Banking Network and Systemic Risk via Forward-Looking Partial Default Correlations

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(May 3, 2016)

Abstract

This paper studies systemic risk in a global network with over 1,000 exchange-traded banks. Network construction follows a methodology comprising three parts: (1) the use of the default correlation model of Duan and Miao (2015) to produce a forward-looking probability of default (PD) total correlation matrix and then transform it into a partial correlation matrix by applying the CONCORD algorithm; (2) the measurement of banks' systemic importance hinging on six network centrality indicators based on the partial correlations, which represent the direct connections among banks; and (3) a graphical analysis of the global banking network which can then be partitioned into overlapping bank/group centric local communities. We then specifically study the banks' systemic importance in 2008 and 2014. Using the 2014 sample, we are able to compare the systemic importance rankings under alternative measures, including G-SIBs identified by the Financial Stability Board. Our results suggest the Board rankings appear biased towards singling out large institutions as systemic, with connectivity playing a rather minor role.

Keywords: systemic risk, banking network, forward-looking, probability of default, partial correlation, banking community

JEL Code: G17, G21, G28

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1. Introduction

The recurrence of financial crises entails large costs directly associated with disruptions in the banking system and huge impacts indirectly on the real economy, as evidenced by the global financial crisis of 2008 and onward. That financial crisis has naturally focused both academic and policy work on the identification of systemic risk in the financial system, and in particular, in the global banking network.

To this end, a variety of systemic risk measures emphasizing connectedness between banks and other financial firms have been proposed. Examples include the equity returns volatility (Demirer et al., 2015), capital shortfall of an individual institution in the crisis (Acharya et al., 2012), CoVar (Adrian and Brunnermeier, 2014), and insurance premium against a firm's financial distress (Huang et al., 2009). The construction of these measures relies more or less on equity returns, which only imply the risk indirectly. In addition, these measures are backward-looking in nature and thus can only be of limited use when it comes to predicting the future. In this paper, we contribute to the literature by creating a directly relevant and forward-looking measure of risk — the probability of default (PD). PD captures a firm's likelihood of not fulfilling its financial obligations over some future horizon. It focuses directly on the realization of a rare event of significance, which may trigger cascading defaults and cause widespread distress throughout the financial system.
Measuring the connectedness between banks is a crucial step in constructing a proper financial network. Connectedness is, not surprisingly, one among several criteria that the Basel Committee on Banking Supervision considers in assessing the global systemic importance of a bank (BCBS, 2013). Connectedness between financial jurisdictions has also played a role in determining whether countries should undergo a mandatory financial sector assessment by the IMF on a recurring basis (Demekas et al., 2013).

Correlation, which captures the tendency of two parties moving together, or their linear dependence, has been commonly used to serve this purpose (e.g. Tumminello et al., 2010). Although intuitive, the correlation contains both direct and indirect impacts from the rest of the system. It naturally confounds the measurement of the direct connection between the two parties, which we believe a good network ought to reflect. To disentangle the direct connection between banks in terms of their future default likelihoods, we contend that partial correlations are more appropriate, a view advanced first by Kennett et al. (2010).

Most of the work on financial networks, which we will review in more detail in the next section, relies on the historical, past co-movements and/or correlations of stock returns or other market-based risk measures. In contrast, we choose to construct a dynamic, ever-evolving and forward-looking default correlation network. We choose not to use historical correlations of PDs, despite the fact that they are easy to calculate from the time series of PDs available from databases managed by the Credit Research Initiative (CRI) at the Risk Management Institute (RMI) of the National University of Singapore, Moody's Analytics, Kamakura, or Bloomberg. Historical correlations would represent the connectedness between banks for a fixed horizon, say, one month, averaged over a long time span. This averaged measure of co-movement is unlikely to adequately reflect connectedness going forward. Much like forward-looking volatilities which are informative beyond the sample standard deviation computable from the past data, correlations among PDs are expected to be dynamic in response to the state of economy.

Instead, we use the default correlation model of Duan and Miao (2015) to generate a set of forward-looking PDs for a specific horizon of interest, which reflects the current market conditions while also capturing the eventuality that some firms may cease to be publicly traded or disappear for reasons other than default. Our forward-looking PDs are constructed for over 1,000 banks in the RMI-CRI database and we use them to obtain the regularized partial correlation matrix, which allows isolating the direct dependence between two firms. This matrix serves as the basis for building our global banking network.

Regularization is required for two reasons. The first reason is technical, as the estimation of high dimensional partial correlation matrices can be unstable in the absence of regularization. The second reason has an economic underpinning: without regularization, the partial correlation matrix would be relatively dense, which would tend to bunch all in one big global component, with all banks being systemically important. By imposing a regularization condition, a substantial number of edges may drop from the network but we ensure that there are no totally disconnected banks, i.e. "orphans." This "regularized" network, therefore, is consistent with the intuition of a globally connected banking system with only a certain number of systemic firms.

Besides the use of forward-looking PDs, another novel feature of our analysis is that edges, which capture the strength of the connection between banks, are not only weighted by the values of the partial correlations but also by firm characteristics, i.e. their share in the network's total assets. While node characteristics have been used before in Demekas et al. (2013), the resulting network was reduced to an unweighted network after the removal of edges with low weights. In contrast, we calculate several centrality measures using the weighted network, and the analysis of the measures help us determining the systemic ranking of banks.

For comparison purposes, we also construct partial correlation networks with historical PDs and stock returns, respectively, for the same sample of banks. There are substantial differences between the systemic risk rankings obtained from historical, backward-looking correlations and those obtained using the forward-looking partial correlations. These differences persist whether the edges are weighted or not by the size of the firms, suggesting that our approach based on forward-looking correlations is materially different. More importantly, the overlap between the set of global systemically important banks determined by the Financial Stability Board (FSB) and the forward-looking PD systemic risk ranking is substantial only when edges are weighted by size. We argue, hence, that the FSB ranking is severely biased towards singling out large institutions, and connectivity plays a rather minor role.

Before offering a detailed explanation of the methodology and a discussion of the results, the review of the related literature next serves to frame and put into context the contribution of this paper.

2. Related Literature

A recent strand of the literature has focused on the dimensions of systemic risk and related costs associated with the possibility of multiple failures among banks. For instance, Acharya et al. (2012) measure the cost of a financial crisis by assessing potential capital shortfalls driven by large equity price declines relative to required regulatory capital ratios. While it is not necessarily the case, large capital shortfalls are likely to occur simultaneously since there is dependence between the equity price movements of individual firms and the overall market (Brownlees and Engle, 2015). Duan and Zhang (2013) use asset-liability dynamics with several common risk factors to measure the systemic exposure and systemic fragility arising from cascading defaults, which correspond to the expected losses and pervasiveness of defaults under a stress scenario similar to that in Brownlees and Engle (2015).

Rather than relying on dependence through common risk factors, other measures look at pairwise dependence on the movement of equity prices in distress periods, i.e. CoVaR (Adrian and

Brunnermeier, 2014), or risk measures such as credit default swap (CDS) spreads, i.e. CoRisk (IMF, 2009; Chan-Lau, 2013, Chapter 6). In these approaches, quantile regressions can capture the dependence between two firms after correcting for the effect of common drivers of risk, such as cyclical indicators or volatility indices. Results by Patro et al. (2013) show that simple risk indicators based on daily stock return pair-wise correlations seem to capture well changes in systemic risk in the U.S. financial system.

While pairwise dependence measures can serve to construct a financial network by connecting two banks with an edge weighted by the dependence measure, the edges may still be capturing dependence effects from a source independent from the two banks, i.e., common dependence with a third bank or a set of other banks. From a network perspective, hence, it may be better to construct the network following a global rather than a pairwise approach. Furthermore, the pairwise approach could be subject to some estimation issues. For instance, a correlation matrix constructed using pairwise correlations based on time series observations of unequal length may not yield a legitimate correlation matrix.

Mantegna (1999) is an earlier example of a global approach for constructing financial networks. In this network, nodes (i.e., firms) are connected by edges weighted by the correlation of their equity returns. Tumminello et al. (2010) expand on this work, by constructing hierarchical trees, correlation based trees and networks from stock return correlation matrices.

In a similar vein, Billio et al. (2012) use monthly stock returns for financial institutions, including hedge funds, broker/dealers, banks, and insurers, to construct a Granger causality network, where edges between firms run in the direction of non-linear Granger causality. Billio et al. (2013) use credit spreads-based Granger causality networks to analyze interconnectedness between financial firms and sovereign countries. Since there are common drivers of equity returns as suggested by the empirical evidence from factor pricing models (Ferson, 2003, among others), as well as of credit spreads, measures based on plain correlations or Granger causality may be misleading when it comes to quantifying dependence between firms.[1]

To a certain extent, using stock return residuals after correcting for common factors or principal components could remove the effects of other firms on the dependence between two firms. But the choice of common factors or number of principal components is non-trivial. Spatial-dependence methods, developed in the panel vector autoregression literature, could be applied to remove strong common factors.[2] Craig and Saldias (2016), building on work by Bailey et al. (2015b), follow this approach to construct a banking network using stock returns, approximating the common factors with principal components.

Another alternative is to use partial correlation analysis, as in the analysis of stock returns networks by Kennett et al. (2010). Their results highlight substantial differences between standard correlation networks and the corresponding partial correlation ones. More recently, Barigozzi and Brownlees (2016) also use partial correlations to construct financial networks, building on the vector autoregressive model introduced by Diebold and Yilmaz (2014).

Moving beyond stock return correlations, Demirer et al. (2015) propose that a directed edge corresponds to a firm's stock returns' contribution to the generalized forecast error variance decomposition of the other firm's stock returns, where the decomposition is obtained as suggested by Koop et al. (1996), and Pesaran and Shin (1998). Results by Lanne and Nyberg (2016), however, suggest that these measures may not be comparable across time since, in contrast to the forecast

[1] See Chudik et al. (2011) and Bailey et al. (2015a).
[2] See the survey by Canova and Ciccarelli (2013).

variance decomposition in a structural vector autoregressive model, the sum of the proportions of the impact accounted for the innovations may not sum to unity.

A common feature shared by the different approaches presented in this section is that the price-based measures used, either based on stock returns or credit spreads, are backward-looking in the sense that they only capture co-movements of past, observed data. As highlighted in the introduction, they may fail to capture dynamics associated with an evolving economic environment. The next section explains how to construct forward-looking PDs, allowing us to overcome the backward-looking problem faced by earlier studies.

3. Methodology

Our approach comprises three parts: (1) constructing a forward-looking probability of default (PD) partial correlation matrix for banks under consideration, (2) utilizing the partial correlation matrix to devise measures for ranking banks in terms of their systemic importance, and (3) building a banking community centered at a bank or a group of banks so that different communities of interest may naturally overlap.

For the first part, we adopt the default correlation model of Duan and Miao (2015) to produce via simulation a forward-looking PD total correlation matrix for any future horizon of interest in a time-consistent manner. The total correlation matrix is then used to obtain the corresponding partial correlation matrix by applying the CONCORD (CONvex CORrelation selection methoD) algorithm of Khare, et al. (2015). We choose to rely on partial PD correlations, because they are ideal for disentangling the pure and direct default risk linkages between two banks as opposed to reflecting the indirect influence via third parties.

With the forward-looking PD partial correlation matrix in place, we then focus on the two remaining components of our methodology. To measure systemic importance of a bank in the network, we rely on the concept of network centrality where the nodes and edges are defined by the forward-looking PD partial correlation matrix. Six measures of network centrality are used, and of which four are standard and based on network edge characteristics, and two are novel. The two new centrality measures introduced here utilize the eigenvector centrality concept by explicitly incorporating the size of banks, i.e., combining edge and node characteristics.[3] For example, a large bank, say, HSBC, may be connected with many smaller banks. A simple size-weighted measure would make these connections less important. The edge-node combined eigenvalue centrality would, however, make those connected smaller banks systemically more important due to their connection to HSBC, which in turn also increases the systemic relevance of HSBC via feedback.

The last component of our methodology is to devise a bank/group-centric banking community. Instead of partitioning banks into non-overlapping communities, a group-centric community is defined. Within the defining group, a member bank may not have any partial correlation with others, but it is nevertheless a member of the community by definition. This group-centric community can be straightforwardly obtained, be it a global banking community which contains all banks, or, say, a New York-centered banking community where all New York-based banks are included, with or

[3] Demekas et al. (2013), in their financial jurisdictions network, weigh edges using node characteristics such as the PPP-GDP of the jurisdiction and the share in the global derivatives market of the banks headquartered there. The weights in their analysis are used to prune edges with values below a certain threshold instead of fundamentally altering systemic importance as in ours. These authors also use the clique percolation method (Palla et al. 2005) for identifying communities which, in contrast to the group-centric community proposed by us, requires that at least a subset of the banks in the community are fully connected to each other.

without connections with each other, along with other banks whose partial correlations with at least one New York-based bank are non-zero. The focal group can also be narrowed down to just one bank; for example, forming a Banco Santander-centered banking community. Naturally, different overlapping communities will emerge to reflect different focal groups.

2.1 Constructing the forward-looking PD partial correlation matrix

The default correlation model of Duan and Miao (2015) is adopted to generate forward-looking PD total correlation matrix, which is then used to deduce its corresponding partial correlation matrix. The Duan and Miao (2015) model specifies a factor model for one-month PD and probability of other exits (POE) of individual firms in the universe of exchange-traded corporates, with the factors being some predetermined credit risk indices constructed from the same universe of corporates. As reported in Duan et al. (2012), POEs are many times larger than PDs for typical US firms. Thus, the survival probability of a firm is largely determined by POE rather than PD. Naturally, POE is critical to default modeling, because the survival probability is a key determinant of any multiple-month PD. The Duan and Miao (2015) model also handles missing data, which naturally occur as a result of defaults and other corporate exits.

Duan and Miao (2015) employ 11 pairs of predetermined factors consisting of (1) the pair of global median PD and POE based on a pool of over 40,000 exchange-traded corporates that have PDs and POEs for at least 60 months over the sample period, and (2) 10 pairs of industry median PD and POE based on the Bloomberg Industry Classification System. The PDs and POEs of these firms are taken from the Credit Research Initiative (CRI) database, a public-good undertaking at the Risk Management Institute (RMI) of the National University of Singapore (NUS). The RMI-CRI produces and publishes daily updated term structures of PDs, using the forward-intensity corporate default prediction model of Duan et al. (2012), for exchange-traded corporates around the world. As of December 2015, RMI-CRI provides PDs, with horizons ranging from 1 month to 5 years, on over 60,000 firms in 119 economies. Among them, over 30,000 corporates are currently active with daily updated PD and POE values. The PD and POE time series in some cases date back to 1990. We use this RMI-CRI database for the analyses in this paper.

The factors (pairwise with one for PD and the other for POE) are dynamically evolving, modeled using a vector autoregressive structure which allows factor model residuals to be also individually autoregressive. Since the individual time series model residuals are allowed to form locally correlated clusters, default correlations in the Duan and Miao (2015) model could arise globally and/or locally. The factor model is estimated with a SCAD penalized likelihood method of Fan (1997) to deal with noisy parameter estimates due to many regressors, or alternatively too few observations.

This factor model with sparsely correlated residuals enables us to generate PDs during a target horizon, say, one year, at any future time point, say, one month later, for any subset of firms in the RMI-CRI universe. The one-year PD for a firm one month later is a random variable, and can therefore be correlated with the one-year PD of another firm at that time, which is the kind of PD correlations that we intend to capture. Operationally, one can simulate forward one month the 11 pairs of factors along with individual PD and POE residuals of a target group of firms. This initial simulation yields the starting point for a second set of simulations. Moving forward one month, one can further simulate M paths over 12 months for the risk factors and individual PD and POE residuals, and for each of the M paths deduce the corresponding one-year PD using the standard survival-default formula, and finally average over the M paths to compute the Monte Carlo estimate of the one-year PD one month later. We repeat the procedure for every firm in the target group to generate one set of random one-year PDs one month later.

Repeat the two-step simulation process *N* times to generate *N* sets of one-year PDs for the target group of firms. One is then in a position to estimate the correlation matrix using these *N* sets of one-year PDs over the one-month horizon. In the implementation later, we set *M*=1000 and *N*=1000. By increasing *M* and *N*, the correlation matrix can be obtained with any desired level of accuracy, but the sampling error intrinsic to the estimated Duan and Miao (2015) default correlation model cannot be eliminated by increasing simulation accuracy. Note that this correlation matrix is actually for the change in, say, one-year PDs over, say, one month, because *N* one-year PDs for a firm all start from the same one-year PD one month earlier.

Our next task is to convert the forward-looking PD total correlation matrix into a partial correlation matrix. By definition, partial correlation is the residual correlation after subtracting any indirect impact from other parties in the system. Empirically, it can be obtained from linear regressions. The problem with this approach is that the resulting partial correlation matrix will likely be dense with many entries close to zero. These minuscule entries tend to disguise the more meaningful and important relationships that we are after.

To make the partial correlation matrix more sparse and meaningful, a Lasso-type penalty is typically utilized to trim the partial correlation matrix, which in essence imposes zero partial correlations on pairs that have weak ties. We apply the CONCORD algorithm introduced in Khare et al. (2015) and Oh et al. (2014), which uses a proximal gradient method to solve an objective function with a purposely designed penalty matrix. The CONCORD algorithm guarantees convergence since it preserves convexity through an appropriate selection of weights and the design of a penalty term based on the inverse of the correlation matrix rather than on the partial correlation matrix. This is not the case with other penalty-based methods for generating sparse partial correlations, such as the SPACE (Sparse PArtial Correlation Estimation) method of Peng et al. (2009).

Following equation (4) of Oh et al. (2014), we set equation (1) as our minimization target with the CONCORD objective function as:

$$Q_{con}(\mathbf{\Omega}) = \frac{N}{2}\left[-\ln[\det(\mathbf{\Omega}_D^2)] + \mathrm{tr}(\boldsymbol{S}_N\mathbf{\Omega}^2) + \lambda \parallel \mathbf{\Omega}_X \parallel_1\right] \qquad (1)$$

where $\det(\bullet)$ and $\mathrm{tr}(\bullet)$ denote the determinant and trace operators, respectively; $\boldsymbol{S}_N$ is the sample correlation matrix computed with a sample size of *N*; and where the inverse of the correlation matrix, $\mathbf{\Omega}$**,** can be split as $\mathbf{\Omega} = \mathbf{\Omega}_D + \mathbf{\Omega}_X$, where $\mathbf{\Omega}_D$ and $\mathbf{\Omega}_X$, denote respectively the diagonal and off-diagonal elements of $\mathbf{\Omega}$. The L_1-penalty term is $\lambda \parallel \mathbf{\Omega}_X \parallel_1 = \lambda \sum_{i \neq j} |\omega_{ij}|$, where ω_{ij} is the off-diagonal element in $\mathbf{\Omega}_X$ and the scaling parameter λ ($\lambda > 0$) determines the shrinkage rate, or how aggressively one penalizes the non-zero entries in $\mathbf{\Omega}_X$. Cross-validation by dividing the data sample into randomized training and validating datasets is the usual way to determine the optimal shrinkage rate. However, we choose to select λ such that it is just slightly below the value at which an orphan bank, i.e., totally isolated bank in the network, begins to emerge.[4] Economic intuition justifies using this selection criterion because in reality, all banks in the banking system should be connected with some other banks.

[4] We set the tolerance error for finding the optimal λ at 10^{-3} and the partial correlation precision at 10^{-4}. These tolerance and precision levels are set to conserve computing time. The results are not sensitive to further tightening of their levels.

After obtaining the optimal $\mathbf{\Omega}$, one can compute the partial correlation matrix $\mathbf{P}$ whose (*i*,*j*) element equals $-\frac{\omega_{ij}}{\sqrt{\omega_{ii}\omega_{jj}}}$. For the discussion of centrality measures next, let us set $\mathbf{P}_X$ equal to $\mathbf{P}$ except that its diagonal elements are set to 0 since there is no interest in analyzing the effects of a bank on itself.

2.2 Ranking systemically important banks via different network centrality measures

A natural outcome of studying the linkages in a financial network is to determine the relative importance of each bank, which could help policy makers rationalize different risk management measures/actions. The linkages in our analysis are described by the forward-looking PD partial correlation matrix. A bank's systemic importance is its centrality in the network. Different centrality measures typically reflect different kinds of systemic importance, and no single measure can be expected to serve all purposes well. Here, we utilize four standard centrality measures hinging on the concept of adjacency matrix: degree centrality, connection-strength centrality, eigenvector centrality, and connection-strength eigenvector centrality. For a network with *n* firms, we define the adjacency matrix **A** as the *n x n* matrix whose elements are set to 0 or 1 depending on whether their corresponding elements in $\mathbf{P}_X$ equal 0 or not.

The degree centrality of Bank *i* is defined as the *i*-th row sum of **A**, whereas the connection-strength centrality is the *i*-th row sum of $|\mathbf{P}_X|$, the absolute value of $\mathbf{P}_X$, divided by the total number of banks in the network. The later normalization makes possible comparing results across networks comprising different number of banks. The eigenvector centrality is based on the eigenvector of **A** that corresponds to the largest eigenvalue. Since **A** is a non-negative matrix, the Perron-Frobenius theorem implies that this eigenvector can be made to have all non-negative elements, with the *i*-th element representing the centrality of the *i*-th bank. Similarly, the connection-strength eigenvector centrality is the eigenvector associated with $|\mathbf{P}_X|$. The eigenvector centrality measures a node's importance by factoring in the extent to which its connected nodes are further connected. In short, it measures impacts in a network globally, and has been widely applied to rank the importance of individual nodes in networks.

The four centrality measures discussed thus far are all based on the number and values of edges to and from a node as opposed to the node's characteristics beyond connections, for example, the relative size of a bank. Moreover, node's characteristics may also affect the node's number and nature of its connections. For instance, a large, well-capitalized bank may be better able to provide interbank loans to a large number of counterparties. We thus devise two novel edge-node combined centrality measures. First, let q_i be the size of a bank (total assets measured in USD) over the total size (total assets) of the banking network, and **Q** be a diagonal matrix with q_i as its *i*-th diagonal element. The two new measures are, respectively, the non-negative eigenvector (corresponding to the largest eigenvalue) of the size-adjusted adjacency matrix, **QAQ** and that of the size-adjusted partial correlation matrix, $\mathbf{Q}|\mathbf{P}_X|\mathbf{Q}$. Under these new centrality measures, a smaller bank by connecting to a large bank will become relatively more important, which in turn feeds back to increase the large bank's systemic importance through the eigenvector solution. We favor the two new centrality measures because they go beyond the complexity of linkages (i.e., edge characteristics). Since there is little question about bank size (i.e., a node characteristic beyond connections) being critical to systemic importance, the two new centrality measures seem more suitable for banking networks.

2.3 Determining the bank/group-centric banking community

Communities within a network can be constructed as either overlapping or non-overlapping ones, using quite different techniques. To create non-overlapping communities is to partition the nodes into several disjoint sets with methods such as spectral bisection (Fiedler, 1973, and Pothen et al., 1990), benefit function optimization (Kernighan and Lin, 1970), hierarchical clustering (Scott, 2000), and edge removal (Girvan and Newman, 2002). For our purposes, however, hard partitioning banks into non-overlapping communities is not appealing, because forcing a bank to just belong to one community is inconsistent with the common notion of banking communities.

An alternative is to create overlapping communities, for which several methods are available; for example, clique percolation of Palla et al. (2005) and its variants.[5] The clique percolation method to create overlapping communities relies on first forming cliques based on edges and then putting connected cliques into a community. Thus, it is also not ideal for our purpose; for example, a banking community centered in the New York area and connected by credit risk linkages should naturally include all New York-centered banks along with some banks belonging to, say, the London-centered community. In short, focal groups (i.e., individual banks, financial centers, and countries) are more natural communities from a user's perspective, and different banking communities centered at different focal groups should be allowed to overlap.

We use the network analysis tool, *Gephie*, to graphically present banking communities. In the network, each node represents a bank, and the node size is determined by its total asset. Each edge linking two nodes represents a non-zero partial correlation between the two banks' forward-looking PDs. The thickness of the edge represents the connection strength, and the color of the edge reveals a positive (red) or negative (blue) connection. We use the software's built-in algorithm *ForceAtlas2* to set the graphical configuration. *ForceAtlas2* is a force-directed algorithm. Under this algorithm, the attraction and repulsion forces between the nodes move them around and eventually to a balanced state. Essentially, this algorithm turns proximities in a network into visual communities with denser connections (Jacomy et al. 2014). As per our partial correlation construction method, there will not be any genuine orphan or unconnected bank in the overall banking network, but within some communities, certain banks may be orphan banks.

3. Global Banking Network, Systemically Important Banks, Banking Communities, and the 2008 Banking Crisis

This section illustrates the use of our methodology for assessing the systemic importance of banks. First, the section evaluates how the six different network centrality measures compare to each other; second, it analyzes their performance vis-a-vis the ranking methodology proposed by the Financial Stability Board (FSB), which currently supports the regulatory reform proposals for systemic banks; and third, it assesses their performance during August 2008, in the eve of the global financial crisis.

The sample includes firms, which according to the Bloomberg Industry Classification System (BICS) are commercial banks (BlCS 10008-20051), and investment banks and brokerage firms (BICS 10008-20054-159.[6] We refer to these entities as 'banks' for simplicity. Forward-looking PDs are calculated using a five-year rolling data window so that the estimated factor loadings can vary over time. This will presumably capture the potentially variable dependencies of the PDs on the general economic conditions. A bank is included in the sample if its shares were actively traded at the time the forward-looking PD is calculated, and had at least two years of data (24 monthly observations) in the

[5] See Xie et al., 2013, for a recent survey of overlapping community detection methods.

[6] The analysis also includes a number of financial holding companies in Taiwan and Korea. Although classified as 'diversified financial services' (BICS 10008-20054-176), these firms actually perform services and functions similar to 'banks'. Leaving them out of the analysis would make the banking sectors of the two economies less representative. We exclude three exchange-listed central banks, Schweizerische Nationalbank, Banque Nationale de Belgique, and Bank of Greece, due to their special nature.

five-year rolling data window. For the factors' own time series dynamics, we use an expanding-data window (i.e., all data up to the prediction time) in estimation, because the factors are broad-based credit risk indices that need longer time series to estimate with reasonable precision.

In the analysis that follows, the forward-looking PDs are for the one-year prediction horizon, and the PD correlation matrix is calculated for the one-year PDs one month ahead ofthe prediction time. We conduct the analysis for two time points, August 2008 and December 2014. The choice of the first time point is rather obvious, as it is right before the failure and bankruptcy of Lehman Brothers, which set off a global financial crisis. The second point corresponds to the economic environment prevalent once the crisis largely subsided. The number of banks in the August 2008 and December 2014 samples are quite similar, 1,269 and 1,275 respectively.

The partial correlation matrices computed for August 2008 and December 2014 exhibit substantial sparsity, as zero entries account for about 97 percent of all entries in both dates. Not surprisingly, this result is expected because, first, only direct connections are measured, and second, CONCORD, a penalty-based method, shrinks partial correlations towards zero. Recall that our partial correlation matrix construction increases sparsity up to the point that an orphan bank begins to emerge. Any higher sparsity will result in some bank(s) to be totally isolated from the global banking network in terms of credit risk, a hardly sensible outcome.

3.1 Comparing the six network centrality measures

As section 2 noted, different centrality measures capture the relative importance of each bank in the network from different angles. To show the relations among these measures, Table 1 presents the rank correlations among the six centrality measures and the asset size for both the August 2008 and December 2014 samples. The degree centrality, which measures the number of connected parties a bank has, is highly correlated with the eigenvector centrality, as the latter factors in both connectedness and the extent to which its connected parties are further connected. The same thing applies to the connection strength and connection strength eigenvector centrality due to the same reason. As expected, the asset size is considerably correlated with the two bank size-weighted centrality measures.

Neglecting node characteristics, i.e., the size of the banks, leads to some surprising and possibly counterintuitive results. In August 2008, the largest positive partial correlation is between the Bank of Nova Scotia, a Canadian Bank, and Powszechna Kasa Oszczednosci Bank Polski SA, a Polish bank, at 0.6125. As a comparison, the most negative partial correlation is between the Peoples Financial Corp, a US bank, and Banco Bilbao Vizcaya Argentaria (BBVA) Chile SA, the Chilean subsidiary of Spanish bank BBVA, at -0.1930. Corp Bank, an Indian bank, ranks first in terms of the number of connections to other banks, at 83. By contrast, Centrum Capital Ltd, an Indian bank, ranks last with only one connection to another Indian bank, Kirayaka Holdings Inc. In terms of average connection strength, CIL Securities Ltd, another Indian bank, has the highest strength at 23bps, whereas Centrum Capital Ltd has the lowest with a negligible magnitude.

In December 2014 the largest positive partial correlation is between The Hyakujushi Bank Ltd, a Japanese bank, and Arab Jordan Investment Bank, a Jordan-based bank, at 0.6366, while the most negative one is between the Woori Investment Bank Co Ltd, a Korean bank, and Euro Yatirim Holding AS, a Turkish bank, at -0.2524. Royal Bancshares of Pennsylvania Inc, a US bank, has the highest number of connections at 83, and Banco Davivienda SA, a Colombian bank, has only one connection with Saudi Hollandi Bank, a Saudi Arabian bank. As to the average connection strength, Bank of China, a Chinese bank, ranks first at 23bps, and Banco Davivienda SA ranks the lowest with a negligible value.

Table 1. Rank correlations among the six network centrality measures and the bank asset size

Panel 1. Spearman correlations in August 2008

	Degree	Connection Strength	Eigenvector	Connection Strength Eigenvector	Weighted Eigenvector	Weighted Connection Strength Eigenvector	Bank Asset Size
Degree	1	0.39	0.92	0.34	0.17	0.17	0.07
Connection Strength	0.39	1	0.32	0.86	0.08	0.15	0.06
Eigenvector	0.92	0.32	1	0.34	0.05	0.04	0.02
Connection Strength Eigenvector	0.34	0.86	0.34	1	-0.04	0.03	0.02
Weighted Eigenvector	0.17	0.08	0.05	-0.04	1	0.96	0.59
Weighted Connection Strength Eigenvector	0.17	0.15	0.04	0.03	0.96	1	0.56
Bank Asset Size	0.07	0.06	0.02	0.02	0.59	0.56	1

Panel 2. Spearman correlations in December 2014

	Degree	Connection Strength	Eigenvector	Connection Strength Eigenvector	Weighted Eigenvector	Weighted Connection Strength Eigenvector	Bank Asset Size
Degree	1	0.44	0.95	0.48	0.28	0.30	0.03
Connection Strength	0.44	1	0.42	0.91	0.14	0.20	0.06
Eigenvector	0.95	0.42	1	0.53	0.30	0.33	0.01
Connection Strength Eigenvector	0.48	0.91	0.53	1	0.13	0.21	0.01
Weighted Eigenvector	0.28	0.14	0.30	0.13	1	0.91	0.67
Weighted Connection Strength Eigenvector	0.30	0.20	0.33	0.21	0.91	1	0.57
Bank Asset Size	0.03	0.06	0.01	0.01	0.67	0.57	1

Source: RMI-CRI (National University of Singapore) and authors' calculations.

3.2 The FSB G-SIBs vs. network centrality based-rankings as of December 2014

In the aftermath of the global financial crisis, the FSB proposed a number of criteria to identify Global Systemically Important Banks (G-SIBs), with the purpose that better monitoring of these banks' activities and enhanced buffer requirements could reduce the risks of experiencing another severe financial crisis. The FSB released a list of systemic banks in November 2014 based on the weighted value of 12 indicators over five categories, or their systemic importance measures. Each of the G-SIBs is required by FSB to meet extra loss absorbency requirement, according to their systemic riskiness, in order to better withstand financial distress.[7]

We assess the rankings of the 2014 G-SIBs based on the FSB recommendations for loss absorbency requirements as well as the six network centrality measures obtained from our December 2014 partial default correlation network, and present the results in Table 2. According to the first two network measures (columns 3 and 4 in Table 2), i.e., degree and connection strength, JPMorgan Chase, a US bank, and Bank of China, supposedly the most international among Chinese banks, not only have a large number of immediate counterparties, but also strong connections. In contrast, Standard Chartered, a British bank, and Agricultural Bank of China, a large Chinese state-owned bank, have very few counterparties and weak ties. No G-SIB except for Bank of China makes it to the top

[7] For a detailed discussion on the 2014 G-SIBs methodology, please refer to "The G-SIBs assessment methodology-score calculation," http://www.bis.org/bcbs/publ/d296.pdf.

ten according to degree or connection strength centrality, whereas JP Morgan ranks only in the 95th place based on the former, and 58th based on the latter.

Table 2. FSB loss absorbency and systemic importance rankings for the 2014 G-SIBs

Bank Name	FSB Loss Absorbency Requirement	Degree	Connection Strength	Eigenvector	Connection Strength Eigenvector	Weighted Eigenvector	Weighted Connection Strength Eigenvector
HSBC Holdings PLC	2.50%	432	309	288	205	1	2
JPMorgan Chase & Co	2.50%	95	58	118	22	3	7
Barclays PLC	2.00%	703	350	566	223	2	1
BNP Paribas SA	2.00%	473	548	649	574	19	104
Citigroup Inc	2.00%	1,014	833	1,126	1,100	25	59
Deutsche Bank AG	2.00%	255	656	238	541	22	33
Bank of America Corp	1.50%	703	663	792	772	60	186
Credit Suisse Group AG	1.50%	390	938	428	1,076	9	16
Goldman Sachs Group Inc	1.50%	338	975	589	1,113	31	48
Mitsubishi UFJ Financial Group Inc	1.50%	195	836	195	923	5	8
Morgan Stanley	1.50%	125	532	319	1,023	61	122
Royal Bank of Scotland Group PLC	1.50%	390	597	450	513	11	3
Agricultural Bank of China Ltd	1.00%	1,215	1,247	1,161	1,251	16	93
Bank of China Ltd	1.00%	2	1	3	2	42	108
Bank of New York Mellon Corp	1.00%	1,158	333	1,215	886	91	115
Banco Bilbao Vizcaya Argentaria SA	1.00%	296	813	237	880	73	235
Groupe BPCE*	1.00%	526	1,025	467	843	120	112
Credit Agricole SA	1.00%	526	544	526	615	13	15
Industrial & Commercial Bank of China Ltd	1.00%	125	762	169	699	14	100
ING Groep NV	1.00%	149	586	106	597	4	6
Mizuho Financial Group Inc	1.00%	223	154	424	272	189	185
Nordea Bank AB	1.00%	637	265	611	264	36	41
Banco Santander SA	1.00%	338	509	223	818	26	207
Societe Generale SA	1.00%	851	697	644	447	12	22
Standard Chartered PLC	1.00%	1,260	1,260	1,198	1,147	17	11
State Street Corp	1.00%	637	1,063	906	1,109	27	39
Sumitomo Mitsui Financial Group Inc	1.00%	851	366	868	510	319	243
UBS Group AG	1.00%	801	559	637	736	6	12
UniCredit SpA	1.00%	576	774	699	661	34	126
Wells Fargo & Co	1.00%	1,173	604	1,199	961	108	349
Rank correlations with FSB (1,275 banks)		0.01	0.01	0.01	0.04	0.59	0.36
Rank correlations with SRISK (453 banks)		0.10	0.13	0.14	0.14	0.25	0.23

* Groupe BPCE is not a listed firm. We use Natixis SA, the major listed entity in this banking group, to proxy for its systemic ranking.
Source: RMI-CRI (National University of Singapore) and authors' calculations.

Accounting for network effects, using either the eigenvector centrality (column 5) or the connection strength eigenvector centrality (column 6) boosts the systemic importance of banks such as HSBC and Societe Generale, because their immediate counterparties are better/more strongly connected with others. In contrast, Morgan Stanley and Mizuho move down the list under eigenvector-based centrality measures. Finally, as section 2 explained, the weighted eigenvector centrality (column 7) and weighted connection strength eigenvector centrality (column 8), by taking into account both the node and edge characteristics in a network setting, deliver a more comprehensive view of individual banks' importance in the system. Under these two node-weighted centrality measures, most of G-SIBs gain a higher systemic ranking. Distinct examples include HSBC, JPMorgan Chase, Barclays, and UBS Group AG. In comparison, Wells Fargo does not seem quite as systemically important as its big-bank peers, probably due to its simple business model and conservative risk taking strategies as a main street lender, which reduce both its number of connections and the importance of connected banks.

The bottom of Table 2 presents the Spearman rank correlations between the six network centrality measures extracted from the forward-looking partial correlation network and two other systemic importance indicators. The first calculation compares the FSB ranking against ours for the 1,275 banks in the December 2014 sample. To create the FSB ranking, we rank the 30 G-SIBs from 1 onward, allowing for ties when multiple banks fall in the same loss absorbency basket, and assign a ranking of 31 to the remaining 1,246 banks assuming they all fall in the same and last basket.

Under the six centrality measures, on the other hand, the highest ranked 30 banks keep their genuine ranking, while the others are assigned the number 31. The Spearman coefficients indicate that the FSB methodology does not seem to account much for the number and strength of inter-bank connections. As a reference, the rank correlation between the FSB indicator and the bank size, not reported in Table 2, is 0.80. It suggests that the FSB methodology relies heavily on bank size, which also explains the relatively high correlation of the FSB ranking with the two size-weighted centrality measures, 0.59 and 0.36 for the weighted eigenvector and weighted connection strength eigenvector, respectively.

For comparison purposes, Table 2 also presents the rank correlations between the six centrality measures and the SRISK, which we extract from the Systemic Risk Analysis of World Financials by the V-Lab of the Volatility Institute at the New York University Stern School of Business.[8] Given the different coverage of banks in the two analyses, the comparison is conducted only for 453 banks that are both in our and V-Lab's samples as of December 31, 2014. The rank correlation coefficients are generally modest. This phenomenon reflects the fundamentally different approach used by the V-lab, where co-movements between firms are based on equity returns and depend on a single risk factor, the broad market equity index. Due to its use of equity returns, the SRISK only offers indirect information about default connections. Moreover, the SRISK does not exploit the network structure fully as is the case with our systemic risk measures.

3.3 Systemic risk rankings of banks in August 2008

Performing the network analysis in August 2008 is interesting in its own right. Within the following month, the US Treasury placed Fannie Mae and Freddie Mac into conservatorship, Lehman Brothers filed for bankruptcy, Merrill Lynch sold itself to Bank of America, and the Federal Reserve bailed out AIG. These events not only shook the global financial system but they also prompted the US government to implement the $700-billion Troubled Asset Relief Program (TARP) shortly afterwards.

[8] The SRISK measure of a firm is set equal to its expected capital shortfall in a crisis scenario characterized by a 40 percent decline in the broad market index. The measure is used to rank the systemic risk of global financial firms, with the rank updated on a weekly frequency. Details are available at http://vlab.stern.nyu.edu/en/.

In the following paragraphs, we will use our tools and metrics to help reflect on some of these unusual occurrences.

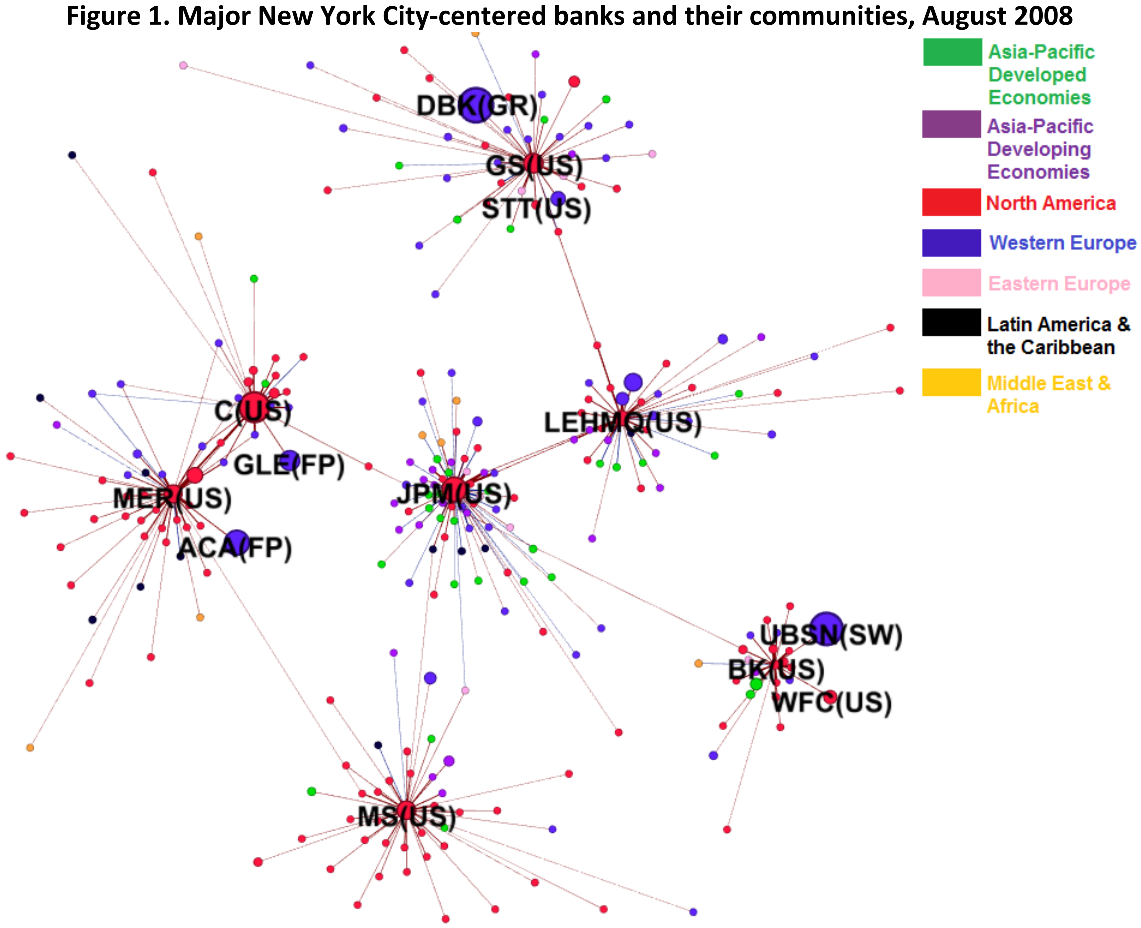
Table 3. Systemic rankings and the total assets for New York City-based banks, August 2008

	Degree	Connection Strength	Eigenvector	Connection Strength Eigenvector	Weighted Eigenvector	Weighted Connection Strength Eigenvector	Bank Asset Size (in billions of USD)
Citigroup	1,014	274	1,104	680	20	14	2,199,848
JPMorgan Chase	12	7	14	10	391	395	1,642,862
Goldman Sachs	287	967	464	848	152	66	1,189,006
Morgan Stanley	287	817	118	1,167	440	607	1,090,896
Merrill Lynch	209	157	448	525	10	8	1,042,054
Lehman Brothers	452	355	480	206	26	25	786,035
Bank of New York Mellon	1,080	247	1,180	634	18	24	204,935

Source: RMI-CRI (National University of Singapore) and authors' calculations.

Table 3 displays the systemic importance indicators for then major banks centered in New York City in August 2008. With the exception of Lehman Brothers and Merrill Lynch, these banks benefitted from large government bailout funds. The two size-weighted centrality measures (columns 6 and 7 in Table 3), which we believe capture better the systemic risk of banks, suggest that among New York-based banks, JPMorgan Chase and Morgan Stanley do not pose a major threat to the global banking system. These two firms had linkages mainly with other smaller banks. In the particular case of JPMorgan Chase, not accounting for the size of the bank and its connected counterparties would have ranked the bank among the top 20 in the world (columns 2 to 5 in Table 3).

Figure 1. Major New York City-centered banks and their communities, August 2008



Lehman Brothers, Merrill Lynch and Citigroup, one the other hand, were connected to some of the largest banks in the United States and the rest of the world. Although Lehman was smaller than other major investment banks when measured in terms of total assets, its size-weighted ranking among the top 30 banks in the world did not justify the decision to let it go into bankruptcy.[9] This event may have contributed to the cascading defaults of its major counterparties later on. Indeed, our data indicates that among the 32 banks that had positive partial correlations with Lehman Brothers in August 2008 analysis, 12 of them were subsequently delisted from their respective exchanges, with four of the delisted banks occurring within one year of Lehman's collapse.

Figure 1 presents the seven major New York City-based banks, identified by their equity tickers, with their associated banking communities as of August 2008. Different colors denote the geographical domicile of the banks and counterparts, with other major banks also identified by their equity tickers.

The first striking feature in Figure 1 is that the community of each of the seven New York banks had very different characteristics. For instance, Goldman Sachs and the Bank of New York Mellon had large counterparties. In the case of the former, this may be due to its large role as a large correspondent bank. In contrast, Morgan Stanley was mainly connected to smaller banks domiciled in North America, and its community was somewhat isolated from those of other banks. The communities of JPMorgan Chase and Lehman Brothers comprised a more diverse pool of banking counterparties from around the world, and tended to overlap with other communities. The closer banks, in terms of overlapping communities and direct connections between them, were Citigroup and Merrill Lynch.

4. Banking Networks Based on Other Correlation Measures

In the financial network literature, a variety of measures has been used to construct the network (e.g., Kenett et al. 2010; Demirer et al. 2015). The following two examples employ alternative measures and data, and the resulting networks can be substantially different from those obtained by using the forward-looking PD partial default correlations.

4.1 Historical PDs vs. simulated PDs

The first example compares the systemic measures obtained with the 1-year PDs on a forward-looking basis with those using the historical time series of 1-year PDs obtained from the RMI-CRI database. As explained earlier, the forward-looking PDs characterize one month later the potential default risk of a bank over a 1-year horizon. Therefore, the partial correlations and the resulting network are forward-looking in nature. In contrast, the historical PD series of a firm captures the past evolution of its default risk over time. The partial correlation of two series reveals the co-movement of default risk averaged over the sample period in the past and is therefore backward-looking.

To construct the backward-looking measure, we take monthly series of the RMI-CRI 1-year PDs from 1990 to 2014 to form a historical series for each bank in the sample. We then obtain the partial correlations among the monthly difference of each series in the sample.

One challenge in dealing with the historical PD series is that the banks in the sample may not have the same or enough overlapping periods of observations. As a consequence, it may be difficult to

[9] This result supports earlier analysis based on pair-wise interconnectedness suggesting that Lehman Brothers was too systemic to fail (Chan-Lau, 2009, among others).

obtain the sample correlation matrix, which is a crucial input in estimating the true partial correlation matrix. Our solution is to compute the sample correlations in a pairwise fashion in order to make use of the maximum number of observations in each series. We subsequently adjust the resulting correlation matrix element by element to render it positive semi-definite following Qi and Sun (2011), and then convert it to a partial correlation matrix.

Table 4 compares the systemic rankings of the forward-looking and backward-looking networks, for the 2014 G-SIBs. As can be seen, the two approaches yield substantially different results for each of the six network centrality measures. For the two bank size-weighted centrality measures, forward-looking rankings raise the importance of Credit Suisse, Mitsubishi, and UBS Group among other banks relative to their backward-looking counterparts. In contrast, for banks including BNP Paris, Bank of America and Sumitomo Mitsui Financial Group, their forward-looking systemic importance is below their average level across time. From this comparison, it is apparent that using the ‘backward-looking’ PDs to imply the banks’ would-be connectedness in the future will be quite different from relying on the forward-looking PDs at the time of analysis.

4.2 Equity returns vs. PDs

This example compares the banking network generated using equity returns against the network generated with historical PD series. We collect from Bloomberg historical daily equity returns for the period between 1990 and December 2014 for all banks in our sample. As the banks in our sample are listed in many exchanges in different countries/economies, we denominate the returns in US dollar to ensure comparability. For this comparison study, we collect from the RMI-CRI database the daily historical 1-year PD series because daily equity returns are used. This example highlights how different types of risk measures can generate substantially different partial correlation networks. Table 5 reports the rankings for the six systemic importance indictors for the 2014 G-SIBs.

It is apparent that rankings can differ markedly depending on whether equity returns or historical PDs are used. This is the case for the degree and connection strength centralities. Once node characteristics are accounted for, i.e., the banks’ total assets sizes, the rankings from different raw data sources start to get closer with each other. For example, the PD-based bank size-weighted eigenvector centrality has a Spearman coefficient of 0.63 with that constructed with equity returns. This reflects in a way the important role that the node characteristics play in determining the banks’ importance in the global network.

Table 4. Rankings under the six network centrality measures: using historical PDs vs. forward-looking PDs

Bank Name	(1)_F	(1)_H	(2)_F	(2)_H	(3)_F	(3)_H	(4)_F	(4)_H	(5)_F	(5)_H	(6)_F	(6)_H
HSBC Holdings PLC	432	80	309	720	288	140	205	575	1	2	2	6
JPMorgan Chase & Co	95	870	58	1,067	118	1,038	22	1,074	3	1	7	23
Barclays PLC	703	676	350	517	566	666	223	584	2	13	1	69
BNP Paribas SA	473	393	548	706	649	353	574	684	19	3	104	2
Citigroup Inc	1,014	393	833	524	1,126	608	1,100	623	25	4	59	72
Deutsche Bank AG	255	561	656	721	238	710	541	722	22	11	33	59
Bank of America Corp	703	975	663	561	792	890	772	686	60	10	186	53
Credit Suisse Group AG	390	1,253	938	1,063	428	1,266	1,076	1,235	9	324	16	642
Goldman Sachs Group Inc	338	919	975	848	589	1,055	1,113	1,011	31	7	48	70
Mitsubishi UFJ Financial Group Inc	195	676	836	796	195	635	923	759	5	83	8	154
Morgan Stanley	125	346	532	511	319	535	1,023	693	61	20	122	73
Royal Bank of Scotland Group PLC	390	181	597	135	450	282	513	321	11	26	3	123
Agricultural Bank of China Ltd	1,215	80	1,247	160	1,161	243	1,251	29	16	459	93	795
Bank of China Ltd	2	783	1	866	3	695	2	560	42	73	108	219
Bank of New York Mellon Corp	1,158	1,093	333	678	1,215	1,195	886	1,115	91	890	115	1,021
Banco Bilbao Vizcaya Argentaria SA	296	1,012	813	927	237	1,052	880	1,166	73	29	235	40
Groupe BPCE*	526	676	1,025	977	467	795	843	860	120	19	112	4
Credit Agricole SA	526	512	544	465	526	548	615	690	13	6	15	1
Industrial & Commercial Bank of China Ltd	125	284	762	666	169	378	699	555	14	305	100	245
ING Groep NV	149	346	586	331	106	543	597	540	4	44	6	82
Mizuho Financial Group Inc	223	512	154	597	424	428	272	672	189	96	185	196
Nordea Bank AB	637	618	265	879	611	760	264	859	36	9	41	32
Banco Santander SA	338	1,246	509	1,158	223	1,213	818	1,221	26	25	207	18
Societe Generale SA	851	727	697	239	644	1,002	447	956	12	5	22	57
Standard Chartered PLC	1,260	676	1,260	964	1,198	845	1,147	955	17	77	11	140
State Street Corp	637	229	1,063	127	906	221	1,109	273	27	195	39	272
Sumitomo Mitsui Financial Group	851	393	366	322	868	259	510	600	319	78	243	173

Inc												
UBS Group AG	801	727	559	520	637	746	736	589	6	381	12	343
UniCredit SpA	576	452	774	615	699	529	661	534	34	12	126	43
Wells Fargo & Co	1,173	727	604	445	1,199	770	961	530	108	490	349	521

Notes: 1. The column numbers are: (1) degree centrality, (2) connection strength centrality, (3) eigenvector centrality, (4) eigenvector connection strength centrality, (5) TA-weighted eigenvector centrality, (6) TA-weighted eigenvector connection strength centrality.

2. '_H' means results derived from the historical PD series. '_F' denotes results derived from the forward-looking PDs.

* Groupe BPCE is not a listed firm. We use Natixis SA, the major listed entity in this banking group, to proxy for its systemic ranking.

Table 5. Rankings of the six network centrality measures: using historical daily PD changes vs. historical daily equity returns

Bank Name	(1)_PD	(1)_EqRtn	(2)_PD	(2)_EqRtn	(3)_PD	(3)_EqRtn	(4)_PD	(4)_EqRtn	(5)_PD	(5)_EqRtn	(6)_PD	(6)_EqRtn
HSBC Holdings PLC	22	588	141	231	6	718	129	250	2	1	30	42
JPMorgan Chase & Co	416	676	333	353	565	707	516	229	4	12	51	37
Barclays PLC	83	403	19	141	31	425	7	122	10	4	15	33
BNP Paribas SA	150	840	250	368	128	746	195	138	1	2	18	49
Citigroup Inc	75	258	53	204	34	311	13	174	5	8	37	34
Deutsche Bank AG	17	285	69	202	32	312	76	110	3	3	9	73
Bank of America Corp	474	658	184	207	355	518	23	148	14	18	40	28
Credit Suisse Group AG	1,060	305	1,186	274	935	323	1,121	219	28	9	143	102
Goldman Sachs Group Inc	372	568	254	88	296	541	130	62	24	21	34	57
Mitsubishi UFJ Financial Group Inc	562	700	367	302	552	835	398	663	36	67	13	64
Morgan Stanley	69	194	18	87	58	204	41	65	33	25	28	22
Royal Bank of Scotland Group PLC	136	490	56	170	107	374	6	98	20	14	57	38
Agricultural Bank of China Ltd	372	403	185	163	502	450	248	103	37	35	3	6
Bank of China Ltd	22	108	86	99	18	195	69	81	17	31	4	2
Bank of New York Mellon Corp	876	544	380	235	928	448	702	172	57	42	307	91
Banco Bilbao Vizcaya Argentaria SA	676	864	555	293	715	846	725	253	21	16	50	126
Groupe BPCE*	217	285	421	397	130	231	211	156	25	34	63	120
Credit Agricole SA	217	143	171	53	244	135	220	27	8	5	21	48
Industrial & Commercial Bank of China Ltd	562	242	553	133	589	609	512	184	19	24	1	4
ING Groep NV	96	588	106	281	40	492	77	147	13	6	54	83
Mizuho Financial Group Inc	562	752	537	252	499	899	468	582	26	70	10	32
Nordea Bank AB	399	342	387	156	258	459	196	227	16	11	35	97
Banco Santander SA	876	937	944	470	834	870	950	302	11	10	78	98
Societe Generale SA	545	613	388	284	539	494	477	97	6	7	25	43
Standard Chartered PLC	198	544	285	448	208	462	284	279	27	20	85	77
State Street Corp	62	443	11	294	37	317	3	185	50	74	112	55

Sumitomo Mitsui Financial Group Inc	242	727	263	237	216	769	324	525	23	27	11	51
UBS Group AG	116	568	168	280	79	480	121	159	9	15	31	100
UniCredit SpA	316	789	312	607	345	661	235	199	15	17	47	26
Wells Fargo & Co	37	403	84	223	78	354	65	191	22	19	87	13

Notes: 1. The column numbers are: (1) degree centrality, (2) connection strength centrality, (3) eigenvector centrality, (4) eigenvector connection strength centrality, (5) TA-weighted eigenvector centrality, (6) TA-weighted eigenvector connection strength centrality.
2. '_PD' means results derived from the historical daily PD series. '_EqRtn' denotes results derived from the series of the historical daily equity returns.
* Groupe BPCE is not a listed firm. We use Natixis SA, the major listed entity in this banking group, to proxy for its systemic ranking.

5. Conclusion

The recent financial crisis has highlighted the need to identify the systemic risk in the global financial network and to design policy measures capable of containing potential system-wide distress. In this paper, we devise a new methodology for constructing a global banking network and ranking the systemic importance of the banks in the network. We implement the methodology on a sample of more than one thousand public banks which literally covers all exchange-listed banks worldwide.

Methodology-wise, we use the default correlation model of Duan and Miao (2015) to generate by simulation banks' forward-looking PD correlation matrix over a future time horizon. To disentangle the direct linkages between any bank pair from the effects of other banks in the global network, we apply the CONCORD algorithm of Khare et al. (2015) to transform the forward-looking PD correlation matrix into a partial correlation matrix. We then apply the concept of network centrality to create six measures of systemic importance. Apart from the simple connectedness indicators, we use eigenvector centrality measures to capture the importance of a bank based on its connections and how its connected parties are further connected. Two of the measures use both the node (bank asset size) and edge characteristics to construct the systemic importance. To graphically present the global banking network, we use the tool *Gephie* to partition the network into bank/group centric communities.

With this methodology, we analyze the banking networks at the height of the global financial crisis in 2008 as well at the end of 2014 when the crisis has subsided. Our systemic importance rankings suggest that Lehman Brothers was more systemically importance than what the US authorities then thought. We also show that our rankings are substantially different from other alternatives, such as the FSB G-SIBs. Among our systemic risk measures, the ones factoring in both edge (partial default correlation) and node characteristic (bank size) are closer to the FSB rankings.

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