Using network method to measure financial interconnection

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Abstract

This paper uses a different approach to measuring financial openness, highlighting interconnectedness in a network of financial flows. Applying an adapted version of eigenvector centrality, often used in network analysis, the new measure captures multidimensional and high-degree financial relations among countries. It provides a nuanced picture of financial integration and interconnectedness in the global and regional financial networks. The United Kingdom and the United States remain the 'core' in the global banking network, with all other countries scattered in the 'periphery'. The application of the new measure of financial integration to the empirical analysis reveals the nonlinear relationship between financial integration and output volatility.

Keywords: financial integration, financial networks, network approach, cross-border banking, output volatility

JEL Classifications: F21, F36, G01

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1. Introduction

The network approach has been employed in a number of disciplines, ranging from computer science, social network, infrastructure, ecology and epidemic, but only recently in economics and finance. The literature on financial networks can be roughly divided into two strands. The first strand was pioneered by a group of modellers who used simulation techniques to model shock transmission in a financial network (Allen and Gale 2000; Gai, Haldane and Kapadia 2010; Francisco, Brauning and van Lelyveld, 2015; Elliott, Golub and Jackson 2014). These studies share a focus on identifying particular network structures that are prone to shock transmission and amplification in the network.

A different approach to harnessing the richness of network methods is taken by studies exploring key facts about networks that emerge from actual data. Two distinctive approaches are observed. The first approach often uses graphs of financial networks to visualize the increased financial interconnectedness and how an individual country is connected to other countries in the network. Often a set of standard network statistics (e.g. in-degree, out-degree, closeness, and clustering; further described below) are calculated to identify financial/banking centres (von Peter,2007), financial clusters where countries form more of a closed system (IMF 2010 and 2011; Garratt et al. 2011), and the structure of financial networks (Bech and Atalay, 2008; Kubelec and Sa 2012).

Financial interconnectedness is closely related to financial stability and systemic risks have emerged to be a key stability concern after the 2007-8 global financial crisis (Haldane 2009; Yellen 2013). The second approach in this empirical strand of literature applies network methods to generate measures of connectedness and systemic risks for financial institutions. Diebold and Yilmaz (2014) identify a suite of network metrics that can be readily used to measure connectedness of financial firms and show they are intimately related to systemic risk measures commonly used in the finance literature. Following this line of research, Dungey, Luciani and Veredas (2014) measure system risks via interconnectedness of the banking, insurance and real economy firms in the United States for 500 firms. Their systemic risk index, SIFIRank, is derived using a network algorithm, the PageRank algorithm, from an undirected, weighted network of risk-interconnected financial and real firms where the links in the network are stock volatilities and correlations of volatilities provide weights. Their results show banking firms are consistently systemically risky in the economy and insurance firms also display substantial systemic risks. Similarly, the DebtRank measure developed by Battiston, et al (Battiston, 2012b) is designed to measure systemic importance of individual financial institutions employing data on US FED’s external claims for a short period during the GFC (. it has been applied to other markets and data but always at the individual institutional level).

Our paper adapts the PageRank algorithm to the global banking network to create a measure of “financial interconnectedness” among countries. There are three important differences in our approach from the above studies. First, we modify the PageRank algorithm in a way that best addresses our data structure as detailed in the methodology section. Second, our measure of interconnectedness is at the country level, obtained from a network of financially-connected countries, while both Diebold and Yilmaz (2014), Battiston, et al. (2012b) and Dungey, Luciani and Veredas (2014)'s use firm-level measures. Third, the directed network in our study is linked by aggregates of banks' foreign claims from one country on another (i.e. banks loans to or from a country), rather than using price data (stock price volatilities are used by Dungey et al) for the links as in these firm-level network studies.

This study therefore shares some features with both the literature on country-level networks and that on institution level ones. The aim of the paper is to establish a richer measure of country-level financial interconnectedness and to bring the insights from studies of networks between financial institutions to bear on the understanding of a network between countries. We then apply the index of financial interconnection or, more precisely, the probability of being connected (taking a probabilistic interpretation of the index), to an empirical analysis of the relationship between financial interconnection and output volatility.

The remainder of the paper is structured as follows. Section 2 reviews the recent trend of the network approach used in analysing financial interconnectedness. Section 3 presents some standard network statistics to establish the stylized facts for the global banking network based on our data and then compares these with other studies and the emerging consensus on features of "the" global financial system. Sections 4 and 5 detail our methodology and data, with selected empirical findings presented in Section 6. Section 7 concludes.

2. **The global banking network: stylised network facts**

The concept of networks is helpful for characterising interdependent interactions, where the interaction between components A and B influences the interaction between components B and C (Rosvall and Axelsson 2009). This is a hallmark of the modern day global financial system, where increased and complex cross-holding of debt and liabilities make financial institutions closely linked to one another (Allen and Babus 2009).

We treat the global financial system as a network consisting of N countries that are linked together by L financial links, with strength of links measured by the size of banks' foreign claims on each country[2]. Our data are described in more detail below in Section 6 but in outline, this global banking

[2] A simple network is graphed in Figure A1.

network is constructed by using banks' foreign claims as links connecting 217 countries in the world. Foreign claims data are compiled from the BIS consolidated banking statistics in the period (1983-2016) based on the data from "reporting" countries. There were 24 reporting countries at the beginning of our period and 47 by the end.

Table 1a and 1b in Appendix A show the standard measures of network connection for BIS reporting countries in the global banking network. Table 1a lists the 24 countries that report foreign claims data through the whole period (1983-2016) and Table 1b lists the top 25 countries in terms of total inflow of foreign claims in 2016 . In each table, we report means of individual metrics over two subperiods – the pre-2000 (1983-1999) and the post-2000 (2000-2016) periods.

In and out-degrees are the simplest measures of connections that one country has in a financial network. The former measures the total number of links that point in to the country (i.e loans to that country made by any other country) and the latter the total number of links departing from the country (i.e loans from that country to any other), and a directed link is established if nonzero foreign claims are recorded between the country and other countries in either direction [3]. By the end of the period there are in total 47 countries that report their own foreign claims data to the BIS, so the maximum number of in-bound links, or in-degree, for each country each year is 47. For the individual 24 countries that reported data for the whole period, all show roughly the same average in-degree in each of the two periods and almost all nearly doubled in the second period, reflecting increased financial connections across the board. Since we are limited by the number of reporting countries, the in-degree measures underestimate the actual span of financial interconnections. The out-degree values provide a more complete picture of outward links because we have data on all the destinations of lending by the reporting countries., Out-degree values also increased over the two periods but show a diverse range of values among countries. United Kingdom, France, Switzerland, on the one end, extend bank credits to as many as 180 countries, while, on the other end, the majority of countries extend no bank credit overseas. Together with other European countries, including Germany, Belgium, Luxembourg, Denmark, Ireland and Sweden, they are lenders to more other countries than any other member of the network. These countries extend bank credit to the largest geographical coverage, seen by their high values of out-degree, on average, more than 100.

While in/out-degrees measure the span of financial interconnection, in/out-strength measure the scale of the interconnection as they account for the volume of in and out flows. In addition, as the advantage of the BIS location banking statistics is its volume coverage (90 percent of cross-border lending of all banks around the world), the in/out-strength measures are more reliable measures of

[3] See formal definitions in Table 3 in Appendix A.

financial connections compared to those of in/out degrees. Among the 24 countries, Table 1a shows that the volumes of inflows to the United Kingdom and the United States top the list, indicating that a large part (1/4 of the total to 24 countries) of bank credit flowed to these two economies in the pre-2000 period and the share increased to 1/3 in the post-2000 period. While the United Kingdom is the largest exporter of bank credit to the rest of the world in both periods, Japan comes second, ahead of the United States, in the first period whereas the United States rises to second place in the second period. Other European countries are among the top lenders, including German and France. As a group, the top 5 account for about 2/3 of the total outflows of the 24 BIS reporting countries.

Although Table 1b includes new reporting countries it does not seem to change the big picture that the 24 countries depict, except for two noteworthy points: (1) three new reporting economies (Taiwan, Korea and Australia) show out-degree averages more than 100 in the recent period, reflecting their outreaching international banking networks and (2) while these economies also record the highest level of out-strength among the new reporting countries, China's in-strength increases nearly 20 times and tops the in strength rank, reflecting the huge amount of capital inflows intermediated by banks post its WTO accession.

Closeness and betweenness are measures of distance between one country and all the other countries in the network. Closeness captures the number of links one country has to traverse to connect to any other country in the network, with higher closeness showing a smaller number of links needed to reach any other node. Betweeness captures the number of shortest paths linking one country to all other countries: higher betweenness indicates a greater number of shortest paths linking that country to all other countries.[4]. As these two measures are based on links and do not account for volumes, they are limited by missing data/links. Given the data available, Tables 1a and 1b show that the United Kingdom, France and Switzerland are ranked top on closeness and betweeness, highlighting their intermediation roles in the global banking network due to their direct links to many countries in the world. These findings bear a strong resemblance to those of Von Peter (2007) and Kubelec and Sa (2012)[5].

In addition to measures for individual components in a network, summary statistics for the whole network are often used to reveal the shape or pattern of network connectedness. For some types of networks these differences may have important network-wide stability implications. Skewness and kurtosis are two such statistics, both measuring the asymmetry of the distribution of links. A positive skewness value and a large kurtosis value indicate that many nodes in the network are connected with

[4] Refer to formal definitions in Table 3 in Appendix A. n

[5] In addition to BIS data, Kubelec and Sa (2012) also incorporate IMF Coordinated Portfolio Investment Survey (CPIS) data.

a small number of links and few nodes with a large number of links[6], characteristics ofso-called 'long-tailed' or 'scale-free' networks (Albert, Jeong, and Barabasi 2000). Such networks are usually regarded as more robust to random shocks but vulnerable to targeted attacks (Kubelec and Sa 2012). Another informative measure is average path length which measures the shortest distance between all pairs of nodes in the network. This can be used to calculate clustering coefficients that measure the degree to which nodes in a network tend to cluster together. A homogenous network (i.e. each node has approximately the same number of links) with a small average path length and a large clustering coefficient are characteristics of 'small world' networks (Watts and Strogatz 1998). Kubelec and Sa (2012) contend that 'small world' networks contain a high risk of shock contagion due to a high-degree of interconnectivity among the nodes. The formal definitions of the network measures are given in Table 2 in Appendix A.

Figure 1 Summary statistics of the global banking network, 1983-2016

Figure 1 provides an overview of the summary statistics of our global banking network. Although outward links of a large number of small countries are missing in the data , the major countries'

[6] A normal distribution has skewness equal to 0 and kurtosis equal to 3.

interconnections are available and complete in the global banking network over the period. The global banking network shows high kurtosis, with some countries having a large number of cross-border linkages, whereas the majority have only a few connections, giving rise to the ‘peakedness’. This indicates that a small number of countries dominate the lending network in terms of linkages. A small kurtosis would indicate more countries lending with more evenly spread amounts. Both skewness and kurtosis indicators exhibit the shape of a long tail quickly being formed since early 2000 but slightly dissoving after the GFC. Moreover, the global banking network is not homogenous as the number of links differs greatly across countries. In addition, an overall fall of the average path length, and a steady increase of the clustering coefficient,suggest that the global banking network is gradually resembling a ‘small world’ network.

Several other studies have also mapped networks in this way. Table 3 in Appendix A provides an overview of the major studies and what is beginning to emerge as a consensus view on the nature of the global financial network. For instance, Kubelec and Sa construct a country-level dataset on the stocks of bilateral external assets for 18 countries in the period from 1980 to 2005 and combine this with a variety of other data. A key finding from their analysis is that the international financial network over the period exhibits a ‘long-tail’ structure.

3. Methodology: construction of a new measure of financial interconnectedness

Going beyond the standard network metrics to bring out more deeply the interconnection among countries, we establish a new measure of financial interconnectedness for countries. Our measure of financial interconnectedness is an adjusted version of an eigenvector centrality measure used in network analysis and essentially an adapted version of the PageRank algorithm[7]. The PageRank algorithm was first introduced by Brin and Page (1998) to enable Google Search to rank the importance of websites and present the ranking in their search engine results. The underlying assumption is that more important websites are likely to receive more links from other websites. “Importance” is essentially a level of connectedness. In our context, we use the PageRank algorithm to search for the most connected countries in the financial network, accounting for connectedness of counterparties and therefore the indirect connections.

Our choice of the PageRank algorithm results from scrutinizing a set of related connection measures available in network analysis (Table 6). Among them, in/out-degree measures the number of (in and out) direct financial ties with other countries, whilst in/out-strength accounts for the weight (value) of those direct connections. We aim to capture both direct and indirect connections so eigenvector

[7] Eigenvector centrality or prestige often applies to undirected networks. Page Rank is a variant of the eigenvector centrality measure that handles well-directed networks.

centrality, Katz-bonacich centrality measures, and PageRank form a group of possible options. They adopt a similar recursive methodology to integrate multi-layered connections into a single measure. However, the eigenvector centrality measure fails to address the 'dangling nodes' issue that commonly features in financial and banking data. Both the Katz-Bonacich algorithm and the PageRank algorithm tackle the issue but in different ways. The former involves inclusion of two parameters the selection of which is somewhat ad hoc[8]. The PageRank algorithm addresses the issue by forcing links with equal weight to connect the dangling nodes. Itis a simple and robust algorithm adopted by other papers such as Diebold and Yilmaz (2014) and Dungey, Luciani and Veredas (2014) to measure financial connectedness and systemic importance of financial firms.

Table 6. Comparison of centrality measures

	Direct connections	**Indirect connections**	**Weight on connections**	**Dangling nodes**
In/out-degree	v			
In/out-strength	v		v	
Eigenvectorcentrality	v	v	v	
PageRank	v	v	v	v

The financial interconnectedness index of any country i at year t, x_{it}, is calculated as the weighted sum of the interconnectedness of all other countries j ($j = 1..J$), x_{jt}, that link to it through bank claims l_{ijt}.

$$x_{it} = \sum_{j=1}^{N} \frac{l_{ijt}}{\sum_{i=1}^{N} l_{ijt}} x_{jt}, \tag{1}$$

Equation 1 reflects two key principles associated with the index. First, the interconnectedness of a country i depends on the interconnectedness of the ones ($j = 1,2, \ldots N$) that it links to. By adding individual connectedness x_j of all countries that country i is connected to, this index goes beyond the bilateral connections between i and j to include higher-degree (indirect) connections in the network brought out by x_j. Second, each connection transfers portions of its connectedness to the one that it connects to, with the size of portions depending on the strength of individual links. We define strength as weight or share of bank claims from j to i, l_{ijt}, in country j's total cross-border bank claims at year t. If there is stronger connection measured by greater weight of the claims to country i in country j's total claims, then a higher portion of j's connectedness is transferred to country i through the link ij.

[8] $V = \alpha A'V + \beta$, α and β are exogenously given.

Equation (1) generates a recursive system of interconnectedness indexes that can be written in matrix form[9],

$$V = A \cdot V, \tag{2}$$

where V is a $(n \times 1)$ vector of interconnectedness indexes for all countries in the network at time t. A is a square matrix,

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix},$$

and it consists of weights for individual links, $a_{ij} = \frac{l_{ij}}{\sum_{i=1}^{N} a_{ij}}$. By construction, A is a column stochastic matrix[10], $\sum_{i=1}^{N} \frac{l_{ij}}{\sum_{i=1}^{N} a_{ij}} = 1$. For such a matrix, Perron-Frobenius theorem ensures the existence of a steady-state vector v^* that satisfies Equation (2) [11].

3.1 Addressing incomplete data: The dangling nodes issue

The matrix A can be used to generate interconnectedness indexes for countries in strongly connected networks[12]. However, in our case the structure of the network fails to meet the strong connection criteria and this creates a major difficulty – the problem of "dangling nodes" or nodes that have no outgoing links and where data on outward links is missing for non-reporting countries[13]. The dangling node problem is a classical technical issue in the PageRank literature. For the dangling nodes, the column sums are less than 1 and equal to zero because each entry in this column is zero, so the matrix A is no longer a stochastic matrix and applying the algorithm to the matrix results in convergence to zero (Figure B2 in Appendix B).

To overcome the difficulty, we follow the PageRank solution to normalize the all-zero columns by replacing all entries in the columns with $1/(n-1)$, except itself being zero[14](Brin and Page 1998). The new square matrix M has elements

$$M_{ij} = \begin{Bmatrix} a_{ij}, & r_j \neq 0 \\ \dfrac{1}{n-1}, & r_j = 0 \end{Bmatrix} \tag{3}$$

[9] t is omitted to save space.
[10] A column stochastic matrix is defined as a square matrix with the sum of elements in each column equals 1.
[11] The theorem is attributed to Oskar Perron (1907) and Georg Frobenius (1912).
[12] A network is strongly connected if starting at any node one can reach any other different node by walking on its links. Mathematically, there is a positive integer k such that the matrix $B = I + A + A^2 + \cdots + A^k > 0$, where I is an identity matrix used to account for linking to itself.
[13] The data issue is discussed in the next section.
[14] Brin and Page (1998) use $1/n$ so equal weight is given to all the countries in the network including the country itself. We use $1/(n-1)$ to exclude the country itself to be consistent with the definition $a_{ii} = 0$.

where r_j denotes the column sum of the column j. Because a dangling node contains no outgoing links, the column representing it has its column entries all equal to zero with a sum $r_j = 0$. The matrix M replaces zeros with $1/(n-1)$ so that the column sums become 1. For columns that represent normal nodes (countries), where $r_j \neq 0$, the configuration of M is same as the matrix A. A detailed description on the dangling node problem and its solution is in the Appendix B.

The implication of this modification is that all countries receive the same level of connection from the dangling node rather than none. This modification 'forces' countries without outward links to link with all the other countries with equal weight and passes equal connectedness to all the other countries. Accordingly, the created links have little effect on the *relative* ranking of all the other countries. Given the key information from the index is the relative ranking (level of interconnectedness relative to the others in the network) instead of actual values, the method addresses the dangling node issue and provides consistent rankings for countries with complete data[15].

3.2 The probabilistic point of view of the index

We may also consider the financial interconnectedness index from a probabilistic point of view. The financial interconnectedness index provides the probability of a country being connected to all the other countries in the network directly or indirectly.

Initially, all countries in the network have equal chances to be chosen as a lending destination. If it is chosen, a connection is established. The probability of each country to be chosen as a starting point is $1/n$,

$$v = \begin{bmatrix} 1/n \\ \dots \\ 1/n \end{bmatrix}$$

The matrix A then maps the probabilities of connections among countries in the network through the existing structure of cross-border lending, because entries in A, a_{ij}, are shares of bank claims from country j to i. A larger share indicates a bigger chance of j lending to i and therefore a higher probability of being connected to i; 0 indicates no chance. Hence, the probability of j being connected to i through direct connections or first-degree connections is Av.

[15] For countries with missing data, because they are treated as no-links, the rankings would be different from the actual rankings if data were available. Given the countries with missing data are not major lending countries, the deviation is understandably small. Detailed discussion is found in the data section.

$$Av = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} \cdot \begin{bmatrix} 1/n \\ \ldots \\ 1/n \end{bmatrix} = \begin{bmatrix} 1/n(a_{11} + \cdots + a_{1n}) \\ \ldots \\ 1/n(a_{n1} + \cdots + a_{nn}) \end{bmatrix}$$

The probability of second-degree connections or indirect connection via one country in-between is $A^2 v$ because A^2 maps all the paths involving two steps and the possibility for each step. Accordingly, the probability of k-degree connections accounting for indirect connections through k countries is $A^k v$. Given that matrix A is column stochastic, the iteration converges to a unique stationary probability distribution vector v^* and the i^{th} entry in v^* is the probability or the overall likelihood of country i being connected of any degree.

$$v^* = \begin{bmatrix} v_1^* \\ \ldots \\ v_n^* \end{bmatrix}$$

This power iteration process is essentially the process to derive the steady state solution to the recursive system (Eq.2). At every iteration, the vector V is multiplied by the matrix A. In the end, the sequence of V converges to a non-zero steady state eigenvector v^* associated with the eigenvalue of 1 such that Eq. (2) holds[16]. The entries in v^* are the interconnectedness indexes for all countries, which are essentially the probabilities of countries being connected of any degree to all the other countries in the network at a specific point in time.

One note of caution is in order. As indexes are network-dependent and networks are formed at each period, cross-period comparison of indexes are not sensible. At each time t, countries under observation form a network, in which the method constructs an index for each country. As networks evolve over time with new entries and exits, the indexes built upon different networks are not comparable across time. For instance, a lift in the index for UK from 0.5 in 2000 to 0.6 in 2008 may not be entirely due to an increase in its financial interconnection (a weighted sum of connection with all the other countries) but could be the fact that several countries previously in the network dropped out during the GFC.

Nevertheless, the probabilistic view of the index addresses this limitation and becomes valuable for the application of the index in empirical analysis. From the probabilistic view, the index also

[16] The open source software 'igraph' (Csardi and Nepusz 2006) in the R package is used to conduct the power iteration. An example of a small network of four countries and the iteration process are shown in the Appendix B.

measures the overall probability or chances of a country being connected at each period. For the above example, notwithstanding change of composition in the network, the chance of UK's being either directly or indirectly connected indeed increased from 2000 to 2008.

4. The data set: international banking data

We use international banking statistics to measure a key channel of financial integration – bank-channelled financial integration. Financial accounts in the Balance of Payments imply that financial integration may result from three types of financial flows among countries -- portfolio flows, foreign direct investment, and other flows which consist mostly of bank-channelled financial flows. In theory, we can construct an index based on all three types of flows but data availability on counterparties of financial transactions explains our focus on integration via the flow of bank funds. Furthermore, different flows are driven by different forces, so a focus on one type of flow that accounts for a significant portion of the total flows seems a reasonable choice.

International banking statistics compiled by Bank of International Settlement (BIS) provide the widest coverage of banks' international activities with country level locational information. The series on foreign claims in the set of international locational banking statistics captures for each BIS reporting country its banks' total on-balance sheet financial claims (assets) against other countries[17]. The compilation of this set of statistics is consistent with the principles of the balance of payments but different in that it measures amounts outstanding, changes in which are an approximation of flows recorded in the balance of payments. Compared with consolidated banking statistics that BIS also publishes which include the claims of banks' foreign affiliates, country claims on a residential basis (locational) are more suitable for constructing a measure of financial integration among countries. We compile our dataset using the annual, end-of-year stock of international locational claims for all BIS reporting countries on 217 countries for the period (1983-2016). The claims consist of all instruments issued by banks from reporting countries to all sectors of the economy of counterparty countries[18].

The starting year of the period of analysis is 1983. The BIS notes that their international banking statistics are recorded systematically and consistently from 1983 in which year the cross-border claims covered by the dataset as a share of the estimated cross-border claims of all banks worldwide

[17] Banks refer to BIS reporting institutions including commercial banks, savings banks, credit unions or cooperative credit banks, and other financial credit institutions. Claims include deposits and balances placed with banks, loans and advances, trade-related credits, holdings of securities (certificates of deposit, promissory notes, collateralised debt obligations and asset-backed securities), loan or other claim positions funded with claims under sale and repurchase agreements; and participations including equity holdings in non-bank subsidiaries.

[18] Refer to Table 4 in Appendix A for the BIS reporting countries and Chart 1 for the first year when data are available for each country.

reached more than 80 per cent. This share further increased to 93% in 2016 (Chart 1). The three decades cover remarkable changes in the world's financial landscape; an 'up' period, when cross-border financial linkages intensified driven by financial liberalization policies in emerging economies and financial innovation in the developed world, and 'down' periods, when the global financial integration process was broadly interrupted during 1997-98 Asian Financial Crisis and the 2008-09 global financial crisis (Chart 1).

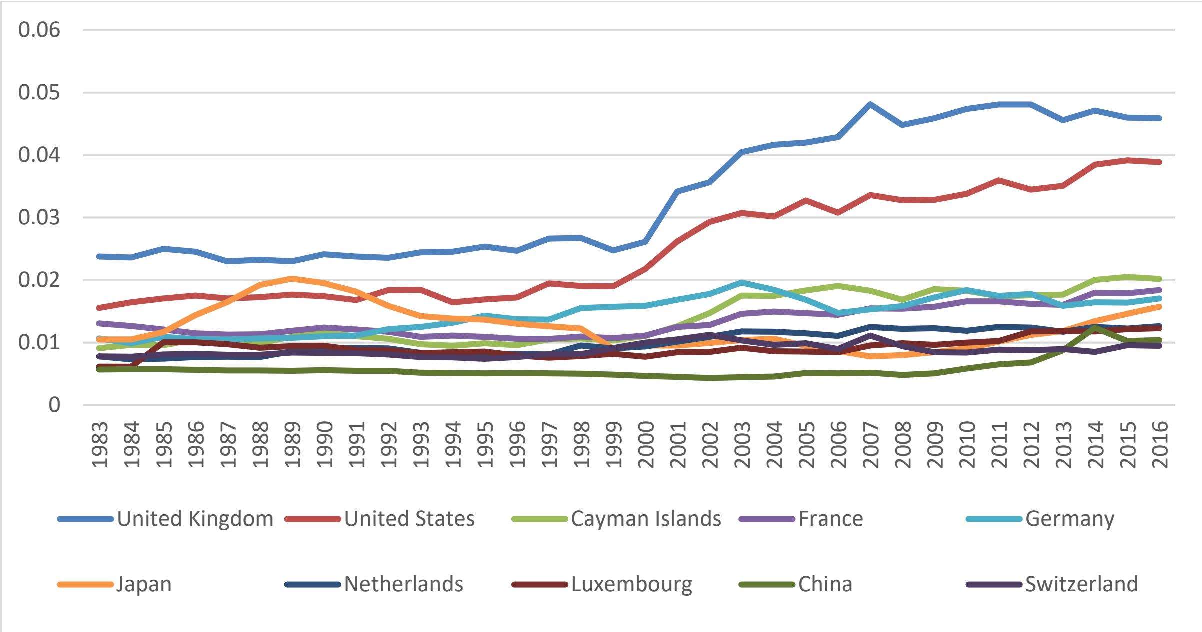
The BIS data has the advantage of being inclusive of banks' international activities. Although a restricted number of reporting countries, mostly OECD countries in the 1980s and 1990s, are initially covered.,the list expands to include emerging market economies so that by the end of 2016 the total number of reporting countries as source countries of foreign claims reaches 47. For network analysis, the implication is that only the reporting countries have complete in-bound and out-bound links but the non-reporting countries have only in-bound links. Nevertheless, this is not likely to pose a big issue since the BIS reporting countries make up the majority of active players in the global financial market, accounting for, on average, around 90 per cent of the cross-border bank claims of all banks around the world during the observation period and more than 90 per cent in more recent years (Chart 1).

5. The Financial interconnectedness indexes

We calculate and report our financial interconnectedness indexes for individual countries in the global network including all countries (data available on request) for the period 1983-2016. The financial interconnection is captured through cross-border bank transactions among countries[19]. For a given network in a particular year, the indexes add up to 1 by construction and reflect countries' average likelihood of being connected to any other countries directly or indirectly in the network in that year. Figure 3 shows the interconnectedness indexes for the top 10 countries in the global banking network. The most financially interconnected countries in the world are the United Kingdom and the United States. They possess the highest probability or likelihood to be financially connected of any degree to the rest of the world.

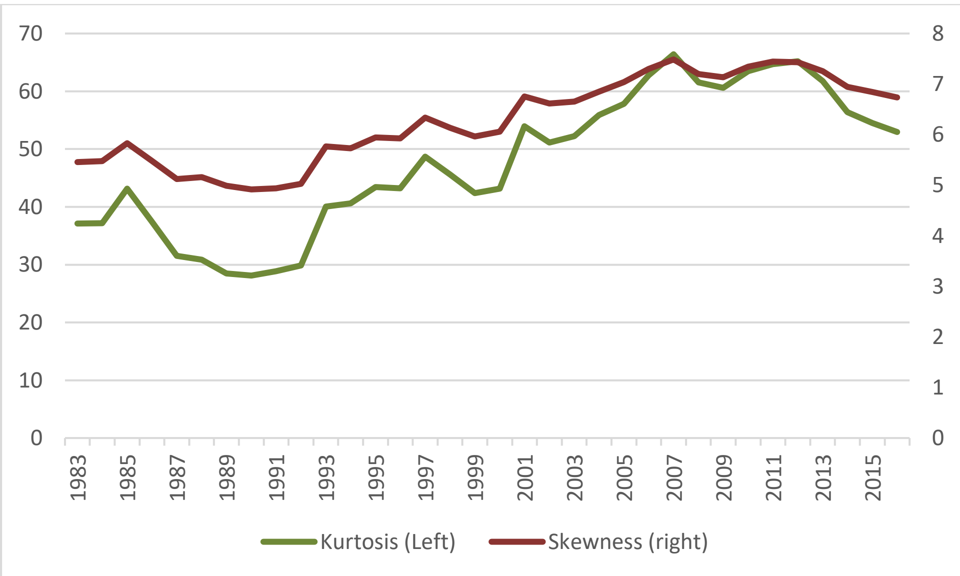
Figure 3 Financial interconnectedness in the global banking network, top 10

19 Based on the data from our updated and extended version of the original dataset constructed by Lane and Milesi-Ferretti (2007) with 2011 as the latest year. The next extension of BIS data is expected to include more Asian countries. Apparently, there are reporting issues on African data after the GFC.



Moreover, the structure reflected in the ranking remains largely unchanged over the whole observation period and the countries in the core remain the same (Figure 3). Over the period, the indexes for the top 5 show ups and downs. They rise in the early 2000s depicting a golden age of financial integration until a plunge in 2007. Over the next two years, the United Kingdom and the United States show substantially looser (reduced) financial links to the rest of the world. Since 2011, this is observed in both countries and may reflect the serious concern over the European Sovereign Debt crisis. Despite brief disturbances, these top runners remain the most integrated with the global financial market and are still the 'core' of the system.

Figure 4 Skewness and Kurtosis of the FI index



The existing literature focuses on a standard set of network statistics (Hattori and Suda 2007; Von Peter 2007; Kubelec and Sa 2012). Measured by the same set of conventional network statistics, our global banking network depicts a similar picture as in the literature: the global banking network is a network with a high connectivity, a high kurtosis, a low average path length, and a high clustering coefficient. In other words, countries are tightly connected among each other through banking transactions. However, they are connected in a way that leads to a particular structure of the network ('scale-free') in which a few countries are connected with a large number of countries, but the majority of countries link with just a few other countries. As Kubelec and Sa (2012) note, this structure could be subject to large-scale financial contagion if well-connected countries collapse.

Adding to the literature, our financial interconnectedness index not only confirms a 'scale-free' network structure but reveals a more extreme form of it after accounting for all connections in the system. Comparing Figure 1 and Figure 4, we find that the latter, using our financial interconnectedness index accounting for both direct and indirect links, shows with much higher skewness and kurtosis (Figure 4) than the former using only the direct links. The increased long tail results mainly from the substantially higher = financial connectedness of the top runners compared to rest of the world which is not captured by the simpler measures of in and out degree or closeness and betweeness.

Our measure also reveals that the network structure is persistent. Once put in place, it is difficult to displace (Authur 1989). This is specially the case for financial networks where the high-profile financial centres enjoy a long and extended period of dominance. Despite the Global Financial Crisis, the United Kingdom and United States remain the core of the network. This is consistent with Hattori and Suda (2007)'s observation that neither the LTCM (Long-Term Capital Management) default nor the 1997-98 East Asian currency crisis caused any major disruption to the *structure* of the global financial network.

6. **Application: Financial Interconnection and Output Volatility**

This section examines one of the key questions about the growing interconnectedness of global financial systems, that is how it affects macroeconomic stability. Since our index captures different network features from existing measures of financial integration we first explore its relationship with output volatility. We then analyse comparisons of our index against other types of measures of financial integration to expand understanding of how different features of financial interconnectedness relate to output volatility.

Financial integration is a widely researched topic. Since the end of the 1990s there has been particular interest in its macroeconomic implications as many transition economies embarked on the path of financial liberalization. Historically, both the international macroeconomic and international finance literature have highlighted the arguments for a positive effect from financial openness on output volatility. The classic consumption smoothing hypothesis, built upon an intertemporal consumption model, suggests that by allowing countries to borrow abroad, financial openness helps smooth consumption. If output is volatile because of random external shocks, then access to international financial markets can insulate consumption from income volatility and thereby improve welfare. If for some reason consumption itself is volatile, then the ability to smooth consumption by borrowing and lending abroad could help reduce output volatility. Arguably the same could be true about shocks to investment. Moreover, the international finance literature highlights the additional benefits of risk diversification that accrue to financially-open economies that share risks among each other. By diversifying sources of income streams from their capital stock through differentiating geographical locations or types of assets, financial openness enables countries to reduce income volatility.

While deeper financial openness is often considered conducive to risk sharing, an increasingly important policy concern is whether it brings greater vulnerability to shocks. Modern financial systems are tightly linked together and financial flows between them are now very large. Quick escalation of local economic problems into full-fledged regional or global crises can arise from the fact that rapid financial integration brings about increasingly complex financial linkages and a complex network as a result. Our measure of financial interconnection can therefore provide a useful tool to understand the modern-day financial openness and its effects on important macroeconomic variables.

The 2017-18 Global Financial Crisis has revived the financial network literature and prompted a set of new research on the extent of financial interconnection contributions to financial contagion. Elliott et al. (2014) suggest that as an institution's financial network initially becomes more diversified (i.e. has more connections) financial shocks are able to travel across borders but, as the diversification increases, interconnections better insure the network against each other's failure. They assume an intermediate scale of shock. Acemoglu et al.'s (2015) study, looks at both the interconnectedness of a network of individual banks and the scale of shocks. They reveal that a more diversified pattern of financial interconnection enhances financial stability when negative shocks are sufficiently small, but increases financial volatility when shocks are sufficiently large. The pattern of network connection (network "type") matters for whether shocks are transmitted, and which is the most susceptible type of network changes for large shocks compared to small. Their results are consistent with Haldane's (2017) view that highly interconnected networks may be robust to certain levels of shock but fragile in the face of greater shocks.

Our new index provides a succinct method for shedding additional light on these claims at the country level. The following empirical study examines the relationship between financial interconnectedness and output volatility employing our measure of countries' financial interconnection based on international banking data.

We estimate a two-way fixed-effects model on a large panel dataset covering 197 countries during 1977-2016.

$$Y_{it} = \alpha + \beta' FI_{it} + \gamma' FI * preGFC + \delta' FI * GFC + \rho' GFC * FI\text{^}2 + \theta' \cdot X_{it} + \tau_t + \mu_i + \varepsilon_{it}$$

Y_{it} is output volatility measured by the standard deviation of real GDP growth rates in country i for each (5-year) period, t. $preGFC$ is an indicator variable identifying a 5-year period (2002-2006) in which the global financial network formed its most recent structure, occasionally disrupted by small and idiosyncratic shocks. In contrast, the following 5-year period (2007-2011), GFC marks a volatile period when intensified financial interconnection and large financial turbulence/shocks (Global Financial Crisis and the subsequent European Sovereign Debt Crisis) coexisted. $\boldsymbol{X}_{it}$ is a vector of standard controls including logarithm of absolute value of inflation rates (monetary policy) and standard deviation of the ratio of government expenditure to GDP (fiscal volatility), and ratio of exports plus imports to GDP (trade openness). τ_t and μ_i are time and country-fixed effects.

Our index of financial interconnectedness gives a nuanced picture of the link between engagement with the global banking network and output volatility. The results in Table C1 suggest that financial interconnectedness per se does not increase volatility of output in a simple way. The main influences on output volatility are the policy variables. Consistent with common theoretical models and empirical studies, output volatilities are linked to fiscal and monetary volatilities. A standard deviation increase in fiscal volatility increases output volatility by about 0.75 standard deviation; countries with higher (1 per cent increase in) inflation experience higher (about 0.6 standard deviation increase in) output volatility. The results confirm a statistically and economically significant sensitivity of output volatility to both fiscal and monetary instabilities. In contrast, there is no evidence linking trade openness to output volatility. Over time, output volatility is declining, likely a reflection of enhanced capacities of governments employing monetary and fiscal policies to smooth business cycles. Financial interconnectedness itself has no significant effect on output volatility when the period is taken as a whole, but an informative and interesting picture emerges once the two sub-periods, pre-GFC and post-GFC, are considered separately. During the pre-GFC period beginning in 2000, but not before, financial interconnectedness helped reduce volatility. In the GFC period, on the other hand, financial interconnectedness increased volatility, but the effect diminished the higher the degree of interconnectedness. Model 5, with both FI and FI^2 and the GFC interaction terms has better explanatory power than models without this combination, and inclusion of these variables has a small impact on the size of other coefficients but they are generally stable over the model variants. Interestingly, these results suggest that the picture that Acemoglu et al. paint for individual institutions is also visible at the country level. In addition, we are able to add global level information to Elliott's small, country-level illustration of their simulation model. Since their study does not capture the changing nature of shock transmission through networks in the face of different scales of shock our picture also adds another dimension.

What we can see from these results is that, as the world entered the period when the global network moved from a very disconnected structure to a more connected one, countries reduced their output volatility as they became more interconnected with the global banking network. This is consistent with the early literature and the theoretical conjectures about the possibilities for risk mitigation. During the GFC period, however, increases in financial interconnectedness exposed countries to higher output volatility but only up to a certain level. Beyond a certain point, higher levels of interconnection begin to reduce the impact on output volatility. As in Acemoglu et al, the impact of being closely integrated to the financial network changes with both the size of shocks and the changing nature of the network itself.

We, and others, have argued that understanding the nature of financial networks gives new insight into what it means for a country to be financially open or "integrated". Before the recent interest in network analysis there were several heuristic measures used to capture the notion of a country's level of international financial integration. Two popular measures are the Chinn-Ito (de jure) measure of openness based on policy settings, and the Lane-Milessi-Ferreti (de facto) index based on quantities of foreign assets held.

Our next empirical exercise includes our measure alongside these two, widely-used measures to see whether each separately contributes to explaining output volatility. That is, we look at whether a model containing our measure provides a better explanation than models containing other measures of financial integration. For this we consider the effects of the Corbett-Xu indicator of financial connection alongside the Chinn-Ito (de jure) and the Lane-Milessi (de facto). Our estimating equation now includes a vector of financial integration indices (FI) rather than just the Corbett-Xu indicator.

The key insights derived from the first empirical exercise discussed above, containing just our new index, carry across to the analysis including other indexes. Table C2 in Appendix C reports the key results. Again, the results are consistent with standard theoretical models and empirical studies showing that output volatilities are linked to fiscal and monetary volatilities. In a model that takes no account of financial openness or interconnection (equation 1 in both Tables C1 and C2), a standard deviation increase in fiscal volatility increases output volatility by about 0.8 standard deviation, countries with higher (1 per cent increase in) inflation experiences higher (0.6standard deviation increases in) output volatility, trade openness has no effect and volatility declines over time.

The key variables of interest are the group of financial integration related measures. De jure measures with a focus on removal of rules and regulations against cross-border financial transaction show a high and positive relationship with output volatility. In other words, the trade-off from lifting capital controls and removing various barriers to tapping the global financial market is elevated – on average around 1.6 standard deviation increase in – output volatility. On the other hand, the de facto index measuring the volume of international financial transactions relative to GDP is not significantly linked to output volatility.

While our financial interconnection measure and its square term seem not to affect output volatility, we again see the complex and distinct effects revealed by its interaction terms with the two period dummies. The coefficient associated with the interaction term with the pre-GFC period is negative and significant, compared to a positive and significant coefficient associated with the interaction term with the GFC period. Introducing the other measures of financial integration does not change the additional information that is gained from the network-based measure. We still see the phenomenon that high financial interconnection enhances financial (output) stability when negative shocks are sufficiently small, but increases volatility when shocks are sufficiently large. Finally, the coefficient of the interaction term of financial interconnection squared and the GFC remains negative and significant, confirming the idea that financial interconnection initially spread shocks but eventually provides better insurance through diversification as the interconnection increases further.

We have not yet carried out full specification tests on the alternative models to form a view on what is added by our measure over others, but two information criteria measures reported in the tables suggest that our measure alone captures most of the information, without the other two measures.

7. Conclusion

Based on an adapted version of the eigenvector centrality measure often used in the network approach, we have built a new measure of financial integration for individual countries, highlighting interconnectedness of countries through financial linkages in global financial markets. An important and distinctive feature of the measure lies in its complete coverage of both direct and indirect connections among countries in the system, which is potentially vital for understanding how shocks spread in the system.

We find that the United Kingdom and the United States remain the most interconnected countries in the global banking network despite the 2007-08 global financial crisis. These countries remain the 'core' of the global financial system with the remaining roughly 200 countries forming the 'periphery'. A simple application of the financial interconnectedness index in the analysis of financial integration and output volatility suggests that complex interconnections captured by the index provide a nuanced picture of the way in which financial interconnection is linked to output volatility.

There is large scope for future work which could include improving the data by expanding the number of countries with both inward and outward lending (further data is held by BIS but is not currently publicly available). Also, we use banks' foreign claims as financial links connecting countries in this study. This is an important, but only one, dimension of the existing financial linkages among countries. Other dimensions, such as cross-border portfolio positions and foreign direct investment, could also be considered to capture potentially different facets of interconnectedness.

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Appendix A

Table 1a Standard measures of network connectedness for the original 24 BIS reporting countries, 1983-2016

	indegree		Outdegree		instrength		outstrength		betweeness		closeness	
	1983-1999	2000-2016	1983-1999	2000-2016	1983-1999	2000-2016	1983-1999	2000-2016	1983-1999	2000-2016	1983-1999	2000-2016
United Kingdom	12	22	135	182	351	2889	704	3939	154	341	0.87	0.90
United States	12	22	102	83	286	2555	418	2107	72	52	0.73	0.63
Cayman Islands	12	22	0	0	109	1168	0	0	0	0	0.52	0.53
Germany	12	22	126	158	165	1141	227	2043	104	196	0.82	0.81
France	12	22	143	181	148	1072	285	1734	177	332	0.89	0.89
Netherlands	12	22	47	56	72	770	105	747	5	18	0.59	0.58
Italy	13	23	0	0	124	687	0	0	0	0	0.52	0.53
Japan	12	22	91	105	256	617	502	2128	45	76	0.70	0.67
Luxembourg	6	21	118	147	69	598	196	689	42	149	0.78	0.78
Spain	13	23	0	23	36	503	0	61	0	17	0.52	0.57
Switzerland	12	22	117	175	63	495	199	849	118	278	0.79	0.87
Ireland	11	20	38	116	20	483	12	469	5	85	0.57	0.70
Belgium	11	22	119	154	104	336	123	611	82	185	0.79	0.80
Singapore	13	20	0	0	106	307	0	0	0	0	0.52	0.53
Hong Kong SAR, China	12	22	0	23	185	273	0	186	0	17	0.52	0.56
Canada	13	23	0	19	47	258	0	196	0	7	0.52	0.55
Sweden	12	21	84	106	35	198	17	247	28	70	0.68	0.68
Denmark	12	21	57	117	27	172	23	147	12	104	0.61	0.72
Bahamas, The	12	20	0	0	80	170	0	0	0	0	0.52	0.53
Norway	12	21	0	0	15	162	0	0	0	0	0.52	0.53
Austria	12	21	0	61	27	146	0	188	0	36	0.52	0.62
Finland	12	20	42	69	17	119	7	142	7	23	0.58	0.61
Netherlands Antilles	10	13	0	0	13	39	0	0	0	0	0.52	0.51
Bahrain	11	18	0	0	10	26	0	0	0	0	0.52	0.52

Table 1b Standard measures of network connectedness for 25 top BIS reporting countries by instrength, 1983-2016

		indegree		outdegree		instrength		outstrength		betweeness		closeness	
Country	Group	1983-1999	2000-2016	1983-1999	2000-2016	1983-1999	2000-2016	1983-1999	2000-2016	1983-1999	2000-2016	1983-1999	2000-2016
United Kingdom	1	12	22	135	182	351	2889	704	3939	153.71	341.34	0.87	0.90
United States	1	12	22	102	83	286	2555	418	2107	72.05	51.65	0.73	0.63
Cayman Islands	1	12	22	0	0	109	1168	0	0	0.00	0.00	0.52	0.53
Germany	1	12	22	126	158	165	1141	227	2043	103.77	195.78	0.82	0.81
France	1	12	22	143	181	148	1072	285	1734	176.76	332.01	0.89	0.89
Germany	1	12	22	47	56	72	770	105	747	5.03	18.12	0.59	0.58
Italy	1	13	23	0	0	124	687	0	0	0.00	0.00	0.52	0.53
Japan	1	12	22	91	105	256	617	502	2128	45.02	76.17	0.70	0.67
Luxembourg	1	6	21	118	147	69	598	196	689	42.35	149.35	0.78	0.78
Spain	1	13	23	0	23	36	503	0	61	0.00	17.19	0.52	0.57
Switzerland	1	12	22	117	175	63	495	199	849	118.17	277.52	0.79	0.87
Ireland	1	11	20	38	116	20	483	12	469	5.00	85.24	0.57	0.70
Belgium	1	11	22	119	154	104	336	123	611	82.43	185.17	0.79	0.80
Singapore	1	13	20	0	0	106	307	0	0	0.00	0.00	0.52	0.53
Hong Kong SAR, China	1	12	22	0	23	185	273	0	186	0.00	17.02	0.52	0.56
Canada	1	13	23	0	19	47	258	0	196	0.00	7.07	0.52	0.55
Sweden	1	12	21	84	106	35	198	17	247	28.01	70.00	0.68	0.68
China	2	11	21	0	0	9	192	0	0	0.00	0.00	0.52	0.53
Australia	2	12	21	0	92	20	186	0	191	0.00	99.57	0.52	0.66
Denmark	1	12	21	57	117	27	172	23	147	11.84	103.63	0.61	0.72
Bahamas, The	1	12	20	0	0	80	170	0	0	0.00	0.00	0.52	0.53
Norway	1	12	21	0	0	15	162	0	0	0.00	0.00	0.52	0.53
Austria	1	12	21	0	61	27	146	0	188	0.00	35.97	0.52	0.62
Finland	1	12	20	42	69	17	119	7	142	6.57	23.00	0.58	0.61
Brazil	2	12	20	0	24	44	104	0	43	0.00	4.31	0.52	0.54

Note: Authors calculations from BIS, International Banking Statistics, various years. The calculations are done for the whole network that consists of 216 countries in each year. Listed countries (BIS reporting countries) have data on inflows and outflows with various starting points. The remaining countries have inflow data. In-strength and out-strength are in billions of USD.

Table 2 Formulas for network metrics and statistics

In-degree	In-degree of country i is the total number of links that point to the country, $$d_i^{in} = \sum_j^N l_{i \leftarrow j}$$ where j is the source country of each link $l_{i \leftarrow j}$, $(j = 1, \ldots N)$. A directed link is established if country j records nonzero foreign claims to country i.
Out-degree	Out-degree of country i is the total number of links departing from the country, $$d_i^{out} = \sum_j^N l$$ where j is the recipient country of each link l_{ji}, $(j = 1, \ldots N)$. A directed link is established if country i records nonzero foreign claims to country j.
In-strength	In-strength of country i is the sum of bank claims received by the country, $$D_i^{in} = \sum_j^N W_{i \leftarrow j}$$ where $W_{i \leftarrow j}$ is the amount of bank claims issued by country j to country i.
Out-strength	Out-strength of country i is the sum of bank claims issued by the country, $$D_i^{out} = \sum_j^N W_{j \leftarrow i}$$ where $W_{j \leftarrow i}$ is the amount of bank claims issued by country i to country j.
Closeness	Closeness of country i is the inverse of the average distance from country i to all other countries j in the network, $$C_i = \left[\frac{\sum_j^N d(i,j)}{N-1}\right]^{-1}$$ where the distance between two countries i and j, or $d(i,j)$, is the smallest number of links that must be traversed to go from i to j. N is the total number of countries in the network.
Betweeness	The betweeness measure for country i, B_i is defined as $$B_k = \frac{\sum_{i \neq j \neq k \neq i} \frac{P_{ij}(k)}{P_{ij}}}{(N-1)(N-2)}$$ where P_{ij} denotes the number of shortest paths from country i to j and $P_{ij}(k)$ denotes the number of shortest paths from country i to j containing vertex k.
Skewness	Skewness measures the asymmetry of a distribution. The skewness of a network is defined as

	$$S = \frac{\sum(X-\mu)^3/n}{[\sum(X-\mu)^2/n]^{3/2}}$$ where X is the value of a link between country i and j, measured by the size of the foreign claims from j to i and n is the total number of links.
Kurtosis	Kurtosis measures the 'peakedness' of a distribution. The kurtosis of a network is defined as $$K = \frac{\sum(X-\mu)^4/n}{[\sum(X-\mu)^2/n]^2}$$ where X is the value of a link between country i and j, measured by the size of the foreign claims from j to i and n is the total number of links.
Average Path Length	Average Path Length is the average of the shortest paths between all pairs of countries in the network, $$P = \frac{2}{N(N-1)}\sum_{i\neq j} d(i,j)$$ where the distance between two countries i and j, or $d(i,j)$, is the smallest number of links that must be traversed to go from i to j. N is the total number of countries in the network.
Clustering	Clustering measures the probability that, given that country i is directly linked to countries j and k, country j is also directly linked to k. The clustering coefficient is given by, $$Cl = \frac{\sum_{i,j\neq i,k\neq j,k\neq i} L_{ij}L_{ik}L_{jk}}{\sum_{i,j\neq i,k\neq j,k\neq i} L_{ij}L_{ik}}$$ where L_{ij} represents the link between country i and j and L_{jk} represents the link between country j and k.

Notes: the main source of the definitions is Kubelec and Sa (2012)

Table 3 Overview of the major studies on the global financial network

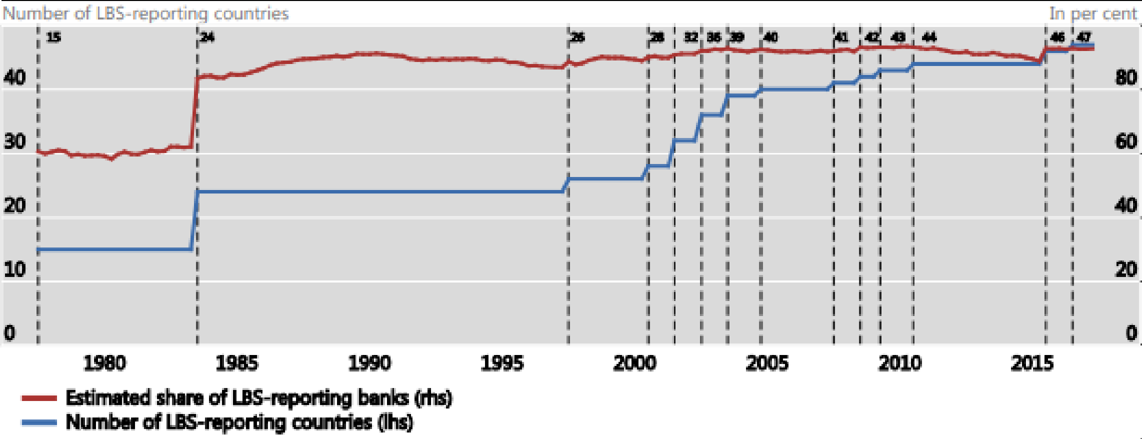
Author(s)	Data source/type	Measures	Main results
Hattori and Suda (2007)	Quarterly data for 215 countries on foreign claims of banks in reporting countries over the period (1985-2006), BIS consolidated banking statistics	Connectivity, average path length, in-degree and out-degree, clustering coefficient	The network of cross-border bank exposure has become more tightly connected over the sample period, reflected by a higher connectivity, shorter average path length, higher average degree, and higher clustering coefficient. This tendency is not interrupted by the 1997-98 East Asian currency crisis. The stability implication is two-fold: an increased probability of systemic risk in international financial markets (once one country is in crisis) but improved efficiency in capital and risk allocation.
Goetz von Peter (2007)	Financial claims (to banking and non-banking sectors respectively) of 212 countries, BIS locational banking statistics	In-degree and out-degree, closeness, betweeness, intermediation, prestige	The best connected locations are generally the largest centres with large market share, but the network also captures locations with relatively small market share that play important role of regional intermediation.
Haldane (2009)	External stocks of external assets and liabilities in 18 countries in 1985, 1995 and 2005, data constructed by	Skewness, kurtosis, and average path length	The international financial network displays a high and rising degree of interconnection. In particular, the network shows a 'long-tailed' distribution and 'small world' properties.

	Kubelect and Sa (2008)		The stability implication is the system has become 'robust-yet-fragile' with more countries sharing risk among themselves but more exposed to flow-on effects from financial hubs.
Kubelec and Sa (2012)	Bilateral FDI data mainly from the OECD International Direct Investment, portfolio equity asset data from the IMF Coordinated Portfolio Investment Survey (CPIS), and portfolio debt asset data from the IMF CPIS and BIS locational banking statistics; the data period is 1985-2005	In-degree and out-degree, closeness, betweeness, intermediation, prestige, skewness, kurtosis, average path length, clustering coefficient	The global financial network has shown growing interconnectivity over the past two decades. The distribution of the financial links has shown a long tail. It reemphasizes the trade-off of higher interconnectivity: enhanced risk sharing but increased risk of contagion. In particular, the long-tail structure implies system-wide vulnerability of the network to targeted attack on the most-connected nodes.
Ours I	End of year data for 216 countries on foreign claims of banks in reporting countries over the period	In-degree and out-degree, closeness, skewness, kurtosis, average path length, clustering coefficient	United States, United Kingdom, France and Germany score highest in terms of standard connection measures. The global banking network displays features of a long-tail. These findings bear a strong resemblance to the above studies.

Ours II	(1999-2013), BIS consolidated banking statistics	Interconnectedness	United States and United Kingdom remain the most interconnected countries in the global banking network in spite of the 2007-08 global financial crisis. The global banking network resembles an explicit 'core-periphery' structure. China is rapidly integrated with the world and Asian financial market since the GFC.

Graph 1 Global coverage of the BIS locational banking statistics and list of reporting countries by year of access

Global coverage of the locational banking statistics | Graph 1



# LBS[1]	15	24	26	28	32	36	39	40	41	42	43	44	46	47
Date[2]	**Q4 1977**	**Q4 1983**	**Q4 1997**	**Q4 2000**	**Q4 2001**	**Q4 2002**	**Q4 2003**	**Q1 2005**	**Q4 2007**	**Q4 2008**	**Q3 2009**	**Q4 2010**	**Q4 2015**	**Q4 2016**
	AT	AN[3]	AU	TR	GG	BM	GR	KR	MY	CY	ZA	~~AN~~[3]	CN	PH
	BE	BH	PT	TW	IN	BR	MO					CW	RU	
	CA	BS			IM	CL	MX					ID		
	CH	ES			JE	PA								
	DE	FI												
	DK	HK												
	FR	KY												
	GB	NO												
	IE	SG												
	IT													
	JP													
	LU													
	NL													
	SE													
	US													

[1] Number of LBS-reporting countries. [2] First period when data are available, ie date of change in the reporting population. The first period when data are published is usually two to three quarters later. [3] AN was succeeded by CW as of Q4 2010.

Source: BIS (2018)

Table 4 Country list

Asian Countries:

Australia, Japan, Hong Kong SAR, Singapore, Bangladesh, Brunei, Cambodia, China, Chinese Taipei, India, Indonesia, Korea, Laos, Malaysia, Myanmar, New Zealand, Philippines, Sri Lanka, Thailand, Vietnam

European countries:

Austria, Belgium, Cyprus, Denmark, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Luxembourg, Malta, Netherlands, Portugal, Slovakia, Slovenia, Spain, Sweden, United Kingdom, Bulgaria, Croatia, Czech Republic, Hungary, Lithuania, Poland, Romania

Other countries:

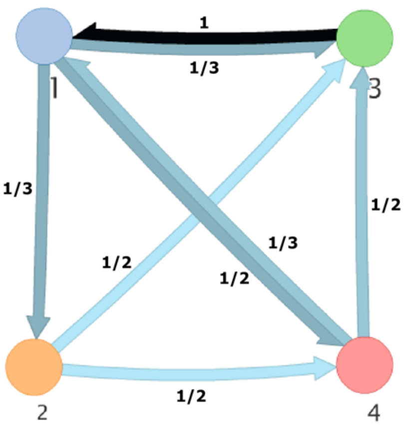
Afghanistan, Albania, Algeria, Andorra, Angola, Argentina, Armenia, Aruba, Azerbaijan, Bahamas, Bahrain, Barbados, Belarus, Belize, Benin, Bermuda, Bhutan, Bolivia, Bonaire, Saint Eustatius and Saba, Bosnia and Herzegovina, Botswana, Brazil, Burkina Faso, Burundi, Cameroon, Canada, Cape Verde, Cayman Islands, Central African Republic, Chad, Chile, Colombia, Comoros Islands, Congo, Congo Democratic Republic, Costa Rica, Côte d'Ivoire, Cuba, Curacao, Czechoslovakia, Djibouti, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Eritrea, Ethiopia, Falkland Islands, Fiji, French Polynesia, Gabon, Gambia, Georgia, German Democratic Republic, Ghana, Gibraltar, Grenada, Guatemala, Guernsey, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Iceland, Iran, Iraq, Isle of man, Israel, Jamaica, Jersey, Jordan, Kazakhstan, Kenya, Kiribati, Kuwait, Kyrgyz Republic, Lebanon, Lesotho, Liberia, Libya, Liechtenstein, Macau SAR, Macedonia, FYR, Madagascar, Malawi, Maldives, Mali, Marshall Islands, Mauritania, Mauritius, Mexico, Micronesia, Moldova, Mongolia, Montenegro, Morocco, Mozambique, Namibia, Nauru, Nepal, Netherlands Antilles, New Caledonia, New Zealand, Nicaragua, Niger, Nigeria, North Korea, Norway, Oman, Pakistan, Palau, Palestinian Territory, Panama, Papua New Guinea, Paraguay, Peru, Qatar, Russia, Rwanda, Samoa, Sao Tomé and Principe, Saudi Arabia, Senegal, Serbia, Serbia and Montenegro, Seychelles, Sierra Leone, Sint Maarten, Solomon Islands, Somalia, South Africa, Soviet Union, St. Helena, St. Lucia, St.Vincent, Sudan, Surinam, Swaziland, Switzerland, Syria, Tajikistan, Tanzania, Timor Leste, Togo, Tonga, Trinidad and Tobago, Tunisia, Turkey, Turkmenistan, Turks and Caicos, Tuvalu, Uganda, Ukraine, United Arab Emirates, United States, Uruguay, US Pacific Islands, Uzbekistan, Vanuatu, Vatican, Venezuela, Wallis/Futuna, Yemen, Yugoslavia, Zambia, Zimbabwe.

BIS reporting countries:

Australia, Chinese Taipei, Japan, Korea, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherland, Portugual, Spain, Sweden, Switzerland, Turkey, U.K., U.S., Canada, Brazil, Chile, Mexico, Panama

Appendix B Financial Interconnectedness Index: An Example

Figure B1 A small network of 4 countries



The above is a small network that consists of 4 countries with links through bank claims among them. A third of country 1's total (normalized) bank claims goes to each of the other three countries; half of country 2's total claims to country 3 and the other half to country 4; all country 3's claims are received by country 1; country 4's total claims are split into equal halves to country 1 and 3. Accordingly, the weight matrix A is

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} = \begin{bmatrix} 0 & 0 & 1 & 1/2 \\ 1/3 & 0 & 0 & 0 \\ 1/3 & 1/2 & 0 & 1/2 \\ 1/3 & 1/2 & 0 & 0 \end{bmatrix}$$

The entries in the matrix A, a_{ij} represents the weight of each link $j \rightarrow i$ and each entries records the portion of claims of j on i in the source country j's total claims. All the entries in each column sum to 1. Based on Equation (2), to obtain the indexes is to solve for entries in V^* corresponding to eigenvalue 1.

$$A \cdot V = \lambda V$$
$$\lambda = 1$$
$$\begin{bmatrix} 0 & 0 & 1 & 1/2 \\ 1/3 & 0 & 0 & 0 \\ 1/3 & 1/2 & 0 & 1/2 \\ 1/3 & 1/2 & 0 & 0 \end{bmatrix} \cdot \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

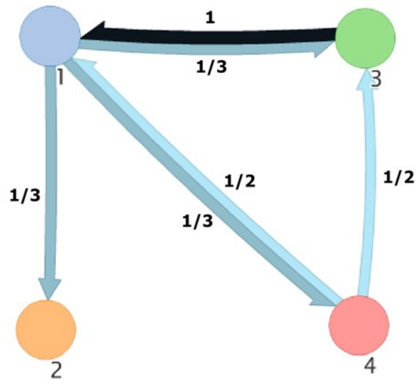
We start by setting all entries in V equal to ¼, indicating the initial state that all 4 countries are equally integrated. Then we iterate the process. At step 2, the updated integration index vector is $V_2 = A^2V$, and at step 3, $V_2 = A^3V$. At step k, the sequences tend to converge to the equilibrium value,

$$V^* = \begin{bmatrix} 0.38 \\ 0.12 \\ 0.29 \\ 0.19 \end{bmatrix}$$

If solving the recursive system by linear algebra, there are a number of V^*, but they are scalar multiples of each other, so one can normalize to have the dependence indexes so that the sum of all entries equal to 1[20], which is equal to V^*.

20 Other dimensions of international financial transactions such as portfolio securities and foreign direct investment would be measurable in future studies using the same methodology if systematic locational data is available.

Figure B2 Addressing incomplete data: The issue of dangling nodes



$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 1 & 1/2 \\ 1/3 & 0 & 0 & 0 \\ 1/3 & 0 & 0 & 1/2 \\ 1/3 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

We continue to use the 4-country small network example to explain the dangling node issue (i.e. incomplete data on links) and our solution. In Figure C2, country 2 has inward links only but not outward links, which are missing due to incomplete dataset. Accordingly, entries in column two of the weight matrix are all zero. The weight matrix is no longer a column stochastic matrix and the equilibrium values for V are zero as a result. Incorporating the PageRank solution, we replace entries in the zero column with $1/(n-1)$, so the weight matrix turns stochastic,

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} 0 & 1/3 & 1 & 1/2 \\ 1/3 & 0 & 0 & 0 \\ 1/3 & 1/3 & 0 & 1/2 \\ 1/3 & 1/3 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

Now we can solve for eigenvector V^* to get

$$V^* = \begin{bmatrix} 0.39 \\ 0.17 \\ 0.26 \\ 0.17 \end{bmatrix}$$

V^* provides sensible ranking: country 1 and 3 are highly connected and therefore sit on the top two. Inflows to country 2 and 4 are the same, 1/3 of country 1's connectedness so they share the same ranking.

Appendix C Regressions of Financial Indicators and Output Volatility

Table C1 Corbett-Xu Financial Interconnectedness with Output Volatility

	1	2	3	4	5
gov	0.770**	0.767**	0.764**	0.756**	0.750**
	(0.348)	(0.349)	(0.349)	(0.350)	(0.351)
trade	0.030	0.030	0.029	0.030	0.029
	(0.022)	(0.022)	(0.023)	(0.023)	(0.023)
lpai	0.608***	0.606***	0.607***	0.605***	0.552***
	(0.170)	(0.171)	(0.171)	(0.170)	(0.174)
period	-0.197**	-0.188**	-0.156	-0.156	-0.246**
	(0.095)	(0.095)	(0.107)	(0.108)	(0.110)
fi		0.534	1.955	1.676	1.430
		(0.356)	(1.643)	(1.750)	(1.591)
fi2			-0.275	-0.219	-0.227
			(0.264)	(0.275)	(0.262)
fi_pregfc				-0.965*	
				(0.563)	
fi2_pregfc				0.189	
				(0.172)	
fi_gfc					1.716***
					(0.606)
fi2_gfc					-0.299**
					(0.149)
_cons	-0.079	-0.389	-1.175	-1.009	-0.423
	(1.913)	(1.799)	(1.470)	(1.442)	(1.545)
N	910	910	910	910	910
R^2	0.136	0.136	0.136	0.139	0.143
F	7.747	6.233	5.287	11.014	25.066
p	0.000	0.000	0.000	0.000	0.000
AIC					4698.447
BIC					4746.582

Standard errors in parentheses* p<.105, ** p<.055, *** p<.015

Table C2 Output volatility and financial integration measured by de jure, de facto and FI (1977-2016)

	1 No fin integ	2 De Jure only	3 De Facto only	4 Both DJ & DF	5 All index	6 FI square	7 FI interact	8 FI interact	9 De Jure interact	10 De Facto interact
Fiscal volatility	0.770**	0.691**	0.556**	0.515*	0.513*	0.513*	0.497*	0.497*	0.671**	0.527*
	(0.348)	(0.305)	(0.285)	(0.276)	(0.276)	(0.276)	(0.275)	(0.276)	(0.305)	(0.288)
Trade openness	0.030	0.035	0.034	0.035	0.035	0.035	0.035	0.035	0.035	0.034
	(0.022)	(0.024)	(0.027)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.025)	(0.027)
Inflation	0.608***	0.648***	0.609***	0.672***	0.671***	0.671***	0.681***	0.617***	0.577***	0.603***
	(0.170)	(0.186)	(0.168)	(0.184)	(0.184)	(0.184)	(0.184)	(0.187)	(0.197)	(0.170)
Period	-0.197**	-0.252***	-0.214**	-0.278***	-0.276***	-0.267***	-0.261***	-0.350***	-0.323***	-0.233***
	(0.095)	(0.092)	(0.094)	(0.090)	(0.089)	(0.091)	(0.091)	(0.091)	(0.096)	(0.093)
De jure		1.778**		1.620**	1.627**	1.622**	1.752**	1.494*	0.631	0.276
		(0.788)		(0.802)	(0.804)	(0.803)	(0.810)	(0.801)	(2.406)	(0.256)
De facto			0.037	0.180	0.174	0.171	0.176	0.160		
			(0.142)	(0.201)	(0.204)	(0.205)	(0.208)	(0.205)		
FI					0.190	0.499	0.487	-0.047		
					(0.213)	(0.812)	(0.884)	(0.749)		
FI^2						-0.044	-0.038	0.010		
						(0.091)	(0.097)	(0.085)		
*FI*PreGFC*							-1.364***			
							(0.404)			
*FI*GFC*								1.607***		
								(0.501)		
*FI ^2*GFC*								-0.231***		
								(0.090)		
Dj2 or Df2									0.925	-0.003**
									(2.585)	(0.001)
*Dj or Df*preGFC*									-0.733	-0.217**
									(1.794)	(0.110)
*Dj2 or Df2*preGFC*									0.095	0.003**
									(1.972)	(0.001)
*Dj or Df*GFC*									1.983	0.028
									(1.768)	(0,132
*Dj2 or Df2*GFC*									-1.032	0.000
									(1.944)	(0.001)
Constant	-0.079	-1.000	-0.177	-0.891	-1.002	-1.181	-1.211	-0.397	-0.301	-0.350
	(1.913)	(2.059)	(2.156)	(2.253)	(2.297)	(2.307)	(2.306)	(2.358)	(1.988)	(2.093)
N	910	870	904	867	867	867	867	867	870	904
R^2	0.136	0.140	0.123	0.139	0.139	0.139	0.144	0.146	0.150	0.134
F	7.747	6.728	6.929	5.732	4.918	4.585	4.725	14.857	9.270	389.183
p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AIC									4441.475	4657.755
BIC									4489.16	4657.755

Standard errors in parentheses *p< 0.105 ** p<0.055 *** p< 0.015