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A network analysis of global banking: 1978–2010☆

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ABSTRACT

We analyze the global banking network using data on cross-border banking flows for 184 countries during 1978–2010. We find that the density of the global banking network defined by these flows is pro-cyclical, expanding and contracting with the global cycle of capital flows. We also find that country connectedness in the network tends to rise before banking and debt crises and to fall in their aftermath. Despite a historically unique build-up in aggregate flows prior to the global financial crisis, network density in 2007 was comparable to earlier peaks. This suggests that factors other than connectedness, such as the location of the initial shock to the core of the network, have contributed to the severity of the crisis. The global financial crisis stands out as an unusually large perturbation to the global banking network, with indicators of network density in 2008 reaching all-time lows.

1. Introduction

Following the seminal work of Allen and Gale (2000), a growing literature argues that the structure of financial networks matters for how they react to shocks. Higher connectedness, a basic property of financial networks, carries both benefits and risks. On the one hand, it can improve risk sharing by more easily absorbing shocks when they occur. On the other hand, it can lead to contagion because shocks can reach further out in the web of relationships. We contribute to this literature by taking the first step in assessing how the global banking system reacts to negative shocks––that is, by describing its structure and assessing how it evolves over time. To this end we use network analysis, a powerful methodological toolkit for modeling interactions between economic agents.[1]

We explore the properties of the global banking network (henceforth 'GBN') over the past three decades and its dynamics around periods of financial stress. To this aim, we use a range of binary and weighted network indicators that capture the importance of countries in the network and the degree of connectedness in the network as a whole. Our data represent cross-border (bilateral) financial flows intermediated by national banking systems

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[1] For reviews of network theory applications in economics and finance, see Nagurney (2003) and Allen and Babus (2009). Allen et al. (2009) review the literature that uses network theory to study financial crises.

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and was confidentially provided by the Bank of International Settlements (BIS). These flows define a global banking network with a core–periphery structure. Unlike many studies of financial linkages, we use flows rather than exposures because they are more likely to reflect liquidity conditions in international markets and provide variation that is particularly informative of how the GBN changes during financial crises.

We find that network density is pro-cyclical as it tends to expand and contract with the global cycle of private capital flows. In particular, network indicators have structural breaks that broadly identify two waves of capital flows, respectively, leading up to the 1997–1998 East Asian crisis and the 2008–2009 global financial crisis. The empirical distributions of network indicators tend to change shape over time, especially for borrowers in the network's periphery, but they underpin relatively stable country rankings in terms of connectedness. Before each major crisis, a new set of periphery countries rises to the top of connectedness rankings, only to be replaced by another set of countries before the following crisis. Using regression analysis we show that financial connectedness both in the core and periphery tends to rise prior to banking and debt crises, and falls in their aftermath – a result that complements the literature on post-crisis access to international capital markets. Furthermore, countries in the network's periphery fail to recover in terms of connectedness in the five years following a financial crisis.

Our analysis also reveals that total cross-border banking flows experienced a historically unique build-up in the run-up to the global financial crisis, rising several-fold compared to their long-term average. However, this rise was not matched by similar developments in connectedness. In 2007, connectivity and clustering, two of the measures we use to assess network density, reached levels comparable to earlier peaks. Despite the seemingly benign pre-crisis level of network density, the 2008–2009 episode stands out as an unusually large perturbation to the GBN, with a number of indicators plunging to historical lows. We hypothesize that the unusually large pre-crisis banking flows coupled with the initial shock hitting the core of the network created the conditions for a "perfect storm." Our results also present a puzzle. During the 2008–2009 crisis, aggregate flows decreased to levels close to their long-term average while network density fell to 30 percent below its lowest level over the sample period. Hence there is an asymmetry in the behavior of aggregate flows and connectedness, with the former experiencing a more pronounced boom but a less pronounced bust than the latter.

Our paper is closely related to studies that employ network analysis to describe the architecture of financial flows among institutions or countries and to assess the resilience of financial systems to shocks.[2] Hale (2012) constructs a global network of lending and borrowing relationships using data on bank participation in syndicated loans during 1980–2010. This network has become more tightly connected over time and more asymmetric, with the distributions of network indicators becoming increasingly skewed.[3] While Hale's network is more granular than ours, our studies are similar in that both our networks focus on flows rather than exposures. Using a BIS cross-country dataset similar to ours, Hattori and Suda (2007) analyze the global network of banking exposures over 1985–2006 and document a long-term trend toward higher financial connectedness.[4] Kubelec and Sa (2012) document similar findings using data on cross-country exposures for asset classes such as foreign direct investment and portfolio investment. Chinazzi et al. (2013) focus on changes in network topology around the 2008–2009 crisis using cross-country equity and debt exposures. They find that network density declined, asymmetry increased, and investments from periphery countries fell. Like Hale (2012) and Chinazzi et al. (2013), our results show that the GBN changes markedly during times of financial stress and that the 2008–2009 crisis stands out as an unusually large perturbation to the network.

The theoretical literature on financial networks provides a rationale for documenting the topological properties of real-world networks by showing that different network structures react differently to shocks. In their seminal contribution, Allen and Gale (2000) assess resilience to shocks in a stylized four-bank network and show that complete networks, in which every bank is connected to every other bank, are more resilient due to risk sharing. By contrast, incomplete networks, in which every bank is connected with fewer than all banks, are more fragile as less connected banks have difficulty diffusing the shocks.[5] The literature spurred by the global financial crisis has focused rather on the positive link between connectedness and instability. For instance, Battiston et al. (2012a) study connectivity and systemic risk in a model of the economy as a credit network. In their setup, higher connectivity allows for improved risk sharing but 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; hence financial fragility feeds on itself. Battiston et al. (2012b) relate credit risk diversification to systemic risk under different structures of the credit market, and identify conditions under which systemic risk increases with network density.

There is also a large and fast-growing simulations-based literature on the resilience of financial systems to shocks (see Upper, 2011 for a review). Nier et al. (2007) document a non-monotonic effect of connectedness in a bank network on contagious defaults: at small levels of connectivity, a small increase in connectivity raises the likelihood of contagion; in more connected networks, higher connectivity improves the ability of the financial system to absorb shocks. Gai and Kapadia (2010) show that although the likelihood of contagion in arbitrary financial networks may be low, when it occurs it can be widespread. They also suggest that similar aggregate shocks can have different impacts on the financial system depending on the importance of the affected nodes in the network. Martinez-Jaramillo et al. (2010) analyze contagion that emerges in an interbank network after one or more financial institutions' balance sheets are weakened by a random shock. They show that in order to assess financial sector stability it is important to know not only the network topology, but also the distribution of the initial shocks, the size of the losses, and the correlation of defaults.

Financial networks have also been prominent in recent models of panic during financial crises, in which the focus is on the role of macroeconomic complexity in the sense of a very complicated environment in which economic agents operate. Many observers believe that the complexity of this environment is at least partly responsible for the severity and global reach of the

[2] Recent contributions include, e.g., Garratt et al. (2011), Hale (2012), Kubelec and Sa (2012), Hattori and Suda (2007), Von Peter (2007) on the global financial architecture; Degryse et al. (2010), Gai et al. (2011), Gai and Kapadia (2010), and Georg (2011) on resilience to shocks; and Iori et al. (2008) and Soramaki et al. (2007) on the dynamics of interbank markets.

[3] This increased skewness may be associated with increased fragility (Sachs, 2010).

[4] Hattori and Suda (2007) use the BIS bilateral consolidated banking statistics, which are fit for analyzing the global balance sheet of banks. By contrast, the locational statistics that we use are better suited for examining geographical patterns. See BIS (2009) for a comparison of the BIS locational vs. consolidated statistics.

[5] In the same 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.

2007–2008 subprime crisis and argue that network theory can be useful in modeling systemic risk and the factors that cause market freezes (Caballero, 2010; Haldane, 2009).[6] Caballero and Simsek (forthcoming) develop a model in which banks assess the health of their trading partners by collecting information about them. When financial distress occurs 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. Then banks withdraw from loan commitments and illiquid positions, and the financial crisis spreads. This line of research also stresses the importance of understanding the structure of the financial system and documenting how it changes during crises.

The remainder of this paper is structured as follows. In Section 2 we describe our data and define the network indicators. In Section 3 we describe properties of the GBN over the past three decades. In Section 4 we document the behavior of financial interconnectedness during financial crises. Concluding remarks are deferred to Section 5.

2. Data and definitions

We focus on the lending activity of international banks. Banking flows, a major source of private capital to corporations worldwide,[7] suffered a sharp drop during the global financial crisis. Fig. 1 shows cross-border bank loans relative to other types of capital flows separately for advanced and developing economies. The great retrenchment of capital flows during the crisis was heterogeneous across asset classes, with banking flows being the hardest hit (Milesi-Ferretti and Tille, 2011; Hoggarth et al., 2009).

2.1. The BIS locational statistics

Our data are the BIS bilateral locational statistics and represent changes in cross-border bank claims during 1978–2010 (up to 2010Q3 inclusive). The dataset contains flows of financial capital channeled through the banking system in every country and is well suited for analyzing geographical patterns in financial linkages. The 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 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, which we use to construct the GBN, are estimated as changes in cross-border stocks and are adjusted for fluctuations in exchange rates.[9]

Our sample contains 184 countries, of which 15 are advanced economies that report bilateral positions to the BIS (reporting countries) and 169 are countries vis-à-vis which positions are reported (non-reporting countries).[10] We focus on the 15 reporting economies that have submitted data to the BIS continuously since 1978 in order not to confound changes in the network with changes in sample composition. These economies account on average for 96 percent of total bank-intermediated flows in all BIS reporting countries. The 15 BIS reporting countries make up the *core* of the GBN while the non-reporting countries make up the *periphery*. We note that due to the large number of non-reporting countries in the BIS dataset, our results should be interpreted with some caution, as cross-border flows between non-reporting countries (hence connections within the periphery) are missing from our dataset. This implies that some of our network measures will misstate the true extent of connectedness.[11]

Fig. 2 depicts the GBN in 1980 and 2007 and shows how the network changed between the beginning and the end of the sample period. Connecting lines are more numerous as bank relationships have expanded. They also appear thicker as flows have increased. Prior to the recent crisis, countries in Eastern Europe were tightly connected to the core. Although the expansion of the GBN is clear from this figure, more could be said about its characteristics and dynamics by analyzing its topology with a series of network indicators.

2.2. The network

Each country in our dataset is a *node* in the network. *Links* between nodes represent positive cross-border banking flows, i.e., increases in cross-border bank assets of a reporting country vis-à-vis another country. These are net flows in the sense that they account for repayments. For instance, a link from country A to country B represents investments (new loans, purchases of securities and other assets, etc.) of country A's banking system in country B minus repayments from B to A. All negative flows (net repayments) are replaced with zeros and are ignored in the analysis.[12]

We model each year over the sample period as a separate network and analyze the following three networks: (i) the full network based on all available data (shown in Fig. 2); (ii) the core–periphery network, which refers to links between the core and the periphery; and (iii) the core–core network, which refers to links among the 15 core countries. In the core–core network, the links can be bidirectional because countries in all countries in the core report cross-border positions to the BIS. However, in the core–periphery network the links are unidirectional (from the core to the periphery nodes) because periphery countries do not report data to the BIS.

2.3. The indicators

We consider a range of commonly used indicators that include both country-specific measures of importance in the network as well as aggregate measures of network density. To obtain a comprehensive view of connectedness in the network, we analyze both binary and weighted network indicators. Recent studies of the global trade network (Fagiolo et al., 2008, 2009, 2010) show that

6 See Allen and Carletti (2013) for a general discussion of the areas where theoretical work is needed to underpin financial regulation.

7 Banking flows to emerging and developing nations had reached unprecedented levels prior to the crisis, rivaling foreign direct investment as a source of private capital.

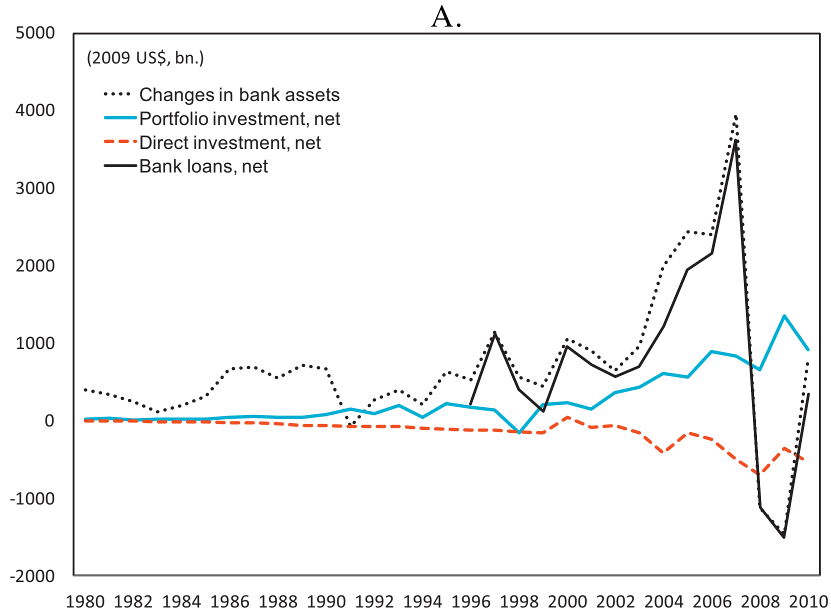
8 Although bank lending takes the lion's share of total cross-border bank claims, banks' reliance on debt securities has increased over time (Fender and McGuire, 2010; McGuire and Tarashev, 2006).

9 It is unclear to what extent the BIS locational statistics reflect changes in market valuations and write-downs. Since large parts of bank assets are not marked to market, it is unlikely that many of the flows are due simply to such changes rather than new credit (Gourinchas et al., 2012). The data are adjusted for inflation using the US Consumer Price Index for urban areas.

10 The following BIS reporting countries are included in our analysis: Austria, Belgium, Canada, Denmark, France, Germany, Ireland, Italy, Japan, Luxembourg, The Netherlands, Sweden, Switzerland, UK, and US.

11 See Cerutti et al. (2012) for a discussion of data quality and availability problems in analyses of this kind.

12 Although not analyzed here, the network of negative flows could reveal interesting patterns in capital reversals.



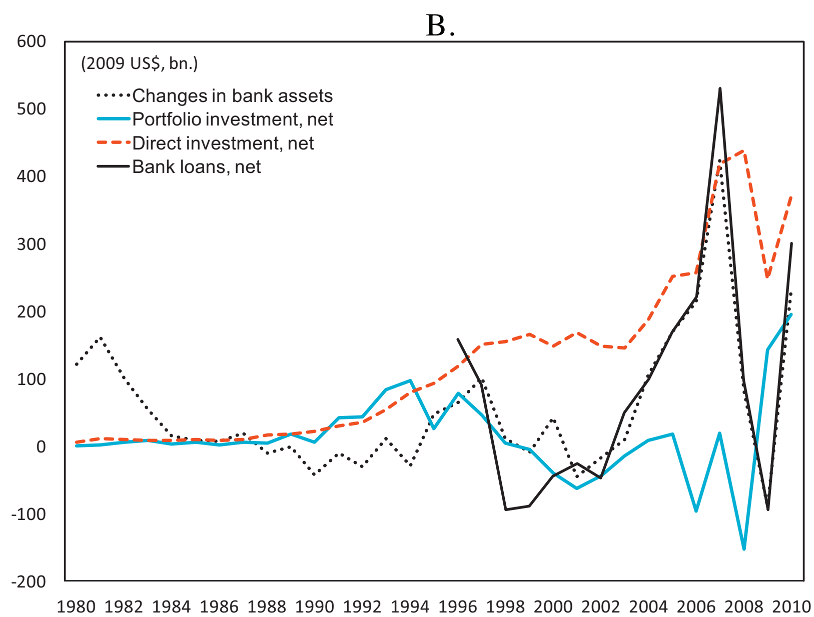


Fig. 1. Private capital flows, 1980–2010. Panel A: to advanced economies; Panel B: to emerging and developing countries.
Data sources: BIS bilateral locational banking statistics for changes in bank assets. BIS aggregate locational banking statistics for bank loans (Table 7a available on http://www.bis.org/statistics/bankstats.htm); and the IMF's World Economic Outlook for portfolio investment and direct investment.

weighted network indicators often provide different insights compared to binary indicators hence both are useful for a thorough understanding of a network's topology. Analyzing the network from a weighted perspective is particularly important in our context due to the secular increase in the size of cross-border banking flows.

We begin by constructing matrices W^t for every time period t where rows represent lenders and columns represent borrowers. Each entry w_{ij}^t is the value of the flow from country i to country j at time t. The entry w_{ij}^t is also called a *link weight* and W^t is a matrix of link weights. These matrices are transformed into their *binary* counterparts (or adjacency matrices) $A^t = \left\{a_{ij}^t\right\}$ where each cell a_{ij}^t takes value 1 if $w_{ij}^t > 0$ and 0 otherwise. In what follows we omit the time index t for simplicity. We consider the following indicators:

Node degree represents the number of links for each node. Since the network is directed (flows occur from a source to a destination country), there are outgoing links for lenders and incoming links for borrowers. We compute *out-degree*, the number of outgoing links, for lenders, and *in-degree*, the number of incoming links, for borrowers. Out-degree is given by $d_i^{out} = \sum_{j \neq i} a_{ij} = A_i 1$ and in-degree is given by $d_i^{in} = \sum_{j \neq i} a_{ji} = (A_i)^T 1$, where A_i denotes the ith row of matrix A, $(A_i)^T$ denotes the ith row of the transpose of matrix A and 1 is a unitary vector with N elements. The maximum value for in-degree is 15 and the maximum value for out-degree is N. Node degree is an indicator of "local centrality" and captures the extent to which a country is well connected in the network. A high

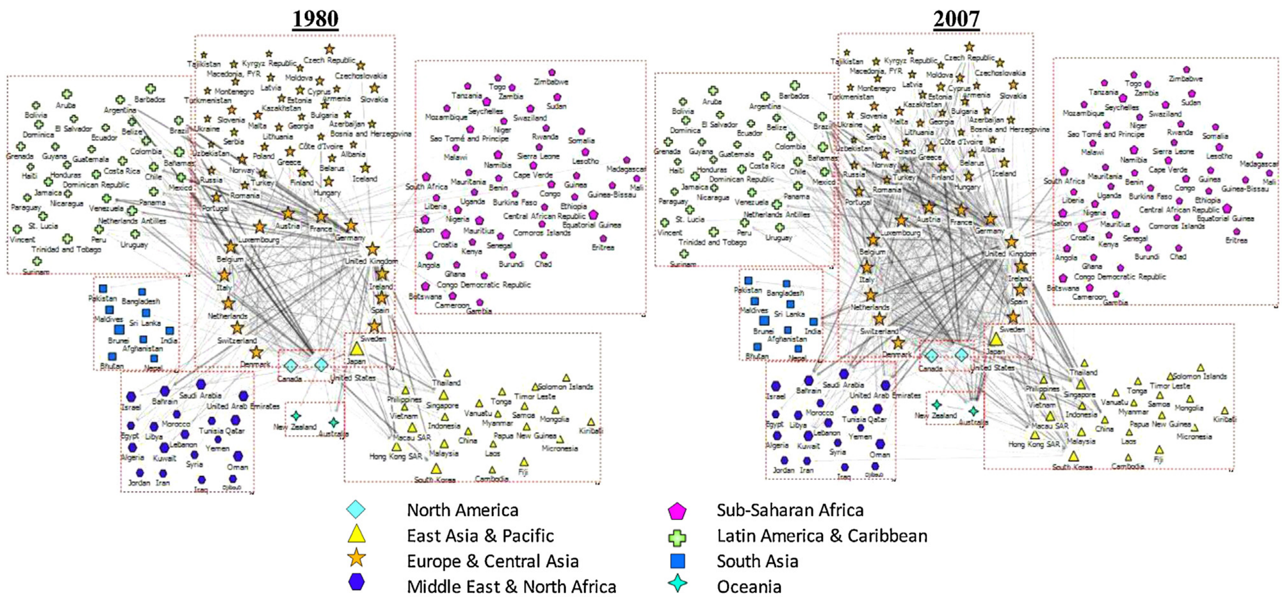


Fig. 2. Global banking network: 1980 vs. 2007. Note: Representation of the full network. The countries represent nodes and the links between nodes represent cross-border banking flows (expressed in constant 2009 USD). Thicker links indicate larger flows. Arrows indicate the direction of the flows. When reciprocal flows occur between core nodes, the link is split into two, with each half-link reflecting the magnitude of one flow.

Data sources: BIS bilateral locational banking statistics.

degree indicates that the node has a large neighborhood of local contacts, be it lenders or borrowers, hence is relatively prominent in its neighborhood.

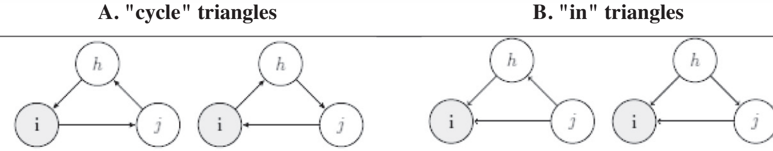
Network connectivity, a measure of network density, represents the number of links observed in the network divided by the total possible number of links. It represents the probability of a connection between two countries in the GBN.

Node strength is the total value of flows originating or terminating in a node (Barrat et al., 2004). Here, *in-strength* for country *i* is the total amount of cross-border flows it borrows, whereas *out-strength* is the total amount it lends. Node strength, the simplest weighted network indicator, is computed by substituting matrix A for matrix W in the node degree formulas, and it is the simplest network indicator that captures the intensity of financial relationships among countries.

Node clustering is measured with a clustering coefficient. We compute clustering both on the binary and weighted networks because a node may have high binary clustering if it is tightly connected with other nodes, but low weighted clustering if the flows among those nodes are low. We calculate clustering coefficients for two triangle patterns: "cycle" and "in" (shown in Text Fig. 1) based on the definitions developed in Fagiolo (2007). In the "cycle" representation, which can be computed only for nodes in the core–core network, a node has a cyclical relation with its two neighbors (Panel A). In the "in" representation, which can be computed for nodes in all three networks, flows from two core nodes that are lending to each other terminate into a node (Panel B). For either pattern, both representations are required to qualify a triangle.

Text figure 1. Triangle patterns for clustering coefficients

A. "cycle" triangles	B. "in" triangles



Source: Fagiolo (2007).

The binary clustering coefficient for each node represents the ratio between the number of triangles with a given flow pattern that the node actually forms (t_i) and the total possible number of the same pattern that the node can form (T_i). Let the number of bilateral links between node i and its neighbors be $d_i^{\leftrightarrow} = \sum_{i \neq j} a_{ij} a_{ji} = A_{ii}^2$. The binary clustering coefficient is given by

$$C_i = \frac{t_i}{T_i} \tag{1}$$

where, for "cycle" triangles, $t_i = (A)_{ii}^3$, i.e., the ith element of the main diagonal of $A^3 = A{\cdot}A{\cdot}A$ and $T_i = d_i^{in} d_i^{out} - d_i^{\leftrightarrow}$. For "in" triangles, $t_i (A^T A^2)_{ii}$ and $T_i = d_i^{in}(d_i^{in} - 1)$. The binary clustering coefficient ranges between 0 and 1, with higher values representing nodes with a greater tendency to form tightly connected directed neighborhoods.

The weighted clustering coefficient only differs from its binary counterpart in that the numerator takes into account the size of the flows on a triangle. Letting $M = W^{[1/3]} = \left\{ w_{ij}^{1/3} \right\}$ be the matrix obtained from W by taking the third root of each entry, the numerator represents the sum of geometric means of link weights on all observed triangles formed by node i, i.e., in the clustering coefficient formula, $t_i = (M)_{ii}^3$ for "cycle" triangles and $t_i = (M^T M^2)_{ii}$ for "in" triangles. We calculate the weighted clustering coefficient on the raw

Table 1
Summary statistics.

	Units of measurement	1980					2007				
		Mean	Median	St. dev.	Minimum	Maximum	Mean	Median	St. dev.	Minimum	Maximum
Panel A: full network											
In-degree	# links	5.7	5.0	4.1	0.0	15.0	7.0	7.0	4.1	0.0	14.0
Out-degree	# links	53.9	54.0	21.4	18.0	95.0	85.9	82.0	18.7	55.0	116.0
In-strength	USD bn	4.0	0.3	9.9	0.0	65.7	24.7	0.3	90.2	0.0	890.7
Out-strength	USD bn	37.6	27.7	46.4	0.6	180.0	302.6	209.8	305.9	46.2	1212.6
In-HHI	[0,1]	0.32	0.28	0.30	0.00	1.00	0.43	0.38	0.25	0.00	1.00
Out-HHI	[0,1]	0.17	0.15	0.11	0.07	0.44	0.19	0.14	0.13	0.05	0.48
Binary clustering (“in”)	[0,1]	0.62	0.70	0.29	0.00	1.00	0.75	0.79	0.21	0.00	1.00
Panel B: core–periphery network											
In-degree	# links	5.2	5.0	3.9	0.0	15.0	6.6	6.0	4.1	0.0	14.0
Out-degree	# links	44.1	43.0	20.0	12.0	83.0	74.8	71.0	18.2	44.0	104.0
In-strength	USD bn	1.8	0.2	4.3	0.0	28.9	6.4	0.2	16.3	0.0	129.9
Out-strength	USD bn	15.2	6.4	22.8	0.2	72.3	72.0	56.3	66.6	7.1	252.3
In-HHI	[0,1]	0.33	0.28	0.31	0.00	1.00	0.44	0.39	0.25	0.00	1.00
Out-HHI	[0,1]	0.11	0.08	0.06	0.04	0.21	0.11	0.10	0.05	0.06	0.21
Panel C: core–core network											
In-degree	# links	9.8	10.0	3.3	0.0	13.0	11.1	12.0	2.4	5.0	14.0
Out-degree	# links	9.8	10.0	2.4	5.0	13.0	11.1	11.0	1.8	8.0	14.0
In-strength	USD bn	22.4	23.9	20.1	0.0	65.7	230.6	157.0	231.6	36.9	890.7
Out-strength	USD bn	22.4	21.3	26.3	0.4	107.7	230.6	153.5	244.7	28.6	960.3
In-HHI	[0,1]	0.28	0.26	0.15	0.00	0.64	0.29	0.27	0.13	0.15	0.56
Out-HHI	[0,1]	0.31	0.27	0.14	0.17	0.63	0.29	0.24	0.15	0.15	0.66
Binary clustering (“in”)	[0,1]	0.68	0.71	0.20	0.00	0.84	0.80	0.80	0.03	0.76	0.85
Binary clustering (“cycle”)	[0,1]	0.12	0.12	0.05	0.00	0.23	0.10	0.10	0.02	0.06	0.14

Data sources: BIS bilateral locational banking statistics.
Notes: Summary statistics for selected indicators for the 1980 and 2007 networks. Strength expressed in constant 2009 USD.

link weights for ease of interpretation, with the consequence that the weighted clustering coefficient is not bounded. Network-level clustering coefficients are obtained by averaging the individual coefficients across nodes.

In a recent study Tabak et al. (2011) compute clustering coefficients based on triangle patterns such as the ones considered here to assess systemic risk. The authors argue that higher clustering of the “in” type may reflect higher systemic risk because failure of the borrowing node in an “in” triangle can trigger simultaneous non-repayments to the lending nodes, and this, in turn, can make them unable to honor their own obligations. The implication of high clustering of the “cycle” variety is more ambiguous, since nodes in a “cycle” triangle act as both borrowers and lenders in the interbank market, so the consequences of a node failure are unclear. Tabak et al. (2011) find little empirical evidence of systemic risk based on these interpretations of clustering in the Brazilian interbank market during 2004–2007.

Our last indicator, the **node Herfindahl-Hirschmann Index** (HHI), is the traditional index of market share concentration, and allows us to assess concentration (or diversification) of nodes' lending and borrowing activities. The HHI, which ranges from 0 to 1, is computed as follows. For lenders, we sum up the borrower's squared shares in each lender's total outflows (out-HHI). For borrowers, we sum up the lenders' squared shares in each borrower's total inflows (in-HHI). A higher value of the HHI reflects a higher concentration of lending or borrowing and potentially a higher risk associated with a particular node (see Martinez-Jaramillo et al., 2011).

In what follows we refer to all measures as “network indicators” for ease of presentation, although node strength and the HHI are not network indicators in the strict sense.

3. Results

Here we describe the properties of the GBN using the indicators defined above in order to determine how the global web of banking relationships has changed over the past three decades, especially during periods of financial stress.

3.1. Network indicators during 1978–2010

Table 1 provides summary statistics for selected indicators at the beginning and at the end of our sample. Looking at the full network (Panel A), we note that in 1980 countries borrowed on average from 5.7 countries and lent to 53.9 countries. By 2007 these figures increased, respectively, to 7.0 and 85.9 countries. In terms of aggregate flows, USD 37.6 billion were lent out on average by core economies in 1980; by 2007 the volume of flows per node increased by a factor of eight, reaching USD 302.6 bn. The strength indicators for the core–core network (Panel C) show that an outsize share of these outflows stayed in the core.[13] The high standard deviation of the strength indicators reflects a large degree of variation in the volume of flows across nodes; moreover, the difference between the mean and median of flows suggests that the distribution of link weights is skewed.

Flows from the core to the periphery rose markedly between 1980 and 2007 (Panel B). Average flows per node increased by a factor of almost five (from USD 15.2 bn to USD 72 bn for lenders; and from USD 1.8 bn to USD 6.4 bn for borrowers). Even more impressive is the ten-fold increase in flows within the core (from USD 22.4 bn to USD 230.6 bn per node). As link weights rose, connectivity increased as well. Average degree within the core was 11.1 links per node in 2007 compared to 9.8 links per node in 1980.[14]

[13] Cross-sectional correlations (not shown) between degree and strength vary between 40 and 53 percent in our three networks, which suggests that nodes with more financial partners tend to also have higher intensity relationships.

[14] The findings for in- and out-degree should be interpreted bearing in mind that they hinge on our selection for the core network of 15 countries which report to the BIS continuously during the period of analysis. Had we allowed more countries to enter the sample when they began reporting to the BIS, we may have uncovered more significant swings in this indicator.

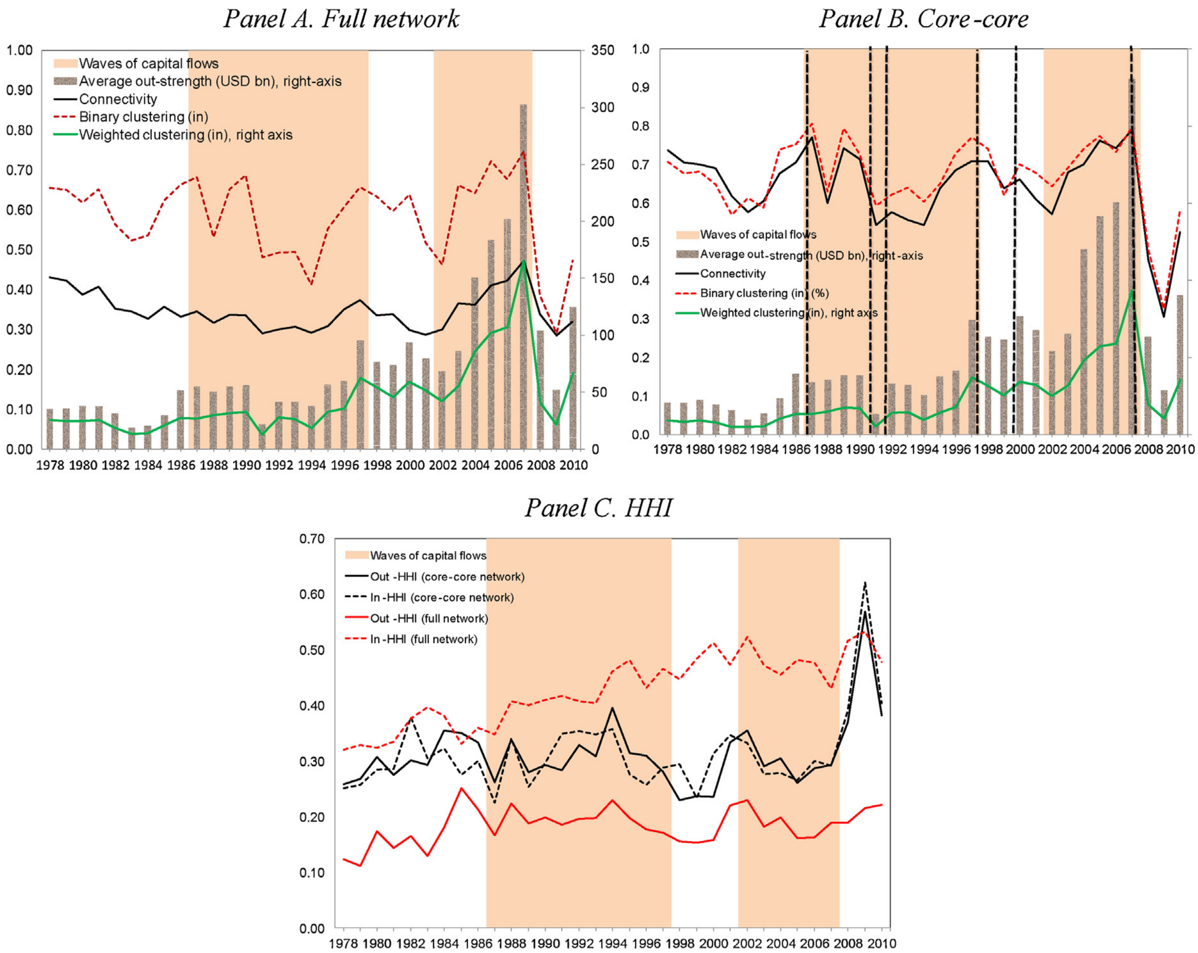


Fig. 3. Network indicators, 1978–2010. Notes: Time-evolution of selected network indicators. Shaded areas indicate the 1987–1998 and 2002–2008 global waves of capital flows (IMF, 2007). In Panel B vertical lines mark the dates of crisis events in advanced economies, i.e., the 1987 US stock market crash, the 1991–1992 Scandinavian banking crises and 1992 Exchange Rate Mechanism crisis, the 1998 Long Term Capital Management near-collapse, the 2000 Internet bubble collapse, and the 2008 Lehman Brothers bankruptcy.

Data sources: BIS bilateral locational banking statistics.

Out-degree in the core–periphery network rose from 44.1 in 1980 to 74.8 in 2007, with Switzerland attaining the maximum number of links in 2007 – to 104 periphery nodes and 116 nodes overall. The degree of connectedness proxied by the "cycle" clustering coefficient, hence based on the restrictive requirement that all lending relationships in triangles from the core–core network be reciprocal, was about 10 percent in 2007.

Fig. 3 plots the cross-sectional averages of network indicators during 1978–2010. Panels A and B show that connectivity, the likelihood that any two nodes in the network are connected, has historically varied between 30 and 45 percent in the full network and between 60 and 80 percent in the core. By this measure, the core–core network appears significantly denser than the core–periphery network. Binary clustering of the "in" variety was relatively high in the core at 80 percent in 2007, a level not seen since the 1987 US stock market crash. In the full network, where we also consider "in" triangles formed by periphery nodes, binary clustering in 2007 was also relatively high at 75 percent. This partly reflects the high degree of connectivity in the core, as "in" triangles require the lending nodes to also be lending to each other.

Connectivity and binary clustering both increased during the 2000s in the full network and within the core, and peaked before the 2008–2009 crisis.[15] We notice the same pattern for weighted clustering, the indicator that captures the intensity of flows on existing triangles scaled by the number of triangles that nodes can form. By definition weighted clustering, for either "in" or "cycle" triangles, rises with binary clustering and higher aggregate flows (both of which increase the numerator). It declines with higher connectivity (which increases the denominator).[16] While binary clustering and connectivity do not display a clear long-run trend in the core–core network, aggregate flows have

[15] In results not reported, we calculated total degree (representing the sum of in- and out-degree for core nodes, and in-degree for periphery nodes) in the full GBN, and correlated it respectively with binary and weighted "in"-clustering. We found that every year during the sample period the correlation between total degree and binary clustering in the full GBN is positive, which suggests that countries with many partners tend to form very connected clusters of financial relationships. In contrast, two thirds (a quarter) of the time the correlation between total degree and binary (weighted) clustering in the core–core network is negative, which implies that core nodes with many partners tend to form poorly connected clusters of financial relationships. In both networks, total strength (the sum of in- and out-strength) is positively correlated with binary and weighted clustering.

[16] As noted in Section 2.3, we computed this indicator based on the raw link weights, which means that it is unbounded and we were able to re-scale it by an appropriate constant to plot it.

Table 2
Unit root tests.

	One-break test		Two-break test			
	Break	*p*-Value	First break	*p*-Value	Second break	*p*-Value
Panel A: full network						
Out-strength	**2003**	0.01	**1994**	0.00	**2003**	0.00
In-strength	**2003**	0.00	**1995**	0.00	**2003**	0.00
Connectivity	**2001**	0.01	1980	0.56	**2003**	0.01
Binary clustering (“in”)	1993	0.98	1989	0.12	1993	0.18
Weighted clustering (“in”)	**2002**	0.02	**1995**	0.00	**2003**	0.00
Panel B: core–periphery network						
In-strength	**2003**	0.00	1981	0.41	**2003**	0.00
Connectivity	**2001**	0.01	1980	0.22	**2003**	0.08
Binary clustering (“in”)	1993	0.99	1989	0.10	1993	0.16
Weighted clustering (“in”)	**2002**	0.00	**1994**	0.01	**2003**	0.00
Panel C: core–core network						
Out-strength	**2003**	0.03	**1995**	0.01	**2003**	0.02
Connectivity	1986	0.59	1989	0.16	1993	0.27
Binary clustering (“in”)	1983	0.52	1983	0.39	1988	0.47
Binary clustering (“cycle”)	**1989**	0.05	**1989**	0.01	**2007**	0.00
Weighted clustering (“in”)	2002	0.32	**1995**	0.00	**2003**	0.07
Weighted clustering (“cycle”)	**1995**	0.01	**1995**	0.03	**2002**	0.01

Data sources: BIS bilateral locational banking statistics.
Notes: Unit root tests for selected network indicators over 1978–2010. Breaks that are statistically significant at the 5 percent level of significance in boldface. For the core–core network we only report the results for average out-strength because it is equal to average in-strength (as nodes serve as both lenders and borrowers).

continuously risen since the 1970s. This suggests that the long-run upward trend in weighted clustering is driven by the rise in aggregate flows. Weighted clustering also increased markedly in the run up to the 2008–2009 crisis as aggregate flows went up faster than connectivity.[17]

Panels A–B in Fig. 3 allow us to compare changes in aggregate flows (strength) on the one hand with measures of connectedness (connectivity, binary clustering) on the other. Focusing on the core–core network, we mark the dates of crisis events in advanced economies in Panel B to examine the cyclical properties of network density. Three observations are in order. First, network density is pro-cyclical. Connectivity and clustering tend to rise before crises and fall afterward. Second, network density increased *less* prior to the global financial crisis than did aggregate flows. Clustering and connectivity at their peak in 2007 were not significantly higher than before earlier peaks, such as before the 1980s debt crisis or before the East Asian crisis. By contrast, total flows increased several-fold over the last cycle. Third, after the crisis network density fell to historically low levels, i.e., by almost one third below the lowest level observed over the period.[18] Thus, the 2008–2009 episode stands out as an unusually large perturbation to the network. Sharp movements in network density around financial crises have been documented in previous studies of the international financial network. Chinazzi et al. (2013) for instance examine the network of debtor-creditor relationships in equities and debt, and find that the recent crisis was accompanied by large changes in the topological structure of the network in addition to a significant reduction in the amount of securities traded. We explore some implications of these findings in Section 4.

The HHI measures of lending and borrowing concentration provide a different perspective on developments in the GBN (Panel C). In the full network there is a long-run trend toward higher concentration of both lending and borrowing activities. By contrast, the degree of concentration in the core–core periphery appears stationary over the two decades before the recent crisis, much like connectivity and clustering. However, in the midst of the crisis both concentration measures rise by more than 50 percent over their long-term average, mirroring the sharp reductions in network density and total flows that occurred at the same time. As flows dried up and connectedness fell to historical lows during the 2008–2009 crisis, some nodes started to account for an outsized share of total lending and borrowing, which reflects a sharp reduction in the diversification of financial relationships in the GBN.

3.2. Network connectivity and the global cycles of capital flows

We turn our attention to the dynamics of the GBN during two global waves of capital flows, respectively, leading up to the 1997–1998 Asian crisis and the 2008–2009 crisis. These waves were dated in IMF (2007) based on aggregate private capital flows. To determine whether the changes in network topology are consistent with the dating of the global cycle of capital flows, we undertake unit root tests of one or two structural breaks in the mean of several network indicators (Clemente et al., 1998). The results, shown in Table 2, generally indicate a single break around 2001–2003; 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. Breaks are always found in aggregate flows (in and out-strength) and the weighted clustering coefficient, but less so in network density (degree/connectivity and binary clustering), particularly in the core.

3.3. Shape and stability of network indicator distributions

We turn to analyzing the distributions of country-specific measures to gain insights into cross-node heterogeneity in terms of relative importance in the network and to set the stage for looking at the main players in the GBN. We proceed in two steps. First, we compare two snapshots of the degree and clustering distributions, at the beginning and end of the sample period. Second, we assess the stability of these distributions over time using a series of Kolmogorov–Smirnov tests.

[17] The findings are qualitatively similar for weighted clustering for čycleẗriangles and are not shown for brevity.

[18] The minimum attained before the crisis was 54 percent for connectivity; and 57 percent for “inb̈inary clustering. In 2008–2009, average connectivity and clustering respectively fell to 38 and 40 percent, which represents a drop of about 30 percent compared to the historical minimum.

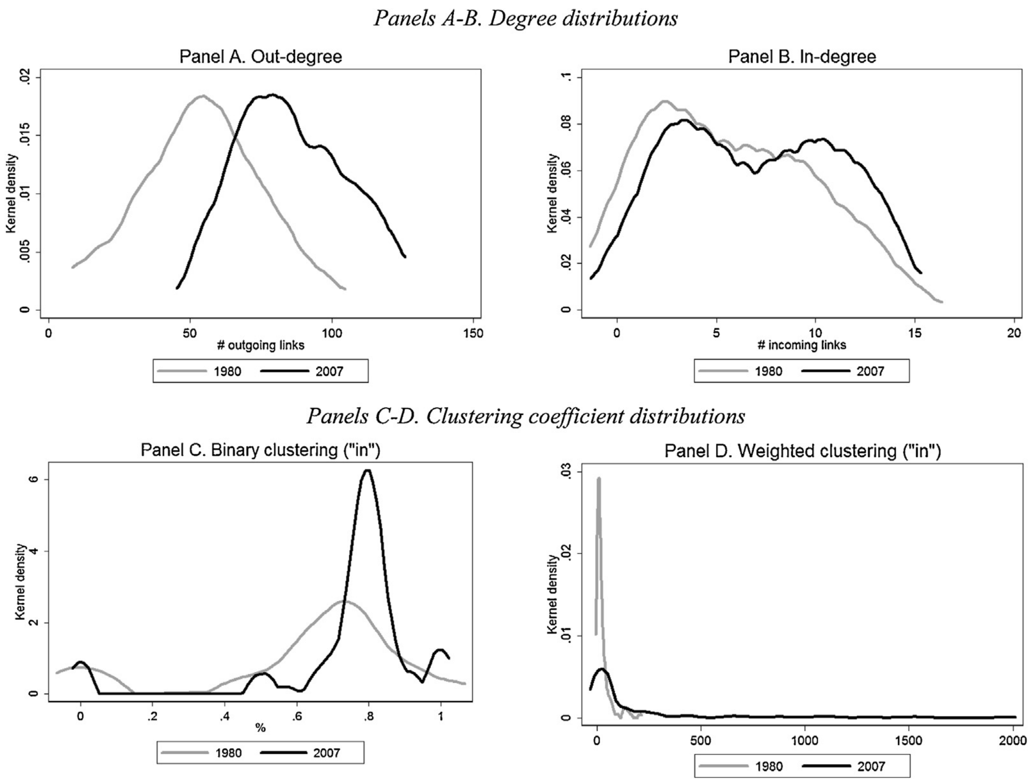


Fig. 4. Empirical distributions of network indicators: 1980 vs. 2007. Notes: Empirical distributions of selected network indicators in 1980 and 2007 for the full network. Density estimates based on the kernel density estimator with Epanechnikov kernel and an optimal bandwidth (Silverman, 1986).

Data sources: BIS bilateral locational banking statistics.

Fig. 4 plots nonparametric density estimates for degree and clustering for the 1980 and 2007 GBNs. We notice that the distribution of out-degree, the number of outgoing links, preserved its shape between 1980 and 2007, but moved rightwards as an increasing number of core nodes lent out financial capital across borders (Panel A). The distribution of in-degree, the number of incoming links, moved rightwards as well, with borrowers tapping into a larger pool of lenders by 2007 (Panel B). The in-degree density also became bimodal, with a large group of better-connected borrowers (large emerging markets from the periphery and advanced economies from the core) co-existing in 2007 with a large group of less-connected (periphery) borrowers.

The density estimate for binary clustering has a higher mean in 2007 compared to 1980 as a larger share of periphery nodes formed "in" triangles (Fig. 4, Panel C). As mentioned earlier, this indicator captures dynamics both in the periphery and the core. Binary "in" clustering can increase in several ways: (a) for a fixed set of links in the core, more nodes in the periphery borrow from the core; (b) for a fixed set of links between the core and the periphery, more nodes in the core lend to each other; and (c) both happen at the same time. Panel D shows that the distribution of weighted clustering coefficients (for "in" triangles) became more right-skewed. Given that weighted clustering largely reflects the evolution of aggregate flows, the shape of its distribution suggests that the weight link distribution may be highly skewed as well.

To explore this possibility we test whether the link weight distributions follow a power law or a log-normal distribution. Fig. 5 presents the fitted and the empirical distributions for a power law fit (Panel A) and a lognormal fit (Panel B). We find that the distributions of cross-country flows are a poor match for a power law but a better one for the lognormal. A Kolmogorov–Smirnov test of the null hypothesis that the link weights follow either theoretical distribution (p-values shown below the charts) reject the power law and fail to reject the lognormal distribution. This suggests that the majority of flows in 1980 and in 2007 were relatively weak and co-existed with a few high-intensity ones.[19] As both aggregate flows and network density increased between the two years, the periphery appears to have become more tightly connected to the core but a large share of the links remain low-intensity.

We finalize the analysis of network indicator distributions by assessing their stability over time through a series of two-sample Kolmogorov–Smirnov tests. The null hypothesis is that the observed empirical distributions in distinct years are sufficiently close in order not to reject that they come from the same data generating process. We run the tests by comparing each indicator's empirical distribution in the first year of each decade (1980, 1990, and 2000) with that in subsequent years within that decade and in later decades (1981–1989, 1991–1999, and 2001–2010). In Table 3 we report the proportion of years when the empirical distributions of network indicators were statistically *different* in each decade compared to 1980, 1990, and 2000 (at the 5 percent level of significance). The higher are the values in this table, the more unstable are the distributions of network indicators over time. The results, shown for the core–periphery network, suggest that lender distributions of degree and strength are relatively stable within and across decades (Panel A). For example, the zero entries in the first column suggest that the out-degree and out-strength distributions in 1980 are often statistically close to those in subsequent years. By contrast, Panel B mostly contains non-zero entries, which suggests that borrower distributions at the beginning of each decade

[19] This finding is also common in studies of the world trade network (see, e.g., Fagiolo et al., 2009).

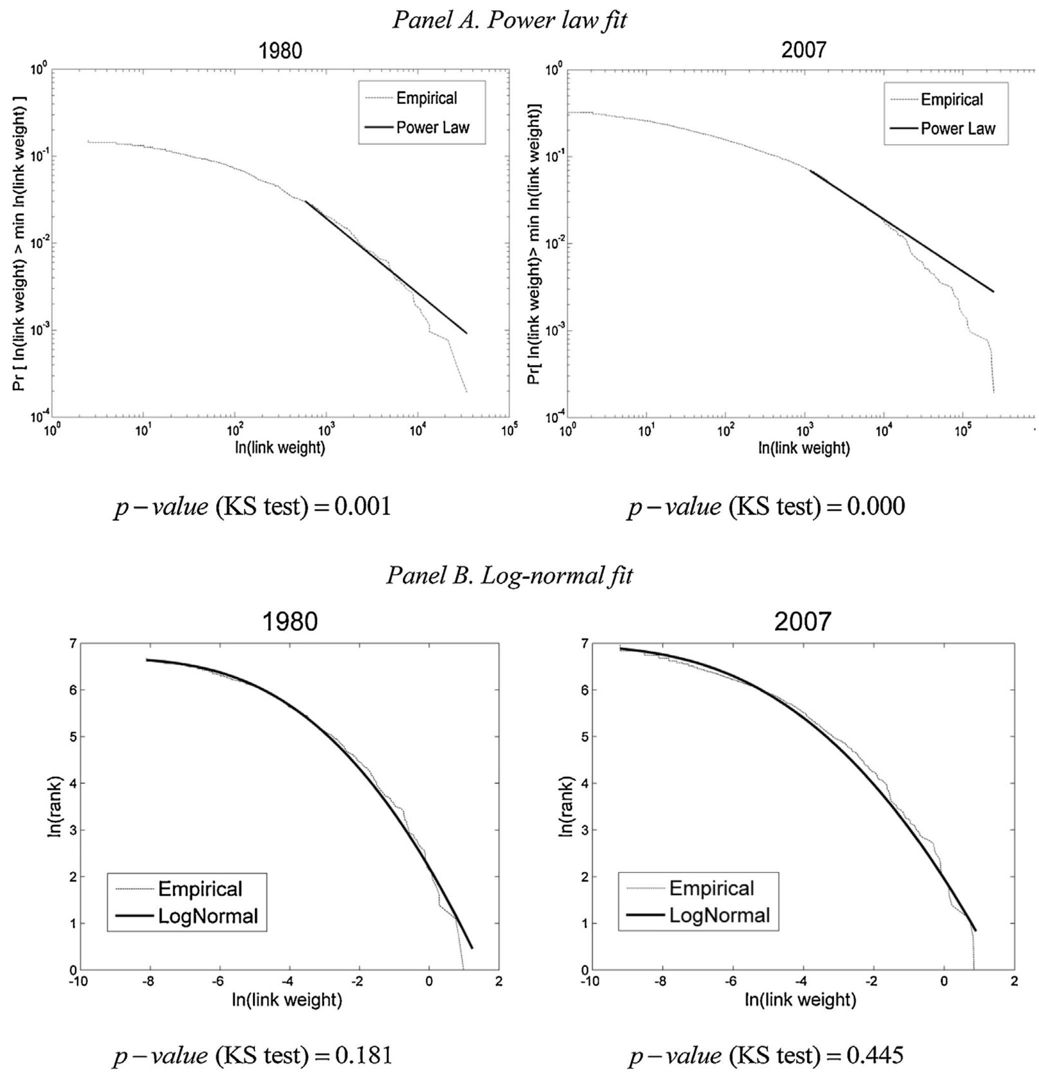


Fig. 5. Parametric fitting of the link weight distribution, 1980 vs. 2007. Notes: Parametric fitting of the link weight distribution in 1980 and 2007. Results for the full network. The solid line is a power-law fit in Panel A (according to the methodology described in Virkar and Clauset (2012) and Clauset et al. (2009), and the code available on http://tuvalu.santafe.edu/∼aaronc/powerlaws/) and a log-normal fit in Panel B. We report the p-values of Kolmogorov–Smirnov tests with the null hypothesis that the distribution is a power law (Panel A) or log-normal (Panel B).

Data sources: BIS bilateral locational banking statistics.

Table 3
Stability of the empirical distributions of network indicators.

Panel A: core				Panel B: periphery			
	1980	**1990**	**2000**		**1980**	**1990**	**2000**
Out-degree				In-degree			
1981–1990	0.00			1981–1990	0.00		
1991–2000	0.00	**0.10**		1991–2000	**0.20**	0.00	
2001–2010	**0.20**	**0.60**	**0.30**	2001–2010	**0.40**	**0.30**	**0.50**
Out-strength				In-strength			
1981–1990	0.00			1981–1990	**0.60**		
1991–2000	0.00	0.00		1991–2000	**1.00**	**0.20**	
2001–2010	**0.50**	**0.50**	**0.70**	2001–2010	**0.60**	**0.40**	**0.40**
Out-HHI				In-HHI			
1981–1990	**0.30**			1981–1990	**0.30**		
1991–2000	**0.50**	0.00		1991–2000	**1.00**	0.00	
2001–2010	**0.90**	**0.10**	**0.10**	2001–2010	**1.00**	**0.80**	**0.70**

Data sources: BIS bilateral locational banking statistics.

Notes: Kolmogorov–Smirnov tests of the stability of empirical distributions of selected network indicators for core–periphery network. We report 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 (1980, 1990 or 2000) at the 5 percent level of significance. For instance, the Figure 0.20 for out-degree in column 1 shows that 20 percent of the time during the 2000s (i.e., in 2 out of the 10 years) the empirical distribution of out-degree was different than that in 1980. Non-zero figures are in boldface.

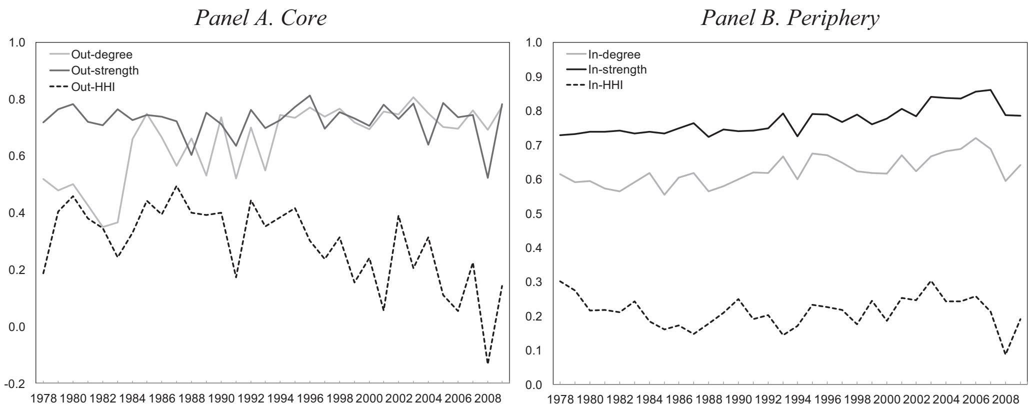


Fig. 6. Ranking stability indices. Notes: Rankings stability indices for the core–periphery network (see Section 3.4 for definition). In Panel B we retain only the borrowers that are present throughout the sample period to avoid sample composition effects, and exclude high income countries.
Data sources: BIS bilateral locational banking statistics.

are poor predictors of future ones. The HHI distributions, especially for borrowers, are also very likely to change shape over time, both within and across decades. Overall, the core–periphery network features a combination of unstable distributions of borrower importance on the one hand and stable distributions of lender importance on the other.[20]

3.4. Country rankings: top players in the global banking network

Two questions arise from our results above. The first is whether the empirical distributions of network indicators underpin stable or turbulent country rankings of connectedness. Unstable distributions can underpin stable rankings if nodes tend to maintain their relative positions in terms of importance but bundle up to generate distributional mass in diverse ways. Similarly, stable indicator distributions can coexist with unstable rankings if countries tend to swap places in terms of importance in the network. The second question concerns which countries and regions are the 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 address 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:

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

The RSI has the usual properties of a correlation coefficient and is useful in detecting shape-preserving rankings turbulence, or conversely, shape-altering rankings stability.

The RSIs for indicators pertaining to the core–periphery network are shown in Fig. 6. On the lender side, the RSIs for out-degree and out-strength have been stable at around 0.7–0.8 for most of the period (Panel A). The borrower RSIs for in-degree and in-strength are relatively high and rising during the sample period but also experience a dip during the recent crisis (Panel B). Coupled with our earlier assessment of network distribution stability, this suggests that the core is relatively stable both in terms of rankings and distributional shapes. By contrast, the periphery is experiencing rankings-preserving distributional turbulence, i.e., countries in the periphery tend to maintain their relative positions in the network (at least based on degree and strength) despite the changing distributions. More rankings turbulence is apparent in the lending and borrowing concentration indices. The RSI of lending concentration rankings is around 0.3 in the first half of the sample period but declines subsequently and becomes negative during 2008–2009. This may be indicative of portfolio rebalancing during the crisis. Rankings based on borrowing concentration are also unstable, with an average ranking stability index of 0.2 throughout the period.

Focusing on the top end of the distributions, we report the first ten lenders in terms of connectedness in 1980, 1995, and 2007 (Table 4). The most connected lenders based on degree are France, Germany, Switzerland, and the UK, with Japan and the US joining the top ranks in terms of aggregate flows (Panels A–B).[21] The lenders with the least diversified outflows (across borrowers) are Denmark, Japan, and Sweden (Panel C). The most diversified lenders are large banking centers such as Luxembourg, Switzerland, and the UK.

Looking at the periphery, we notice that each wave of capital flows brings new borrowers at the top of the connectedness rankings (Panels D–E).[22] In 1980 Latin American countries were the most interconnected. By 1995 they had given way to the fast-growing East Asian countries and the BRIC (Brazil, Russia, India, and China) began their ascending path. By 2007 the BRIC had become the most connected borrowers alongside emerging Europe. Interestingly, before each major crisis a new group of periphery countries rises to the top in terms of network connectedness only to be the hardest hit when the crisis occurs. Prior to the 1980s debt crisis Latin American countries (Argentina, Brazil, Chile, Mexico, and Venezuela) dominated the top 10 for in-degree and in-strength; before the East Asian crisis we notice the ascent of the East Asian tigers (Indonesia, Philippines, Thailand). Countries from emerging Europe (Latvia, Poland, Romania, Ukraine) were also highly connected before the latest crisis. Periphery nodes that only borrow from one lender (in-HHI equal to 1) have the highest borrowing

[20] The distributions of lender importance only exhibit instability (relative to the initial years considered) in the 2001–2010 period. In results not reported, we investigated whether this instability occurred in the first (pre-crisis) or second half of the decade (post-crisis), and consistently found that the distributions started to change in 2007, i.e., in the wake of the global financial crisis.

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

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

Table 4
Country rankings based on connectedness.

Rank	1980	1995	2007	Rank	1980	1995	2007
	Panel A: out-degree				*Panel D: in-degree*		
1	UK	Switzerland	Switzerland	1	Argentina	Indonesia	China
2	France	Germany	France	2	Venezuela	China	Brazil
3	Belgium	Netherlands	UK	3	Brazil	Thailand	Ukraine
4	US	France	Germany	4	Egypt	Philippines	Poland
5	Luxembourg	UK	Belgium	5	Chile	Iran	Chile
6	Austria	Luxembourg	Luxembourg	6	Indonesia	Pakistan	Russian Fed.
7	Germany	Belgium	Netherlands	7	Mexico	Argentina	India
8	Netherlands	Austria	Denmark	8	Colombia	Chile	Latvia
9	Canada	Italy	Austria	9	Ecuador	Malaysia	South Africa
10	Italy	US	Japan	10	Nigeria	India	Uruguay
	Panel B: out-strength				*Panel E: in-strength*		
1	UK	Japan	UK	1	Mexico	Thailand	Russian Fed.
2	US	UK	France	2	Brazil	Brazil	China
3	France	US	US	3	Argentina	Indonesia	Brazil
4	Japan	Germany	Japan	4	Venezuela	Panama	Poland
5	Belgium	France	Germany	5	Chile	China	India
6	Luxembourg	Luxembourg	Austria	6	Romania	South Africa	Turkey
7	Germany	Netherlands	Netherlands	7	Philippines	Turkey	Romania
8	Canada	Belgium	Belgium	8	Panama	Chile	Ukraine
9	Netherlands	Austria	Luxembourg	9	Poland	Argentina	Panama
10	Austria	Italy	Switzerland	10	Egypt	India	Mexico
	Panel C: out-HHI				*Panel F: in-HHI*		
1	United States	Denmark	Denmark		Namibia	Ethiopia	Fiji
2	Denmark	Sweden	Sweden		Ethiopia	Cameroon	Sierra Leone
3	Sweden	Canada	Germany		Macao SAR	Seychelles	Guinea
4	Japan	Japan	Japan		Papua New Guinea	Swaziland	Kiribati
5	Ireland	Ireland	United States	Highest	Somalia	Somalia	Somalia
6	Canada	Luxembourg	France	concentration	Guinea-Bissau	Guyana	Timor Leste
7	Italy	Italy	Italy		Nepal	Rep. of Moldova	Botswana
8	Austria	Netherlands	Luxembourg		Swaziland	Burundi	Vanuatu
9	Belgium	United States	Ireland		Seychelles	Togo	Cambodia
10	Germany	Belgium	Switzerland		Barbados	Sao Tome	Turkmenistan
11	Switzerland	United Kingdom	Belgium		Hungary	China	Poland
12	Netherlands	Austria	Austria		Indonesia	Indonesia	Turkey
13	United Kingdom	France	Canada		Venezuela	Iran	Hungary
14	France	Germany	Netherlands		Bolivia	Israel	Sri Lanka
15	Luxembourg	Switzerland	United Kingdom	Lowest	Tanzania	Romania	Ukraine
				concentration	Argentina	Pakistan	Brazil
					Poland	Czech Republic	Czech Republic
					Turkey	Slovakia	Uruguay
					Algeria	Argentina	Azerbaijan
					Nigeria	Hungary	Iraq

Data sources: BIS bilateral locational banking statistics.
Notes: Country rankings of connectedness based on the core–periphery network. Panels A–C refer to core nodes (lenders). Panels D–F refer to periphery nodes (borrowers) and exclude high-income countries. In Panel F all periphery nodes shown have the highest concentration possible (in-HHI equal to 1) as they only borrow from one core node.

concentration (Panel F). At the other end of the spectrum, emerging markets such as Indonesia, Hungary, Poland, and Turkey consistently top the borrowing diversification ranks.

3.5. The GBN during financial crises

We conclude the exploration of the GBN's topology by more formally examining the behavior of network indicators before, during, and after financial crises. Cetorelli and Goldberg (2011) identified cross-border banking as a leading transmission channel of the 2007–2008 subprime crisis. In the wake of the crisis, 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. Against this backdrop, in Fig. 8 (Panels A–B) we visualize the GBN before and after the Lehman Brothers bankruptcy and notice a significantly lower level of connectivity after the shock (both in the full network and its core) (Fig. 7).

To assess the behavior of country-level financial connectedness during financial crises, we focus on two types of events, systemic banking crises and sovereign debt episodes, as defined by Laeven and Valencia (2008). 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 dates of sovereign debt default vis-à-vis private creditors and the start of debt restructuring negotiations. 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 and 47 sovereign defaults during 1982–2003 (that is, within at least five years of the sample endpoints). The total number of crises in the sample rises to 116 when we add the 2007–2008 systemic banking crises from Laeven and Valencia (2012).[23]

[23] The 2007–2008 crises are: UK and US (2007); 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).

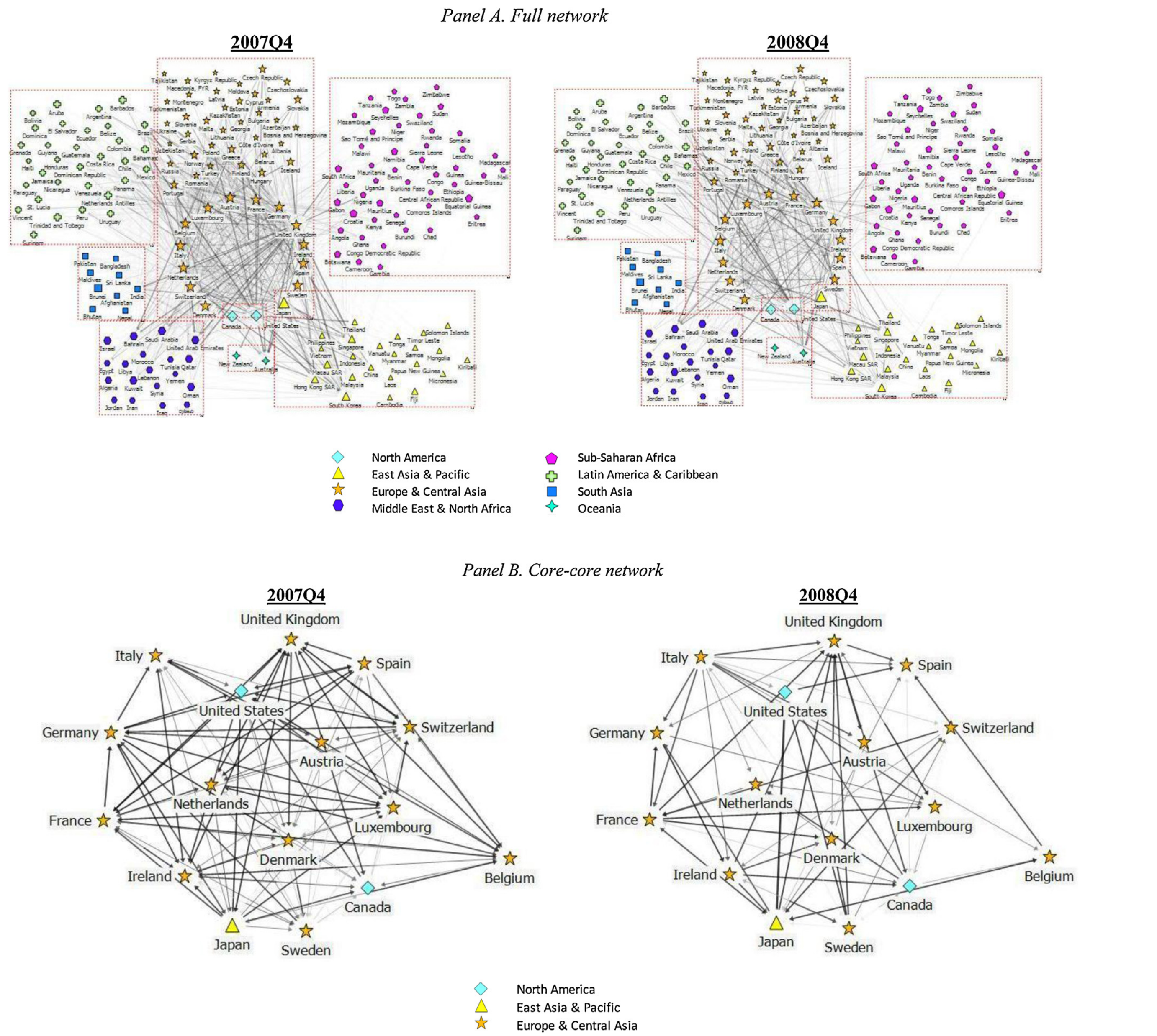


Fig. 7. Global banking network: 2007Q4 vs. 2008Q4. Note: The countries represent nodes and the links between nodes represent cross-border banking flows (expressed in constant 2009 USD). Thicker links indicate larger flows. Arrows indicate the direction of the flows. When reciprocal flows occur between core nodes (in either panel), the link is split into two, with each half-link reflecting the magnitude of one flow.

Data sources: BIS bilateral locational banking statistics.

We plot average degree and strength around the onset of crises in Figs. 8–9. In Fig. 8, the window around crises is −/+5 years for Panels A–B (where we exclude the 2007–2008 crises) and −5/+2 years for Panels C–D (where we include them). We notice that borrower importance in the GBN, measured by in-degree and in-strength, generally falls during systemic banking crises, but the decline begins before the event. Lender importance, measured by out-degree and out-strength, also falls despite the paucity of financial crises in core countries before 2007, but the effect is more visible when we include the 2007–2008 crises as well (Panels C–D). For sovereign debt episodes we only focus on borrowers since there was no sovereign default in the core over the sample period, and find the same pattern (Fig. 9).[24] We also notice that crisis-hit borrowers do not recover their pre-crisis connectivity or strength during the five years

[24] An interesting related question is whether network measures of interconnectedness are useful in predicting episodes of financial stress and should be incorporated in early warning systems (see, e.g., ECB, 2010; IMF, 2010b). Battiston et al. (2012c) propose a novel measure of systemic risk called "DebtRank"that can be used to rank financial institutions according to their potential economic impact on the financial system in case of bankruptcy; and show how DebtRank (as opposed to total assets) can be used as a predictor of distress. Chinazzi et al. (2013) empirically document a statistically significant relationship between country-specific network indicators (in the network of equities and debt investments) and stock market performance but the coefficient magnitudes are similar during crisis and non-crisis times.

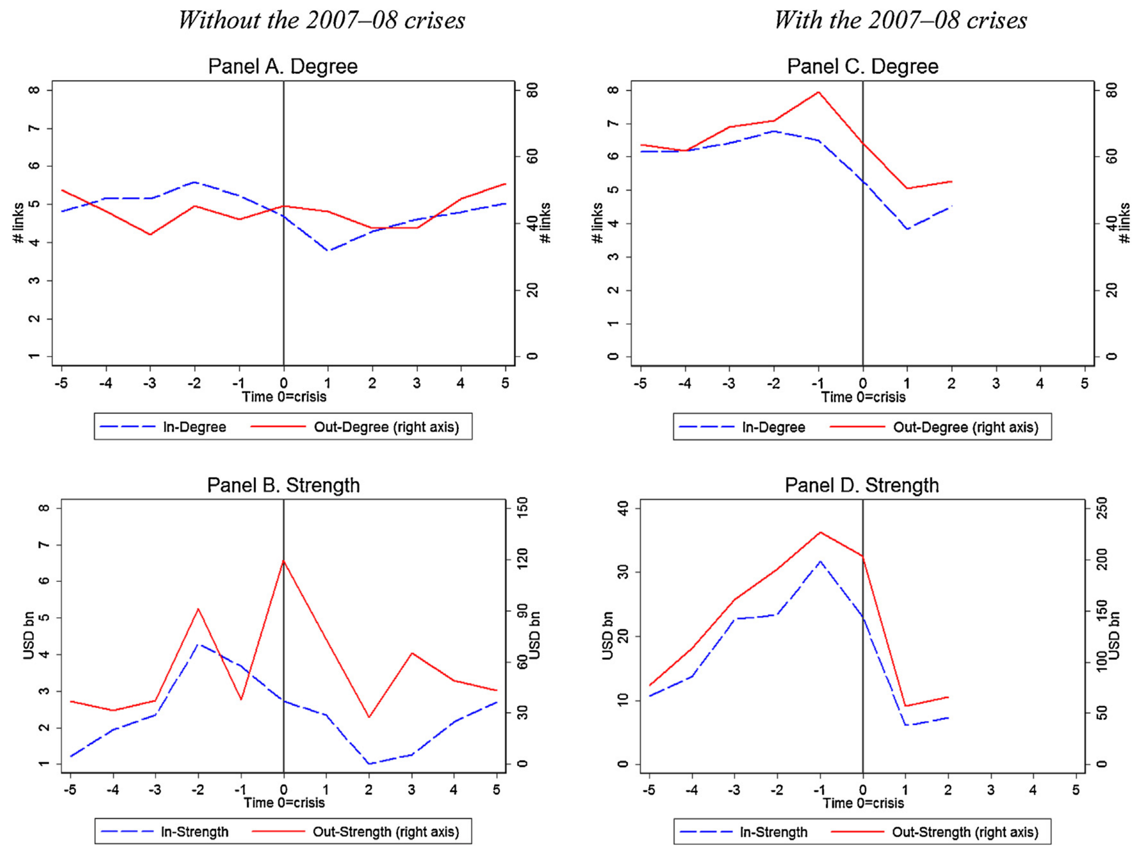


Fig. 8. Financial interconnectedness before and after banking crises. Notes: Average level of country connectedness before and after banking crises. Results for the full network. The window around the onset of crises is −/+5 years (Panels A–B) and −5/+2 years (Panels C–D). In Panels A–B we include systemic banking crises that occurred during 1982–2003 and are at least 10 years apart so we can allow for a 5-year non-overlapping window around them. Countries with two crises within 10 years are dropped. In Panels C–D we add the following 2007–2008 systemic (or borderline systemic) banking crises: UK and US (2007); 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).

Data sources: BIS bilateral locational banking statistics and Laeven and Valencia (2012).

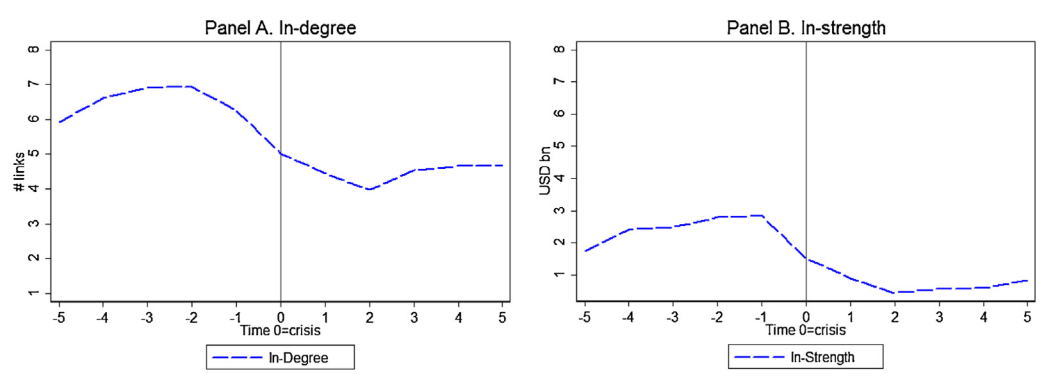


Fig. 9. Financial interconnectedness before and after sovereign defaults. Notes: Average level of country connectedness before and after sovereign defaults. Results for the full network.

Data sources: BIS bilateral locational banking statistics and Laeven and Valencia (2012).

after the event. Furthermore, connectedness declines more during the two years after systemic banking crises when we add the 2007–2008 episodes (Panels C–D), which reflects the sharp adjustment in core–core network density during the global financial crisis.

To formalize the analysis we regress using Ordinary Least Squares (OLS) all measures considered so far on a set of dummies for pre- and post-crisis years while controlling for country fixed effects.[25] The strength and weighted clustering variables are log-transformed to reduce skewness. We do not aim to establish causality and interpret our results as simply being indicative of statistical correlations.

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

Table 5
Financial interconnectedness and crises: regression estimates.

	In-degree [1]	Log (in-strength) [2]	Out-degree [3]	Log (out-strength) [4]	In-HHI [5]	Binary clustering ("in") [6]	Log (Weighted clustering ("in")) [7]	In-degree [8]	Log (in-strength) [9]
Panel A: full network									
3–4 years before	0.34*	0.39***	10.27**	0.91***	−0.01	−0.01	0.20	1.00*	0.78***
	(0.20)	(0.12)	(4.72)	(0.20)	(0.02)	(0.02)	(0.13)	(0.52)	(0.24)
1–2 years before	0.50**	0.32**	12.82**	1.03***	−0.02	0.02	0.23*	1.34***	1.04***
	(0.23)	(0.13)	(4.51)	(0.20)	(0.02)	(0.02)	(0.12)	(0.41)	(0.22)
Onset of crisis	−0.61**	−0.18	1.87	0.60*	0.02	−0.06*	−0.30*	0.08	0.45**
	(0.27)	(0.15)	(2.07)	(0.30)	(0.03)	(0.03)	(0.17)	(0.42)	(0.21)
1–2 years after	−0.98***	−0.50***	−2.29	−0.18	0.07***	−0.03	−0.37***	−0.72**	−0.04
	(0.23)	(0.14)	(3.70)	(0.17)	(0.02)	(0.02)	(0.14)	(0.33)	(0.22)
3–4 years after	−0.40**	−0.15	−0.46	0.01	0.05**	−0.01	−0.05	−0.41	−0.11
	(0.18)	(0.10)	(4.69)	(0.30)	(0.02)	(0.02)	(0.10)	(0.31)	(0.16)
p-Value *F*-test	0.00	0.00	0.00	0.00	0.00	0.52	0.01	0.00	0.00
Obs.	4173	4173	375	375	4625	3375	3375	4173	4173
R-squared	0.641	0.813	0.563	0.615	0.251	0.212	0.630	0.639	0.812
	In-degree	Log (in-strength)	Out-degree	Log (out-strength)	Out-HHI	Binary clustering ("in")	Log (weighted clustering ("in"))	Binary clustering ("cycle")	Log (weighted clustering ("cycle"))
Panel B: core–core network									
3–4 years before	0.96**	1.06***	0.74*	0.95***	−0.00	0.04**	0.95***	−0.00	0.79***
	(0.42)	(0.21)	(0.37)	(0.19)	(0.02)	(0.02)	(0.17)	(0.01)	(0.12)
1–2 years before	1.62***	1.20***	0.86**	1.05***	−0.00	0.04***	1.03***	−0.00	0.86***
	(0.51)	(0.20)	(0.38)	(0.19)	(0.03)	(0.01)	(0.14)	(0.01)	(0.12)
Onset of crisis	−0.87	0.50*	0.14	0.97**	0.06	0.01	0.31	0.01	0.49
	(0.99)	(0.24)	(1.15)	(0.33)	(0.08)	(0.03)	(0.39)	(0.02)	(0.40)
1–2 years after	−1.87	−1.63	−2.02*	−0.11	0.01	−0.00	−0.86	−0.04***	−0.87
	(1.64)	(1.31)	(0.99)	(0.40)	(0.06)	(0.13)	(0.94)	(0.01)	(0.59)
3–4 years after	−0.04	−0.16	−0.86	−0.26	0.08	−0.02	−0.02	−0.01	−0.25
	(0.40)	(0.25)	(0.67)	(0.63)	(0.08)	(0.03)	(0.35)	(0.02)	(0.60)
p-Value *F*-test	0.00	0.00	0.18	0.00	0.49	0.00	0.00	0.00	0.00
Obs.	375	375	375	375	375	375	375	375	375
R-squared	0.183	0.374	0.185	0.541	0.200	0.092	0.279	0.323	0.285

Notes: We regress country-level network indicators on dummies for two-year periods before and after financial crises (including the 2007–2008 crises). All results refer to banking crises except columns 8–9 in Panel A, which refer to sovereign defaults. The estimation method is OLS with country fixed effects. We report *p*-values for an *F*-test of the null hypothesis of joint insignificance of all the lead and lag coefficient estimates. Standard errors are clustered at the country level. The constant is estimated, but not reported. * represents significance at the 10% level, ** at the 5% level, and *** at the 1% level. Data sources: BIS bilateral locational banking statistics and Laeven and Valencia (2012).

The results are reported in Table 5 separately for the full network (Panel A) and core–core network (Panel B). All estimates correspond to banking crises except columns 8–9 in Panel A, which correspond to sovereign defaults. The results for the full network suggest that financial interconnectedness tends to rise prior to financial crises and fall afterward (Panel A). In the four years before the onset, borrowers gain access on average to 0.84 more lenders (column 1) and lenders expand their set of borrowers by 23.09 countries (column 3) compared to non-crisis times.[26] Banking inflows per borrower increase by 85 percent in the four years prior to systemic banking crises (column 2) whereas outflows per lenders rise by a factor of three (column 4).[27]

After financial crises, connectivity and flows both decline but the coefficient estimates are significant for borrowers (columns 1–2) and insignificant for lenders (columns 3–4), possibly because of the fewer crises available in our dataset on the lender side. We do not find any statistically significant changes in borrowing concentration before crises, but there is evidence of lower post-crisis diversification (column 5). In the case of sovereign defaults (columns 8–9) the estimated coefficients suggest a stronger boom and a weaker bust in in-degree and strength than in the case of banking crises. The results are broadly similar for the core–core network (Panel B), where we exploit primarily the variation afforded by the most recent crises in advanced economies. We observe statistically significant increases in connectivity and flows before crises (columns 1–4) but no changes in lending concentration (column 5) or "cycle" clustering (column 8). *F*-tests for joint statistical significance of the coefficients on the lead and lag variables around crises reject the null of zero effect in 15 out of 18 specifications, suggesting that country-specific connectedness measures are systematically different around crises compared to tranquil times.

These results bring a novel network-based perspective on the post-crisis dynamics of market access. Our findings regarding the pro-cyclicality of network connectivity complement those of the cost-of-default literature, which has shown that capital inflows across different classes and to a wide range of economic agents are drastically reduced after sovereign default and debt restructuring episodes (Fuentes and Saravia, 2009; Arteta and Hale, 2008). Our findings are also complementary to Hale (2012), who examines the link between banking crises and local recessions on the one hand, and financial interconnectedness on the other. The evidence shows that macroeconomic shocks affect bank connectedness but the impact depends on the persistence of the shock. A more thorough econometric analysis is needed to establish the direction of causality between network indicators of connectedness and the business cycle.

[26] The marginal effects are calculated as $0.34+0.50=0.84$ for in-degree and $10.27+12.82=23.09$ for out-degree.

[27] The marginal effects are calculated as: $(\exp(0.39)-1)+(\exp(0.32)-1)=0.85$ for in-strength and $(\exp(0.91)-1)+(\exp(1.03)-1)=3.29$ for out-strength.

4. Connectedness around the 2008–2009 crisis

We have shown that measures of network density such as connectivity and clustering follow a boom-bust cycle similar to aggregate flows. Connectedness in the binary network, especially in the core, was stationary over the long run and reached a peak before the 2008–2009 crisis that was comparable to earlier peaks. Nevertheless, network density experienced a downward adjustment during this crisis that was deeper than during other crises. What could be the reason for this? Put differently, if connectedness as captured by our binary network measures was not unusually high, to what extent can it explain the virulence of the global financial crisis?

The literature on financial networks shows that denser networks are better able to absorb shocks due to international risk diversification but can also harbor more systemic risk. However, these results may not straightforwardly apply here because they rely on assumptions of link weight homogeneity both across nodes and over time. In our GBN there is significant link weight heterogeneity – both cross-sectionally and over time.[28] The trade-off between the benefits and risks of connectedness may interact with the size and distribution of cross-border flows in ways that are yet to be fully explored in the literature. Some insights in this direction are provided by DasGupta and Kaligounder (2012) who calculate global stability measures for a large variety of network topologies. The authors present the following relevant findings. First, a more unequal distribution of link weights is associated with greater vulnerability, and failure of nodes with very large strength can cause significant damage in the network. Second, total link weight plays a lesser role in the stability of the network than does the inequality of the link weight distribution. Third, in networks with unequal link weight distribution, higher connectivity is associated with more stability. Conditional on the parameter values chosen by DasGupta and Kaligounder (2012) to separate homogenous from heterogeneous networks, the policy implication is that regulators should watch out for two types of networks: those with low connectivity and highly skewed link weight distribution; and those with high connectivity but less skewed distributions.

While our analysis does not equip us with a definite view on the role of connectedness during the global financial crisis, our conjecture is that additional factors need to be considered. A first factor is the *size* of the flows in the GBN. Prior to the crisis, the global banking network was intermediating cross-border flows that were larger than in previous decades by several orders of magnitude. Moreover, aggregate flows rose faster than connectedness, potentially reducing the benefits of increased diversification. In a model of contagion in the interbank market, Gai and Kapadia (2010) show that the benefits of greater diversification owing to a denser network can be quickly wiped out when exposures rise faster than connectivity; in such a case, higher network density unambiguously increases contagion risk.

A second factor is the *location* of the initial shock in the network. While the debt and the East Asian crises affected countries located in the periphery, the global financial crisis started with a shock to its core nodes, and within the nodes, it affected market participants that were themselves highly interconnected. Gai and Kapadia (2010) perform simulations on the network of interbank exposures to show that similar shocks can have different consequences for a financial system depending on the point in the network where the shock hits. Shocks that are ex-ante seemingly identical may impact the financial system differently if they hit vulnerable nodes.[29] Degryse et al. (2010) analyze the propagation of shocks to a country's cross-border foreign liabilities toward banking systems in other countries. They show that negative shocks need not start in financial centers; furthermore, the layout of cross-border banking exposures is such that since the mid-2000s shocks to Eastern Europe, Turkey, and Russia would affect most countries and could trigger contagion episodes. Martinez-Jaramillo et al. (forthcoming) also underscore the importance of the location of an initial macroeconomic shock. They give the example of a stock market shock that leads to the collapse of a small bank – a seemingly unimportant event – but ends up threatening the entire system due to contagion through the interbank market. The authors argue that a thorough knowledge of the network topology must accompany information on initial shocks, their likelihood, and the distribution of losses in order to develop a proper stress testing framework for assessing systemic risk.

A puzzling finding emerges when we compare the evolution of the GBN before and after the 2008–2009 shock. In the run-up to the crisis aggregate flows rose faster than the connectedness, indicating a more pronounced cycle. However, when the 2008–2009 shock hit, aggregate flows fell to their 1994 levels, that is, close to their long-run average, whereas connectivity and binary clustering plunged to levels not seen before. What caused the global financial system in 2008 to be unable to sustain the 1994 level of connectivity given that it was intermediating the same amount of flows? What could explain this asymmetry in the behavior of aggregate flows and connectedness before and after the 2008–2009 shock? These are open questions that warrant further research.

5. 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 how systemic risk emerges. In this paper we analyzed geographical linkages created by cross-border banking activities in 184 countries during 1978–2010 using a network approach. Using country-specific and network-wide indicators of connectedness, we described the topology and assessed the dynamics of the global banking network. We also ranked countries based on their importance in the network and examined changes in connectedness during periods of financial stress.

Our results suggest that the global banking network, and especially its core–periphery part, is relatively unstable. Network density co-moves with the global cycle of private capital flows. Empirical distributions of network indicators change markedly over time, especially for borrowers in the periphery. The network's core, comprising the lenders, is relatively more stable. We also found evidence that country-level connectedness tends to increase before the onset of financial crises and to decrease afterward. Periphery countries fail to reach their pre-crisis connectivity levels five years after the initial shock. Finally, the sharp drop in network density indicators during the 2008–2009 crisis is unique during the sample period.

One challenge in future work is to integrate some of the stylized features of the global financial network into models of systemic risk. For that, more studies of network topology are needed, covering more asset classes and expanding the analysis with additional indicators. A thorough understanding of real-world network

[28] We are grateful to an anonymous referee for drawing our attention to this point.

[29] This leads the authors to challenge the view that the history of a financial system's reaction to shocks can be used to infer how it would react to similar shocks in the future.

topologies is needed to develop realistic frameworks for stress testing and simulation-based studies of contagion and default. It would also be interesting to explore the link between financial interconnectedness on the one hand and the timing, duration, and severity of crises on the other.

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