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

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Abstract

This paper studies systemic risk in a global network with over 2,000 exchange-traded banks and insurance companies. Network construction follows a methodology comprising three parts: (1) using the default correlation model of Duan and Miao (2016) 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) measuring financial institutions' systemic importance based on six network centrality indicators derived from the partial correlation matrix with or without factoring in asset sizes of financial institutions so as to capture both too-connected-to-fail and too-big-to-fail; and (3) relying on a graphical analysis of the global financial network which can then be partitioned into overlapping firm/group centric local communities. We specifically study the financial institutions' systemic importance in 2008 and 2015. Using the 2015 sample, we are able to compare the systemic importance rankings under alternative measures, including the G-SIBs and G-SIIs identified by the Financial Stability Board (FSB) in 2016. Our results suggest the FSB rankings tilt toward singling out large institutions as systemic, with connectivity playing a minor role.

Keywords: systemic risk, network, bank, insurer, forward-looking, probability of default, partial correlation, financial community

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1. Introduction

The recurrence of financial crises entails large costs directly associated with disruptions in the financial 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 global financial system.

A variety of systemic risk measures emphasizing connectedness between banks and other financial firms have been proposed in the literature. 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, 2016), 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 credit 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 relying on a directly relevant and forward-looking measure of credit 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 through default correlations trigger cascading institution failures and cause widespread distress throughout the financial system.

Measuring the connectedness between financial institutions 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, is 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 any two parties, which we believe a good network ought to reflect. To disentangle the direct connection between financial institutions in terms of their future default likelihoods, we contend that partial correlations are more appropriate, a view advanced first by Kenett 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 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 such as the Credit Research Initiative (CRI) at the National University of Singapore, Moody's Analytics, Kamakura, or Bloomberg. Historical correlations would represent the connectedness between firms 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 or more specifically the phase of a credit cycle.

Instead, we use the default correlation model of Duan and Miao (2016) 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 2,000 banks and insurers in the CRI database. We use them to obtain the regularized forward-looking partial correlation matrix, which allows for isolating the direct dependence between two financial institutions. This matrix serves as the basis for building our global financial 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 firms 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 firms, i.e. "orphans." This "regularized" network, therefore, is consistent with the intuition of a globally connected financial system with only a certain number of systemically important 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 firms, are not only weighted by the magnitudes of 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 determine the systemic rankings of financial institutions.

For comparison purposes, we also construct partial correlation networks with historical PDs and stock returns, respectively, for the same sample of firms. 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 identified by the Financial Stability Board (FSB) and the forward-looking PD-based systemic risk ranking is substantial only when edges are weighted by size. We argue, hence, that the FSB ranking is severely tilted towards singling out large institutions, and connectivity only plays a 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, 2017). In contrast, 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 (2017).

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, 2016), 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 firms with an edge weighted by the dependence measure, the edges may still be capturing dependence effects from a source beyond the two firms, i.e., common dependence with a third firm or a set of other firms. 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 institutions 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 among 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), adopt 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 Kenett 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

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

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 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 and insurers under consideration, (2) utilizing the partial correlation matrix to devise measures for ranking these financial institutions in terms of their systemic importance, and (3) building a financial community centered at an institution or a group of institutions so that different communities of interest may naturally overlap.

For the first part, we adopt the default correlation model of Duan and Miao (2016) 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 among institutions 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 an institution 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, 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 institutions, i.e., combining edge and node characteristics.[3] For example, a large bank, say, HSBC, may be connected with many smaller financial institutions. A simple size-weighted measure would make these connections less important. The edge-node combined eigenvalue centrality would, however, make those connected smaller institutions 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 an institution/group-centric financial community. Instead of partitioning institutions into non-overlapping communities, a group-centric community is more appealing. A member institution may not have any partial correlation with others within the defining group, but it is nevertheless a member of the community by definition. This kind of group-

[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.

centric community can be straightforwardly obtained, be it a global banking community which contains all banks but not insurers, or, say, a New York-centered financial community where all New York-based banks and insurers as well as their respective connected parties are included. The focal group can also be narrowed down to just one institution; for example, forming a Banco Santander-centered financial community. Naturally, different overlapping communities will emerge to reflect interest in different focal groups.

3.1 Constructing the forward-looking PD partial correlation matrix

We adopt the default correlation model of Duan and Miao (2016) to generate the forward-looking PD total correlation matrix, which is then used to deduce its corresponding partial correlation matrix. The Duan and Miao (2016) 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 cycle 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 always a key determinant of any multiple-month PD. The Duan and Miao (2016) model also handles missing data, which naturally occur as a result of defaults and other corporate exits.

Duan and Miao (2016) employ 11 pairs of predetermined common factors consisting of (1) the pair of global median PD and POE based on a pool of 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. In this study, we employ one more pair of economy-specific median PD and POE, because they substantially improve the performance of the factor model. In short, we deploy 12 pairs of predetermined common factors.

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 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 globally. As of March 2018, the CRI provides PDs, with horizons ranging from 1 month to 5 years, on over 67,000 firms in 128 economies.[4] Among them, over 34,000 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 CRI database for the analyses.

The factors (pairwise with one for PD and the other for POE) are the logit-transformed values[5], i.e., $\ln\frac{X}{1-X}$ where X is either PD or POE. The pair of logit-transformed global factors are standardized by subtracting their respective sample mean and then dividing by their respective sample standard deviation. The standardized common factors are dynamically evolving and modeled by a bivariate vector autoregressive process with their means set to zero. For the pair of the economy-specific

[4] For implementation details on the CRI-PDs, please refer to the "NUS-RMI Credit Research Initiative Technical Report, 2017, update 1" and subsequent addenda.

[5] We use the logit function to transform PDs and POEs, differing from that of Duan and Miao (2016) where a double-log transformation was deployed. We adopt this modification for two reasons. First, PDs and POEs are naturally bounded between 0 and 1, the logit transform leading to a more natural Gaussian approximation. Second, simulation quality is essential to the numerical accuracy of our high-dimensional default correlation model. This transformation enables a substantial improvement in simulation quality without increasing computational costs because the empirical martingale simulation technique of Duan and Simonato (1998) can be applied, which in our case utilizes the closed-form solution for $\mathrm{E}\left\{\frac{X}{1-X}\right\}$ when $\ln\frac{X}{1-X}$ is modeled as a Gaussian random variable.

factors and each of the 10 industry factor pairs, we linearly project them onto the global factor pair and take the pair of standardized residuals as the economy/industry factor pair.[6] Each economy/industry factor pair is again modeled as a bivariate vector autoregressive process with their means set to zero. The individual firm PDs and POEs are also subjected to the same logit transformation before regressing them on the factors.[7] The factor model residuals are also individually autoregressive, and their individual time series model residuals are allowed to form locally correlated clusters. Thus, default correlations could arise globally and/or locally. The factor model is estimated with an adaptive Lasso regression of Zou (2006) to deal with noisy parameter estimates due to many regressors, or, alternatively speaking, too few observations.[8] We also follow Duan and Miao (2016) to recalibrate the parameters governing each factor model residual time series using the 5-year PD term structure available at the time of constructing the forward-looking default correlation matrix.[9] This recalibration step ensures that the prevailing market condition gets reflected in our forward-looking default correlations but not at the expense of poorly matching the available PD term structure individually.

This factor model with sparsely correlated residuals enables us to generate PDs for any target horizon, say, one year, at any future time point, say, one month later, for any subset of firms in the CRI universe. Note that the one-year PD for a firm prevailing one month later is a random variable and can therefore be correlated with the one-year PD of another firm at the same time. It is this kind of PD correlations that we intend to capture. Operationally, one can simulate forward by one month the 12 factor pairs along with individual PD and POE residuals of a target group of financial institutions. This initial simulation yields the random starting point for a second set of simulations. After advancing forward one month, one can think of one-year PDs at the time, for which the second set of simulations kick in. Simulate further *M* paths over 12 months for the factor pairs and individual PD and POE residuals. 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 financial institutions. 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. It is fairly clear that ensuring reasonable simulation quality at this level of *M* and *N* is critical to the successful implementation of Duan and Miao's (2016) default correlation model. Our experiment suggests that adopting the empirical martingale simulation technique of Duan and Simonato (1998) mentioned in an earlier footnote gives rise to satisfactory simulation quality. It is worth mentioning that increasing *M* and *N* can yield the correlation matrix to any desired level of numerical accuracy, but the sampling error intrinsic to the use of actual data to estimate the Duan and

[6] We differ from Duan and Miao (2016) in the construction of 10 pairs of industry factors where they sequentially orthogonalized industry pairs; for example, the first pair of industry is the residuals after projecting onto the pair of global factors, whereas the second pair of industry factors is obtained by projecting onto the pair of global factors and the first pair of industry factors.

[7] Here, individual firm PDs are regressed on the PD factors, and individual firm POEs are regressed on the POE factors.

[8] Duan and Miao (2016) deploy the SCAD regression of Fan (1997).

[9] Differing from the implementation in Duan and Miao (2016) is our use of the 5-year PD term structure in recalibration as opposed to their use of two-year PD term structure. Our implementation simulates longer time series and thus requires the use of the empirical martingale simulation technique of Duan and Simonato (1998) to efficiently dampen Monte Carlo errors, which was discussed in an earlier footnote. As compared to Duan and Miao (2016), we also recalibrate for every financial institution its factor loadings via a single firm-specific scaling factor to adjust all factor loadings up and down in addition to recalibrating the parameters of its residual AR(1) model.

Miao (2016) default correlation model cannot be eliminated by increasing simulation accuracy. Note that this correlation matrix can also be interpreted as the change in, say, one-year PDs over, say, one month, because *N* one-year PDs for a firm all originate 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. In principle, 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 concentration matrix, i.e., 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, for example, 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:

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

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 tuning 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 institution, i.e., totally isolated institution in the network, begins to emerge.[10] Economic intuition justifies using this selection criterion because in reality, all institutions in the financial system should be connected with some other ones.

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 an institution on itself. We use $\overline{\mathbf{P}}_X$ in the later implementation, which is a moving average of 12 monthly estimated $\mathbf{P}_X$. Averaging is to remove excessive noises in individual $\mathbf{P}_X$ surfacing from time to time.

3.2 Ranking systemically important financial institutions via different network centrality measures

[10] 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 as a compromise between computing time and accuracy. The results are insensitive to further tightening of their levels.

A natural outcome of studying the linkages in a financial network is to determine the relative importance of each financial institution, 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. An institution'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: degree centrality, connection-strength centrality, eigenvector centrality, and connection-strength eigenvector centrality. For a network with *n* institutions, 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 $\overline{\mathbf{P}}_{\boldsymbol{X}}$ equal 0 or not.

The degree centrality of institution *i* is defined as the *i*-th row sum of **A**, whereas the connection-strength centrality is the *i*-th row sum of $|\overline{\mathbf{P}}_{\boldsymbol{X}}|$, the absolute value of $\overline{\mathbf{P}}_{\boldsymbol{X}}$, divided by the total number of institutions in the network. The later normalization makes possible comparing results across networks comprising different number of institutions. 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 institution. Similarly, the connection-strength eigenvector centrality is the eigenvector associated with $|\overline{\mathbf{P}}_{\boldsymbol{X}}|$. 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 financial institution. 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 financial institution (total assets measured in USD) over the total size (total assets) of the financial 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, $\mathbf{Q}|\overline{\mathbf{P}}_{\boldsymbol{X}}|\mathbf{Q}$. Under these new centrality measures, a smaller institution by connecting to a large institution will become relatively more important, which in turn feeds back to increase the large institution'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 firm size (i.e., a node characteristic beyond connections) being critical to systemic importance, the two new centrality measures seem more suitable for financial networks.

3.3 Determining the institution/group-centric financial 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 institutions into non-overlapping communities is not appealing, because forcing a financial institution to just belong to one community is inconsistent with the common notion of financial 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.[11] 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 New York City and connected by credit risk linkages should naturally include all New York-based banks along with some banks belonging to, say, the London-centered community. In short, focal groups (i.e., individual institutions, financial centers, and countries) are more natural communities from a user's perspective, and different financial communities centered at different focal groups should be allowed to overlap.

We use the network analysis tool, *Gephie*, to graphically present financial communities. In the network, each node represents a financial institution, and the node size is determined by its total asset. Each edge linking two nodes represents a non-zero partial correlation between the two institutions' 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 financial institutions in the overall financial network, but within some communities, certain financial institutions may be orphans.

4. Global Financial Network, SIFIs, Financial Communities, and the 2008 Financial Crisis

This section illustrates the use of our methodology for assessing the systemic importance of financial institutions. First, we evaluate how the six network centrality measures compare to each other; second, we analyze their performance vis-a-vis the rankings by the Financial Stability Board (FSB), which currently supports the regulatory reform proposals for systemic banks and insurers; and third, we analyze the performance outcome in August 2008, in the eve of the global financial crisis.

The sample includes financial institutions, which according to the Bloomberg Industry Classification System (BICS) are commercial banks (BlCS 10008-20051), investment banks and brokerage firms (BICS 10008-20054-159) and insurance companies (BICS 10008-20055).[12] 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 credit market conditions. A firm is included in the sample if its shares were actively traded at the time the forward-looking PD is calculated. Depending on the number of observations an institution has in the five-year rolling data window, sector-level PDs (i.e. bank or insurer) may be used as proxies for the

[11] See Xie et al. (2013) for a recent survey of overlapping community detection methods.

[12] 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 five exchange-listed central banks: Schweizerische Nationalbank, Banque Nationale de Belgique, Bank of Greece, South African Reserve Bank, and Bank of Japan, due to their special nature. Among them, the first three are currently active with daily updated CRI PDs. South African Reserve Bank was traded on Johannesburg Stock Exchange until its delisting on May 2nd, 2002. Bank of Japan was originally listed on JASDAQ, but later switched to Tokyo Stock Exchange on July 16th, 2013. However, the CRI database does not include Bank of Japan due to incomplete financial data provided by Bloomberg.

dependent variable in the factor loading estimation.[13] This way, a financial institution will have a ranking as soon as it has an observation in a five-year history. 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 factor dynamics 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 of the prediction time. We conduct the analysis for two time points, August 2008 and December 2015. The choice of the first time point is rather obvious, as it is right before the bankruptcy of Lehman Brothers, which set off a global financial crisis. The second point corresponds to the economic environment prevalent when the crisis largely subsided. The number of financial institutions in the August 2008 and December 2015 samples are quite similar, 2,075 and 2,029 respectively.

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

Panel 1. Spearman correlations in August 2008

	Degree	Connection Strength	Eigenvector	Connection Strength Eigenvector	Weighted Eigenvector	Weighted Connection Strength Eigenvector	Firm Asset Size
Degree	1	0.41	0.99	0.48	0.19	0.27	0.02
Connection Strength	0.41	1	0.46	0.91	0.23	0.24	0.20
Eigenvector	0.99	0.46	1	0.55	0.20	0.28	0.03
Connection Strength Eigenvector	0.48	0.91	0.55	1	0.27	0.28	0.23
Weighted Eigenvector	0.19	0.23	0.20	0.27	1	0.91	0.90
Weighted Connection Strength Eigenvector	0.27	0.24	0.28	0.28	0.91	1	0.73
Firm Asset Size	0.02	0.20	0.03	0.23	0.90	0.73	1

Panel 2. Spearman correlations in December 2015

	Degree	Connection Strength	Eigenvector	Connection Strength Eigenvector	Weighted Eigenvector	Weighted Connection Strength Eigenvector	Firm Asset Size
Degree	1	0.46	0.99	0.54	-0.05	0.01	-0.15
Connection Strength	0.46	1	0.49	0.93	0.10	0.13	0.07
Eigenvector	0.99	0.49	1	0.58	-0.05	0.00	-0.15
Connection Strength Eigenvector	0.54	0.93	0.58	1	0.09	0.11	0.05
Weighted Eigenvector	-0.05	0.10	-0.05	0.09	1	0.88	0.95
Weighted Connection Strength Eigenvector	0.01	0.13	0.00	0.11	0.88	1	0.81
Firm Asset Size	-0.15	0.07	-0.15	0.05	0.95	0.81	1

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

[13] Specifically, if a financial institution has at least 24 monthly observations in the five-year rolling window, its firm-level PD is used in the factor model estimation. If the number of observations is below 24, we do two regressions and set the factor loadings to be the weighted average of the two sets of parameters. The first regression is the same as the one described above. The second regression uses the sector-level PD as the proxy dependent variable.

The partial correlation matrices $\overline{\mathbf{P}}_X$ computed for both August 2008 and December 2015 exhibit substantial sparsity, as zero entries account for about 87 percent of all entries in both dates. Not surprisingly, one can expect this result because, first, only direct connections are measured, and second, CONCORD, a penalty-based method, shrinks partial correlations toward zero. Recall that our partial correlation matrix construction increases sparsity up to the point that an orphan financial institution begins to emerge. Any higher sparsity would result in some institution(s) to be totally isolated from the global financial network in terms of credit risk, a hardly sensible outcome. Remember that the $\overline{\mathbf{P}}_X$ in our analysis is a moving average of $\mathbf{P}_X$ spanning over 12 months. It is denser than $\mathbf{P}_X$ because a non-zero partial correlation between any two parties in the previous 12 monthly estimated $\mathbf{P}_X$ would result in a non-zero entry in $\overline{\mathbf{P}}_X$.

4.1 Comparing the six network centrality measures

As section 2 noted, different centrality measures capture the relative importance of each financial institution 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 2015 samples. The degree centrality, which measures the number of connected parties a financial institution 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 size-weighted centrality measures.

In the following sections, we will present the financial institutions' ordinal rankings under various centrality measures. Here, however, we would like to display a few patterns of the numerical scores underlying those rankings. For the two size-weighted centrality measures, which in principle capture a more comprehensive picture of the institutions' systemic risks, we observe that a big proportion of the total scores are distributed among about 200 financial institutions, or 10% of the sample. Specifically, for the size-weighted eigenvector centrality, 93% of the total scores in 2008 and 90% of the total scores in 2015 are distributed among the top-ranked 200 financial institutions. Similarly, for the size-weighted connection strength eigenvector centrality, 99% of the total scores are absorbed by 10% of the samples in both months.

Figure 1. Distribution of the size-weighted eigenvector centrality scores

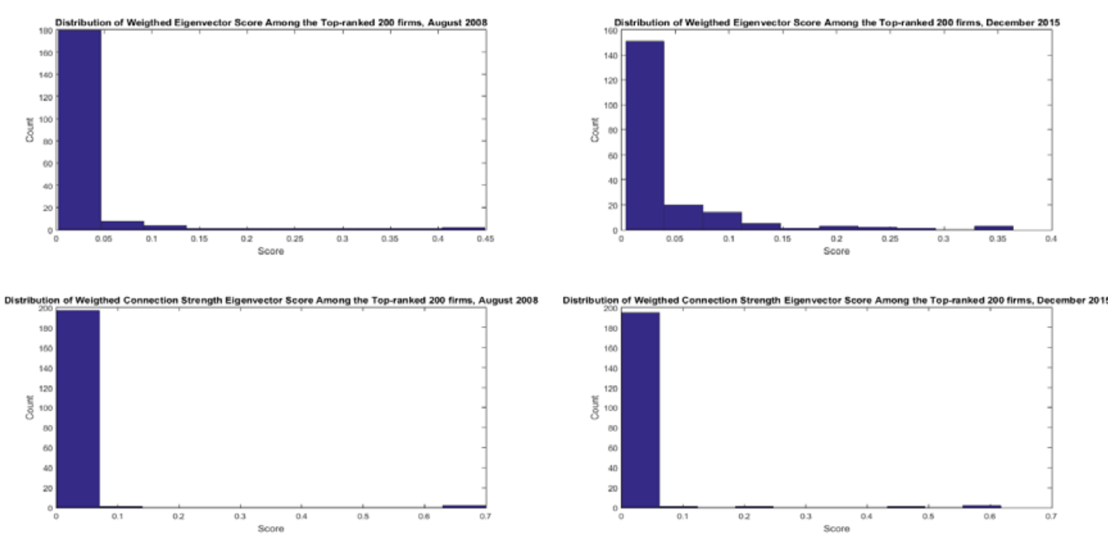


Figure 1 shows the distribution of the two size-weighted scores among the top-ranked 200 financial institutions in August 2008 and December 2015, respectively. Among those institutions, a handful have much distinguishably higher scores than others. When the connection strength is factored in, particularly in 2008 as can be seen in the bottom left figure, the scores for the two top-ranked institutions, in this case Barclays and Royal Bank of Scotland, are way higher than those for the rest of the sample. The data reveals that these two British banks are strongly connected with each other. They also have strong connections with some of the biggest and best connected financial institutions, examples including Citigroup and Credit Agricole.

4.2 The FSB G-SIBs, G-SIIs vs. network centrality based-rankings as of December 2015

In the aftermath of the global financial crisis, the FSB proposed a ranking system based on several criteria to identify Global Systemically Important Banks (G-SIBs) and Global Systemically Important Insurers (G-SIIs). Their purpose is to better monitor these financial institutions' activities and to enhance buffers so as to reduce the risks of experiencing another financial crisis. The FSB released a list of systemic banks and a list of systemic insurers in November 2016 based on their systemic importance metrics with data up to end 2015.[14] Each of the G-SIBs or G-SIIs in the lists is/will be required by the FSB to meet extra loss absorbency requirement, although the phase-in periods for banks and insurers may differ, in order to better withstand financial distress in the future.[15]

We assess the rankings of the 2016 G-SIBs based on the FSB recommendations for loss absorbency requirements against the six network centrality measures obtained from our corresponding December 2015 partial default correlation network. For a better comparison, we present in Table 2 the systemic rankings of the G-SIBs amongst the 1,479 banks in the 2015 data sample. That said, those rankings are computed from the global financial network, because banks are connected to insurers naturally, but are rescaled to the banking subsector. Similarly, we present in Table 3 the systemic rankings for the 2016 G-SIIs amongst the 550 insurers globally.[16]

According to the first two network measures (columns 3 and 4 in Table 2, columns 2 and 3 in Table 3), i.e., degree and connection strength, Prudential PLC has relative large number of immediate counterparties, Standard Chartered is connected with its immediate counterparties strongly, and Bank of China appears to be both. In contrast, most of the other G-SIBs and G-SIIs have very few counterparties and weak ties. Accounting for the "true" network effects (columns 5 and 6 in Table 2, columns 4 and 5 in Table 3) boosts some institutions' rankings, Royal Bank of Scotland for instance, because their immediate counterparties are better/more strongly connected with others. The opposite effect causes some institutions to move down the list.

The most interesting phenomenon in Table 2 and 3 is that most of the G-SIBs/G-SIIs rank toward the top of list under the size-weighted eigenvector centrality (column 7 in Table 2, column 6 in Table 3) and size-weighted connection strength eigenvector centrality (column 8 in Table and column 7 in Table 3). That said, the firm size (both institution's own and its counterparties'), i.e., the node characteristic in our network, plays an important role in determining a financial institution's systemic importance. Neglecting it would sometimes yield counterintuitive results. For a better comparison, we also present

[14] Please refer to "2016 list of global systemically important banks (G-SIBs)" and "2016 list of global systemically important insurers (G-SIIs)".

[15] For a detailed discussion on the G-SIBs and G-SIIs methodologies, please refer to "The G-SIBs assessment methodology-score calculation," and "Global Systemically Important Insurers: Updated Assessment Methodology".

[16] Without a definite loss absorbency requirement for the G-SIIs, we are not yet able to compare the systemic risk ranking from the G-SII methodology with ours.

Table 2. FSB systemic importance rankings for the 2016 G-SIBs (with data up to December 2015)

Bank Name	FSB Loss Absorbency Requirement	Degree	Connection Strength	Eigenvector	Connection Strength Eigenvector	Weighted Eigenvector	Weighted Connection Strength Eigenvector	Firm Size
Citigroup Inc	2.50%	1178	1258	1264	1295	5	9	12
JPMorgan Chase & Co	2.50%	835	892	874	1050	3	5	6
Bank of America Corp	2.00%	920	1043	990	1013	1	7	9
BNP Paribas SA	2.00%	774	704	794	806	12	2	8
Deutsche Bank AG	2.00%	736	1137	719	854	4	6	11
HSBC Holdings PLC	2.00%	878	450	955	524	44	172	5
Barclays PLC	1.50%	570	794	610	605	82	194	10
Credit Suisse Group AG	1.50%	774	395	665	383	19	12	26
Goldman Sachs Group Inc	1.50%	801	1028	1063	1225	18	39	25
Industrial & Commercial Bank of China Ltd	1.50%	786	596	675	689	13	74	1
Mitsubishi UFJ Financial Group Inc	1.50%	1157	618	1149	427	15	50	7
Wells Fargo & Co	1.50%	1240	1024	1236	976	7	17	13
Agricultural Bank of China Ltd	1.00%	847	989	815	928	10	48	3
Bank of China Ltd	1.00%	13	13	11	14	9	62	4
Bank of New York Mellon Corp	1.00%	1204	1105	1258	1249	36	18	57
China Construction Bank Corp	1.00%	1102	1082	1102	978	2	8	2
Groupe BPCE*	1.00%	693	148	698	221	28	4	46
Credit Agricole SA	1.00%	727	1108	829	1140	8	3	14
ING Groep NV	1.00%	904	1352	925	1259	17	13	24
Mizuho Financial Group Inc	1.00%	973	1130	869	841	14	28	15
Morgan Stanley	1.00%	1261	1433	1332	1396	21	44	28
Nordea Bank AB	1.00%	263	279	285	228	30	98	35
Royal Bank of Scotland Group PLC	1.00%	151	507	130	374	22	45	19
Banco Santander SA	1.00%	1145	634	1080	445	27	46	18
Societe Generale SA	1.00%	549	1095	776	1152	6	1	17
Standard Chartered PLC	1.00%	289	33	282	36	25	52	38
State Street Corp	1.00%	1240	555	1193	692	324	842	83
Sumitomo Mitsui Financial Group Inc	1.00%	1049	860	1030	742	29	36	16
UBS Group AG	1.00%	1310	304	1218	378	108	29	22
UniCredit SpA	1.00%	1190	1182	1119	929	24	27	23
Rank correlations with FSB (30 banks)		-0.15	-0.15	-0.15	-0.15	0.38	0.25	0.47
Rank correlations with SRISK (439 banks)**		0.01	-0.02	0.03	0.06	0.52	0.41	0.54

Source: CRI (National University of Singapore) and authors' calculations.
* Groupe BPCE is not a listed bank. We use Natixis SA, the major listed entity in this banking group, to proxy for its systemic ranking.
**The SRISK data are taken from the V-Lab website on January 17, 2018. The data points are from December of each year.

in the last columns of both tables the rankings based on the institutions' total assets. As we can see, they can be highly correlated with the size-weighted rankings (too-big-to-fail), but are not the same, re-enforcing the importance of the connectedness and network effects (too-connected-to-fail) reflected in our methodology.

Many financial institutions not on the FSB list are actually considered systemically risky according to our methodology. Bank of Communications, the 5th largest listed bank in China and 21st in the world as of December 2015, ranks the 10th among all banks globally under the size-weighted connection strength eigenvector centrality. Apart from its own large asset size, it is strongly connected with some of the highest ranked banks under the same measure such as Deutsche Bank (6th).

The riskiest insurer under the size-weighted connection strength eigenvector centrality on our 2015 list is CNP Assurances. Being a major French insurer, it is connected to many large and well-connected financial institutions in the region and abroad, examples including Credit Agricole, Societe Generale, BNP Paribas, SCOR, and Bank of America.

The bottom of Table 2 presents the Spearman rank correlations between the six network centrality measures, firm size and two other systemic importance indicators. The methodology is as follows: for the 2016 G-SIBs (30 banks in total), we give them rankings from 1 onward to 30, allowing for ties when some fall into the same loss absorbency ratio bucket. Under each of our proposed centrality measures, we give 1-30 to the highest ranked banks and 31 to the rest. We subsequently take the banks that are common in both lists and compute the Spearman rank correlation with the two sets of rankings. Similarly, we compute the rank correlation between our 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.[17]

Table 3. FSB systemic importance rankings for the 2016 G-SIIs (with data up to December 2015)

Insurer Name	Degree	Connection Strength	Eigenvector	Connection Strength Eigenvector	Weighted Eigenvector	Weighted Connection Strength Eigenvector	Firm Size
Aegon NV	197	135	213	148	14	26	13
Allianz SE	91	142	125	105	7	5	2
American International Group Inc	392	427	403	414	6	14	12
Aviva PLC	136	268	115	214	4	6	7
AXA SA	272	231	277	286	19	57	1
MetLife Inc	427	363	465	409	2	4	3
Ping An Insurance Group Co of China Ltd	349	277	341	233	3	8	5
Prudential Financial Inc	463	226	449	329	1	11	4
Prudential PLC	52	146	53	114	17	7	8

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

The Spearman coefficients indicate that the FSB methodology does not seem to account much for the number and strength of inter-bank connections. It seems to be biased toward singling out large

[17] 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/.

institutions as evidenced by the correlation coefficient of 0.47 between the G-SIB and bank size rankings. For comparison, the rank correlation between the size-weighted connection strength eigenvector centrality and the bank size for the 30 G-SIBs is 0.07.

The rank correlation coefficients between the six centrality measures and the SRISK are generally modest too. 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 default correlations directly or utilize the network structure as is the case with our systemic risk measures.

4.3 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 was merged into 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 after. In the following paragraphs, we will use our metrics to help reflect on some of these unusual occurrences.

Table 4 displays the global systemic importance rankings for the major banks headquartered in New York City in August 2008. These banks, except for Lehman Brothers and Merrill Lynch, received large government bailout funds. Under the two size-weighted centrality measures (columns 6 and 7 in Table 4), which we believe better capture the systemic risk, all of them were among the top 10% riskiest financial institutions in the world at the time. New York Mellon was the only exception, perhaps due to its relatively small investment banking business.

Table 4. Global systemic rankings and the total assets for New York City-based banks, August 2008

Firm Name	Degree	Connection Strength	Eigenvector	Connection Strength Eigenvector	Weighted Eigenvector	Weighted Connection Strength Eigenvector	Bank Asset Size (in millions of USD)	Bank Size in Ranking
Citigroup	1138	1647	1090	1502	6	9	2,100,385	7
JPMorgan Chase	1588	1601	1521	1440	63	165	1,775,670	11
Goldman Sachs	1407	1587	1496	1549	37	92	1,088,145	22
Morgan Stanley	1201	1322	1146	1432	14	13	1,031,228	25
Merrill Lynch	73	494	63	536	17	15	966,210	28
Lehman Brothers	860	315	794	564	28	43	639,432	39
Bank of New York Mellon	1636	394	1653	737	437	433	201,225	95

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

In the case of Lehman Brothers, it was smaller than the other major investment banks measured by total asset. However, it was more strongly connected with the rest of the global financial system (see column 3 in Table 4), and its size-weighted rankings did not seem to justify the decision to let it go into bankruptcy.[18] Lehman's collapse may have contributed to the cascading defaults of its major counterparties later on. Indeed, our data shows that among the 50 financial institutions that had the strongest positive partial correlations with Lehman Brothers at the time, 21 of them defaulted or were

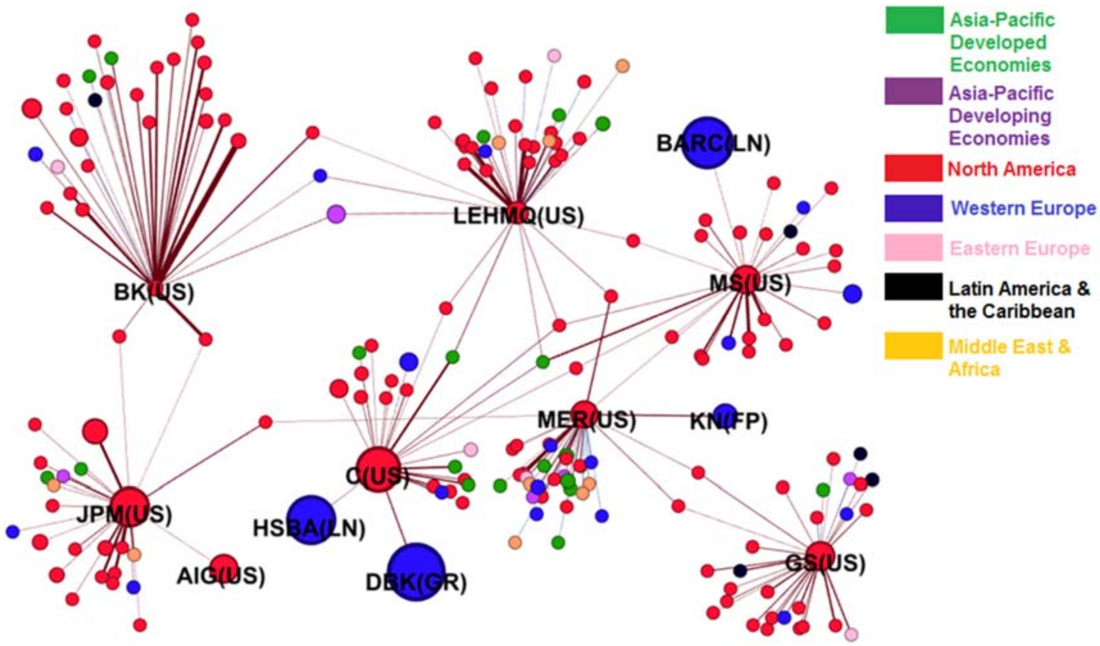
[18] This result supports earlier analysis based on pair-wise interconnectedness suggesting that Lehman Brothers was too systemic to fail (Chan-Lau, 2009, among others).

subsequently delisted from their stock exchanges. Among those events, five occurred within one year of Lehman's demise.

Figure 2 presents the seven major New York City-based banks, identified by their equity tickers, with their associated financial communities as of August 2008. Different colors denote the geographical domiciles of the included institutions, with some major ones identified by their equity tickers too.

We can see from the figure that each of the banks has a surrounding community, which mostly comprises smaller banks and brokerage firms. Some of them have big counterparties, which according to our methodology contribute to their systemic importance via feedback effects. Another distinct feature is that the communities have very different characteristics. For instance, Morgan Stanley and New York Mellon are mostly connected to parties domiciled in North America and Europe. Merrill Lynch, on the other hand, has much diverse pools of counterparties around the world.[19]

Figure 2. Major New York City-centered banks and their communities, August 2008



5. Financial Networks Based on Other Correlation Measures

In the financial network literature, a variety of measures has been used to construct networks (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 partial default correlations. Tables 5 and 6 display the global rankings for the banks and insurers in the 2016 FSB G-SIB/G-SII lists.

5.1 Historical PDs vs. forward-looking model 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 CRI database. As

[19] For a better presentation of the network figure, we keep only the edges with connection strength larger than 0.01 in the figure.

explained earlier, the forward-looking PDs characterize one month later the potential default risk of a firm 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 CRI 1-year PDs from 1990 to 2015 to form a historical series for each financial institution 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 institutions in the sample may not have the same or sufficient overlapping periods of observations. As a consequence, it is impossible to obtain the sample correlation matrix in a usual way, but it is a crucial input in estimating the 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 5 compares the systemic rankings of the forward-looking and backward-looking networks, for the 2016 G-SIBs/G-SIIs. As can be seen, the two approaches yield substantially different results for each of the six network centrality measures. For the two size-weighted centrality measures, forward-looking rankings raise the importance of Bank of America and Credit Suisse, among others, relative to their backward-looking counterparts. In contrast, for financial institutions including Industrial and Commercial Bank of China and Barclays, their forward-looking systemic importance at the time is below their average level over time. This comparison shows that it can be quite misleading if one uses 'backward-looking' PDs to imply the financial institutions' would-be connectedness in the future.

5.2 Equity returns vs. PDs

This example compares the financial network generated with equity returns against that with historical PD series. We collect from Bloomberg historical daily equity returns for the period between 1990 and December 2015 for all financial institutions in our sample, wherever available. As the institutions in our sample are listed in many exchanges across the world, we denominate the returns in US dollar to ensure comparability. We also collect from the CRI database the historical 1-year PD series on a daily frequency because daily equity returns are used. This example highlights how different types of risk measures can generate substantially different partial correlation networks. Table 6 reports the rankings for the six systemic importance indictors for the 2016 G-SIBs/G-SIIs.

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 institutions' sizes, the rankings under different measures start to move closer. For example, the PD-based size-weighted connection strength eigenvector centrality has a Spearman coefficient of 0.56 with that based on equity returns. This reflects in a way the important role that node characteristics play in determining a financial institution's importance in the global network.

Table 5. Global rankings under the six network centrality measures: using historical PDs vs. forward-looking PDs

Firm 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
Citigroup Inc	1594	815	1655	551	1718	527	1758	1032	5	75	10	133
JPMorgan Chase & Co	1119	1186	1167	1592	1167	1545	1401	1706	3	84	6	318
Bank of America Corp	1230	815	1371	1314	1323	516	1352	1209	1	97	8	157
BNP Paribas SA	1038	676	926	1402	1060	579	1063	1288	12	56	2	79
Deutsche Bank AG	978	141	1492	322	948	218	1131	993	4	4	7	6
HSBC Holdings PLC	1171	71	594	633	1278	47	682	716	52	240	222	189
Barclays PLC	756	547	1044	731	818	518	796	1053	106	10	247	10
Credit Suisse Group AG	1038	1870	525	1892	883	1737	505	1730	20	224	13	256
Goldman Sachs Group Inc	1075	1725	1353	1879	1435	1619	1644	1825	19	500	49	586
Industrial & Commercial Bank of China Ltd	1053	1779	784	1824	897	1508	911	1286	14	3	98	5
Mitsubishi UFJ Financial Group Inc	1564	141	813	771	1548	87	559	1121	16	263	66	367
Wells Fargo & Co	1685	1570	1348	1622	1675	956	1296	1415	7	457	25	414
Agricultural Bank of China Ltd	1134	1186	1296	421	1088	1359	1235	131	10	189	62	123
Bank of China Ltd	15	1385	13	1000	12	961	14	823	9	1	79	1
Bank of New York Mellon Corp	1635	1570	1447	832	1708	1652	1680	1576	43	74	26	59
China Construction Bank Corp	1492	937	1421	656	1487	429	1301	872	2	2	9	2
Groupe BPCE*	921	1478	199	1572	922	1377	292	1704	33	23	4	36
Credit Agricole SA	965	1	1450	336	1105	18	1532	592	8	88	3	132
ING Groep NV	1206	71	1776	653	1234	306	1696	1278	18	19	15	24
Mizuho Financial Group Inc	1302	547	1481	434	1162	310	1115	994	15	257	36	341
Morgan Stanley	1714	1478	1889	1725	1813	553	1901	1319	23	540	58	452
Nordea Bank AB	343	1069	363	808	378	920	300	1334	35	14	128	14
Royal Bank of Scotland Group PLC	196	676	670	430	172	441	492	902	24	260	59	186
Banco Santander SA	1548	1870	833	1450	1458	1856	578	1598	30	89	60	100
Societe Generale SA	733	1652	1436	1189	1029	1747	1549	1821	6	37	1	52
Standard Chartered PLC	373	1824	43	1587	372	1805	43	1850	28	22	68	35
State Street Corp	1685	141	732	445	1617	200	916	897	420	231	1018	244

Sumitomo Mitsui Financial Group Inc	1415	676	1121	527	1382	296	983	1029	34	244	46	327
UBS Group AG	1785	187	401	628	1649	61	498	1069	149	120	37	163
UniCredit SpA	1614	1824	1559	1326	1506	1909	1236	1868	27	70	35	101
Aegon NV	782	335	526	576	866	501	646	1303	69	71	104	91
Allianz SE	390	1779	565	481	515	1620	432	1428	41	134	18	145
American International Group Inc	1483	547	1620	183	1556	388	1615	689	37	268	56	376
Aviva PLC	554	37	1091	510	459	82	889	770	31	129	19	130
AXA SA	1063	937	933	563	1114	1005	1161	1368	83	35	224	39
MetLife Inc	1606	52	1417	372	1732	128	1604	1042	21	57	17	127
Ping An Insurance Group Co of China Ltd	1350	187	1134	723	1349	156	947	1047	25	9	23	8
Prudential Financial Inc	1728	1186	906	429	1689	608	1320	1021	13	144	50	278
Prudential PLC	222	335	569	305	230	533	476	1322	76	65	21	80

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

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.

3. Due to the data requirements on the historical PD series, this comparative analysis is conducted on a smaller sample of 1,948 financial institutions as opposed to the 2,029-firm sample used in section 4.2. The global rankings based on the forward-looking PDs are computed from the full sample but rescaled to the 1,948-firm sample to allow for meaningful comparison.

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

Table 6. Global rankings of the six network centrality measures: using historical daily PD changes vs. historical daily equity returns

Firm 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
Citigroup Inc	40	924	109	420	64	983	365	612	8	14	15	50
JPMorgan Chase & Co	1063	1102	1122	794	1027	1315	1266	1106	21	21	62	58
Bank of America Corp	369	1265	209	586	244	1189	334	854	15	24	18	48
BNP Paribas SA	932	1581	890	1002	588	1496	949	858	11	2	28	63
Deutsche Bank AG	216	733	386	431	180	847	592	735	4	4	12	104
HSBC Holdings PLC	24	1075	132	609	88	1256	543	923	19	1	44	62
Barclays PLC	163	766	65	291	104	790	299	581	24	3	35	103
Credit Suisse Group AG	1659	848	1717	587	1466	860	1439	716	60	13	116	151
Goldman Sachs Group Inc	623	1298	675	333	434	1286	973	655	22	28	54	77
Industrial & Commercial Bank of China Ltd	1375	883	1345	577	1205	962	812	493	1	25	2	6
Mitsubishi UFJ Financial Group Inc	553	1325	599	680	345	1416	765	1132	54	81	39	41
Wells Fargo & Co	577	924	812	699	401	1025	676	1034	37	23	32	29
Agricultural Bank of China Ltd	623	645	281	312	803	628	82	221	5	40	6	4
Bank of China Ltd	779	699	667	268	584	900	678	418	3	31	1	1
Bank of New York Mellon Corp	779	1047	840	703	457	1193	1028	1051	367	63	275	132
China Construction Bank Corp	153	670	248	246	221	1037	611	443	2	26	5	2
Groupe BPCE*	1188	766	1344	928	776	549	1264	604	56	50	75	172
Credit Agricole SA	446	670	393	140	403	595	591	334	9	5	20	70
ING Groep NV	330	790	478	448	192	733	715	543	25	12	82	161
Mizuho Financial Group Inc	1094	1520	869	690	703	1561	1010	1300	39	68	37	22
Morgan Stanley	104	645	98	250	85	689	362	447	63	33	100	30
Nordea Bank AB	577	967	541	429	378	1051	831	887	27	10	48	169
Royal Bank of Scotland Group PLC	153	817	44	433	98	735	289	579	13	7	58	141
Banco Santander SA	1599	1491	1270	742	1561	1518	1560	964	147	6	180	119
Societe Generale SA	1636	1178	1269	743	1603	1032	1577	658	45	8	68	43

Standard Chartered PLC	1599	612	1755	774	1160	551	1539	766	51	19	114	68
State Street Corp	76	1127	91	833	52	1111	280	1016	36	117	30	173
Sumitomo Mitsui Financial Group Inc	483	1298	510	565	270	1306	778	1171	49	35	33	34
UBS Group AG	605	574	455	505	361	547	692	564	18	18	41	159
UniCredit SpA	1722	1102	1312	1040	1720	911	1664	614	109	17	175	177
Aegon NV	185	550	399	415	203	527	752	531	28	61	22	96
Allianz SE	957	1127	609	472	1013	1158	1157	909	29	29	40	206
American International Group Inc	216	313	288	185	124	342	629	411	16	51	21	16
Aviva PLC	421	1021	465	475	261	1010	613	748	20	22	53	255
AXA SA	1036	1047	593	664	1022	1129	1158	856	46	15	55	112
MetLife Inc	330	522	381	292	188	655	537	554	44	32	66	142
Ping An Insurance Group Co of China Ltd	685	817	622	344	543	1033	954	537	7	53	8	7
Prudential Financial Inc	132	337	159	98	96	473	371	386	42	69	42	109
Prudential PLC	354	967	404	529	211	930	638	802	77	41	112	167

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

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.

3. Due to data availability, this comparative analysis is based on 1,860 banks and insurers as opposed to the 2,029-firm sample used in section 4.2.

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

5. Conclusion

The 2008 global financial crisis has highlighted the need to identify 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 financial network and ranking the systemic importance of the financial institutions in the network. We implement the methodology on a sample of over 2,000 public financial institutions which literally covers all exchange-listed banks and insurers worldwide.

Methodology-wise, we use the default correlation model of Duan and Miao (2016) to generate by simulation the financial institutions' forward-looking PD correlation matrix over a future time period. To disentangle the direct linkages between any pair from the effects of third parties in the global network, we apply the CONCORD algorithm of Khare et al. (2015) to transform the forward-looking PD correlation matrix into a forward-looking 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 financial institution based on its connections and how its connected parties are further connected. Two of the measures use both the node (institution's asset size) and edge characteristics to construct the systemic importance. To graphically present the global financial network, we use the tool *Gephie* to obtain institution/group centric communities that are typically overlapping.

With this methodology, we analyze the financial networks at the height of the global financial crisis in 2008 as well at the end of 2015 when the crisis has subsided. Our analysis suggests that Lehman Brothers was as systemically important as many others that received the government bailout. We also show that our rankings are substantially different from the alternatives, such as the FSB G-SIBs/G-SIIs and SRISK. Among our systemic risk measures, the ones factoring in both edge (partial default correlation) and node characteristic (firm size) are closer to the FSB rankings.

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