“Too central to fail” Systemic Risk[1]

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Highlight

- We suggest a systemic risk measure by adopting PageRank algorithm from “too central to fail” perspective.
- We model a simulation that financial institutions are interlinked in the financial system.
- We analyze the impacts of network characteristics on the centrality by using the proposed measure, Rank.
- We compare Rank with well-known systemic risk measures, CoVaR and MES whether Rank can capture network structure between financial institutions.

Abstract

The concept of being “too central to fail” has been on the rise since “too big to fail” and “too connected to fail.” We suggest a systemic risk measure, Rank, that adopts the PageRank algorithm. We examine the effects of varying network characteristics on the centrality captured as Rank. Then, we compare this measure which effectively captures network relationships between financial institutions from a centrality perspective with other well-known systemic risk measures, conditional value at risk (CoVaR) and marginal expected shortfall (MES). First, we model a simulation that generates bilateral connections between financial institutions. Second, we use real market data representing sample United States financial institutions. We find that the centrality increases 1) if the percentage of equity in financial institutions is low, 2) if there were small number of financial institutions in the financial system. However, we do not find significant association between the centrality and asset structure of financial institutions. Additionally, we show that Rank can capture network structure between financial institutions better than CoVaR and MES. Rank does not have procyclical properties, which means it is not dependent on market conditions. This paper contributes to developing a timely measure using publicly available market data. The measure overcomes the shortcomings of the balance sheet-based approach, which is that balance sheets have time lags because financial institutions release balance sheets quarterly. We also include both equity-type and liability-type assets, in which systemic risk mainly propagates through intricately connected liability obligations. This work will help regulators and policy makers understand the full implications of monitoring systemic risk from a network perspective.

Key words: Systemic risk, Network structure, Centrality, Too central to fail, Simulation, PageRank

JEL codes: C63, C90, D85, E44, G21, G28

[1] This work was supported by the National Research Foundation of Korea (NRF) Grant funded by the Korean Government (Ministry of Science, ICT and Future Planning) (No. NRF-2013R1A1A1076066).

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“The recent crisis showed that some financial innovations, over time, increased the system's vulnerability to financial shocks that could be transmitted throughout the entire economy with immediate and sustained consequences that we are still working through today. Some of these vulnerabilities were a consequence of innovations that increased the complexity and interconnectedness of aspects of the financial system.”

Chair of the Board of Governors of the Federal Reserve System, Janet L. Yellen at the American Economic Association/American Finance Association Joint Luncheon, San Diego, California on 4 January 2013.[3]

1. Introduction

Managing financial systemic risk from a network perspective has been a major concern since the global financial crisis. To maintain financial stability, systemically important financial institutions (SIFIs) have been identified as a strengthening regulation by the International Monetary Fund (IMF), the Bank for International Settlements (BIS), and the Financial Stability Board (FSB) on the premise that financial institutions should be subject to higher capital buffer requirements if they are identified as SIFIs (IMF-BIS-FSB, 2009). For instance, JP Morgan Chase as a bucket four, and Bank of America, Citigroup, Deutsche Bank, and HSBC as a bucket three are required to have 2.5% and 2.0% higher capital buffers respectively than non-SIFIs as of November 2017 (FSB, 2017).[4]

Identifying SIFIs has significant impacts on both regulatory agencies and individual financial institutions; however, we note two shortcomings regarding current SIFI criteria. First, assessment based on balance sheet data does not reflect the latest circumstances of financial institutions. Balance sheet data have time lags, as financial institutions usually release their balance sheets quarterly. Second, assessment methodology does not consider complex network relationships between financial institutions.[5] Less obvious forms of network relationships, such as common exposure among financial institutions are not covered, although the interconnectedness category of the current criteria does consider intra-financial system assets and liabilities (Table 1).

[Table 1]

We argue that there are gaps across “too big to fail”, “to connected to fail”, and “too central to fail” (Figure 1). The size, connectedness, and centrality of financial institutions do not necessarily overlap. Although a

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[3] See Yellen (2013) for the full speech.

[4] The FSB has identified SIFIs and published policy measures about not only globally systemically important banks since 2011 but also globally systemically important insurers since 2013.

[5] De Bandt and Hartmann (2000) and Nier et al. (2007) point complex networks as mechanisms the failure of multiple banks simultaneously arises: direct bilateral lending and borrowing between banks, a common source of risks from correlated exposure among banks, feedback effects with endogenous fire sale, and informational contagion. Their arguments support the motivation of this paper that SIFI current criteria do not fully capture the financial networks.

certain financial institution has huge assets, the institution could not be closely connected to other financial institutions in the financial system (i.e. "too big to fail" ≠ "to connected to fail"). It also varies depending on situations of financial market, individual financial institutions, or regulations. Similarly, a financial institution could be in a periphery position, although the institution is big or connected with other institutions (i.e. "too big to fail" ≠ "to central to fail" or "to connected to fail" ≠ "to central to fail").

[Figure 1]

The main goal of this paper is to propose a new way to quantify network relationships between financial institutions from "too central to fail" perspective. We compare the proposed measures with well-known systemic risk measures using stock data. First, we model a hypothetical banking system for simulations. We assume a stylized balance sheet that includes asset and liability. Financial institutions in simulations have complex interbank network through their asset-type assets and liability-type assets. They may also default from shocks and financial distress propagates to an entire financial system through interbank network. Second, we check that the measure can capture the network structure using empirical analysis. We then conduct a panel regression analysis using both simulation and real market data.

We represent the centrality of the sample US financial institutions using Rank as a motivating example (Figure 2). Edges denote connections between financial institutions while size of nodes implies the level of Rank. Due to the limited space, ticker replaces names of financial institutions (see Table A1 in the Appendix for tickers). We can notice that the financial network changes with Rank. Additionally, some financial institutions have a few connections with financial institutions but Rank is high. Others have dense connections with financial institutions but Rank is low. Not only characteristics of financial institution but also other factors such as business model can affect centrality.[6]

[Figure 2]

This paper contributes to existing literature in three ways. First, we consider the direction that how a financial institution influences, and is influenced by, another financial institution. In previous research using the PageRank algorithm to determine financial systemic risk, Dungey et al. (2012) suggest correlating a firm's stock price movements with its network. Thus the research makes the restricted assumption that the effect on another financial institution is the same as the effect from another financial institution. Second, we cover both equity and liability connections to fully capture network relationships between financial institutions. Battiston et al. (2012) propose a way to quantify networks using equity investment. However, equity connections based on equity stakes can only cover partial network channels, as systemic risk mainly propagates through intricately connected liability obligations. Third, we support the validity of new network measures through both simulation and real financial data. Previous research proposes measures from a network perspective; however, such studies have used mainly descriptive-level analysis (Battiston et al., 2012; Kuzubas et al., 2014; Demirer et al., 2017).

[6] The centrality measure of Rank can help understand behaviors of financial institutions and entire financial system. Other centrality measures such as degree, closeness, betweenness, eigenvector centrality can be complementary for monitoring financial vulnerability.

This paper is organized as follows. We provide theoretical background through a literature review in Section 2. We explain the sample data and variables for the analysis in Section 3. In Section 4, we present a simulation model to construct a hypothetical banking system. We examine the effects of network characteristics on the centrality through simulations in Section 5. Then, we provide the empirical results in Section 6. Finally, we conclude this paper through summarizing the research and discussing future research in Section 7.

2. Literature review

The global financial crisis has provoked us an approach toward financial systemic risk from a network perspective. After Allen and Gale (2000) and Freixas et al. (2000) note the structure of financial networks, the drive to understand financial systems through networks has drawn attention in earnest with the collapse of Lehman Brothers. The theoretical analysis was that the more financial institutions were connected through various channels, the more resilient the financial system would be to shocks (Brunnermeier and Pedersen, 2009; Geanakoplos, 2010). A shock can be dispersed to each financial institution in a densely connected financial system. The lesson from the global financial crisis, however, changed this understanding: Financial systems can be vulnerable to shocks when financial institutions are excessively connected (Shin, 2010). As intermediation chains of financial institutions lengthen, initially small exogenous shocks are amplified to big endogenous shocks that can affect an entire financial system. Caballero (2015) and Minoiu et al. (2015) also empirically support that high connectedness between financial institutions can increase the probability of a banking crisis.

The increasing interest in financial networks has led to developing a systemic risk measure to reflect network characteristics. The quantification and representation of a financial network as a measure, however, differ depending on the feature under focus.[7] Well-known systemic risk measures used in financial networks include principal components analysis, interbank exposure, and cross-border linkages (Bisias et al., 2012). Principal component analysis gauges the degree of commonality and links significant factors with systemic risk.[8] Interbank exposure illustrates entities as nodes and relationships as edges based on graph theory.[9] Cross-border linkages

[7] Measuring systemic risk considering financial network is somewhat new. Many papers have suggested and studied measures. Kara et al. (2015) divide the network measures with direct and indirect approach: direct approach uses bilateral obligations between financial institutions while indirect approach estimates relationships between financial institutions from real market data. This research's Rank also estimate complex network relationships of financial institutions by mainly using stock returns of financial institutions as real market data. See Kara et al. (2015) for the detailed taxonomy of financial network measures.

[8] Applications of principal components analysis include absorption ratio (Kritzman et al., 2011) and PCAS (Billio et al., 2012).

[9] Chan-Lau et al. (2009) and the IMF (2009) show network models in terms of interbank exposure. The Granger-causality network of Billio et al. (2012) is also based on this property.

focus on the funding of global banks and examine risk transmission.[10] Regulatory agencies such as the International Monetary Fund (IMF), the Financial Stability Board, and central banks have also examined financial networks to maintain financial stability using systemic risk measures. The IMF examines four methods, including a network approach, to assess the systemic implications of financial linkages (IMF, 2009).[11] It also analyzes three indicators by calculating the contribution of an institution to systemic risk (IMF, 2011).[12] Then, Arregui et al. (2013) review tools to measure interconnectedness and analyzes the systemic risk of interconnectedness from a surveillance perspective.[13] Furthermore, Chan-Lau (2010) suggests a way to impose additional regulatory capital charges by considering interconnectedness.

Examining the evolution of network analysis helps us to develop a systemic risk measure from a financial network approach. Network methodologies have been developed at three levels in the field of network analysis (Battiston et al., 2010). The first level depends on a topological approach in which the links between entities simply exist or do not exist. The second level includes just weights or weights and directions to links. The direct interaction between entities is represented as a link, and the interaction can be a transaction, ownership, or credit relation in case of financial institutions.[14] The top level assigns a degree of freedom to nodes, which proceeds to a non-topological variable to shape the network. This is in line with recent research that takes into account dynamics of nodes through centrality. The most commonly used centrality measures derived from social network analysis are degree, closeness, betweenness, and eigenvector centrality.[15] In the finance/economics field, DebtRank of Battiston et al. (2012) identifies systemically important nodes in loans while SinkRank of Soramäki and Cook (2013) identifies systemically important banks in a payment system. Kuzubas et al. (2014) claim that centrality measures perform well in predicting SIFIs. In addition, Thurner and Poledna (2013) suggest that centrality measures can be effectively used to select a counterparty, which could decrease the number of failed firms and the amount of total loss. The interest in centrality from regulatory agencies also supports this research to examine the idea of being "too central to fail" (European Central Bank, 2010; Arregui et al., 2013).

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[10] Cross-border linkages include the bank funding gap of Fender and McGuire (2010).

[11] The IMF Global Financial Stability Report after the global financial crisis represents a network approach, co-risk model, distress dependence matrix, and default intensity model (IMF, 2009).

[12] Another IMF Global Financial Stability Report analyzes the performance of conditional value at risk (CoVaR), joint probability of distress (JPoD), and Diebold-Yilmaz index (Diebold and Yilmaz, 2009; 2014) (IMF, 2011).

[13] The measures include CoVaR, return spillovers, distress spillovers, JPoD, conditional probability of default, and systemic contingent claim analysis (Arregui et al., 2013).

[14] The finance literature using network analysis, for instance, includes interbank markets (Boss et al., 2004; Iori et al., 2006; Iori et al., 2008) and corporate control or ownership (Almeida and Wolfenzon, 2006; Vitali et al., 2011).

[15] Degree centrality counts the number of immediate neighborhood nodes and finds very connected nodes. It counts incoming links (in-degree), outgoing links (out-degree), or all links (degree). Closeness centrality measures the shortest path between a node and all others, implying that a node with shorter paths to other nodes is more central. Betweenness centrality measures the number of times that a node passes the shortest path and finds nodes acting as "bridges." Eigenvector centrality assigns scores to all nodes and finds connections to high-scoring nodes. The idea is that an important node is connected to important neighbors. An application of eigenvector centrality is Google's PageRank.

The existing literature uses simulations because of lack of information about bilateral relationships between financial institutions. Specifically, micro-level bilateral information (from one financial institution to another) rather than aggregate-level bilateral information (from one country to another) is not publicly released. Thus, researchers have constructed hypothetical financial systems with economic agents based on theoretical background and examined the effects of financial networks on financial vulnerability. The simulation research has started with the regulatory purpose of the central bank to maintain a stable financial market. For instance, the National Bank of Belgium simulates the consequences of non-repayment of interbank loans by demonstrating the time-varying structure of the Belgian interbank market (Degryse and Nguyen, 2004). The Austrian National Bank develops the Systemic Risk Monitor (SRM) (Boss et al., 2006) and the Bank of England develops the Risk Assessment Model for Systemic Institutions (RAMSI) (Alessandri et al., 2009).[16] Nier et al. (2007) analyze the impacts of different structures of banking network on systemic risk, and Erol and Ordoñez (2017) recently examine how levels of regulation affect systemic risk in interbank networks. Additionally, recent papers studying financial network have overcome limited data by using simulations. The model and assumptions used in simulation differ depending on the purpose and focus of the research. Gai and Kapadia (2010) and Gai et al. (2011) develop a model of contagion in financial networks and demonstrate the amplification of fragility as a result of complexity and concentration in a financial network. Krause and Giansante (2012) show that a network of interbank lending can be a transmission mechanism of bank failures. They allow for different bank characteristics and interactions with others to capture a more realistic financial network. Elliott et al. (2014) and Acemoglu et al. (2015) analyze the contagion of failures among interdependent financial organizations and the impacts of network structure on stability.[17]

3. Data and variables

3.1. Data

We focus on the US financial institutions to analyze the notion of being "too central to fail" in the financial system. Following Adrian and Brunnermeier (2016), we select our sample financial institutions from among companies with a standard industrial classification (SIC) code from 60 to 65 whose headquarters are located in the United States. To exclude non-financial holding companies, we do not include financial institutions whose SIC are 67.

[16] Simulation analysis of central banks recently advances to stress testing in practice while fear about the European banking crisis was pervasive. Additionally, not only Austria and England but also other countries develop or upgrade their stress testing methods, including Brazil, Canada, Chile, the Czech Republic, France, Germany, Italy, Japan, Netherlands, Norway, Spain, Sweden, Switzerland, the United States, and the European Central Bank (Schmieder et al., 2011; Ong, 2014).

[17] Other simulation studies about financial networks are summarized in Upper (2011).

We also exclude small financial institutions whose market capitalization are less than US$5 billion as of June 2007, before the global financial crisis occurred. Thus we include 92 sample financial institutions (see Table A1 in the Appendix for the list of institutions).

We collect daily stock price and quarterly balance sheet data from the Center for Research in Security Price (CRSP) and Compustat, respectively, for the sample companies from 2000 to 2016. The balance sheet data we use are the financial institutions' total assets in book value, leverage (liability to equity), and liquidity (sum of cash and short-term investments to total assets) (Tables 2 and 3).

[Table 2]

[Table 3]

We also collect daily macroeconomic variables to reflect the US economic situation. We include the S&P 500 to capture overall stock market conditions from CRSP. We use the Volatility Index (VIX) to represent the volatility of the financial market from the Chicago Board Options Exchange (CBOE). In addition, we obtain 3-month LIBOR data based on the US dollar and 3-month Treasury bill rates as money market variables from the Federal Reserve Bank of St. Louis and the Board of Governors of the Federal Reserve System, respectively. We then collect 10-year Treasury note and Baa-rated corporate bond yields as capital market variables from the Board of Governors of the Federal Reserve System and the Federal Reserve Bank of St. Louis, respectively.

3.2. Measurement variables

We represent the idea of calculating Rank and compare the Rank with well-known systemic risk measures of CoVaR (Adrian and Brunnermeier, 2016), and MES (Acharya et al., 2017) after quantifying the three measures as follows.

3.2.1. Rank

We quantify the centrality of individual financial institutions from a "too central to fail" perspective. Rank represents how much a financial institution is linked to another financial institution considering the other financial institution's weight.

First, we calculate an "effect matrix" that shows the extent to which each financial institution is connected to other financial institutions. We apply the Granger causality network of Billio et al. (2012) to make the effect matrix. Dungey et al. (2012) construct an effect matrix based on the correlation of financial institutions' stock returns. Using correlation for an effect matrix, however, cannot capture direction. That is, in terms of correlation, the effect from financial institution *i* to *j* is the same as the effect from financial institution *j* to *i*. Thus we distinguish the effect of financial institution *i* to *j* from the effect of financial institution *j* to *i*. Billio et al. (2012) apply *p*-value to calculate each financial institution's connectedness. In contrast, we use *F* statistics of the Granger causality network as the entity of the effect matrix (e_{ijt}). The use of *F* statistics rather than *p*-values can account for wider variations in order to be more specific.

Second, we calculate the value of financial institutions' centrality. Based on the entity (*i*, *j*) of the effect matrix, we normalize the effect weight of each financial institution as follows:

$$E_{ijt} = \frac{e_{ijt}}{\sum_i e_{ijt}}$$

where e_{ijt} denotes the extent of the effect from financial institution *i* to *j* at time *t*, and E_{ijt} means the effect weight on financial institution *j* from *i* at time *t*. We then apply the PageRank algorithm (Page et al., 1999) to obtain Rank.

$$Rank_{it} = \frac{(1-\alpha)}{N} + \alpha \sum E_{ijt} Rank_{jt}$$

where $Rank_{it}$ is the Rank of firm *i* at time *t*, α is called a dumping factor and is usually set to be 0.85, and *N* is the total number of firms in the system. Rank has always a positive value, and a higher Rank value means that the firm has a greater contribution to systemic risk in the network structure.

3.2.2. CoVaR

Conditional value at risk (CoVaR) measures an individual firm's contribution to systemic risk. We use quantile regression to calculate CoVaR following Adrian and Brunnermeier (2016). We can reflect extreme market situations by relaxing the assumption of error term's normal distribution. The quantile regression model to calculate CoVaR is as follows:

$$X_t^i = \alpha^i + \gamma^i M_{t-1} + \varepsilon_t^i$$

$$X_t^{system} = \alpha^{system/i} + \beta^{system/i} X_t^i + \gamma^{system/i} M_{t-1} + \varepsilon_t^{system/i}$$

where X_t^i the is stock return of firm *i* at time *t*, M_{t-1} is the vector of state variable at time *t*-*1*, and X_t^{system} is the index return at time *t*.

We select state variables generally following Adrian and Brunnermeier (2016). VIX, TED spread, changes in 3-month T-bill rate, maturity spread, credit spread, and return on S&P 500 are used. Details on the variables are provided in Table 2.

We obtain estimated values of α^i, γ^i, $\alpha^{system/i}$, $\beta^{system/i}$, and $\gamma^{system/i}$ using quantile regression. Using estimated parameters from the regression, we obtain the value at risk (VaR) and conditional value at risk (CoVaR) for each firm. Then, we calculate $\Delta CoVaR_t^i$ following the equation

$$VaR_t^i(q) = \hat{\alpha}^i + \hat{\gamma}^i M_{t-1}$$

$$CoVaR_t^i(q) = \hat{\alpha}^{i^{system/i}} + \hat{\beta}^{i^{system/i}} VaR_t^i(q) + \hat{\gamma}^{i^{system/i}} M_{t-1}$$

$$\Delta CoVaR_t^i\,(q) = CoVaR_t^i(q) - CoVaR_t^i(50\%)$$

where $\Delta CoVaR_t^i$ is a proxy for contribution to systemic risk; hereafter we simply call it CoVaR for convenience.

CoVaR usually has a negative value, and a small CoVaR could be interpreted as a greater contribution to systemic risk.

3.2.3. MES

Marginal expected shortfall (MES) is also the measure of an individual firm's contribution to systemic risk (Acharya et al., 2017). Compared to CoVaR, MES averages a firm's stock return on the condition that financial market is based on the lowest returns. The formula for MES is as follows:

$$MES_{5\%}^{i} = -E\left[X_t^i \mid I_{5\%}\right]$$

where X_t^i is the stock return of firm *i* at time *t*, and $I_{5\%}$ denotes index return when the index is in the lowest 5%. MES is usually larger than 0, and a larger value for MES can be interpreted as more contribution to systemic risk.

4. Simulation methodology

We construct a simple but reasonable simulation model to show whether Rank reflects network information compared to other measures. We may prove it theoretically or empirically to check that the measure truly reflects network information. Given the complexity of network relationships of multiple financial institutions as Krause and Giansante (2012) noted, however, it is hard to derive analytic solutions to show that the measure illustrates network information. We could not empirically show the effectiveness of Rank using real data, as information about bilateral exposure between financial institutions is not released publicly.

4.1. Banking system

We assume a hypothetical banking system in simulation model with each financial institution holding primitive assets (any factors of production or other investments) as portfolio.[18] Then the values of financial institutions depend on the values of primitive assets (hereafter simply assets). We can track varying values of financial institutions based on changing values of assets. We set the number of financial institutions and assets in the banking system, respectively. There exist $i = 1, 2, \ldots, N$ financial institutions in the banking system. There are $j = 1, 2, \ldots, M$ assets whose price movements follow geometric Brownian motion (GBM). The price movements of assets are independent of each other. Each financial institution can have several assets by choosing whether

[18] Based on Elliott et al. (2014), the idea that each financial institution has primitive assets portfolio in the banking system simplifies the development of simulations. The primitive assets can extend to debts and other contracts. We can also assume various cases in the experiments: we can examine different number of financial institutions, assets, or structure of balance sheet. In addition, we can prevent problems from model selection that can manipulate simulation results.

they hold each asset at random. Figure 3 depicts the price movement of assets using the GBM.

[Figure 3]

Total assets of financial institutions are composed of two types of assets (Figure 4). One is an equity-type asset, and the other is a liability-type asset.[19] The asset composition of financial institutions is decided randomly in the initializing simulation and will remain fixed.

[Figure 4]

The total equity-type asset of financial institution *i* is the sum of assets that follows GBM (Figure 5).

$$EtAsset_{i,t} = \sum_j P_{j,t} * w_{ij}$$

where $EtAsset_{i,t}$ is the sum of equity-type assets of institution *i* at time *t*, $P_{j,t}$ is price of asset *j* at time *t*, and w_{ij} denotes amount of assets that asset *j* belongs to financial institution *i*.

[Figure 5]

4.2. Interbank network

Financial institutions have liability relationships with each other in the simulation model. That is, one financial institution may lend capital to another financial institution in random. The total liability-type asset of financial institution *i* is the sum of liability connections considering depreciation such as loan loss (Figure 6).

$$LtAsset_{i,t} = \sum_j c_{i,j} * min\left(\frac{\boldsymbol{E_{j,t-1}}}{\boldsymbol{E_{j,0}}}, 1\right)$$

where $LtAsset_{i,t}$ is the sum of liability-type assets of institution *i* at time *t*, $c_{i,j}$ denotes the debt obligation of firm *j* that belongs to institution *i*, and $\boldsymbol{E_{j,t}}$ is total equity of financial institution *j* at time *t*.

[Figure 6]

The initial state of liability and equity for each firm will be decided by randomly selected leverage. Then, liability will be fixed (Figure 7).

$$EtAsset_{i,o} + LtAsset_{i,o} = \boldsymbol{E_{i,0}} + \boldsymbol{L_i}$$

where $\boldsymbol{E_{i,0}}$ is the total equity of financial institution *i* at time 0, and $\boldsymbol{L_i}$ is the total liability of financial institution *i*. The market value of each firm is equal to its book value of equity.

[Figure 7]

We note that liability-based connection among financial institutions were more important than equity

[19] We construct a stylized balance sheet of individual financial institutions extending Nier et al. (2007) and Krause and Giansante (2012). We focus on the assets and liabilities that connect financial institutions each other instead of including all kinds of assets and liabilities.

connections because equity connections are easy to unwind. Recall that equity investors can sell stocks at any time when they want. However, Battiston et al. (2012) and Elliott et al. (2014) focus on equity-based connections among financial institutions. Therefore, their value of a firm's connections linearly depends on each firm's market value. In our simulation model, therefore, we make liability-type price functions as in Figure 8. The value of liability-type assets is only changed if the equity of the firm is lower than its initial value. The equity-based connection can also be covered by equity-type assets.

[Figure 8]

4.3. Shock and default mechanism

A shock influences multiple financial institutions through financial linkages because a shock in financial institutions spreads to other financial institutions. We define a default if the equity of a financial institution becomes zero. We then define a shock as a plunge in the equity-type assets of a financial institution. Thus the probability of a default increases if the level of shock is disruptive, and vice versa.

The simulation model focuses on default from both asset and liability (Figure 9). Financial institutions are more likely to default when they do not hold enough asset and liability. If equity-type assets of a financial institution *1* become fragile because of a shock from GBM, its equity may plunge in the first round. It induces impairment of liability-type assets of other financial institutions *2* and *3* that have claims on *1* in the second round. While depreciation such as loan loss occurs in liability-type assets, the equity of financial institution *2* and *3* may plunge. This chain reaction continues in neighboring financial institutions and makes entire financial system vulnerable.[20]

[Figure 9]

4.4. Parameter calibration

We estimate parameters to generate asset movements that follow geometric Brownian motion (GBM). The simple GBM used in simulations is as follows:

$$S_t = S_0 e^{X_t}$$

$$\mathrm{X_t} = \sigma B(t) + \mu t$$

[20] The lesson from the global financial crisis made us model simulations conservatively. Financial institutions can endure a shock longer through selling assets at a discounted price in reality, i.e., file sale. However, financial institutions in simulations are much more vulnerable to shock. They are directly exposed to drops in asset prices because the structure including assets and liability is fixed in the simulation model. In other words, they do not have buffer to remain liquidity in simulations in case of a shock.

where S_t denotes asset price at time t, S_0 means asset price at time 0, and $B(t)$ is the standard Brownian process. Specifically, we use risk-neutral GBM, and the drift (μ) and volatility term (σ) are as follows:

$$\mu^* = r - \sigma^2/2$$

$$\sigma^* = \sigma$$

where r is the mean of asset returns and σ^2 is the variance of asset returns.

We use the S&P 500 to estimate the parameters of the mean and variance of asset returns. We differentiate regimes after examining low and high peaks in the time series (Table A2 in the Appendix). Then we calculate the mean and variance of the asset returns of each period. In our simulations, we assign the mean and variance of asset return returns between minimum and maximum values, respectively. The two parameters are set following uniform distribution and negatively associated.

5. Centrality dynamics of financial networks

We analyze the impacts of key parameters on centrality through simulation experiments. We can adjust some characteristics of financial networks by changing parameters: the percentage of equity capitalization in financial institutions (*C*), the number of financial institutions in simulations (*N*), the proportion of equity-type assets (*E*) and liability-type assets (*L*) in balance sheet of financial institutions (Table 4). We keep total number of primitive assets in the financial system (*A*) constant based on Nier et al. (2007). Then we vary one parameter at a time and analyze the effects on centrality of financial networks using Rank. We repeat the simulation experiments 100 times and report average values.

[Table 4]

First, we investigate the effects of equity (*C*) of financial institutions on financial networks. Figure 10 (a) reports the decreasing centrality as the percentage of equity increases. Although the trend is not clearly monotonic, we note that maximum of Rank is high if the percentage of equity is close to low end of the range. As financial institutions remain low equity (i.e. business strategy using high leverage), they can save the costs from equity financing and pursue high efficiency in financial ratios. However, the lessons from the global financial crisis lead to more capital buffers on major financial institutions in the world (i.e. systemically important financial institutions). This is in line with the argument that bank equity is not costly (Admati et al., 2013).

Second, we examine the effects of the number of financial institutions in simulations on financial networks (*N*). The maximum Rank peaks if the number of financial institutions is close to zero (Figure 10 (b)). Then the Rank converges to lower values as the number of financial institutions increase from 0 to 30. We assume that a handful of financial institutions occupy so many transactions in lending and borrowing behaviors that the Rank of financial institutions increases. Although one cannot control the concentration in the real financial markets, the results illustrate that the resilience of the system can be affected negatively from small number of financial intermediaries.

Third, we investigate the effects of asset structure of financial institutions on Rank. Figure 10 (c) represents irregular pattern of Rank. We observe high Ranks in the low and high end of the range in equity-type assets. However, there is also an increase in Rank in middle of the range. This is because we assume that we do not divide asset side of financial institutions in detail. For instance, Krause and Giansante (2012) divide asset side of banks as cash, loans, and interbank loans. On the contrary, the asset side consists of equity-type and liability-type assets in our simulations. We remain the impacts of asset structure of financial institutions on the centrality for the future research.

6. Empirical analysis

6.1. Analysis based on simulation

We simulate stock data, firm characteristics, and network structure following the simulation methodology described in the previous section. For each simulation trial, we set the number of assets at N = 1,000, the number of financial institutions at M = 100, and the window length as 300 days. We conduct the simulation 100 times to consider various cases. We also perform the simulation 10,000 times for robustness; however, the results are qualitatively the same. We report empirical results of 100 simulations in this paper. The baseline model of regression analysis is as follows:

$$Measure_{i,t} = \alpha + \beta \cdot Firm\ characteristic_{i,t} + \gamma \cdot Macroeconomic_t + \epsilon_{i,t}$$

where $Measure_{i,t}$ denotes the calculated measures (*Rank*, *CoVaR*, or *MES*) of firm i at trial t, and $Firm\ characteristic_{i,t}$ includes a firm's size, leverage, liquidity, and network connections. We use size as a logarithm of the book value of total assets, leverage as liability over equity, liquidity as equity-type assets to total assets, and network connections as the number of liability connections where the amount of liability-type assets exceeds 0.5% of total assets. $Macroeconomic_t$ includes volatility, which is defined as the standard deviation of the index (a summation of all assets is considered the index in the simulated financial system).

The estimation results in Table 5 show the impact of firm characteristics and network structure on Rank. The results show that firm size has a significantly positive effect on Rank, which means that as the financial institution gets larger, it holds a higher Rank, which is in accordance with being "too big to fail." On the contrary, liquidity has a significantly negative effect on Rank. We infer that Rank gives less value to firms with sufficient cash or cash equivalent. The results are consistent with previous research in that shock may not propagate to other financial institutions when a financial institution has sufficient liquidity. Additionally, network connections have a significantly positive effect on Rank, which is the most remarkable result. This means that Rank gives greater weight to financial institutions that have more connections with other financial institutions. This result supports the "too central to fail" argument. Note that we mention that CoVaR and MES are not associated with network connections in the following results. We argue that Rank is the only measure capturing the network structure from stock data. Lastly, the results illustrate that market volatility has no significant effect on Rank. Thus, we could say that Rank is not a procyclical measure, which means that Rank can detect systemic risk equivalently in both normal and crisis periods.

[Table 5]

Tables 6 and 7 show the results when the dependent variable is changed to CoVaR or MES. Specifically, firm size has a significantly positive effect on CoVaR, and leverage has a positive effect on MES. CoVaR represents market pressure when a firm is experiencing bad days, while MES reflects a firm's average return when the market is in a bad situation. It is reasonable that size rather than leverage is the dominant factor in CoVaR. In contrast, leverage rather than firm size is the dominant factor in MES. Additionally, the results show that liquidity has a significantly negative effect on both measures. We can interpret them in the same way as before. Lastly, the results show that network connections have no significant effect on either measure. Thus, we could say that CoVaR and MES are less capable of capturing network information.

[Table 6]

[Table 7]

Risk measures using stock data usually have procyclical properties. "Procyclical" means the measure has a strong correlation to market conditions. In other words, a particular measure tends to grow when the economy grows and tends to decline when the economy declines. We note that market volatility has a significant effect on CoVaR and MES but not on Rank. This means that Rank is the only measure that does not have procyclical properties. Thus financial institutions' contribution to systemic risk can be captured well regardless of market conditions.

6.2. Analysis based on real market data

We examine whether Rank captures network relationships using real market data. We quantify Rank, CoVaR, and MES for the sample US financial institutions. We calculate each measure over a 1-year window. The baseline model of the panel regression is as follows:

$$Measure_{i,t} = \alpha + \beta \cdot Firm\ characteristic_{i,t} + \gamma \cdot Macroeconomic_t + \epsilon_{i,t}$$

where $Measure_{i,t}$ denotes calculated measures (*Rank*, *CoVaR*, and *MES*), and $Firm\ characteristic_{i,t}$ includes the size, leverage, liquidity, and network connections of financial institution *i* at time *t*. We use size as a logarithm of the book value of total assets, leverage as liability to equity, liquidity as the sum of cash and short-term investments to total assets, and network connections as the number of connections whose p-value on the Granger causality network was less than 0.05. $Macroeconomic_t$ includes VIX, Ted spread, maturity spread, and credit spread. Additionally, Firm classification is a dummy variable based on SIC classification (see Table A1 in the Appendix in detail).

The estimation results in Table 8 show that network connection has a significantly positive effect on Rank. This result supports the finding that Rank can capture network structure, as indicated by the previous empirical analysis based on the simulation. However, firm size does not have a significant effect on Rank, which is inconsistent with previous empirical analyses based on simulations. We assume that Rank cannot capture the difference by firm size, because we focus on big financial institutions.

[Table 8]

Focusing on macroeconomic variables, the results illustrate that Rank is not a procyclical measure. VIX and maturity spread have no significant effect on Rank. Additionally, TED and credit spread have significantly negative and positive effects, respectively. Higher values denote that a financial market is in bad condition, as VIX represents uncertainty and TED represents market fear of interbank money markets. Maturity and credit spread also indicate higher costs for maturity and credit risk, respectively. Lastly, firm classification has no significant effect on Rank. Thus we can say that Rank is not affected by the type of financial institutions.

Table 9 shows the estimation results when the dependent variable is CoVaR. We find that firm size has a significantly positive effect on CoVaR. This result is consistent with our previous results in the empirical analysis based on the simulations. However, leverage has a significantly negative effect on CoVaR, which differs from the empirical analysis based on the simulations. Existing research argues that more-leveraged financial institutions tend to contribute more to systemic risk. CoVaR does not effectively capture leverage information in our analysis. Additionally, the results show that network connection has no significant effect on the measure; thus, we can suggest that CoVaR cannot capture network structure. Furthermore, all macroeconomic variables have a significantly positive effect on CoVaR. Thus, we can say that CoVaR is a procyclical measure. Lastly, as to the type of financial institutions, non-depository institutions tend to have larger CoVaR than depository institutions. Insurance firms have a smaller CoVaR than depositories. Broker-dealers show no significant difference from depositories.

[Table 9]

Table 10 illustrates the case of dependent variable MES. The results show that firm size and leverage have a significantly positive effect on MES. However, network connections have a weak negative effect on MES. It is intuitive that a highly connected firm has a larger contribution to systemic risk. In that sense, MES cannot capture network structure well. Additionally, all macroeconomic variables have a significantly positive effect on MES. Thus we can say that MES is also a procyclical measure, as CoVaR is. Lastly, the type of financial institution shows no difference for the measure, except for non-depositories, which tend to have larger MES value than other types of firms.

[Table 10]

To sum up, when checked empirically, Rank is the only measure that can consider a firm’s network structure from stock data. In addition, we show that Rank is not a procyclical measure, so it could have consistent value regardless of market condition. However, Rank seems unable to capture traditional properties like size and leverage in the empirical analysis.

7. Conclusion

The concept of being “too central to fail” has been on the rise recently since being “too big to fail” or “too connected to fail” received attention during the global financial crisis. The methodology of BCBS (2011) includes the category of interconnectedness to identify systemically important financial institutions (SIFIs). However, the existing measures do not fully consider the centrality of financial institutions.

First, this paper proposes a simulation model that considers centrality of financial institutions. We assume the number of financial institutions and assets, and financial institutions decide to hold how many assets they have as their portfolio. This simplifies the simulation model and prevents problems from model selection. The new method also uses market data to measure a financial institution’s contribution to systemic risk. Analyzing a balance sheet cannot consider complex network of financial institutions. Because a balance sheet has time lags to be released, a balance sheet does not reflect current situations. Additionally, a balance sheet just includes information in structured formats and does not show implicit connections among financial institutions such as common exposure.

Second, we show the impacts of network characteristics on the centrality in the simulations. We examine the effects of the centrality by adjusting key parameters in the simulations. We find that the centrality increases as the percentage of equity in financial institutions and the number of financial institutions decrease. Additionally, we prove that the measure reflects the network structure using both simulation and real market data. We compare Rank with two other well-known measures, CoVaR and MES. The results show that Rank captures network structure more accurately than the other two measures. Rank also shows non-procyclical characteristics.

A policy implication of this research is that regulators should consider an additional measure to reflect financial network. We suggest that considering centrality of financial institutions can achieve a goal of financial stability more effectively. If financial institutions are identified as SIFIs, they should hold capital buffers. This is in line with recent papers including Admati et al. (2013) that argue further capitalization for banks. They support that bank capitalization such as BaselⅢ agreement can be beneficial rather than expensive. In the real world, it is hard to access the proper network information to apply to the network structures due to the opaqueness of financial institutions. Currently, market data can be an alternative to access network structure. Policy makers can utilize our simulation model and predict possible results when they design financial regulations.

The paper proposes new avenues for future research. For example, future research could deal with improving the centrality measure by including various characteristics of firms. Our empirical results suggest that Rank only reflects network structure, not other characteristics of firms such as size or leverage. This problem could be solved by using an adapted version of the PageRank algorithm, suggested by Dungey et al. (2012). Previous research has added a firm’s characteristic weight, like the firm’s size, leverage, and liquidity, instead of a dumping factor.

Acknowledgements

The authors sincerely thank the editor and anonymous reviewers for their constructive comments. The authors would like to thank useful comments on the conference “Finance and Economic Growth in the Aftermath of the Crisis” on Milan, Italy (11-13 September 2017).

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Figure 1. Scheme of “too big to fail”, “too connected to fail”, and “too central to fail”

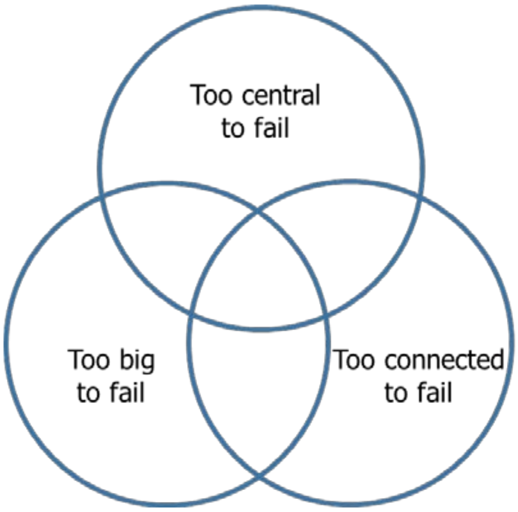
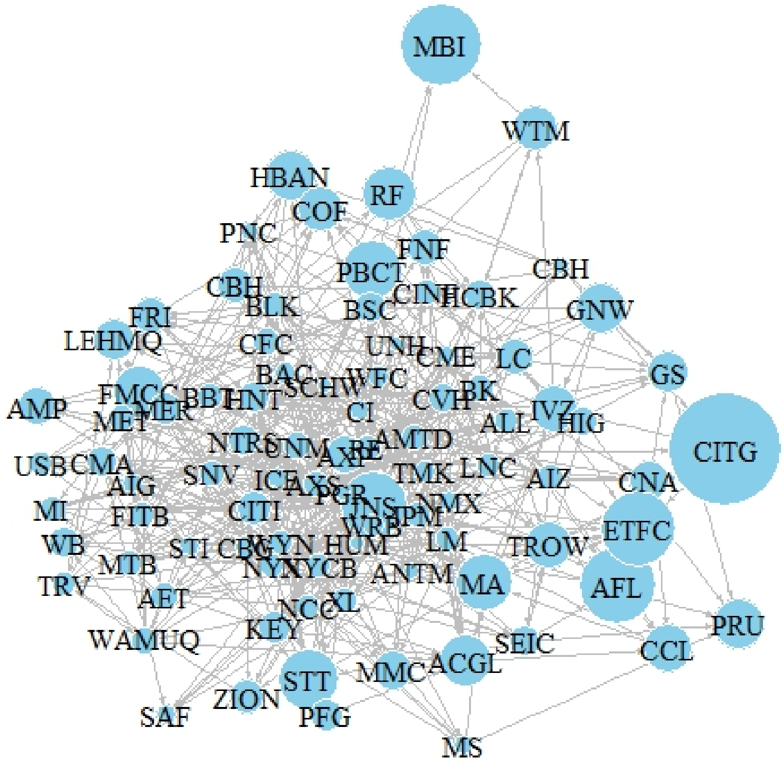
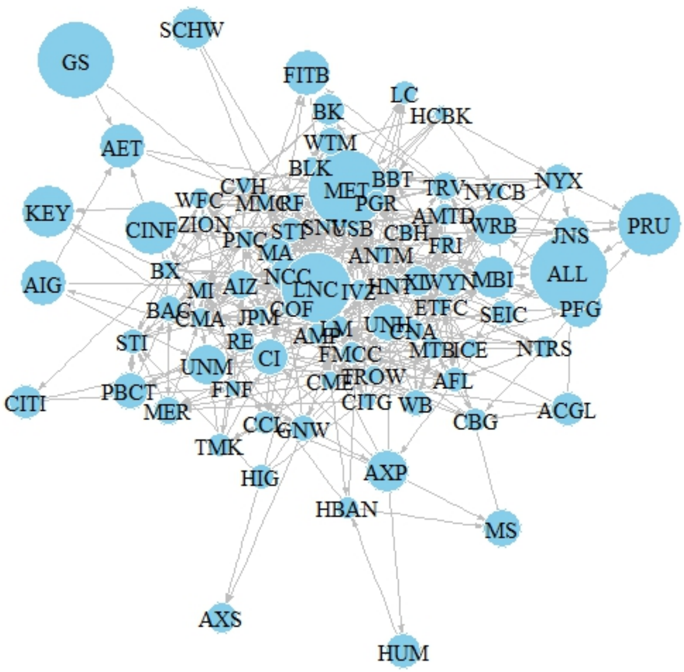


Figure 2. Centrality of the US financial institutions using Rank

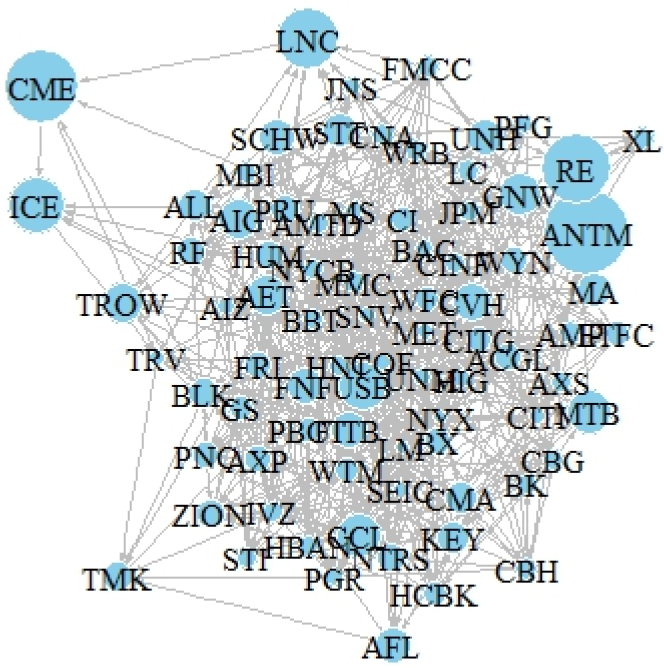
(a) Year of 2007



(b) Year of 2008

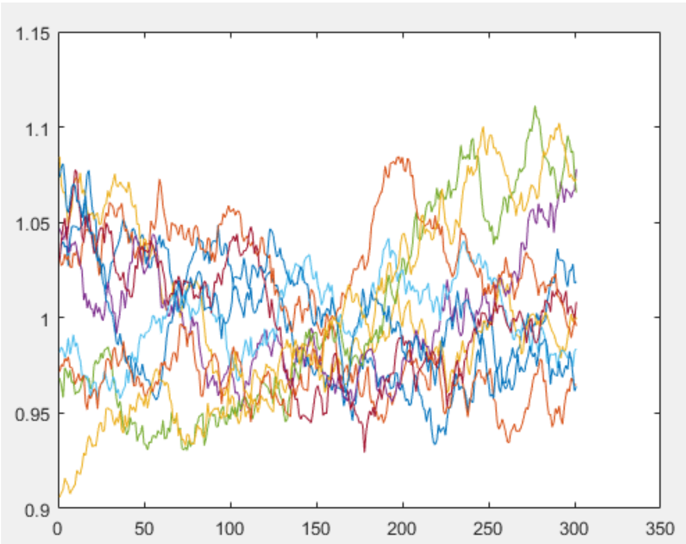


(c) Year of 2012



Notes: Edges denote connections between financial institutions while size of nodes implies the level of Rank.

Figure 3. Price movement of assets under GBM



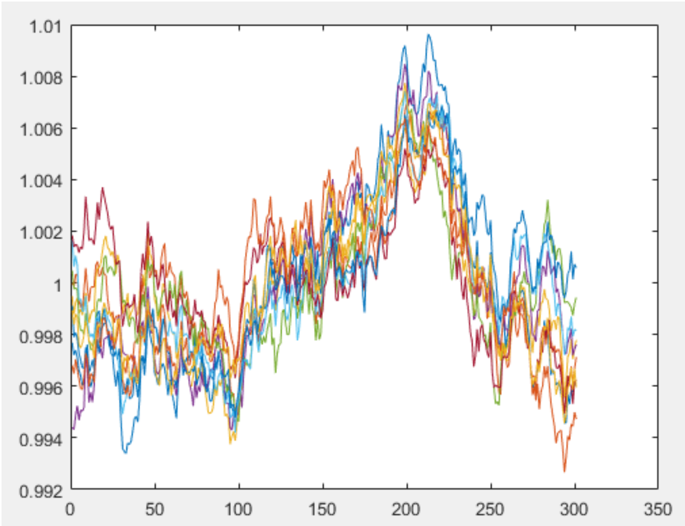
Notes: We assume that there are N assets whose price movements follow geometric Brownian motion (GBM). Their price movements are independent of each other.

Figure 4. Balance sheet framework in simulation

Assets	Liabilities
Liability-type asset (L)	Liability
Equity-type asset (E)	Equity (C)

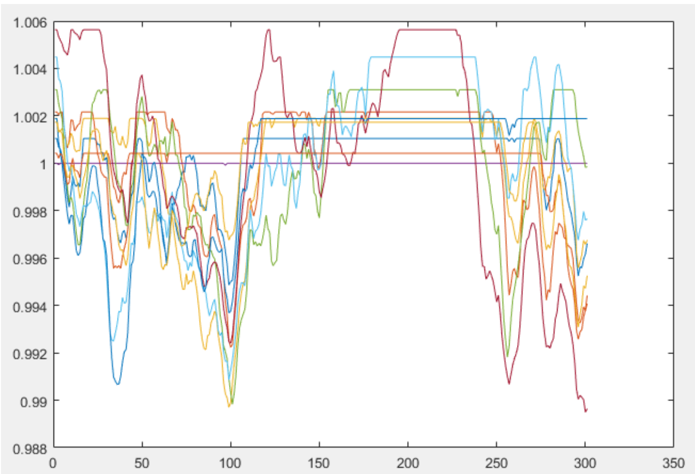
Notes: We suppose simple balance sheet framework. Total assets of financial institutions are divided to two types of assets. One is equity-type asset, and the other is liability-type asset.

Figure 5. Equity-type asset movement in simulation



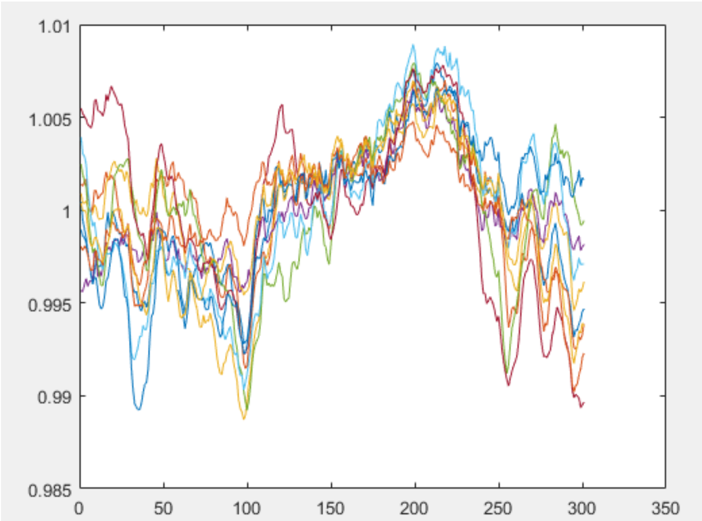
Notes: We assume that total equity-type assets of financial institution are the sum of assets that follow GBM.

Figure 6. Liability-type asset movement in simulation



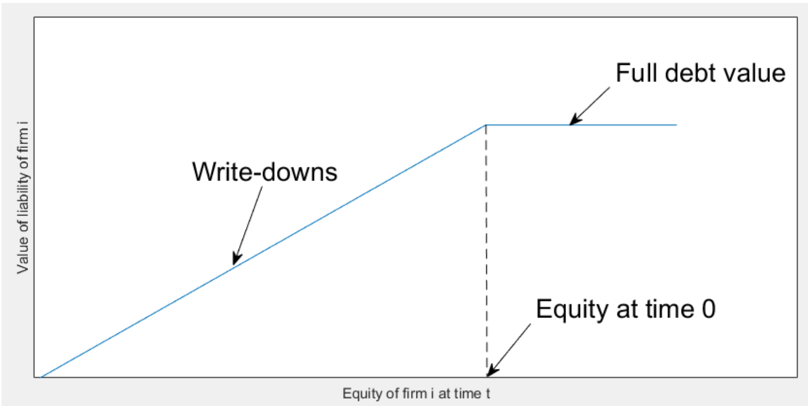
Notes: We assume that total liability-type assets of financial institution are the sum of debt obligation considering depreciation (loan loss).

Figure 7. Equity value changes in simulation



Notes: The equity of financial institution changes as equity-type and liability-type assets changes.

Figure 8. Function of liability value changes



Notes: The value of liability-type asset is only changed if the equity of the financial institution is lower than initial value.

Figure 9. Default mechanism

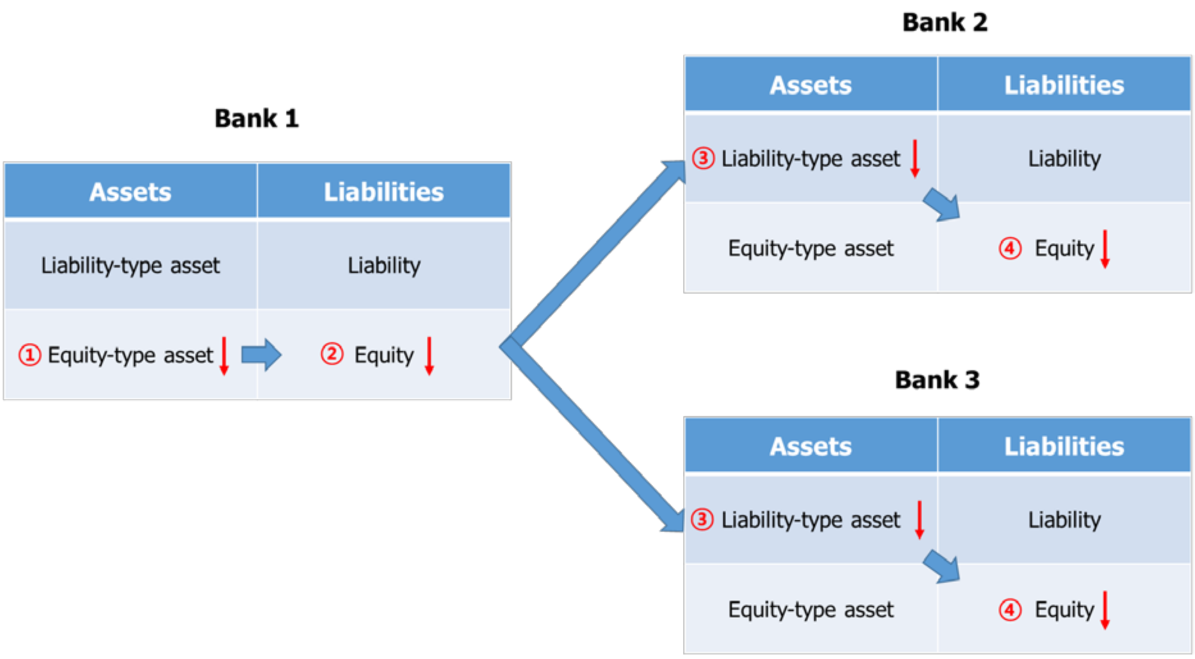
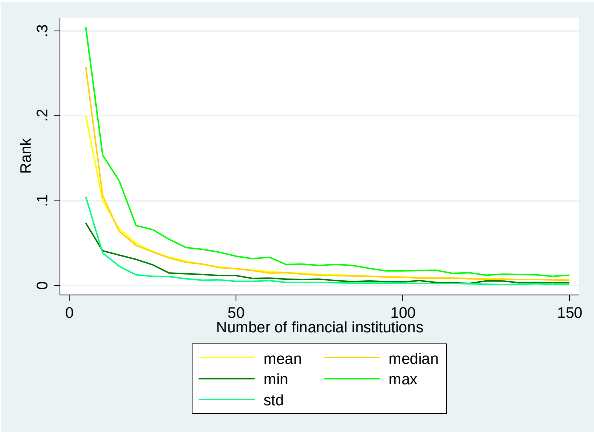


Figure 10. Rank changes depending on parameters

(a) Capitalization and centrality

(b) Concentration and centrality



(c) Asset structure and centrality

Table 1. Indicator-based measurement approach

Category (weight)	**Individual indicator**	**Indicator weight**
Cross-jurisdictional activity (20%)	Cross-jurisdictional claims	10%
	Cross-jurisdictional liabilities	10%
Size (20%)	Total exposures as defined for use in the BaselⅢ leverage ratio	20%
Interconnectedness (20%)	Intra-financial system assets	6.67%
	Intra-financial system liabilities	6.67%
	Wholesale funding ratio	6.67%
Substitutability/financial institution infrastructure (20%)	Assets under custody	6.67%
	Payments cleared and settled through payments systems	6.67%
	Values of underwritten transactions in debt and equity markets	6.67%
Complexity (20%)	OTC derivatives notional value	6.67%
	Level 3 assets	6.67%
	Held for trading and available for sale value	6.67%

Source: BCBS (2011)

Table 2. Variable definitions and data sources

Variables	Definition	Sources
Measurement		
Rank	Measure of centrality of individual financial institutions from 'Too central to fail' perspective	Author's calculation based on Page et al. (1999) and Billio et al. (2012)
CoVaR	Extent of contribution to systemic risk of individual financial institutions	Author's calculation based on Adrian and Brunnermeier (2016)
MES	Average stock return of individual financial institutions on the condition that financial market is in the worst return	Author's calculation based on Acharya et al. (2017)
Firm characteristics		
Size	Total asset in book value of individual financial institutions	Compustat
Leverage	Liability to equity ratio of individual financial institutions	Compustat
Liquidity	Sum of cash and short-term investment to total asset ratio of individual financial institutions	Compustat
Network connection	Bilateral network relationships between financial institutions distinguishing effect to and from another financial institution	Author's calculation based on Billio et al. (2012) and Jeong and Park (2018)
Macroeconomic variables		
S&P 500	Index of Standard and Poor's 500	CRSP
VIX	Volatility index on S&P 500 stock index option prices	CBOE
TED spread	Difference between 3-month LIBOR based on US dollar and 3-month Treasury bill rate	Federal Reserve Bank of St. Louis Board of Governors of the Federal Reserve System
Maturity spread	Difference between 3-month Treasury bill and 10-year Treasury bond rate	Board of Governors of the Federal Reserve System
Credit spread	Difference between 10-year Treasury bond and Baa-rated corporate bond yield	Board of Governors of the Federal Reserve System Federal Reserve Bank of St. Louis

Table 3. Summary statistics

Variables	Observation	Mean	Standard deviation	Min	Max
Measurement					
Rank	5,272	0.0123	0.0055	0.0038	0.0593
CoVaR	5,272	0.0147	0.0111	-0.0026	0.0882
MES	5,272	0.0333	0.0272	-0.0070	0.2159
Firm characteristics					
Size (million USD)	5,711	169,596.1	352,538.2	207.5180	2,577,148
Leverage	5,711	7.1622	5.7796	0.0320	50.8369
Liquidity	5,711	0.1375	0.1402	0.0012	0.9081
Network connection	5,272	1	0.9683	0	9.3729
Macroeconomic variables					
VIX	6,256	20.7412	7.0320	12.6349	49.3615
TED spread (%)	6,256	0.4159	0.3506	0.1621	1.6226
Maturity spread (%)	6,256	1.9110	1.0777	-0.2482	3.4266
Credit spread (%)	6,256	2.1159	0.5999	1.3035	4.6473

Table 4. Parameters of the simulation model

Parameter	Definition	Benchmark	Range of variation
A	Total number of primitive assets in the financial system	1000	Fixed
C	Proportion of equity in financial institutions	20%	11-25%
N	Number of financial institutions in the simulation	100	5-150
E	Proportion of equity-type assets in financial institutions	90%	81-99%
L	Proportion of liability-type assets in financial institutions	10%	1-19%

Notes: Sum of equity-type and liability-type assets should be one (E + L = 1).

Table 5. Impact of network connection on Rank in simulation analysis

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.00692***	0.0326***	0.00678***	0.0324***	0.0324***	0.00986***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm characteristics						
Size	0.000528***	0.000974***	0.000531***	0.000977***	0.000977***	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Leverage	-0.0000836	-0.0000777	-0.0000849	-0.0000792	-0.0000792	
	(0.39)	(0.41)	(0.39)	(0.41)	(0.41)	
Liquidity		-0.0318***		-0.0318***	-0.0318***	
		(0.00)		(0.00)	(0.00)	
Network connection			0.0000179*	0.0000194**	0.0000194**	0.0000173*
			(0.06)	(0.03)	(0.03)	(0.06)
Macroeconomic variable						
Market volatility					2.791	
					(0.84)	
Observations	10,000	10,000	10,000	10,000	10,000	10,000
R-squared	0.0024	0.0641	0.0028	0.0646	0.0646	0.0004

Notes: *p* value in parentheses, **p*<0.10, ***p*<0.05, ****p*<0.01

Table 6. Impact of network connection on CoVaR in simulation analysis

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.0178*	0.0466***	0.0183*	0.0470***	0.00387	0.0366***
	(0.09)	(0.00)	(0.08)	(0.00)	(0.78)	(0.00)
Firm characteristics						
Size	0.00315**	0.00365***	0.00314**	0.00364***	0.00373***	
	(0.02)	(0.01)	(0.02)	(0.01)	(0.00)	
Leverage	-0.000496	-0.000490	-0.000492	-0.000485	-0.000351	
	(0.67)	(0.68)	(0.67)	(0.68)	(0.73)	
Liquidity		-0.0356**		-0.0356**	-0.0332**	
		(0.02)		(0.02)	(0.01)	
Network connection			-0.0000613	-0.0000596	-0.0000759	-0.0000646
			(0.58)	(0.59)	(0.44)	(0.56)
Macroeconomic variable						
Market volatility					8,293.7***	
					(0.00)	
Observations	10,000	10,000	10,000	10,000	10,000	10,000
R-squared	0.0006	0.0012	0.0006	0.0012	0.2381	0.0000

Notes: Dependent variables were multiplied by 10,000 to make the coeficients of the variables easier to recognize.

p value in parentheses, **p*<0.10, ***p*<0.05, ****p*<0.01

Table 7. Impact of network connection on MES in simulation analysis

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.156	1.871***	0.164	1.877***	0.752***	0.855***
	(0.45)	(0.00)	(0.43)	(0.00)	(0.00)	(0.00)
Firm characteristics						
Size	-0.00859	0.0212	-0.00871	0.0211	0.0234	
	(0.74)	(0.41)	(0.74)	(0.42)	(0.24)	
Leverage	0.150***	0.150***	0.150***	0.150***	0.154***	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Liquidity		-2.126***		-2.125***	-2.064***	
		(0.00)		(0.00)	(0.00)	
Network connection			-0.000987	-0.000889	-0.00133	-0.000876
			(0.65)	(0.68)	(0.43)	(0.69)
Macroeconomic variable						
Market volatility					216,338.2***	
					(0.00)	
Observations	10,000	10,000	10,000	10,000	10,000	10,000
R-squared	0.0042	0.0092	0.0042	0.0092	0.4230	0.0000

Notes: Dependent variables were multiplied by 10,000 to make the coeficients of the variables easier to recognize.

p value in parentheses, **p*<0.10, ***p*<0.05, ****p*<0.01

Table 8. Impact of network connection on Rank in empirical analysis

	(1)	(2)	(3)	(4)
Constant	0.0124***	0.0117***	0.0128***	0.0121***
	(0.00)	(0.00)	(0.00)	(0.00)
Firm characteristics				
Size	-0.0000506	-0.0000948	-0.0000835	-0.000136*
	(0.49)	(0.22)	(0.26)	(0.09)
Leverage	0.00000442	0.0000225	0.0000104	0.0000334
	(0.83)	(0.30)	(0.65)	(0.16)
Network connection	0.000351***	0.000353***	0.000353***	0.000356***
	(0.00)	(0.00)	(0.00)	(0.00)
Macroeconomic variables				
VIX		-0.0000104		-0.0000157
		(0.63)		(0.47)
TED spread		-0.00136***		-0.00133***
		(0.00)		(0.00)
Maturity spread		-0.0000435		-0.0000323
		(0.61)		(0.70)
Credit spread		0.000906***		0.000951***
		(0.00)		(0.00)
Firm classification dummy				
Non-depositories			-0.000508	-0.000501
			(0.11)	(0.11)
Insurances			0.000221	0.000254
			(0.41)	(0.34)
Broker-dealers			-0.000216	-0.000315
			(0.63)	(0.47)
Observations	5,256	5,256	5,256	5,256
R-squared	0.0036	0.0106	0.0059	0.0131

Notes: *p* value in parentheses, *p<0.10, **p<0.05, ***p<0.01

Table 9. Impact of network connection on CoVaR in empirical analysis

	(1)	(2)	(3)	(4)
Constant	0.00325*	-0.0370***	0.00343*	-0.0367***
	(0.07)	(0.00)	(0.07)	(0.00)
Firm characteristics				
Size	0.00106***	0.00257***	0.00110***	0.00255***
	(0.00)	(0.22)	(0.00)	(0.00)
Leverage	-0.0000382	-0.000305***	-0.0000421	-0.000311***
	(0.42)	(0.00)	(0.41)	(0.00)
Network connection	0.0000463	0.0000147	0.0000312	0.0000129
	(0.78)	(0.84)	(0.85)	(0.86)
Macroeconomic variables				
VIX		0.000775***		0.000775***
		(0.00)		(0.00)
TED spread		0.00920***		0.00920***
		(0.00)		(0.00)
Maturity spread		0.000676***		0.000676***
		(0.00)		(0.00)
Credit spread		0.00230***		0.00230***
		(0.00)		(0.00)
Firm classification dummy				
Non-depositories			0.00103	0.00161**
			(0.20)	(0.01)
Insurances			-0.00162**	-0.00146**
			(0.02)	(0.01)
Broker-dealers			-0.00128	0.000243
			(0.25)	(0.79)
Observations	5,256	5,256	5,256	5,256
R-squared	0.0115	0.7406	0.0209	0.7558

Notes: *p* value in parentheses, *p<0.10, **p<0.05, ***p<0.01

Table 10. Impact of network connection on MES in empirical analysis

	(1)	(2)	(3)	(4)
Constant	0.0113**	-0.0653***	0.00622	-0.0675***
	(0.02)	(0.00)	(0.22)	(0.00)
Firm characteristics				
Size	0.00162***	0.00369***	0.00194***	0.00376***
	(0.00)	(0.00)	(0.00)	(0.00)
Leverage	0.000641***	0.000129*	0.000624***	0.000112
	(0.00)	(0.08)	(0.00)	(0.14)
Network connection	-0.000311	-0.000351*	-0.000356	-0.000360*
	(0.43)	(0.07)	(0.36)	(0.07)
Macroeconomic variables				
VIX		0.00135***		0.00136***
		(0.00)		(0.00)
TED spread		0.0273***		0.0272***
		(0.00)		(0.00)
Maturity spread		0.00235***		0.00233***
		(0.00)		(0.00)
Credit spread		0.00673***		0.00668***
		(0.00)		(0.00)
Firm classification dummy				
Non-depositories			0.00991***	0.00912***
			(0.00)	(0.00)
Insurances			-0.00157	-0.00229
			(0.41)	(0.15)
Broker-dealers			0.00129	0.00483*
			(0.67)	(0.05)
Observations	5,256	5,256	5,256	5,256
R-squared	0.0292	0.6868	0.0537	0.7180

Notes: p value in parentheses, *p<0.10, **p<0.05, ***p<0.01

Appendix

Table A1. List of sample financial institutions

	Financial institution	Ticker
Depositories SIC = 60	BANK OF AMERICA CORP	BAC
	BANK OF NEW YORK MELLON CORP	BK
	BB&T CORP	BBT
	COMERICA INC	CMA
	COMMERCE BANCORP INC/NJ	CBH
	CREDICORP LTD	CCL
	FIFTH THIRD BANCORP	FITB
	HUDSON CITY BANCORP INC	HCBK
	HUNTINGTON BANCSHARES	HBAN
	JPMORGAN CHASE & CO	JPM
	KEYCORP	KEY
	M & T BANK CORP	MTB
	MARSHALL & ILSLEY CORP	MI
	MASTERCARD INC	MA
	NATIONAL CITY CORP	NCC
	NEW YORK CMNTY BANCORP INC	NYCB
	NORTHERN TRUST CORP	NTRS
	PEOPLE'S UNITED FINL INC	PBCT
	PNC FINANCIAL SVCS GROUP INC	PNC
	REGIONS FINANCIAL CORP	RF
	STATE STREET CORP	STT
	SUNTRUST BANKS INC	STI
	SYNOVUS FINANCIAL CORP	SNV
	U S BANCORP	USB
	WACHOVIA CORP	WB
	WASHINGTON MUTUAL INC	WAMUQ
	WELLS FARGO & CO	WFC
	ZIONS BANCORPORATION	ZION
Non-depository institutions SIC = 61, 62, 65 excluding 6211	AMERICAN EXPRESS CO	AXP
	BLACKROCK INC	BLK
	BLACKSTONE GROUP LP	BX
	CAPITAL ONE FINANCIAL CORP	COF
	CBRE GROUP INC	CBG
	CIT GROUP INC	CITG
	CITIGROUP INC	CITI
	CME GROUP INC	CME
	COUNTRYWIDE FINANCIAL CORP	CFC
	FEDERAL HOME LOAN MORTG CORP	FMCC
	FRANKLIN RESOURCES INC	FRI
	INTERCONTINENTAL EXCHANGE	ICE
	INVESCO LTD	IVZ
	JANUS CAPITAL GROUP INC	JNS
	LEGG MASON INC	LM
	NYMEX HOLDINGS INC	NMX
	NYSE EURONEXT	NYX
	PRICE (T. ROWE) GROUP	TROW

	PRINCIPAL FINANCIAL GRP INC	PFG
	SCHWAB (CHARLES) CORP	SCHW
	SEI INVESTMENTS CO	SEIC
	WYNDHAM WORLDWIDE CORP	WYN
Insurance SIC = 63, 64	AETNA INC	AET
	AFLAC INC	AFL
	ALLSTATE CORP	ALL
	AMERICAN INTERNATIONAL GROUP	AIG
	ANTHEM INC	ANTM
	ARCH CAPITAL GROUP LTD	ACGL
	ASSURANT INC	AIZ
	AXIS CAPITAL HOLDINGS LTD	AXS
	BERKLEY (W R) CORP	WRB
	CHUBB CORP	CBH
	CIGNA CORP	CI
	CINCINNATI FINANCIAL CORP	CINF
	CNA FINANCIAL CORP	CAN
	COVENTRY HEALTH CARE INC	CVH
	EVEREST RE GROUP LTD	RE
	FIDELITY NATL FINL FNF GROUP	FNF
	GENWORTH FINANCIAL INC	GNW
	HARTFORD FINANCIAL SERVICES	HIG
	HEALTH NET INC	HNT
	HUMANA INC	HUM
	LINCOLN NATIONAL CORP	LNC
	LOEWS CORP	LC
	MARSH & MCLENNAN COS	MMC
	MBIA INC	MBI
	METLIFE INC	MET
	PROGRESSIVE CORP-OHIO	PGR
	PRUDENTIAL FINANCIAL INC	PRU
	SAFECO CORP	SAF
	TORCHMARK CORP	TMK
	TRAVELERS COS INC	TRV
	UNITEDHEALTH GROUP INC	UNH
	UNUM GROUP	UNM
	WHITE MTNS INS GROUP LTD	WTM
	XL GROUP LTD	XL
Broker dealers SIC = 6211	AMERIPRISE FINANCIAL INC	AMP
	BEAR STEARNS COMPANIES INC	BSC
	E TRADE FINANCIAL CORP	ETFC
	GOLDMAN SACHS GROUP INC	GS
	LEHMAN BROTHERS HOLDINGS INC	LEHMQ
	MERRILL LYNCH & CO INC	MER
	MORGAN STANLEY	MS
	TD AMERITRADE HOLDING CORP	AMTD

Notes: Following Adrian and Brunnermeier (2016), we select our sample financial institutions from among companies with a standard industrial classification (SIC) code from 60 to 65 whose headquarters are located in the United States. To exclude non-financial holding companies, we do not include financial institutions whose SIC are 67. We also exclude small financial institutions whose market capitalization are less than US$5 billion as of June 2007, before the global financial crisis occurred.

Table A2. Parameter calibration

	Relative value [S&P 500 on 2001-01-02] = 1	Date
First trough	0.628536611	2002-10-09
First peak	1.254168989	2007-07-19
Second trough	0.541885835	2009-03-09

Period	Start date	End date	Mean return	Standard deviation
Bear period 1	2001-01-02	2002-10-09	-0.00000524	0.000220896
Bull period 1	2002-10-10	2007-07-19	0.00000058	0.000069363
Bear period 2	2007-07-20	2009-03-09	-0.0000104	0.000510138
Bull period 2	2009-03-10	2016-12-30	0.00000028	0.000109223