stable at around 0.7–0.8 over the period (Panel A), but more turbulence is apparent in the out-degree rankings. The borrower RSI for relative in-strength displays a smooth upward trend and had stabilized at around 0.85 by the end of the sample period (Panel B). Figure 6 suggests that the empirical distributions in the core-periphery network, which have been more stable for lenders than for borrowers, share a common trend towards higher rankings stability.

Focusing on the top end of the distributions, we report the first ten lenders in terms of degree and strength for 1980, 1995, and 2007 (Table 4). The most interconnected lenders by these measures are France, Germany, Switzerland, and the United Kingdom, with Japan and the United States joining the top ranks in terms of total flows and relative importance (Panel A).[23] On the borrower side, each wave of capital flows brought new borrowers to the top of the GBN (Panel B).[24] In 1980 Latin American countries (Argentina, Brazil, Chile, Mexico, and Venezuela) were the most interconnected in the network. By 1995 they had given way to the fast-growing East Asian countries (Indonesia, Philippines, Thailand) while the BRIC (Brazil, Russia, India, and China) also began their ascending path. By 2007 the BRIC had become the most interconnected borrowers alongside emerging Europe (Poland, Romania, Ukraine).

4.6. Regional Heterogeneity

Global averages of network indicators conceal regional heterogeneity. In Figure 7 we plot average degree, in-strength, and the regional clustering coefficients for the following regions: Europe and Central Asia, Latin America and Caribbean, South Asia, East Asia and Pacific, Middle East and North Africa, and Sub-Saharan Africa. The leading region in terms of interconnectedness is Europe and Central Asia, with the highest average in-degree (number of incoming links) and clustering (likelihood of forming triplets with the core) over the period. During the last wave, it also received the largest cross-border banking flows.

Figure 7 also shows that network indicators provide incremental information compared to aggregate flows (as discussed in Section 4.3). Average flows per country to the East Asia and Pacific region display strong cyclicality, with the most notable peak occurring prior to the Japanese crisis in the early 1990s. Despite four noticeable surges in total lending to the region, changes in degree and regional clustering have been relatively muted. For instance, regional clustering prior to the East Asian crisis was only half the level attained before the global financial crisis. In a similar vein, during the last wave South Asia became as integrated in the GBN as Latin America, as depicted by higher degree and clustering. Nevertheless, the intensity of flows to this region remained low compared to Latin America.

A feature all regions share is the unprecedented collapse in both regional network density and aggregate inflows during the global financial crisis.

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[23] In a recent study, 18 large complex financial institutions in the global financial system were ranked according to size of assets under management (IMF, 2010). The jurisdictions where they operate include the top-ranked players in our GBN (France, Germany, The Netherlands, Switzerland, United Kingdom, and United States).

[24] We exclude high-income countries from borrower rankings. Including them brings to the top countries such as Australia, Finland, Greece, Portugal, and Spain.

5. The Global Banking Network during Financial Crises

We conclude the topological exploration of the GBN by examining its behavior before, during, and after financial crises. Cetorelli and Goldberg (2011) identified cross-border bank linkages as a leading transmission channel of the 2007–08 subprime crisis worldwide. They argue that domestic loan supply contracted due to the collapse of direct cross-border lending by foreign banks, as well as a general weakening of bank balance sheets caused by shortages of liquidity. We visualize changes in cross-border banking flows in the quarter before and after the Lehman Brothers bankruptcy in Figure 8. In 2008Q4 connectivity was substantially lower in both networks, reflecting the high death rate of links as cross-border banking flows dried up.

To assess the behavior of country centrality measures during financial crises, we focus on two types of events, systemic banking crises and episodes of sovereign debt, as defined by Laeven and Valencia (2008, 2010). Systemic banking crises occur when a country's financial institutions have difficulties meeting contractual obligations and the financial sector as a whole experiences a large number of defaults. Sovereign debt episodes are timed based on the date of sovereign debt default vis-à-vis private creditors and debt restructuring. There is a strong link between banking and sovereign debt crises, with the former often preceding the latter (Reinhart and Rogoff, 2011). Our sample contains a total of 93 systemic banking crises during 1982–2003 (that is, within at least five years of the sample endpoints) and 47 sovereign defaults.

We plot average degree and strength across countries within a five-year window around the onset of crises in Figure 9. Borrower centrality in the GBN falls during systemic banking crises, but the decline generally begins before the event (Panels A, C). Out-degree and out-strength also fall despite the paucity of financial crises in source countries before 2007. For sovereign debt episodes we only focus on borrowers since the lenders did not experience sovereign debt crises over the period; we find the same pattern (Panels B, D). In addition, borrowers that experience sovereign default do not attain pre-crisis connectivity levels during the five years after the event. To take advantage of the variation afforded by recent systemic banking crises in the core, we also incorporate the events of 2007−08 into the sample but restrict the window to –5 years/+2 years around the onset of crises. As shown in Figure 10, measures of financial connectedness for lenders sharply decline during the two years after systemic banking crises, reflecting the unusually large impact of the global financial crisis on the GBN.

To formalize the analysis we estimate a simple regression model to document the evolution of borrower centrality measures around financial crises. Specifically we regress in-degree, in-strength, and relative in-strength on a set of dummies for pre- and post-crisis years while controlling for country fixed effects.[25] We estimate the model with Ordinary Least Squares (OLS) and consider specifications with and without time effects to assess the robustness of the estimated coefficients. With time effects we can account for pre-existing trends in financial

[25] We exclude the 2007–08 crises since they would render impossible an analysis of lagged effects beyond two years. Furthermore, because of a lack of financial crises in the core before 2007, we focus solely on borrower centrality measures.

interconnectedness, while without them there is less danger of over-fitting the model.[26] In-strength is log-transformed to reduce skewness. Notably, we interpret our regression results are solely indicative of statistical correlations as we do not aim to establish causality.

The results (reported in Table 5) show that borrower interconnectedness falls in the aftermath of systemic banking crises. In the five years after the onset, borrowers on average lose access to 2.5 lenders (out of 15)[27] and about 90 percent of banking inflows (Panel A, columns 1, 3).[28] In the two years after the crisis, relative borrower importance decreases by 0.16 percentage points (column 2), which is about one fifth of mean relative in-strength in the sample. While post-crisis changes in network measures are statistically significant, there is little evidence of a rise in country-level interconnectedness before banking crises. In contrast, for sovereign debt crises the estimates suggest a large increase in pre-crisis borrower centrality, according to all indicators considered, followed by a decrease in the next two years (columns 4–6). The results appear robust to adding time effects (Panel B) although some coefficient estimates lose statistical significance, likely due to multicollinearity among the dummies. F-tests for joint statistical significance of the coefficients on the leads and lags around crises consistently reject the null of zero effect, suggesting that the behavior of financial interconnectedness indicators is systematically different around crises compared to tranquil times.

The boom-bust cycle in centrality measures around financial crises is visualized by plotting the estimated coefficients against time, with 0 representing the onset of the crisis, in Figure 11. The plots show that before crises, especially sovereign defaults, borrowers become markedly more central in the network, while in the aftermath of crises, especially banking crises, they experience lower financial interconnectedness. These results bring a novel, network-based perspective to describing the post-crisis dynamics of market access, thus complementing the cost-of-default literature. The latter has shown that aggregate capital inflows across different classes and to a wide range of economic agents experience drastic reductions after sovereign default and debt restructuring episodes (Fuentes and Saravia, 2009; Arteta and Hale, 2008). Nevertheless, a more thorough econometric analysis is needed to establish the causal impact of financial crises on network indicators of centrality. Our findings are also complementary to Hale (2011), who examines the link between banking crises and local recessions on the one hand, and network measures of financial interconnectedness on the other. Hale (2011) finds that macroeconomic shocks affect bank relationships, but the impact depends on the persistence of the shock. Temporary shocks tend to increase the number of new links, whereas long-lived recessions tend to reduce it.

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[26] Since in-degree is a count variable, we also estimated a Poisson model with fixed effects but the results were qualitatively very similar and are not reported.

[27] The cumulative marginal effect for in-degree is calculated as: $(-0.6)+(-1.26)+(-0.63)=-2.5$.

[28] The cumulative marginal effect for in-strength is calculated as:
$\left(\exp(-0.11)-1\right)+\left(\exp(-0.63)-1\right)+\left(\exp(-0.41)-1\right)=-0.91$.

6. Concluding Remarks

The structural properties and dynamics of the network of cross-country financial linkages are crucial to understanding how the global financial system reacts to shocks, and whether and where systemic risk emerges. In the aftermath of the global financial crisis, network techniques are considered as a promising methodological toolkit for exploring patterns of financial interconnectedness. In this paper we analyzed geographical linkages created by cross-border banking activities in 184 countries from 1978 to 2010. Using indicators of country centrality and network connectivity, we assessed the importance of borrowers and lenders in the network, described network dynamics, and determined how connectivity changes before, during, and after the onset of financial crises.

Our results suggest that the global banking network is relatively unstable, with empirical distributions of network indicators that change markedly over time, especially for borrowers. The core, comprising the lenders, has become more homogenous, while the periphery, comprising the borrowers, has become more polarized. Structural breaks in network density and country centrality identify two global waves of capital flows respectively preceding the 1997–98 East Asian crisis and the 2008–09 global financial crisis.

We also find that network indicators provide incremental information compared to aggregate flows despite the fact that network density tends to expand and contract according to the global cycle of capital flows. For instance, while total flows experienced a historically unique build-up in the wake of the global financial crisis, pre-crisis network density levels were similar to those experienced before other major events. Nevertheless, the aftermath of the global financial crisis stands out as an unusually large perturbation to the network, with a number of indicators reaching historically low levels in 2008. Finally, we provide evidence that financial interconnectedness of countries, measured by network centrality indicators, tends to fall after the onset of financial crises, and to increase prior to sovereign default episodes.

A number of questions related to our analysis could provide fruitful ground for future research. One challenge is to integrate the stylized features of the global financial network into models of systemic risk. For that, topological studies of financial networks are needed, covering more asset classes when data are available and expanding the analysis with additional network indicators. It would also be interesting to explore the link between network-based measures of financial interconnectedness on the one hand, and the timing, duration and severity of crises on the other. Network analysis tools have the potential to provide useful new insights in these and related topics.

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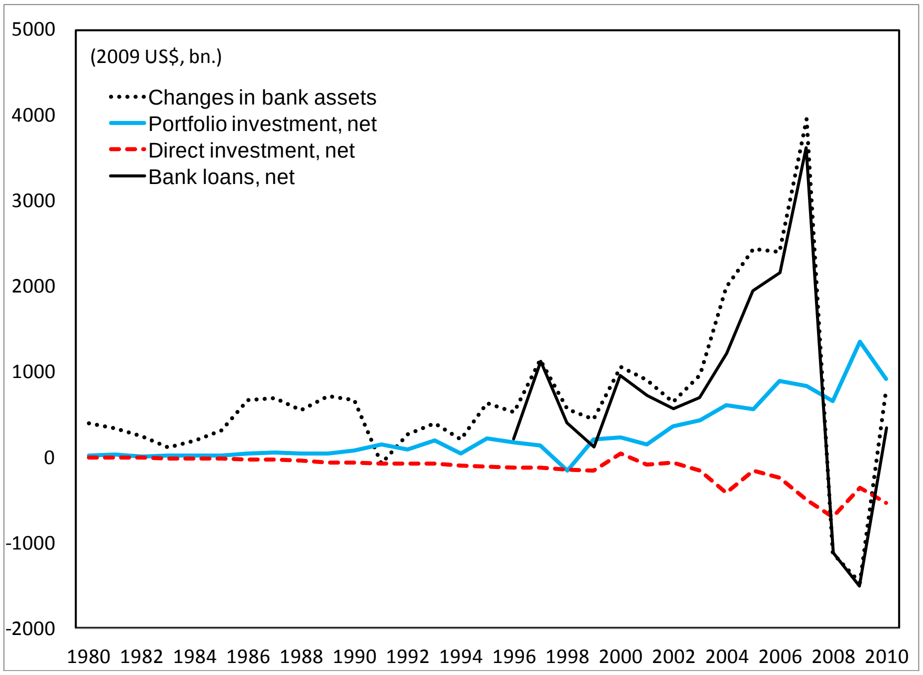
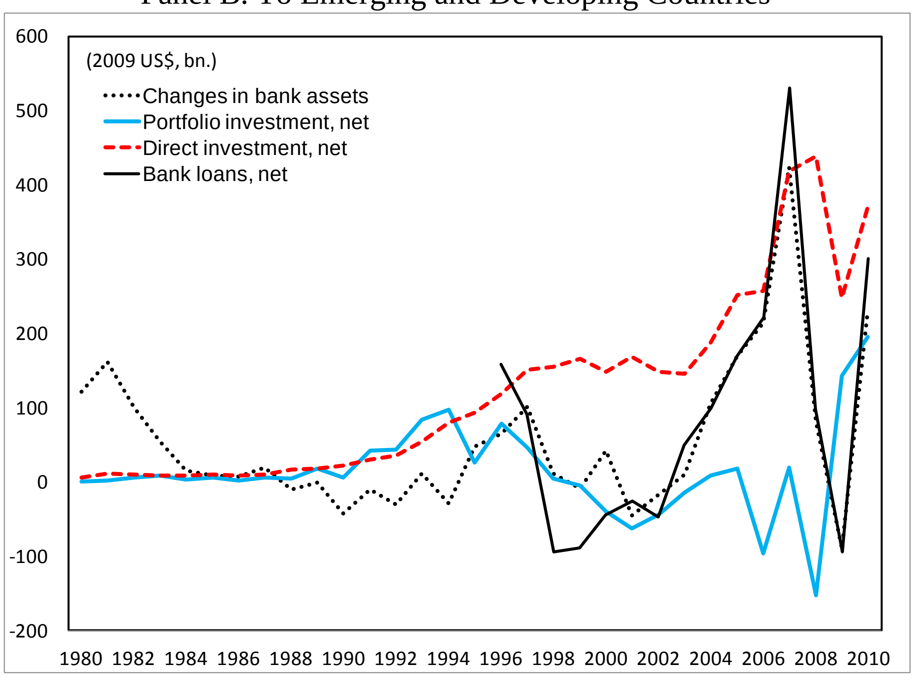
Tables and Figures

Figure 1. Private Capital Flows, 1980–2010

Panel A. To Advanced Economies



Panel B. To Emerging and Developing Countries

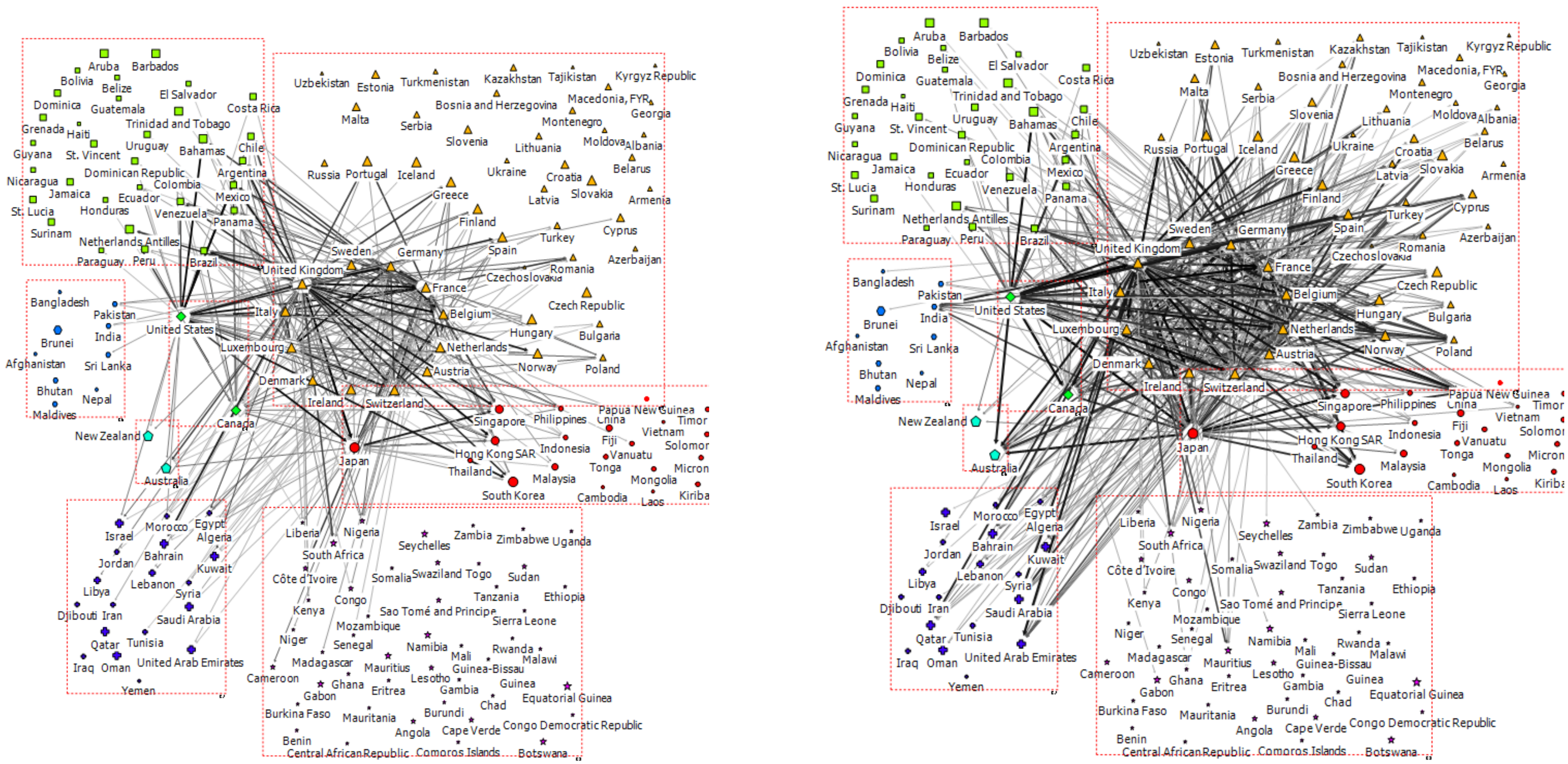


Source: Authors' calculations using BIS locational banking statistics (Table 7a for bank loans); World Economic Outlook for portfolio investment and direct investment.

Figure 2. Global Banking Network: 1980 vs. 2007

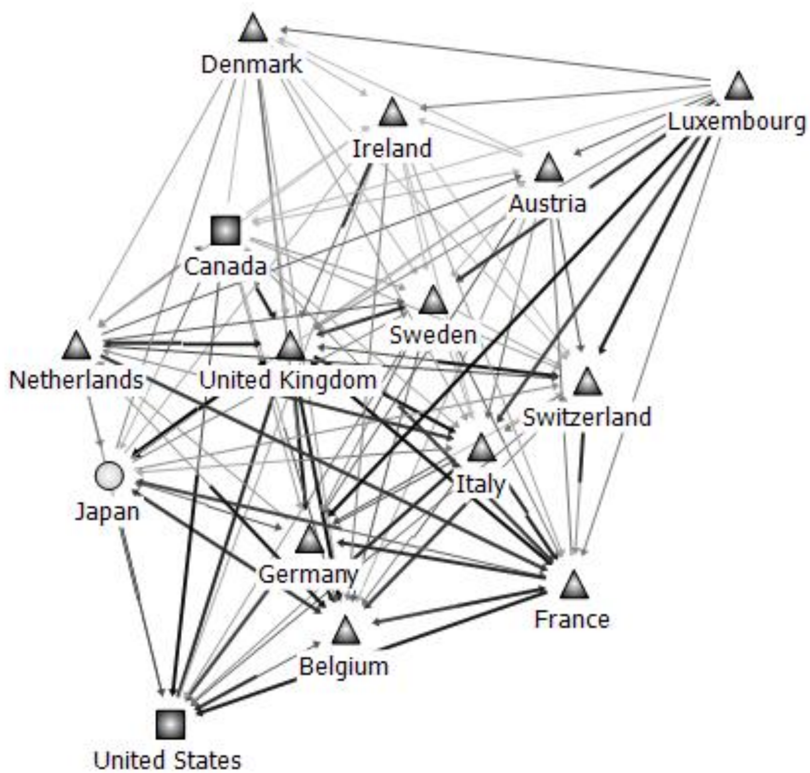
Panel A. Core-periphery

1980 **2007**

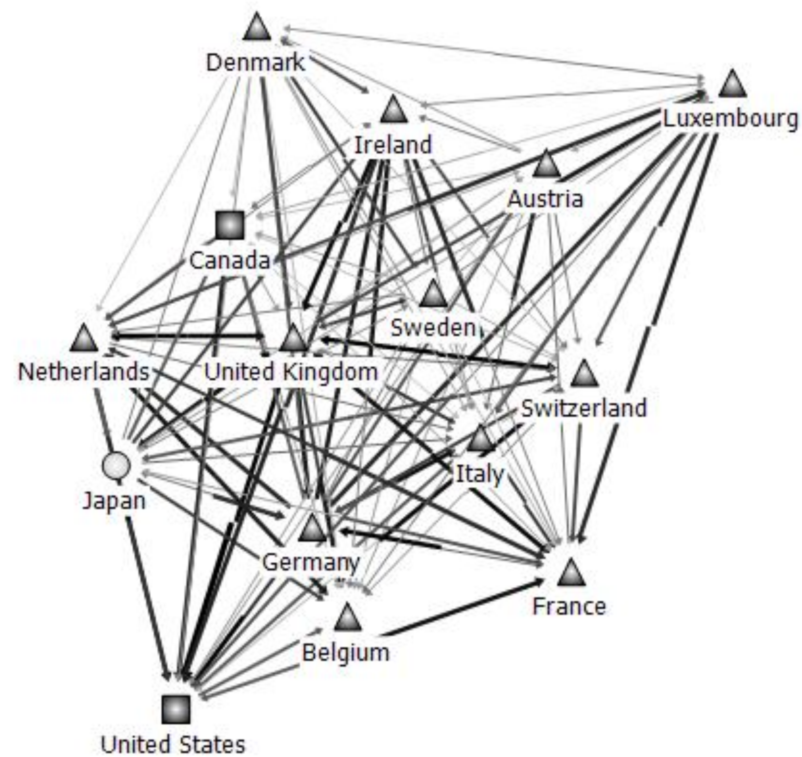


Panel B. Core-core

1980



2007



Source: Authors' calculations using BIS locational banking statistics.
Note: The countries represent nodes and the links between countries represent cross-border banking flows. Thicker and darker colored links indicate larger flows. In Panel B, which refers to the 15 BIS reporting countries, arrows indicate the direction of the flows. When reciprocal flows occur, the connecting link is split into two, each half-link reflecting the magnitude of one flow.

Table 1. Summary Statistics

Network	Units	Obs.	Mean	Median	St. Dev.	Min	Max
		Panel A. Country Centrality Measures					
Full							
In-degree	# links	5,470	5.1	5.0	3.6	0.0	15.0
In-strength	US$ bn.	5,470	6.8	0.1	31.1	0.0	890.7
Relative in-strength	%	5,470	0.6	0.02	2.0	0.0	24.4
Out-degree	# links	495	56.8	55.0	19.6	6.0	123.0
Out-strength	US$ bn.	495	74.6	33.3	114.1	0.2	1,212.6
Relative out-strength	%	495	6.2	4.5	5.5	0.0	29.7
Core-periphery							
In-degree	# links	4,975	4.8	4.0	3.4	0.0	15.0
In-strength	US$ bn.	4,975	2.0	0.1	8.3	0.0	190.0
Relative in-strength	%	4,975	0.7	0.1	1.8	0.0	23.6
Out-degree	# links	495	47.8	46.0	18.9	1.0	109.0
Out-strength	US$ bn.	495	20.2	8.2	31.5	0.0	252.3
Relative out-strength	%	495	6.2	4.4	5.5	0.0	29.0
Core-core							
Degree	# links	495	9.0	9.0	2.6	1.0	14.0
Strength	US$ bn.	495	54.5	24.8	88.4	0.1	960.3
Relative strength	%	495	6.6	4.5	6.9	0.0	39.3
		Panel B. Network Density Measures					
Full							
Connectivity	% links	33	34.7	33.8	4.7	28.5	47.2
Binary clustering	% triangles	33	8.1	7.8	3.6	1.2	17.4
Core-periphery							
Connectivity	% links	33	31.9	59.1	4.5	25.9	44.5
Binary clustering	% triangles	33	6.9	7.8	3.3	1.2	16.0
Core-core							
Connectivity	% links	33	64.4	30.4	10.1	30.5	79.0
Binary clustering	% triangles	33	12.6	13.0	7.2	0.0	26.8

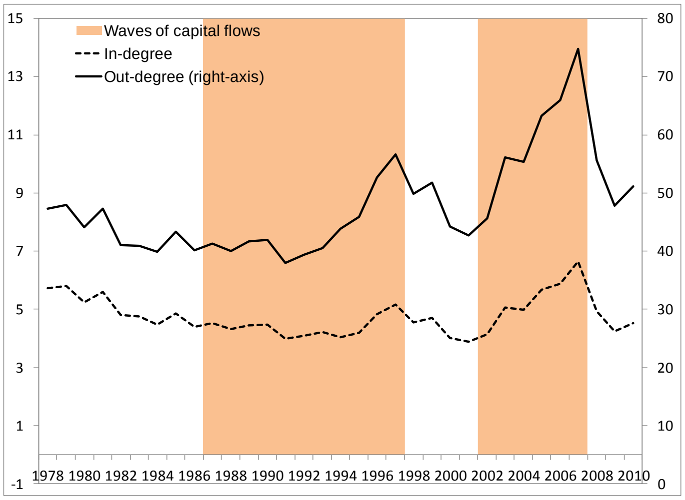
Source: Authors' calculations using BIS locational banking statistics.
Notes: See Section 3.3 for definitions of the network indicators. Strength indicators are expressed in 2009 constant prices.

Figure 3. Trends in Network Indicators, 1978–2010

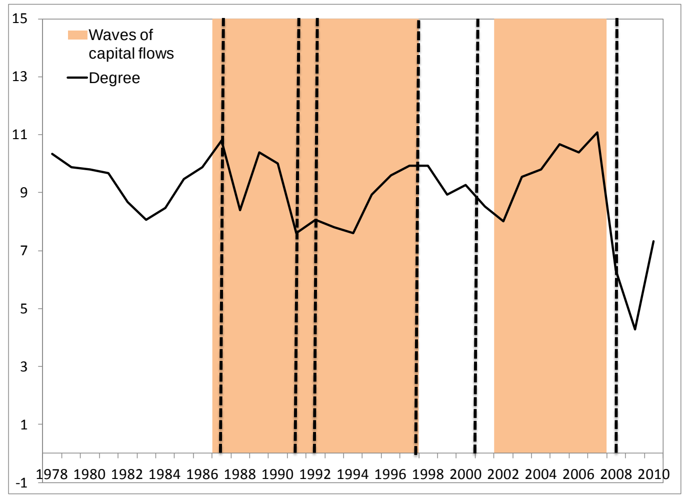
Core-periphery **Core-core**

Average number of links

Panel A

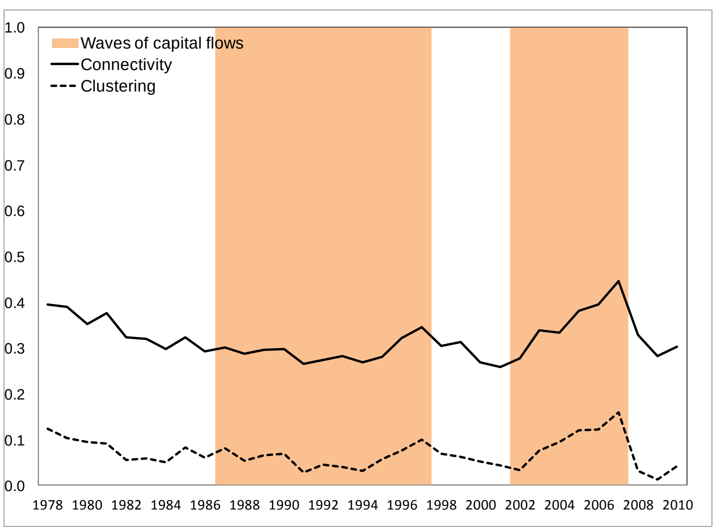


Panel B

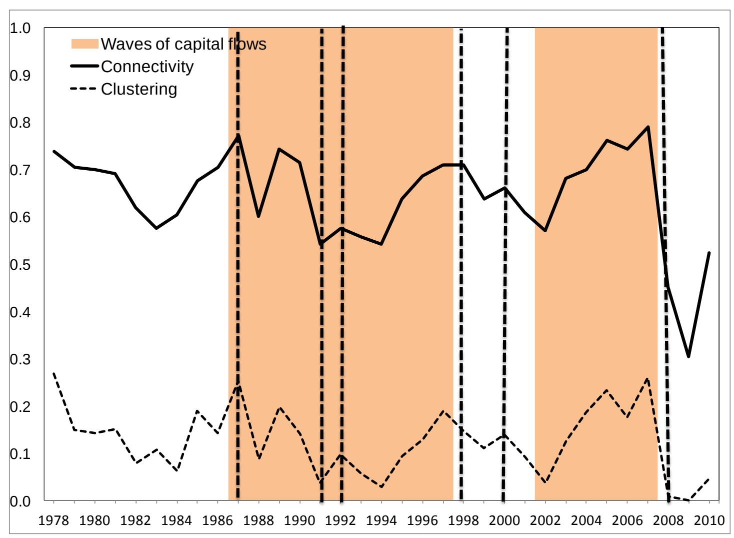


Connectivity and clustering

Panel C



Panel D



Source: Authors' calculations using BIS locational banking statistics.
Notes: In all panels we superimpose the dates of the two global waves of capital flows discussed in the text: 1987–98 and 2002–08 taken from IMF (2007). In the right hand-side panels we also superimpose the dates of major events in advanced economies such as the 1987 stock market crash, the 1991–92 Scandinavian banking crises and 1992 ERM crisis, the 1998 LTCM near-collapse, the 2000 Internet bubble collapse, and the 2008 Lehman Brothers bankruptcy.

Table 2. Unit Root Tests for Empirical Moments of Network Indicators

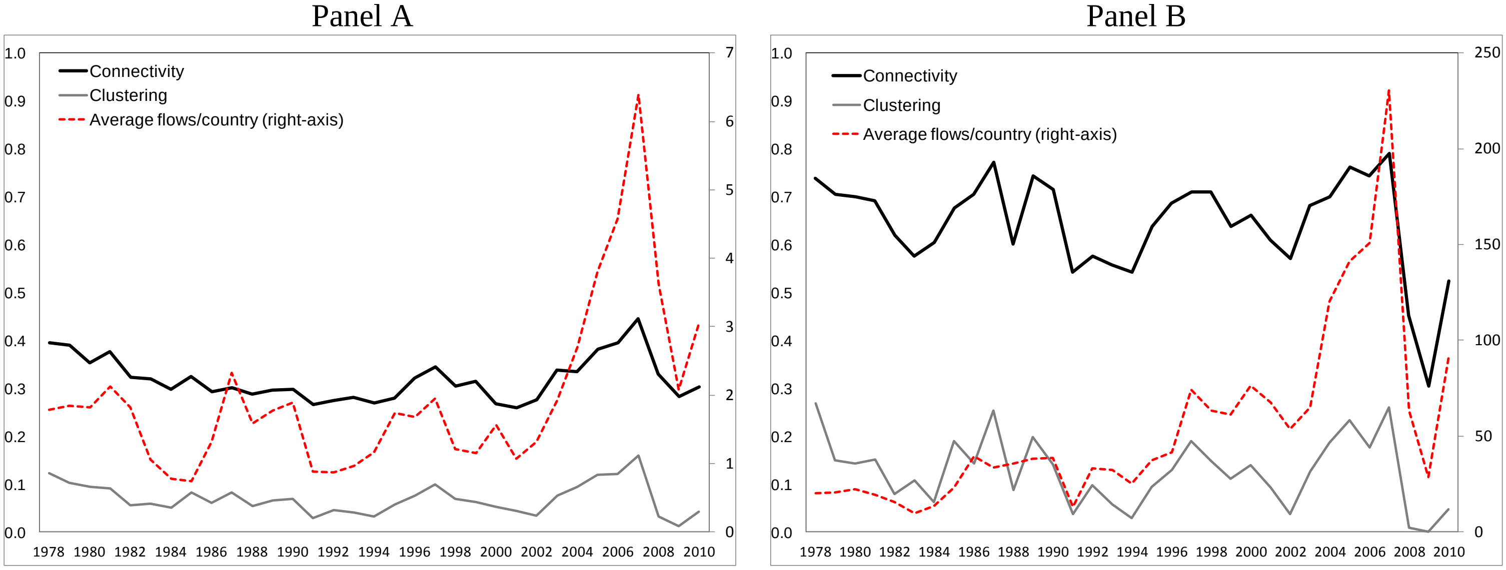
Network	One-break test		Two-break test			
	Break date	p-value	First break date	Second break date	p-value first break	p-value second break
Core-periphery						
Out-degree	**2001**	0.000	**1994**	**2003**	0.001	0.001
In-degree	**2001**	0.008	**1980**	**2003**	0.192	0.076
Out-strength	**2003**	0.000	**2002**	**2004**	0.012	0.008
In-strength	**2003**	0.000	1981	**2003**	0.411	0.000
Connectivity	**2001**	0.006	1980	2003	0.222	0.081
Clustering	2001	0.300	1980	**2001**	0.679	0.035
Core-core						
Degree	1988	0.692	1989	1993	0.163	0.265
Strength	**2003**	0.029	**1995**	**2003**	0.007	0.018
Connectivity	1988	0.692	1989	1993	0.163	0.265
Clustering	2001	0.798	1986	2001	0.476	0.301

Source: Authors' calculations using BIS locational banking statistics.
Notes: The tests refer to the core-periphery network and are run on annual series. Years in boldface identify the structural breaks that are statistically significant at the 5 percent level of significance.

Figure 4. Network Indicators vs. Aggregate Flows, 1978–2010

Core-periphery | **Core-core**

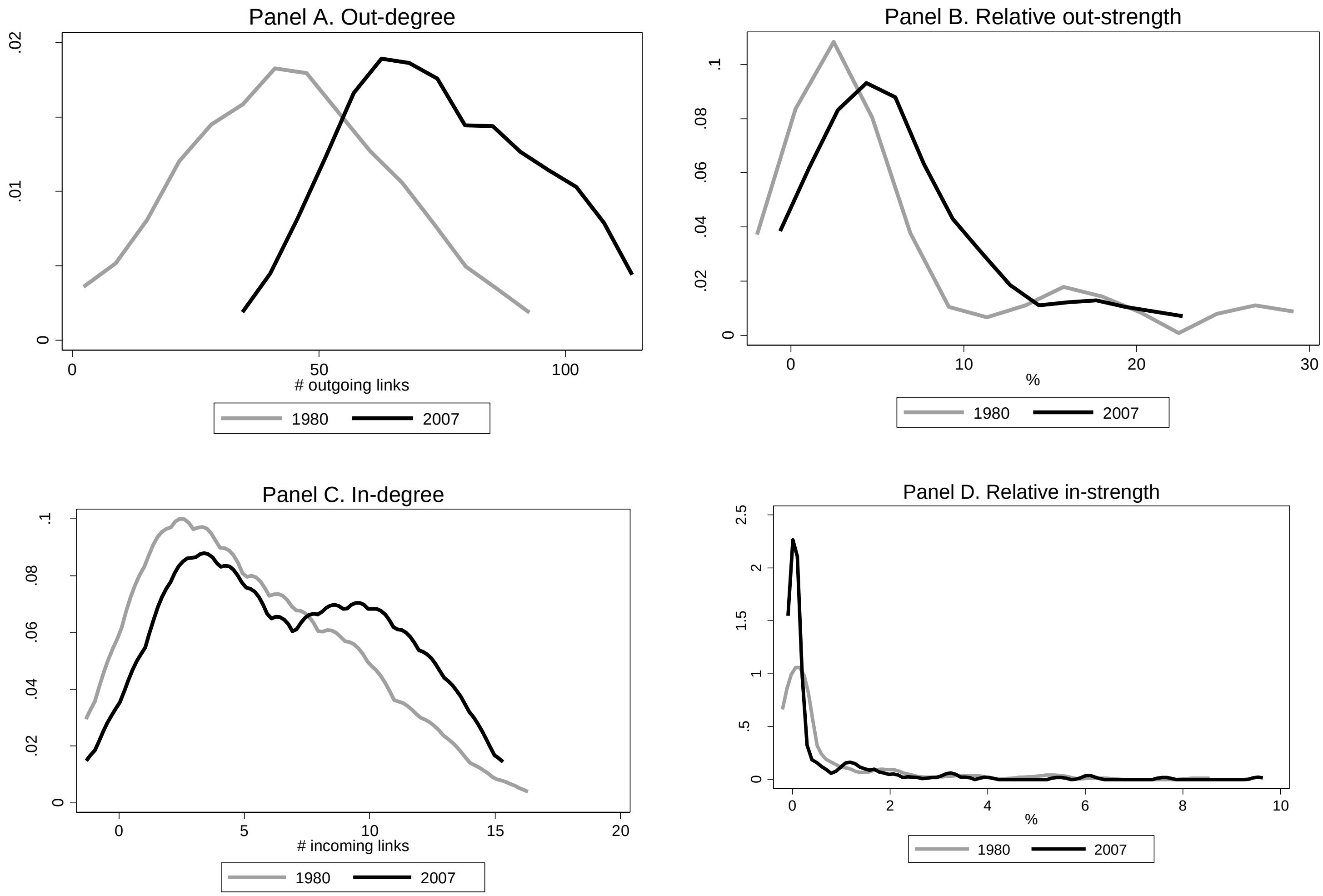
Panel A | Panel B



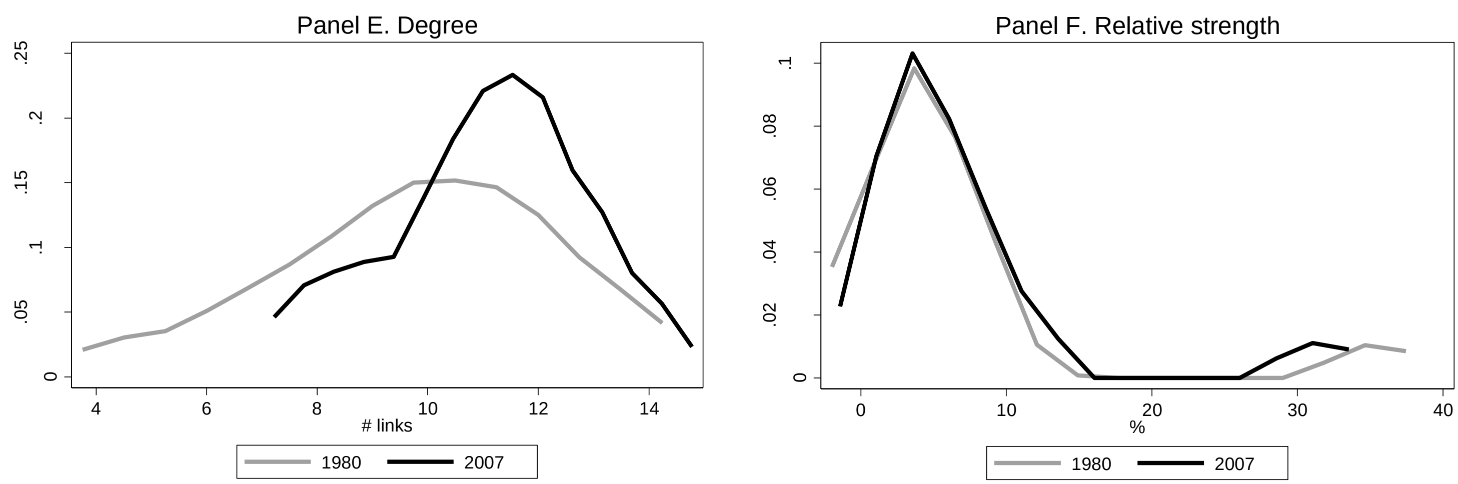
Source: Authors' calculations using BIS locational banking statistics.
Notes: Connectivity and clustering are measured in percent, while average flows/country (in-strength) are reported in US$ 2009 bn.

Figure 5. Empirical Distributions of Network Indicators: 1980 vs. 2007

Core-periphery



Core-core



Source: Authors' calculations using BIS locational banking statistics.
Notes: The results refer to the core-periphery network. The density estimates were obtained using the kernel density estimator with Epanechnikov kernel and an optimal bandwidth (Silverman, 1986).

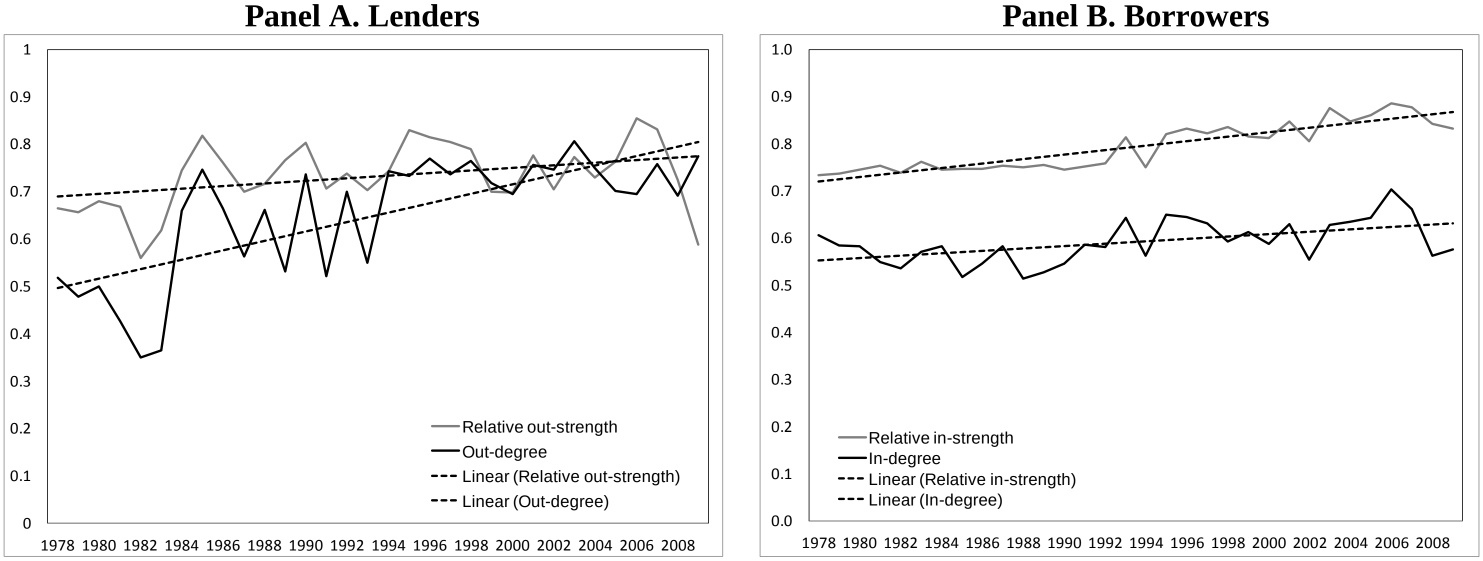
Table 3. Kolmogorov-Smirnov Tests for Network Indicator Distributions

Panel A. Lenders				Panel B. Borrowers			
Out-degree				**In-degree**			
	1980	1990	2000		1980	1990	2000
1980s	0			1980s	0		
1990s	0	10		1990s	20	0	
2000s	20	60	30	2000s	40	30	50
Out-strength				**In-strength**			
	1980	1990	2000		1980	1990	2000
1980s	0			1980s	60		
1990s	0	0		1990s	100	20	
2000s	50	50	70	2000s	60	40	40
Relative out-strength	1980	1990	2000	**Relative in-strength**	1980	1990	2000
1980s	0			1980s	10		
1990s	0	0		1990s	50	10	
2000s	50	0	0	2000s	90	80	0

Source: Authors' calculations using BIS locational banking statistics.
Notes: The results refer to the core-periphery network. The table reports the proportion of years in which the empirical distribution of each network indicator was statistically "different" from that in the year indicated as column head. For instance, the figure 20 in the out-degree indicator (Panel A) signifies that in 20 percent of years throughout the 2000s (i.e., 2 years) the empirical distribution of out-degree was different than that in 1980. Conversely, in 8 out of 10 years throughout the 2000s, the distribution of out-degree was statistically "the same" as in 1980. The figures are based on Kolmogorov-Smirnov tests at the 5 percent level of significance.

Figure 6. Ranking Stability Indices

Panel A. Lenders **Panel B. Borrowers**



Source: Authors' calculations using BIS locational banking statistics.
Notes: The results refer to the core-periphery network. See Section 4.5 for definition of the Rankings Stability Index. In both panels we superimpose a linear trend.

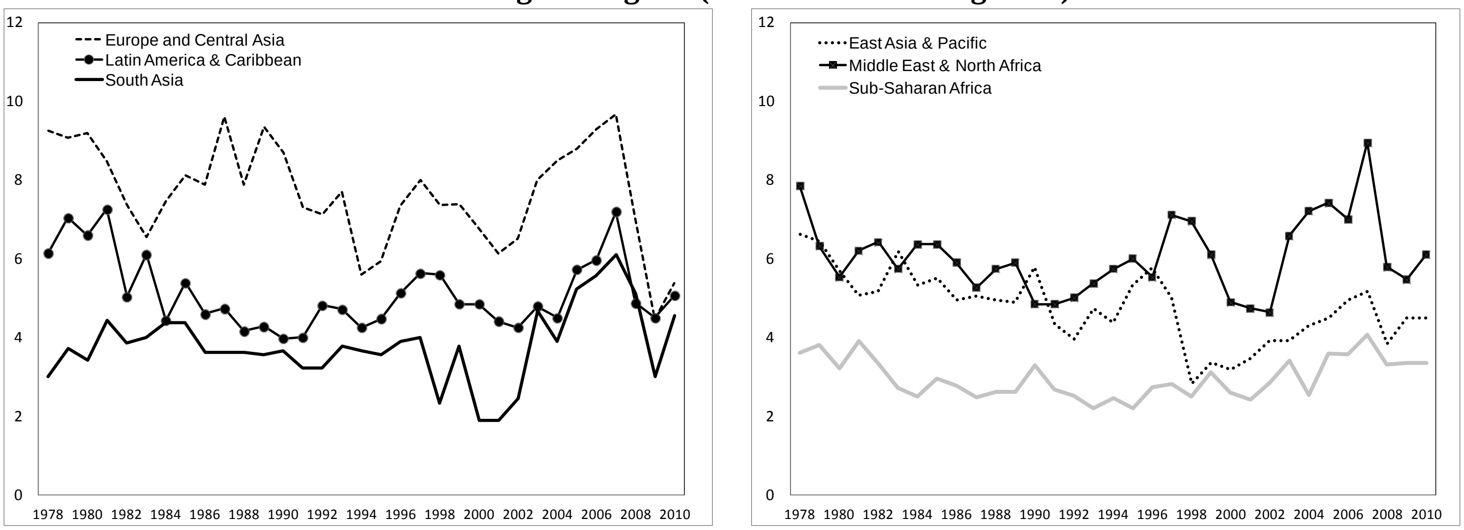
Table 4. Centrality-based Country Rankings: 1980, 1995, and 2007

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

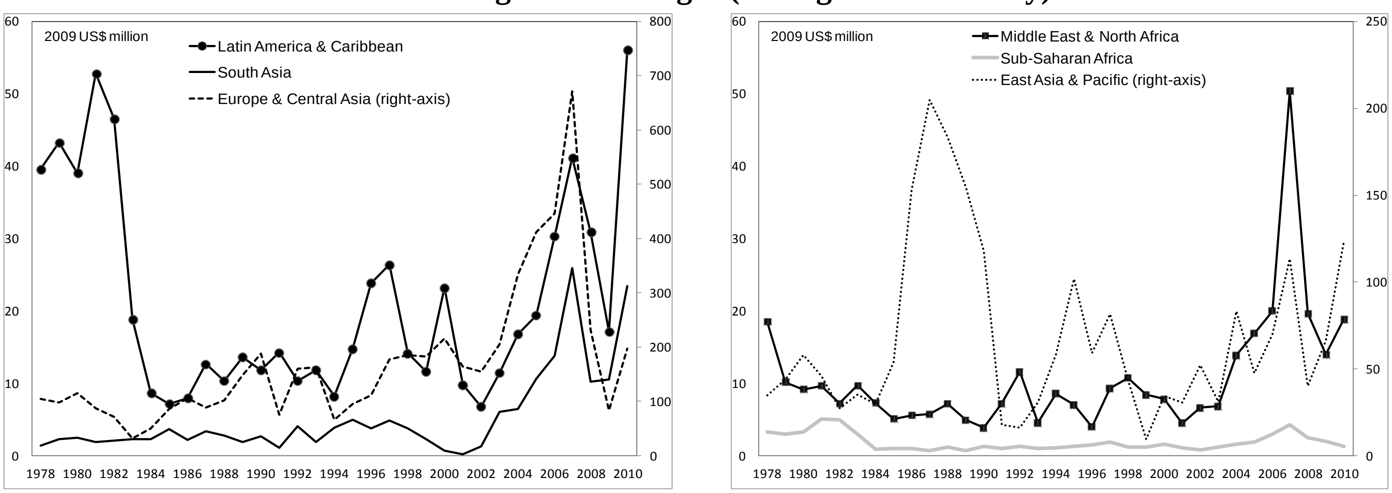
Source: Authors' calculations using BIS locational banking statistics.
Notes: The results refer to the core-periphery network. Panel A refers to lender rankings. Borrower rankings in Panel B exclude high-income borrowers.

Figure 7. Regional Heterogeneity

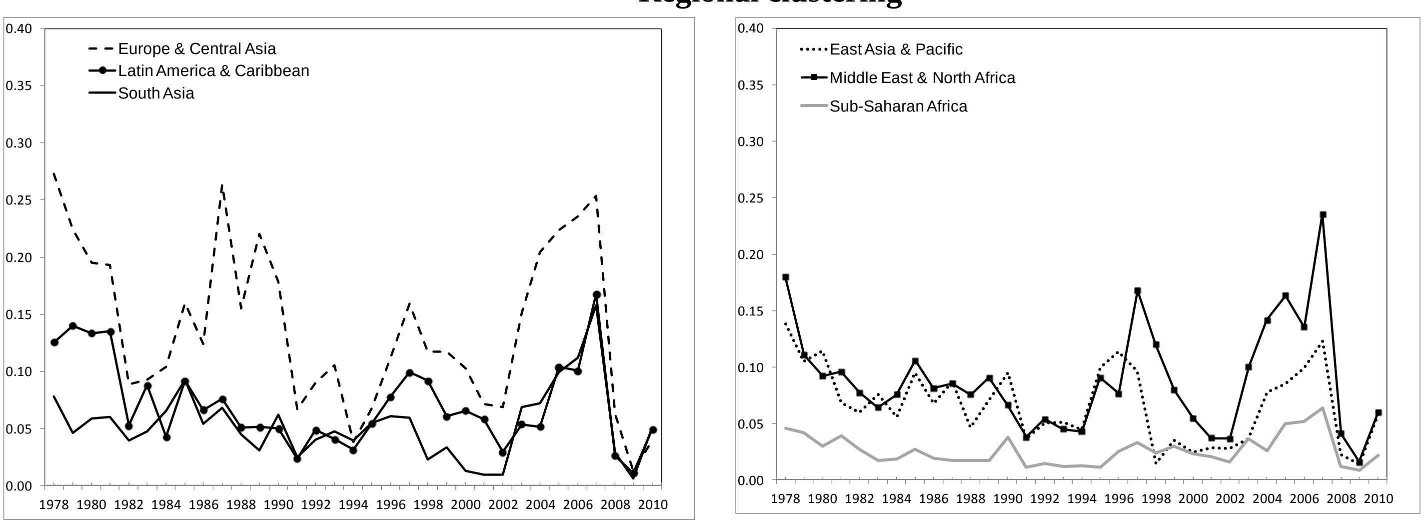
Average in-degree (number of incoming links)



Average node strength (average flows/country)



Regional clustering

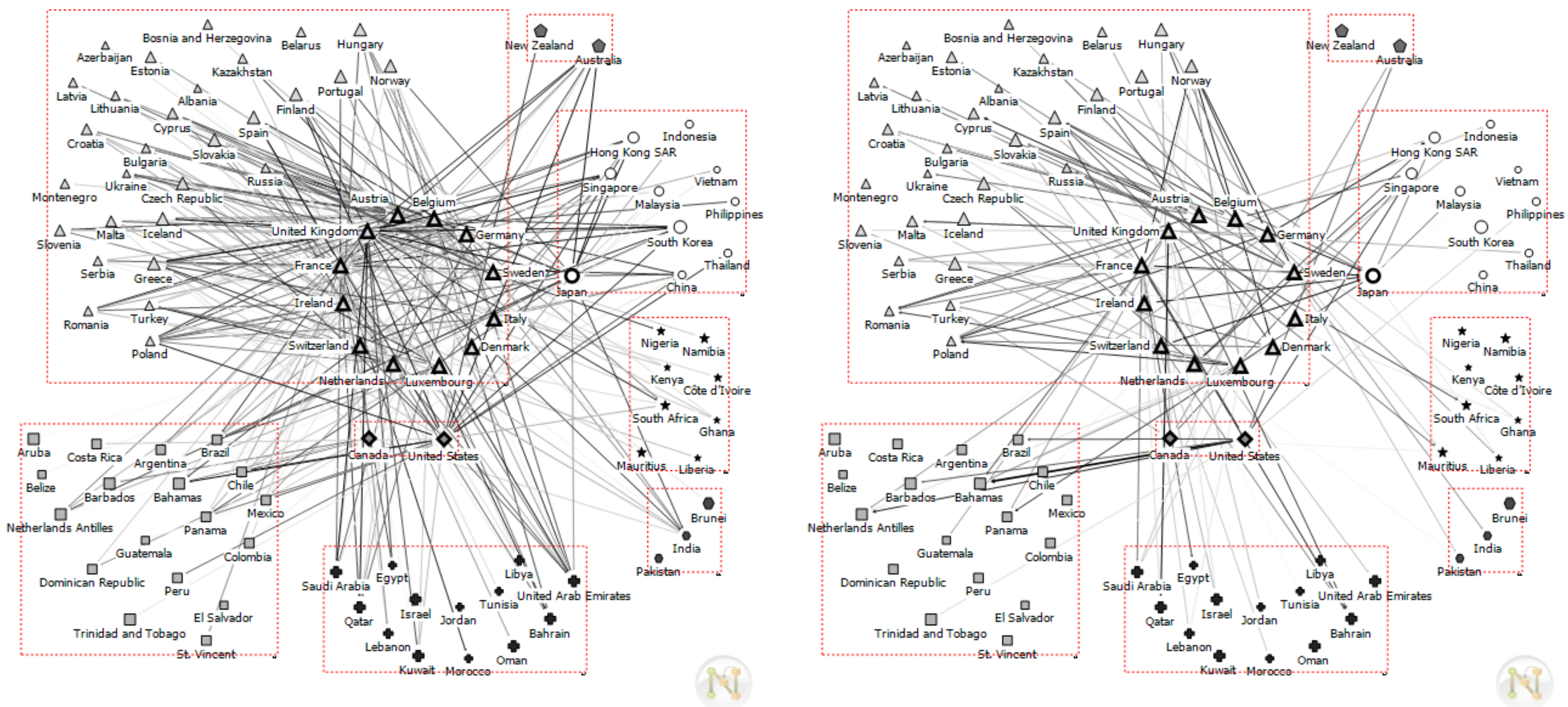


Source: Authors' calculations using BIS locational banking statistics.
Notes: The region North America/Oceania is not shown for visual tractability.

Figure 8. Global Banking Network: 2007Q4 vs. 2008Q4

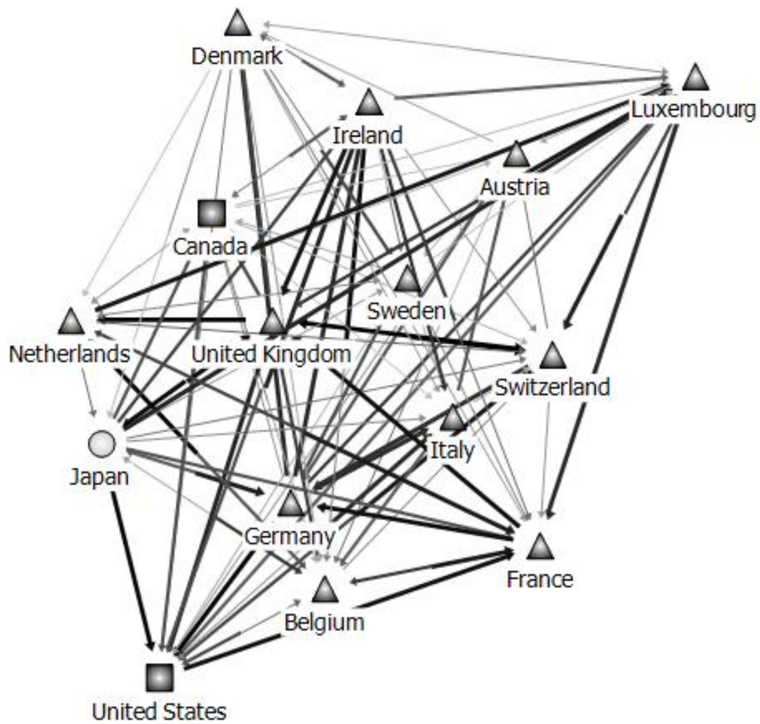
Panel A. Core-periphery

2007Q4 **2008Q4**

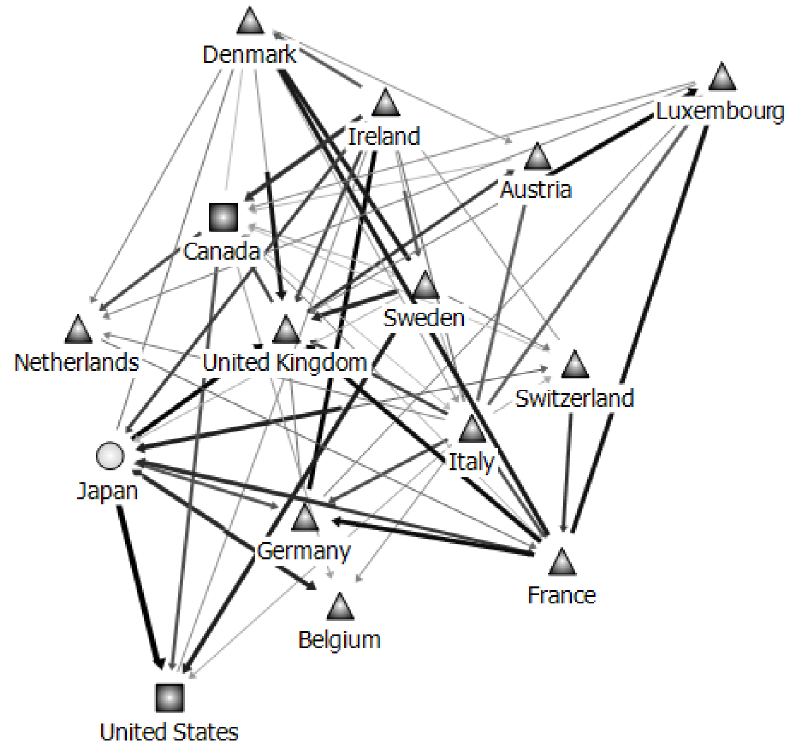


Panel B. Core-core

2007Q4



2008Q4

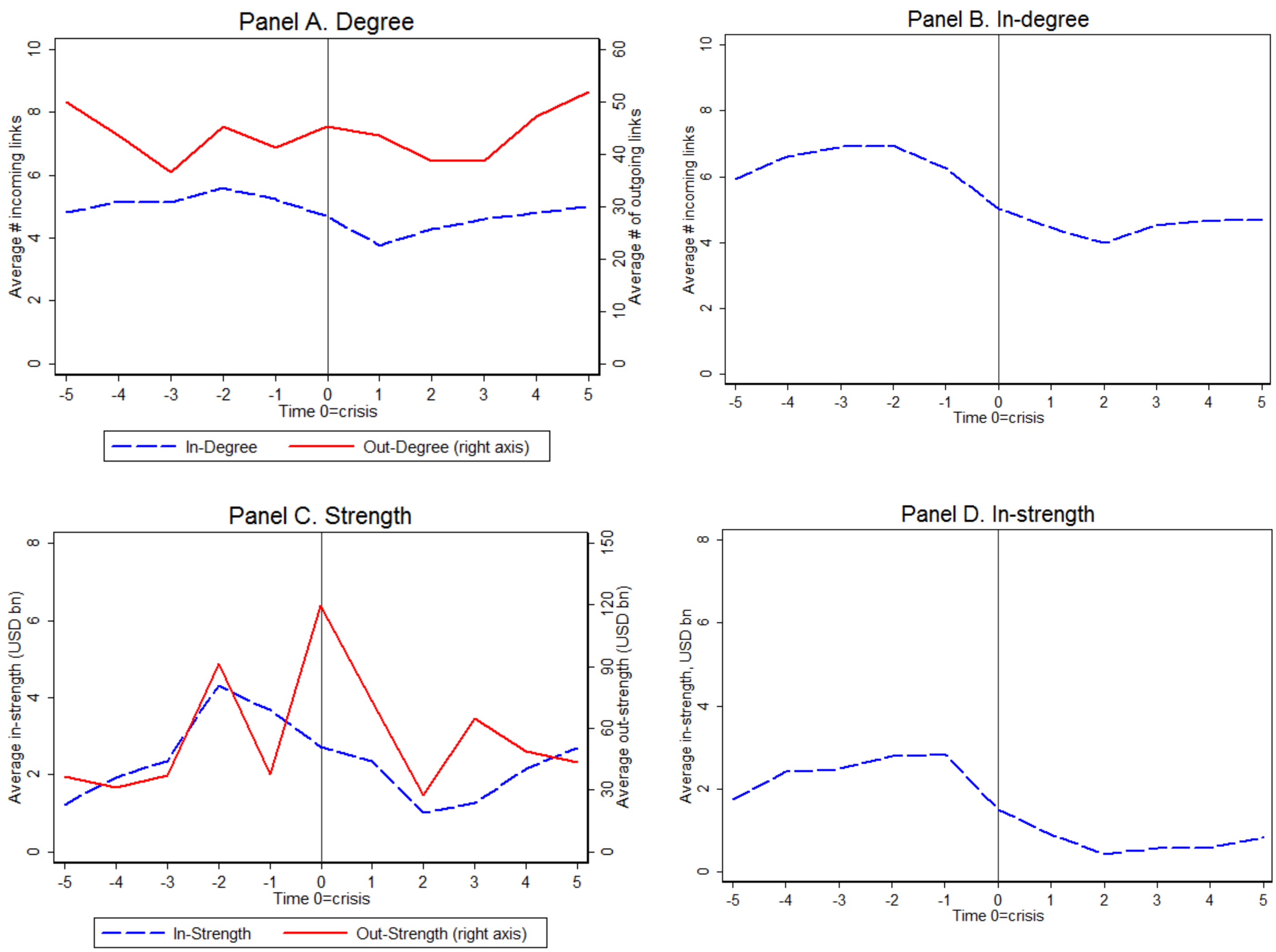


v

Source: Authors' calculations using BIS locational banking statistics (quarterly).
Note: The countries represent nodes and the links between countries represent cross-border banking flows. Thicker and darker colored links indicate larger flows. In Panel B, which refers to the 15 BIS reporting countries, arrows indicate the direction of the flows. When reciprocal flows occur, the connecting link is split into two, each half-link reflecting the magnitude of one flow.

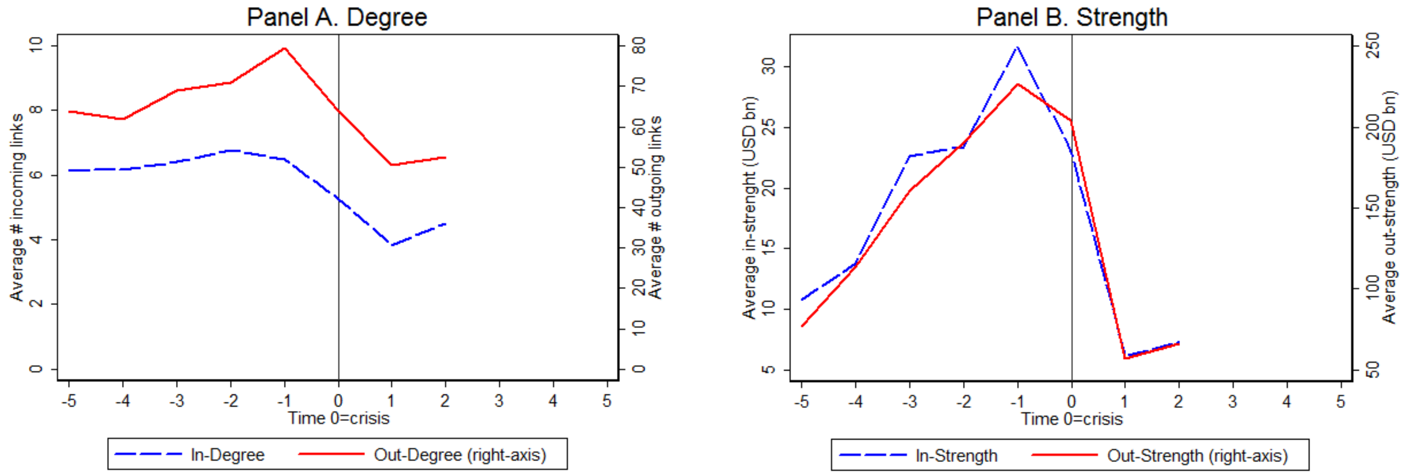
Figure 9. Financial Interconnectedness Before and After Financial Crises

Systemic banking crises **Sovereign debt crises**



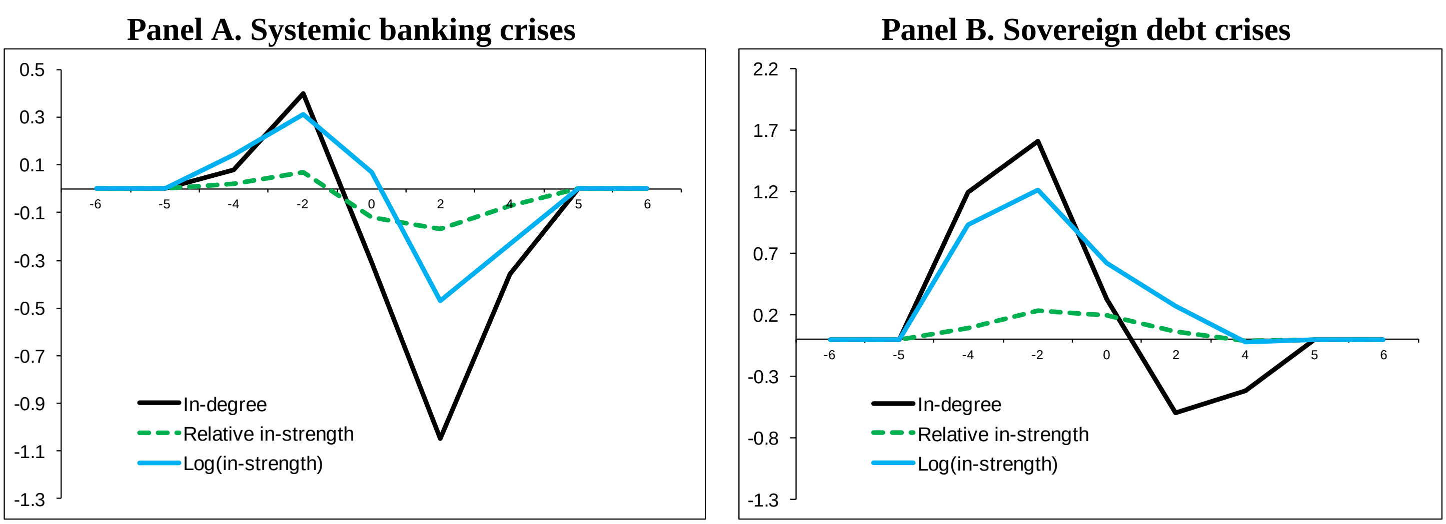
Source: Authors' calculations using BIS locational banking statistics and Laeven and Valencia (2010) database.
Notes: Results are based on the full network. The window around the onset of crises is of +/- 5 years. The left panels include systemic banking and sovereign debt crises that occurred between 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 were dropped, but the results are robust to retaining in the sample either the first or the second crisis for these countries.)

Figure 10. Financial Interconnectedness Before and After Systemic Banking Crises (including 2007–08)



Source: Authors' calculations using BIS locational banking statistics and Laeven and Valencia (2010) database.
Notes: Results are based on the full network. The data is up to 2010Q3 inclusive. The 2007–08 systemic (or borderline systemic) banking crises are: United Kingdom and United States (2007); and Austria, Belgium, Denmark, France, Germany, Greece, Hungary, Iceland, Ireland, Kazakhstan, Latvia, Luxembourg, Mongolia, The Netherlands, Portugal, Russian Federation, Slovenia, Spain, Sweden, Switzerland, and Ukraine (2008). The window around the onset of crises is of –5/+2 years.

Figure 11. Financial Interconnectedness and Crises: Coefficient Curves



Source: Authors' calculations using BIS locational banking statistics and Laeven and Valencia (2010) database.
Notes: The graphs depict the estimated coefficients presented in Table 5, Panel B (columns 1–3 for systemic banking crises; and 4–6 for sovereign debt crises). They represent estimated differences between the level of financial interconnectedness (in-degree, in-strength and relative in-strength) before and after the crises relative to tranquil periods after controlling for pre-existing trends.

Table 5. Financial Interconnectedness and Crises: Regression Estimates

	Systemic banking crises			Sovereign debt crises		
Dependent variable	In-degree	Relative in-strength	Log(in-strength)	In-degree	Relative in-strength	Log(in-strength)
Panel A. Without time effects	**[1]**	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**
3-4 years before	-0.28	0.03	-0.17	1.00*	0.09**	0.82***
	(0.25)	(0.12)	(0.13)	(0.52)	(0.04)	(0.24)
1-2 years before	0.11	0.08	0.07	1.34***	0.23***	1.10***
	(0.29)	(0.06)	(0.15)	(0.41)	(0.07)	(0.21)
Onset of crisis	-0.60**	-0.11	-0.11	0.08	0.19***	0.50**
	(0.28)	(0.08)	(0.15)	(0.42)	(0.07)	(0.20)
1-2 years after	-1.26***	-0.16***	-0.63***	-0.72**	0.06*	0.09
	(0.24)	(0.06)	(0.14)	(0.33)	(0.03)	(0.20)
3-4 years after	-0.63***	-0.07	-0.41***	-0.41	-0.01	-0.14
	(0.20)	(0.05)	(0.11)	(0.31)	(0.02)	(0.16)
F test joint significance	7.623	2.589	7.734	6.044	2.963	10.16
p-value	0.00	0.02	0.00	0.00	0.02	0.00
Obs.	4173	4173	3873	4173	4173	3873
R-squared	0.64	0.80	0.82	0.64	0.80	0.82
Panel B. With time effects						
3-4 years before	0.08	0.02	0.14	1.20**	0.09*	0.93***
	(0.24)	(0.14)	(0.13)	(0.51)	(0.05)	(0.22)
1-2 years before	0.40	0.07	0.31**	1.61***	0.23***	1.22***
	(0.29)	(0.08)	(0.15)	(0.45)	(0.08)	(0.22)
Onset of crisis	-0.31	-0.12	0.07	0.33	0.20**	0.62***
	(0.27)	(0.09)	(0.14)	(0.44)	(0.08)	(0.20)
1-2 years after	-1.05***	-0.17***	-0.47***	-0.60*	0.06	0.27
	(0.23)	(0.06)	(0.14)	(0.34)	(0.06)	(0.22)
3-4 years after	-0.36*	-0.07	-0.23**	-0.42	-0.01	-0.02
	(0.19)	(0.06)	(0.11)	(0.30)	(0.06)	(0.16)
F test joint significance	6.633	3.217	6.551	6.878	3.113	9.689
p-value	0.00	0.00	0.00	0.00	0.02	0.00
Obs.	4173	4173	3873	4173	4173	3873
R-squared	0.66	0.80	0.83	0.66	0.80	0.83

Source: Authors' estimations using BIS locational banking statistics.
Notes: The estimation method is OLS with country fixed effects. The F-statistics are for the null hypothesis of joint insignificance on all the lead and lag coefficients (around the onset of crises). Standard errors are clustered at the country level.

Appendix

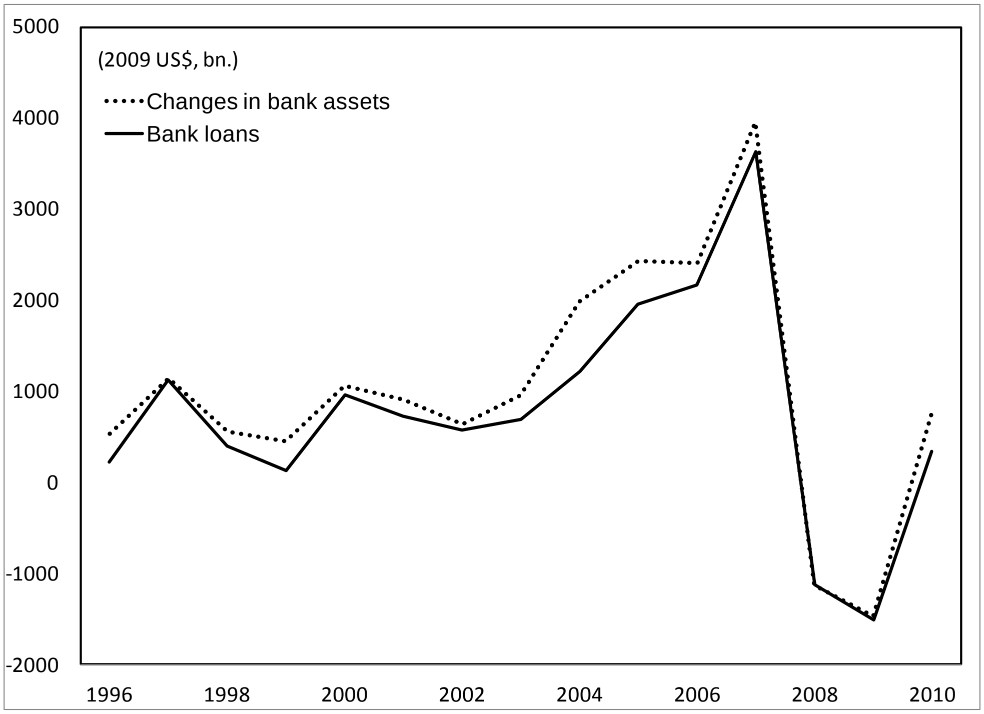
Table A1. Country List

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	

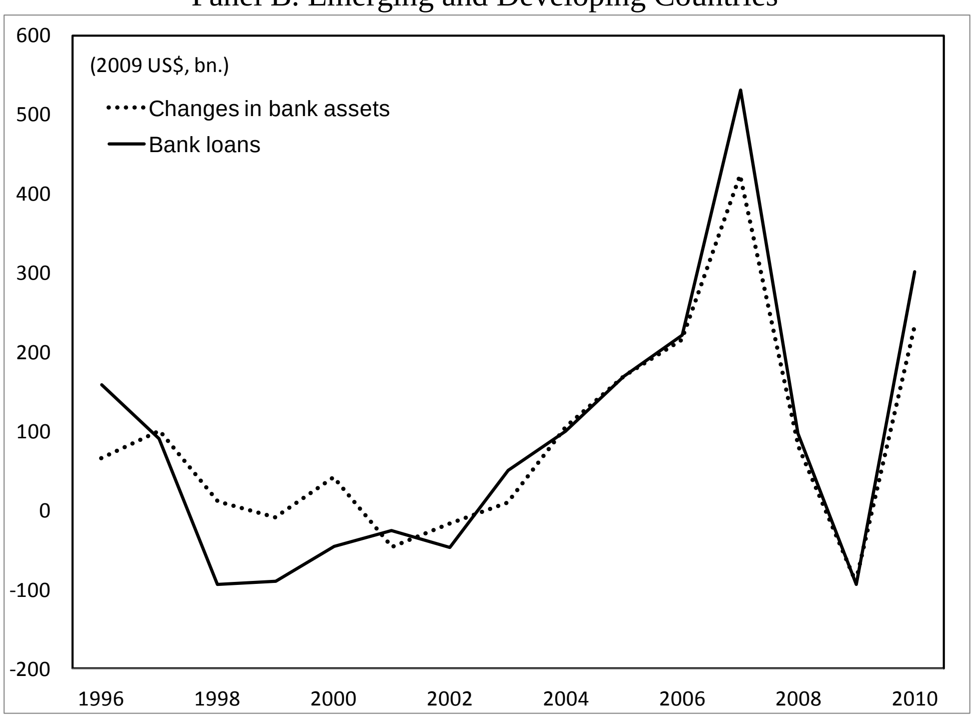
1/ Includes BIS reporting countries with complete data between 1978Q1 and 2010Q3.
2/ Includes all countries vis-a-vis which the sample BIS-reporting countries report bilateral positions.

Figure A1. Cross-border Bank Loans vs. Changes in Total Assets, 1996–2010

Panel A. Advanced Economies



Panel B. Emerging and Developing Countries



Source: Authors' calculations based on BIS locational banking statistics (Table 7a for bank loans).