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 around 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, which represent the direct connections among firms; 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 firms' 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 towards singling out large institutions as systemic, with connectivity playing a minor role.

Keywords: systemic risk, banking network, insurance, 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.

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, 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 trigger cascading defaults 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, 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 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, 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 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 around 2,000 banks and insurers in the CRI database. We use them to obtain the regularized partial correlation matrix, which allows 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 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 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). 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 independent from 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 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 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 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 and insurers under consideration, (2) utilizing the partial correlation matrix to devise measures for ranking these financial firms in terms of their systemic importance, and (3) building a financial community centered at a firm or a group of firms 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 firms 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 firm 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 firms, i.e., combining edge and node characteristics.[3] For example, a large bank, say, HSBC, may be connected with many smaller firms. A simple size-weighted measure would make these connections less important. The edge-node combined eigenvalue centrality would, however, make those connected smaller firms 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 firm/group-centric financial community. Instead of partitioning firms into non-overlapping communities, a group-centric community is defined. Within the defining group, a member firm 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 but not insurers, or, say, a New York-centered financial community where all New York-based banks and

[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.

insurers as well as their respective connected parties are included. The focal group can also be narrowed down to just one firm; for example, forming a Banco Santander-centered financial community. Naturally, different overlapping communities will emerge to reflect different focal groups.

3.1 Constructing the forward-looking PD partial correlation matrix

The default correlation model of Duan and Miao (2016) is adopted 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 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 (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 factors consisting of (1) the pair of global median PD and POE based on a pool 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 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 June 2017, the CRI provides PDs, with horizons ranging from 1 month to 5 years, on over 65,000 firms in 121 economies.[4] Among them, over 33,000 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 in this paper.

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 factors are dynamically evolving and modeled by a bivariate vector autoregressive process with their means set to zero. For each of the 10 industry pairs, we linearly project them onto the pair of global factors and take the pair of standardized residuals as the industry factors.[6] Each industry pair of factors is again modeled a bivariate vector autoregressive process with their means

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

[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 are 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.

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

set to zero. The individual firm PDs and POEs are also subjected to the same transformation through the logit function 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 default correlations are obtained 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 a target horizon, say, one year, at any future time point, say, one month later, for any subset of firms in the 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 the same 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 random 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. It is fairly clear that ensuring simulation quality at this level of M and N is critical to a successful implementation of Duan and Miao's (2016) default correlation model. Our experiment suggests that with the empirical martingale simulation technique of Duan and Simonato (1998) mentioned in an earlier footnote, simulation quality is indeed satisfactory. By increasing M and N, the correlation matrix can be obtained with any desired level of numerical accuracy, but the sampling error intrinsic to the use of actual data to estimate the Duan and Miao (2016) 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 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. 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

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[7] Here, individual firm PDs are regressed on PD factors, and individual firm POEs are regressed on 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 the use of the 5-year PD term structure in recalibration as opposed to their use of two-year PD term structure as the target of recalibration. 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 as 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.

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:

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

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

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 firm 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 firms via different network centrality measures

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. A firm'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,

[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 to conserve computing time. The results are not sensitive to further tightening of their levels.

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 $\overline{\mathbf{P}}_X$ equal 0 or not.

The degree centrality of firm *i* is defined as the *i*-th row sum of **A**, whereas the connection-strength centrality is the *i*-th row sum of $|\overline{\mathbf{P}}_X|$, the absolute value of $\overline{\mathbf{P}}_X$, divided by the total number of firms in the network. The later normalization makes possible comparing results across networks comprising different number of firms. 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 firm. Similarly, the connection-strength eigenvector centrality is the eigenvector associated with $|\overline{\mathbf{P}}_X|$. 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 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, $\mathbf{Q}|\overline{\mathbf{P}}_X|\mathbf{Q}$. Under these new centrality measures, a smaller firm by connecting to a large firm will become relatively more important, which in turn feeds back to increase the large firm'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 firm/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 firms 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.

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

In short, focal groups (i.e., individual firms, 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 firms' 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 orphan firms.

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 different network centrality measures compare to each other; second, we analyze 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 insurers; and third, we assess their performance in 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), 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 a firm has in the five-year rolling data window, sector-level PDs (i.e. bank or insurer) may be used as proxies for the left-hand variable in the factor loading estimation.[13] This way, a firm 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

[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 three exchange-listed central banks, Schweizerische Nationalbank, Banque Nationale de Belgique, and Bank of Greece, due to their special nature.

13 Specifically, if a firm 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 left-hand side variable.

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 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 once the crisis largely subsided. The number of financial institutions in the August 2008 and December 2015 samples are quite similar, 2,040 and 1,969 respectively.

The partial correlation matrices $\overline{\mathbf{P}}_X$ computed for August 2008 and December 2015 exhibit substantial sparsity, as zero entries account for about 89 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 towards zero. Recall that our partial correlation matrix construction increases sparsity up to the point that an orphan firm begins to emerge. Any higher sparsity will result in some firm(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 firm size-weighted centrality measures.

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	0.18	0.99	0.13	0.09	0.12	-0.09
Connection Strength	0.18	1	0.13	0.94	-0.10	-0.07	-0.07
Eigenvector	0.99	0.13	1	0.07	0.11	0.13	-0.09
Connection Strength Eigenvector	0.13	0.94	0.07	1	-0.13	-0.12	-0.08
Weighted Eigenvector	0.09	-0.10	0.11	-0.13	1	0.94	0.85
Weighted Connection Strength Eigenvector	0.12	-0.07	0.13	-0.12	0.94	1	0.72
Firm Asset Size	-0.09	-0.07	-0.09	-0.08	0.85	0.72	1

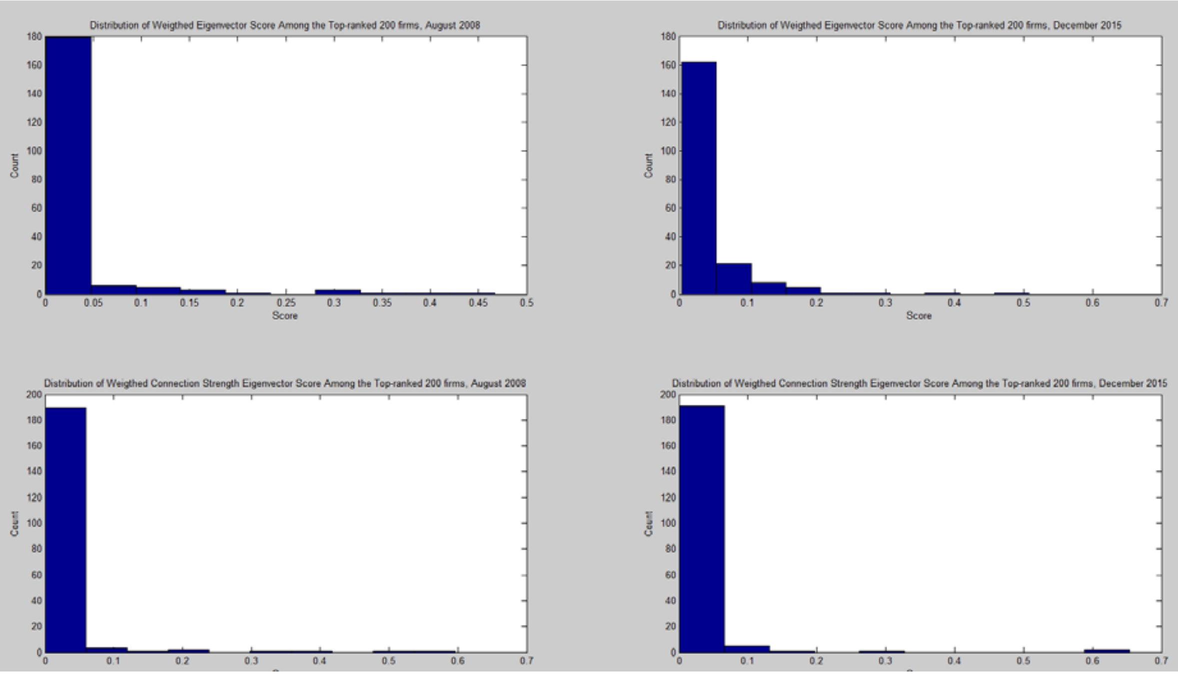
Panel 2. Spearman correlations in December 2015							
	Degree	**Connection Strength**	**Eigenvector**	**Connection Strength Eigenvector**	**Weighted Eigenvector**	**Weighted Connection Strength Eigenvector**	**Firm Asset Size**
Degree	1	0.20	0.99	0.21	-0.03	-0.01	-0.14
Connection Strength	0.20	1	0.20	0.92	-0.16	-0.17	-0.13
Eigenvector	0.99	0.20	1	0.22	-0.02	-0.01	-0.14
Connection Strength Eigenvector	0.21	0.92	0.22	1	-0.18	-0.22	-0.14
Weighted Eigenvector	-0.03	-0.16	-0.02	-0.18	1	0.93	0.94
Weighted Connection Strength Eigenvector	-0.01	-0.17	-0.01	-0.22	0.93	1	0.86
Firm Asset Size	-0.14	-0.13	-0.14	-0.14	0.94	0.86	1

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

In the following sections, we will present 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 firms' 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, 96% of the total scores in 2008 and 91% 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% and 98% of the total scores are absorbed by 10% of the samples in the two dates.

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 firms, a handful have much distinguishably higher scores than others. When the connection strength is factored in, particularly in 2015 as can be seen in the bottom right figure, the scores for the two top-ranked firms, in this case Credit Agricole and Societe Generale are way higher than those for the rest of the sample. The data reveals that these two French banks are strongly connected with each other. They also have strong connections with some of the biggest firms, whose centrality scores are also high, examples including Credit Suisse, Deutsche Bank, UniCredit and ING Groep.

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



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 number of criteria to identify Global Systemically Important Banks (G-SIBs) and Global Systemically Important Insurers (G-SIIs). Their purpose is that better monitoring of these financial institutions' activities and enhanced buffer requirements could reduce the risks of experiencing another severe 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 better comparison, we present in Table 2 the systemic rankings of the G-SIBs amongst the 1,435 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 subsector of banks. Similarly, we present in Table 3 the systemic rankings for the 2016 G-SIIs amongst the 534 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, Credit Agricole and ING Groep have relative larger number

[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.

of immediate counterparties and China Construction Bank has stronger connections with its immediate counterparties. In contrast, most of the other G-SIBs and G-SIIs have very few counterparties and weak ties. Accounting for the network effects (columns 5 and 6 in Table 2, columns 4 and 5 in Table 3) boosts some firms' rankings, such as Standard Chartered, because their immediate counterparties are better/more strongly connected with others. The opposite effect causes some firms to move down the list.

The most interesting phenomenon in Table 2 and 3 is that most of the G-SIBs/G-SIIs rank towards the top of list under the weighted eigenvector centrality (column 7 in Table 2, column 6 in Table 3) and weighted connection strength eigenvector centrality (column 8 in Table and column 7 in Table 3). That said, the firm size (both firm's own and its counterparties'), i.e., the node characteristic, plays an important role in determining a financial institution's importance in a network setting. Neglecting it would sometimes yield counterintuitive results. For better comparison, we also present in the last columns of both tables the rankings for the firms' total assets. As we can see, they can be highly correlated with the size-weighted rankings, but are not the same, re-enforcing the importance of the connectedness and network effects reflected in our methodology.

Many firms not on the FSB list are actually considered systemically risky according to our methodology. Commerzbank AG, the 2nd largest listed bank in Germany as of December 2015, ranks the 4th 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, examples including Credit Agricole (1st) and Societe Generale (2nd).

The riskiest insurer under the size-weighted connection strength eigenvector centrality on our 2015 list is CNP Assurances. Although none of its rankings under the edge-weighted measures is extremely high (i.e. 462th under connection strength centrality and 464th under connection strength eigenvector centrality among 534 insurers), it is connected to some of the largest and well-connected financial institutions such as Credit Agricole, Societe Generale, Credit Suisse, Allianz, Metlife and AXA.

The bottom of Table 2 presents the Spearman rank correlations between the six network centrality measures, firm size ranking and two other systemic importance indicators. The methodology is the following: for the 2016 G-SIBs, we give rankings from 1 onward to the 30 banks, allowing for ties when some of them fall into the same loss absorbency ratio bucket. Under each of our proposed centrality measures, we give 1-30 to the highest ranked firms 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]

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 towards singling out large institutions as evidenced by the correlation coefficient of 0.48 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 0.05.

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[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/.

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.

Table 2. FSB loss absorbency and 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%	884	1,230	1,067	1,218	16	16	12
JPMorgan Chase & Co	2.50%	612	325	586	352	15	70	6
Bank of America Corp	2.00%	963	1,004	1,001	791	33	50	9
BNP Paribas SA	2.00%	828	1,307	1,047	1,324	6	3	8
Deutsche Bank AG	2.00%	421	1,333	425	1,317	7	7	10
HSBC Holdings PLC	2.00%	1,132	469	1,174	482	30	78	5
Barclays PLC	1.50%	751	1,292	949	1,293	24	29	11
Credit Suisse Group AG	1.50%	461	1,195	466	1,176	22	8	26
Goldman Sachs Group Inc	1.50%	643	402	870	665	69	61	25
Industrial & Commercial Bank of China Ltd	1.50%	373	905	353	1,151	1	10	1
Mitsubishi UFJ Financial Group Inc	1.50%	526	699	505	820	17	56	7
Wells Fargo & Co	1.50%	1,089	745	1,100	401	51	73	13
Agricultural Bank of China Ltd	1.00%	516	719	427	786	2	17	3
Bank of China Ltd	1.00%	567	303	613	273	4	15	4
Bank of New York Mellon Corp	1.00%	1,026	989	1,061	1,095	37	30	57
China Construction Bank Corp	1.00%	499	236	560	679	25	76	2
Groupe BPCE*	1.00%	1,238	1,181	1,246	1,206	55	13	46
Credit Agricole SA	1.00%	240	1,138	297	1,254	10	1	14
ING Groep NV	1.00%	267	1,381	363	1,344	18	6	24
Mizuho Financial Group Inc	1.00%	580	1,250	498	1,149	3	20	15
Morgan Stanley	1.00%	1,350	1,102	1,348	948	34	21	28
Nordea Bank AB	1.00%	963	1,154	935	1,071	50	35	34
Royal Bank of Scotland Group PLC	1.00%	388	1,171	407	1,037	8	68	19
Banco Santander SA	1.00%	627	954	627	887	43	51	18

Societe Generale SA	1.00%	1,026	1,331	1,057	1,323	13	2	17
Standard Chartered PLC	1.00%	388	1,227	350	946	23	52	40
State Street Corp	1.00%	1,173	590	1,165	356	65	166	83
Sumitomo Mitsui Financial Group Inc	1.00%	1,051	688	1,109	669	21	37	16
UBS Group AG	1.00%	593	1,192	633	1,224	5	19	22
UniCredit SpA	1.00%	767	1,330	809	1,283	19	5	23
Rank correlations with FSB (30 banks)		NaN***	NaN	NaN	NaN	0.04	-0.06	0.48
Rank correlations with SRISK (439 banks)**		-0.01	0.02	0.02	-0.01	0.42	0.36	0.50

* 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: CRI (National University of Singapore) and authors' calculations.
**The SRISK data are taken from the V-Lab website as of January 2017. The data points are from December of each year.
***The correlation coefficients are NaN because none of the 30 banks identified as systemically important by FSB is ranked among the top 30 banks under our first three measures.

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	21	115	21	214	9	7	13
Allianz SE	87	254	185	448	1	5	2
American International Group Inc	403	105	397	87	13	24	11
Aviva PLC	16	235	12	228	12	20	7
AXA SA	30	496	49	475	7	4	1
MetLife Inc	301	390	298	385	2	2	3
Ping An Insurance Group Co of China Ltd	243	341	271	380	4	42	5
Prudential Financial Inc	252	274	278	207	8	8	4
Prudential PLC	163	410	150	389	10	34	8

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

Table 4 displays the global systemic importance rankings for then the 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. Under the two size-weighted centrality measures (columns 6 and 7 in Table 4), which we believe capture better the systemic risk of banks, all of those New York-based banks (except Merrill Lynch and New York Mellon) were among the top 10% riskiest financial institutions in the world at the time.

In the case of Lehman Brothers, it was smaller than other major investment banks when measured in total assets. However, it was widely connected with the rest of the global financial system (see columns 2 and 4 in Table 4), and its size-weighted rankings did not seem to justify the decision to let it go into bankruptcy.[18] This event may have contributed to the cascading defaults of its major counterparties later on. Indeed, our data indicates that among the top 50 firms that had positive partial correlations with Lehman Brothers in the August 2008 analysis, 13 of them were subsequently delisted from their respective exchanges.

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	745	454	681	909	9	10	2,100,385	7
JPMorgan Chase	1,726	1,055	1,699	496	67	186	1,775,670	11
Goldman Sachs	351	731	445	816	24	50	1,088,145	22
Morgan Stanley	1,791	1,181	1,704	1,314	15	11	1,031,228	25
Merrill Lynch	1,155	1,661	1,345	1,505	136	268	966,210	28
Lehman Brothers	206	1,404	238	1,334	52	137	639,432	39
Bank of New York Mellon	1,186	492	1,327	318	291	347	201,225	97

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

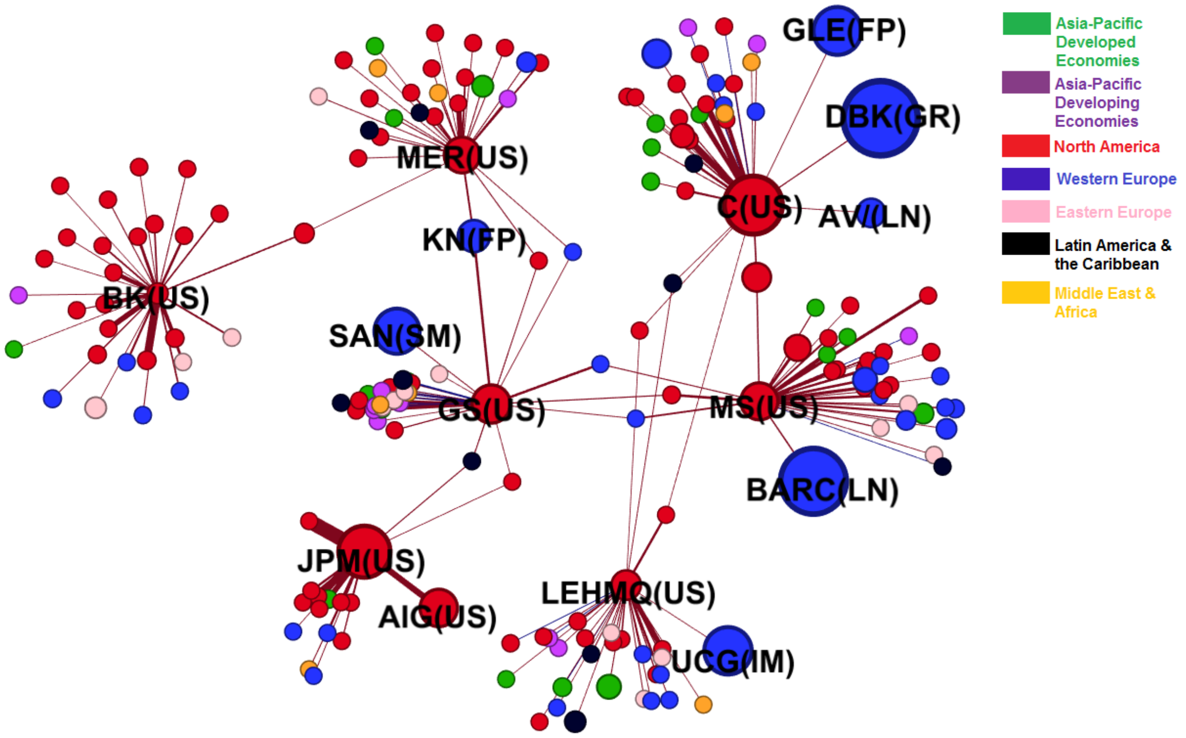
Figure 2 presents the seven major New York City-based banks, identified by their equity tickers, with their associated financial communities as of August 2008. Different colors denote the geographical domicile of the firms and counterparts, with other major financial institutions also identified by their equity tickers.

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, New York Mellon is mostly connected to parties domiciled in North America and Europe. Lehman Brothers and Goldman Sachs, on the other hand, have much diverse pools of counterparties around the world.[19]

[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).

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

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 PD 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 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 firm 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 firms in the sample may not have the same or enough overlapping periods of observations. As a consequence, it may be difficult to 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 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 firm size-weighted centrality measures, forward-looking rankings raise the importance of Morgan Stanley and Agricultural Bank of China among other banks relative to their backward-looking counterparts. In contrast, for financial institutions including HSBC and Bank of America, 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 firms' would-be connectedness in the future will be quite different from relying on the forward-looking PDs at the time of analysis.

5.2 Equity returns vs. PDs

This example compares the financial 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 2015 for all financial institutions in our sample. As the firms 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 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 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 firms' total assets sizes, the rankings from different raw data sources start to get closer with each other. For example, the PD-based firm size-weighted connection strength eigenvector centrality has a Spearman coefficient of 0.57 with that constructed with 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	1,219	415	1,644	359	1,451	399	1,674	935	16	11	20	30
JPMorgan Chase & Co	841	1,561	467	1,100	795	1,695	513	1,734	15	84	98	96
Bank of America Corp	1,317	855	1,372	916	1,363	847	1,107	1,170	41	9	63	44
BNP Paribas SA	1,143	525	1,745	922	1,426	747	1,815	1,271	6	14	3	52
Deutsche Bank AG	573	855	1,775	779	580	740	1,808	1,045	7	6	7	58
HSBC Holdings PLC	1,549	747	662	760	1,599	682	696	1,049	38	26	110	229
Barclays PLC	1,042	317	1,727	458	1,298	246	1,776	995	28	8	36	33
Credit Suisse Group AG	625	1,836	1,601	1,210	631	1,797	1,617	1,632	24	210	8	451
Goldman Sachs Group Inc	899	1,801	572	1,855	1,189	1,688	941	1,846	89	783	83	844
Industrial & Commercial Bank of China Ltd	510	855	1,255	1,152	471	384	1,585	1,145	1	64	10	179
Mitsubishi UFJ Financial Group Inc	726	747	977	1,188	682	600	1,147	1,242	17	138	73	3
Wells Fargo & Co	1,489	1,298	1,047	1,476	1,499	1,191	579	1,357	60	181	103	40
Agricultural Bank of China Ltd	714	747	1,007	403	582	588	1,100	105	2	675	21	775
Bank of China Ltd	781	1,432	432	1,009	845	1,300	399	611	4	2	19	113
Bank of New York Mellon Corp	1,397	1,666	1,356	1,504	1,442	1,723	1,511	1,764	45	562	37	654
China Construction Bank Corp	684	244	345	570	758	311	959	1,009	29	1	106	94
Groupe BPCE*	1,683	1,561	1,588	1,599	1,691	1,437	1,659	1,498	66	59	16	84
Credit Agricole SA	322	14	1,533	288	400	80	1,727	539	10	41	1	75
ING Groep NV	361	153	1,824	495	489	324	1,840	1,168	18	29	6	48
Mizuho Financial Group Inc	800	855	1676	825	672	581	1,583	1,171	3	126	26	2
Morgan Stanley	1,821	1,801	1,492	1,833	1,827	1,792	1,325	1,859	42	1,524	27	1,367
Nordea Bank AB	1,317	747	1,555	1,183	1,278	774	1,479	1,343	59	16	44	108
Royal Bank of Scotland Group PLC	526	153	1,576	137	554	214	1,438	730	8	75	95	37
Banco Santander SA	867	1,768	1,315	1,536	864	1,624	1,243	1,621	50	21	64	89
Societe Generale SA	1,397	1,618	1,771	1,316	1,438	1,530	1,814	1,541	13	22	2	66
Standard Chartered PLC	526	1,618	1,639	1,727	468	1,470	1,323	1,566	26	52	65	129

State Street Corp	1,599	153	830	262	1,584	86	520	686	81	339	219	166
Sumitomo Mitsui Financial Group Inc	1,433	1,026	963	438	1,511	922	946	1,014	22	144	46	1
UBS Group AG	819	11	1,599	666	871	12	1,681	1,077	5	115	25	117
UniCredit SpA	1,062	1,720	1,770	1,441	1,115	1,655	1,763	1,691	19	44	5	82
Aegon NV	87	635	342	633	92	881	689	1,275	55	66	31	98
Allianz SE	336	1,432	832	369	698	1,480	1,609	1,450	21	83	23	128
American International Group Inc	1,461	74	318	113	1,461	126	253	665	70	39	84	47
Aviva PLC	74	944	758	746	63	878	741	1,069	65	62	76	175
AXA SA	117	1,026	1,725	662	215	1,326	1,713	1,376	35	23	18	111
MetLife Inc	1,062	103	1,349	586	1,055	82	1,339	987	23	81	12	28
Ping An Insurance Group Co of China Ltd	860	1,128	1,142	1,345	969	1,265	1,321	1,267	27	28	149	227
Prudential Financial Inc	883	635	886	326	1,003	595	658	800	36	127	40	31
Prudential PLC	595	635	1,446	445	562	1,000	1,347	1,250	56	71	109	61

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 1,880 financial institutions as opposed to the 1,969-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 1,880-firm sample to allow for meaning comparison.
* 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 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	94	900	82	449	136	960	427	635	6	9	11	50
JPMorgan Chase & Co	1,532	1,255	1,284	856	1,554	1,447	1,541	1,187	17	17	62	56
Bank of America Corp	1,014	1,383	473	664	869	1,284	628	903	21	23	13	46
BNP Paribas SA	914	1,649	813	1,095	1,010	1,551	1,015	948	12	2	15	61
Deutsche Bank AG	318	840	242	491	409	969	599	820	5	3	10	108
HSBC Holdings PLC	181	1,078	232	604	200	1,321	553	921	29	1	27	63
Barclays PLC	210	936	38	315	208	950	380	590	42	4	21	107
Credit Suisse Group AG	1,834	806	1,761	645	1,788	844	1,663	776	86	13	165	155
Goldman Sachs Group Inc	1,394	1,292	1,539	368	1,465	1,314	1,529	700	31	26	47	78
Industrial & Commercial Bank of China Ltd	725	959	821	586	662	1,027	476	548	1	18	2	6
Mitsubishi UFJ Financial Group Inc	413	1,438	417	763	545	1,524	779	1,252	22	80	7	41
Wells Fargo & Co	1,066	1,078	852	745	1,094	1,159	1,082	1,087	34	16	38	29
Agricultural Bank of China Ltd	371	592	174	340	87	571	82	246	4	34	8	4
Bank of China Ltd	585	780	455	311	486	1,002	439	464	3	27	5	1
Bank of New York Mellon Corp	1,477	1,078	1,393	738	1,475	1,244	1,537	1,092	138	60	176	133
China Construction Bank Corp	75	592	151	251	190	967	550	465	2	19	1	2
Groupe BPCE*	1,323	780	1,519	981	1,227	591	1,440	650	67	51	52	175
Credit Agricole SA	632	711	433	159	864	629	788	344	13	5	12	67
ING Groep NV	318	840	298	472	420	867	697	600	32	12	48	157
Mizuho Financial Group Inc	914	1,669	993	769	880	1,673	1105	1,380	10	62	6	22
Morgan Stanley	1,082	780	934	279	981	806	1,032	474	53	32	100	32
Nordea Bank AB	676	1,024	443	479	629	1,152	652	961	38	7	42	172
Royal Bank of Scotland Group PLC	297	806	90	487	387	712	415	578	26	8	37	147
Banco Santander SA	1,429	1,617	1,517	914	1,385	1,615	1,457	1,101	24	6	58	117
Societe Generale SA	1,622	1,255	1,640	818	1,603	1,156	1,579	729	46	10	19	44
Standard Chartered PLC	585	936	895	936	581	824	890	805	20	24	53	72

State Street Corp	154	1,141	55	918	249	1,133	422	1,069	50	97	41	178
Sumitomo Mitsui Financial Group Inc	388	1,255	446	595	434	1,297	798	1,267	41	36	3	33
UBS Group AG	457	711	456	533	569	669	852	591	8	20	25	167
UniCredit SpA	1,382	1,328	1,167	1,089	1,454	1,111	1,431	692	40	21	84	181
Aegon NV	222	780	297	438	350	736	677	575	37	65	69	73
Allianz SE	890	1167	667	535	1,155	1,249	1,275	1,025	39	30	22	202
American International Group Inc	250	293	505	173	382	340	787	376	61	44	87	16
Aviva PLC	413	1,167	402	548	339	1,151	567	750	16	35	16	148
AXA SA	890	1,167	880	730	1,161	1,274	1,292	936	44	15	43	115
MetLife Inc	585	505	448	291	595	675	735	545	48	31	76	139
Ping An Insurance Group Co of China Ltd	890	711	622	373	1,074	933	829	597	35	43	40	7
Prudential Financial Inc	222	363	189	95	300	467	534	367	72	67	67	113
Prudential PLC	558	1,167	347	648	583	1,121	630	796	94	55	70	118

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 1,871 banks and insurers as opposed to the 1,969-firm sample used in section 4.2.
* 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 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 about two thousand 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 firm pair from the effects of other firms 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 financial institution based on its connections and how its connected parties are further connected. Two of the measures use both the node (firm asset size) and edge characteristics to construct the systemic importance. To graphically present the global financial network, we use the tool *Gephie* to partition the network into firm/group centric communities.

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 systemic importance rankings suggest that Lehman Brothers was more systemically important 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/G-SIIs. 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.

References

1. Acharya, V., Engle, R. & Richardson, M., 2012, "Capital Shortfall: A New Approach to Ranking and Regulating Systemic Risks," *American Economic Review, Papers and Proceedings of the One Hundred Twenty Fourth Annual Meeting of the American Economic Association*, 102(3), pp. 59-64.
2. Adrian, T. and Brunnermeier, M.K., 2016, "CoVar," A*merican Economic Review*, 106(7), pp. 1705-1741.
3. Bailey, N., Kapetanios, G., and Pesaran, M., 2015a, "Exponent of Cross-Sectional Dependence: Estimation and Inference," *Journal of Applied Econometrics*, forthcoming.
4. Bailey, N., Holly, S., and Pesaran, M., 2015b, "A Two Stage Approach to Spatial-Temporal Analysis with Strong and Weak Cross-Sectional Dependence," *Journal of Applied Econometrics*, forthcoming.
5. Barigozzi, M. and Brownlees, C., 2016, "Nets: Network Estimation for Time Series," SSRN.
6. Basel Committee on Banking Supervision, Nov. 2014, "The G-SIB assessment methodology-score calculation."
7. Basel Committee on Banking Supervision, 2013, "Global Systemically Important Banks: Updated Assessment Methodology and the Higher Loss Absorbency Requirement (Basel)."
8. Billio, M., Getmansky, M., Gray, D., Lo, A., Merton, R.C., and Pelizzon, L., 2013, "Sovereign, Bank, and Insurance Credit Spreads Connectedness and System Networks," *mimeo* (Massachusetts Institute of Technology).

9. Billio, M., Getmansky, M., Lo, A., and Pelizzon, L., 2012, "Econometric Measures of Connectedness and Systemic Risk in the Finance and Insurance Sectors," *Journal of Financial Economics*, 104, pp. 535 - 559.
10. Brownlees, C.T., and Engle, R.F., 2017, "SRISK: A Conditional Capital Shortfall Measures of Systemic Risk," *Review of Financial Studies*, 30(1), pp 48-79.
11. Canova, F., and Ciccarelli, M., 2013, "Panel Vector Autoregressive Models: a Survey," *Working Paper Series* 1507 (European Central Bank).
12. Chan-Lau, J.A., 2013, *Systemic Risk Assessment and Oversight, Risk Books*.
13. Chan-Lau, J.A., 2009, "Default Risk Codependence in the Global Financial System: Was the Bear Stearns Bailout Justified?" in G. Gregoriou, editor, *The Banking Crisis Handbook* (McGraw Hill).
14. Chudik, A., Pesaran, M., and Tosetti, E., 2011, "Weak and Strong Cross Section Dependence and Estimation of Large Panels," *Econometrics Journal*, 14(1), pp. C45-C90.
15. Craig, B., and Saldias, M., 2016, "Spatial Dependence and Data-Driven Networks of International Banks," *mimeo*, Federal Reserve Bank of Cleveland and International Monetary Fund.
16. Demekas, D., Chan-Lau, J.A., Rendak, N., Ohnsorghe, F., Youssef, K., Caceres, C. and Tintchev, K., 2013, "Mandatory Financial Stability Assessments under the Financial Sector Assessment Program: Update," International Monetary Fund (Washington, D.C.).
17. Demirer, M., Diebold, F.X., Liu, L. and Yilmaz, K., 2015, "Estimating Global Bank Network Connectedness," *Working paper*.
18. Diebold, F.X., and Yilmaz, K., 2014, "On the Network Topology of Variance Decompositions: Measuring the Connectedness of Financial Firms," *Journal of Econometrics*, 182(1), pp. 119-134.
19. Duan, J.-C. and Miao, W., 2016, "Default Correlations and Large-Portfolio Credit Analysis," *Journal of Business and Economic Statistics*, 34(4), pp. 536-546.
20. Duan, J.-C. and Simonato, J.-G., 1998, "Empirical Martingale Simulation for Asset Prices," *Management Science*, 44(9), pp. 1218-1233.
21. Duan, J.-C., Sun, J. and Wang, T., 2012, "Multiperiod Corporate Default Prediction: A Forward Intensity Approach," *Journal of Econometrics*, 170(1), pp. 191-209.
22. Duan, J.-C. and Zhang, C., 2013, "Cascading Defaults and Systemic Risk of a Banking Network," *National University of Singapore working paper*.
23. Fan, J., 1997, "Comments on `Wavelets in Statistics: A Review' by A. Antoniadis," *Journal of the Italian Statistical Society*, 6(2), pp. 131-138.
24. Ferson, W. E., 2003, "Tests of Multifactor Pricing Models, Volatility Bounds, and Portfolio Performance," Chapter 12 in G. Constantinides, M. Harris, and R. Stulz, editors, *Handbook of the Economics of Finance*, 1A, pp. 743 - 802.
25. Fiedler, M., 1973, "Algebraic Connectivity of Graphs," *Czechoslovak Mathematical Journal*, 23(2), pp. 298-305.
26. Financial Stability Board, 2014, "2014 Update of List of Global Systemically Important Banks (G-SIBs) (Basel)."
27. Financial Stability Board, 2016, "2016 list of global systemically important banks (G-SIBs)".
28. Financial Stability Board, 2016, "2016 list of global systemically important insurers (G-SIIs)".
29. Girvan, M. and Newman, M. E. J., 2002, "Community Structure in Social and Biological Networks," *Proceedings of the National Academy of Sciences of the United States of America*, 99(12), 7821-7826.
30. Huang, X., Zhou, H. and Zhu, H., 2009, "A Framework for Assessing the Systemic Risk of Major Financial Institutions," *Journal of Banking & Finance*, 33, pp. 2036-2049.
31. International Association of Insurance Supervisors, 2016, "Global Systemically Important Insurers: Updated Assessment Methodology".
32. International Monetary Fund, 2009, Global Financial Stability Report (April).
33. Jacomy, M., Venturini, T., Heymann, S. and Bastian, M., 2014, "ForceAtlas2, A Continuous Graph Layout Algorithm for Handy Network Visualization Designed for the Gephi Software," *PLOS One*.

34. Kenett, Dror Y., Tumminello, M., Madi, A., Gur-Gershgoren, G., Mantegna, R.N. and Ben-Jacob, E., 2010, "Dominating Clasp of the Financial Sector Revealed by Partial Correlation Analysis of the Stock Market," *PLOS One*.
35. Kernighan, B. W. and Lin, S., 1970, "An Efficient Heuristic Procedure for Partitioning Graphs," *Bell System Technical Journal*, 49(2), pp. 291-307.
36. Khare, K., Oh, S.-Y. and Rajaratnam, B., 2015, "A Convex Pseudo-likelihood Framework for High Dimensional Partial Correlation Estimation with Convergence Guarantees," *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, pp. 803-825.
37. Koop, G., Pesaran, M., and Potter, S., 1996, "Impulse Response Analysis in Nonlinear Multivariate Models," *Journal of Econometrics*, 74, pp. 119 - 147.
38. Lanne, M., and Nyberg, H., 2016, "Generalized Forecast Error Variance Decomposition for Linear and Nonlinear Multivariate Models," forthcoming in *Oxford Bulletin of Economics and Statistics*.
39. Mantegna, R. N., 1999, "Hierarchical Structure in Financial Markets," *European Physical Journal B - Condensed Matter and Complex Systems*, 1, pp. 193 - 197.
40. Oh, S.-Y., Dalal, O., Khare, K. and Rajaratnam, B., 2014, "Optimization Methods for Sparse Pseudo-likelihood Graphical Model Selection," Appeared in *conference proceedings for 'Neural Information Processing System* 2014'.
41. Pothen, A., Simon, H. D., and Liou K-P., 1990, "Partitioning Sparse Matrices with Eigenvectors of Graphs," *Siam Journal on Matrix Analysis and Applications*, 11(3), pp. 430-452.
42. Palla, G., Derenyi, I., Farkas, I. and Vicsek, T., 2005, "Uncovering the Overlapping Community Structure of Complex Networks in Nature and Society," *Nature*, 435, pp. 814-818.
43. Patro, D. K., Qi, M. and Sun, X., 2013, "A Simple Indicator of Systemic Risk," *Journal of Financial Stability*, pp. 105-116.
44. Peng, J., Wang, P., Zhou, N. and Zhu, J., 2009, "Partial Correlation Estimation by Joint Sparse Regression Models," *Journal of the American Statistical Association*, 104(486).
45. Pesaran, H., and Shin, Y., 1998, "Generalized Impulse Response Analysis in Linear Multivariate Models," *Economics Letters*, 58, pp. 17 - 29.
46. Qi, H. and Sun, D., 2011, "An Augmented Lagrangian Dual Approach for the H-weighted Nearest Correlation Matrix Problem," *IMA Journal of Numerical Analysis*, 31, pp. 491-511.
47. RMI-CRI, 2017, "NUS-RMI Credit Research Initiative Technical Report Version: 2017 Update 1," accessible via http://d.rmicri.org/static/pdf/2017update1.pdf.
48. Scott, J., 2000, *Social Network Analysis: A Handbook, 2nd edition*, Thousand Oaks, CA: Sage Publications.
49. Tumminello, M., Lillo, F. and Mantegna, R., 2010, "Correlation, Hierarchies, and Networks in Financial Markets," *Journal of Economic Behavior & Organization*, pp. 40-58.
50. Xie, J., S. Kelley, and B.K. Szymanski, 2014, "Overlapping Community Detection in Network: the State of the Art and Comparative Study," *ACM Computing Surveys*, 45, No. 4.
51. Zou, H., 2006, "The Adaptive Lasso and Its Oracle Properties," *Journal of the American Statistical Association*, 101(476), pp. 1418-1429.