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A financial network perspective of financial institutions' systemic risk contributions

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HIGHLIGHTS

- We measure systemic risk contribution by dynamic conditional correlation multivariate GARCH model.
- We construct minimum spanning trees (MSTs) from dynamic conditional correlations (DCC).
- We show the dynamic evolution of systemic risk contribution and financial network structure.
- We investigate quantitative relationships between systemic risk contribution and financial network structure.

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ABSTRACT

This study considers the effects of the financial institutions' local topology structure in the financial network on their systemic risk contribution using data from the Chinese stock market. We first measure the systemic risk contribution with the Conditional Value-at-Risk (CoVaR) which is estimated by applying dynamic conditional correlation multivariate GARCH model (DCC-MVGARCH). Financial networks are constructed from dynamic conditional correlations (DCC) with graph filtering method of minimum spanning trees (MSTs). Then we investigate dynamics of systemic risk contributions of financial institution. Also we study dynamics of financial institution's local topology structure in the financial network. Finally, we analyze the quantitative relationships between the local topology structure and systemic risk contribution with panel data regression analysis. We find that financial institutions with greater node strength, larger node betweenness centrality, larger node closeness centrality and larger node clustering coefficient tend to be associated with larger systemic risk contributions.

1. Introduction

The financial crisis has raised questions about the adequacy of financial regulation to ensure stability of the financial system. A particular feature was the threat of systemic risk [1]. According to the Bank for International Settlements, systemic risk in the financial system is the risk that a failure of a participant to meet its contractual obligations may in turn cause other participants to default, with the chain reaction leading to broader financial difficulties [2]. The related studies mainly focus

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on the measurement of financial institutions' systemic risk contributions, influence factors of systemic risk contribution, and risk contagions among financial institutions [3–8,1].

Measuring the contribution of each financial institution to overall systemic risk can help identify the institution that contributes more to systemic risk. Stricter regulatory requirements for institutions with larger systemic risk contributions would break the tendency to generate systemic risk. Adrian and Brunnermeier [3] proposed CoVaR measure for systemic risk, namely the value at risk (VaR) of the financial system conditional on institutions being under distress. The authors defined an institution's contribution to systemic risk as the difference between CoVaR conditional on the institution being under distress and the CoVaR in the median state of the institution. Other systemic risk contribution evaluations include Shapley value methodology and systemic expected shortfall (SES) [4,5]. The influence factors of financial institutions' systemic risk contribution mainly include institutional characteristics, such as size, leverage, maturity mismatch, etc. [3].

The failure of one institution spreading to other institutions results from financial links between them. These financial links include interbank loans, payment systems or OTC derivatives positions. Such an intricate structure of linkages can be captured by a network representation of the financial system. More recent studies explicitly model the financial links between institutions as networks and employ empirical or simulation techniques to assess the propagation of institution failures [1,9–11]. These networks include interbank networks, payment networks, counter party exposures in credit default swaps, or trade credits between companies [12–15]. However, the network analysis literature only concentrate on the effects of overall network structure on systemic risk. The relationships between institutions' local network structure and systemic risk contributions are neglected. Furthermore, the stock price cross-correlations among financial institutions evaluate the systemic risk [16]. Such correlations are frequently used to construct financial networks. The research includes basic topology characteristics and intrinsic hierarchical structure of stock correlation network, etc. [17–21]. But the stock price cross-correlation network analyses rarely relate systemic risk contributions to financial institutions' local structure.

Our aim is to investigate the relationships between systemic risk contributions and institutions' local topology structure in the financial networks. We first measure dynamic systemic risk contribution of financial institutions by estimating the change of CoVaR denoted by ΔCoVaR. Then dynamic minimum spanning trees (MST) of stock price cross-correlation are constructed from the dynamic conditional correlations (DCC). Finally, we use panel data regression, and relate these time-varying ΔCoVaRs to measures of each institution's local network structures like node strength, node betweenness centrality, node closeness centrality, node occupation layer, and node clustering coefficient. This paper is organized as follows. Section 2 discusses relevant literature. Section 3 outlines the systemic risk contribution measures. Section 4 constructs financial networks and studies properties of the local network structure. Section 5 is the empirical study. The last section presents conclusion.

2. Related literature

First, we discuss the measurement methodology literature of systemic risk contribution. Closest to the present paper is the approach in Ref. [3]. The authors introduced the Conditional Value-at-Risk (CoVaR) and defined it as the VaR of financial system conditional on an institution being in financial distress. Lopez-Espinosa et al. [6] identified main factors driving systemic risk in a set of international large-scale complex banks using the CoVaR approach. They found that the short-term wholesale funding is a key determinant in triggering systemic risk episodes. Girardi and Ergun [7] modified CoVaR from Ref. [3], and changed the definition of financial distress from an institution being exactly at its VaR to being at most at its VaR. Tarashev et al. [4] proposed Shapley value methodology to attribute systemic risk to individual institutions. The systemic expected shortfall (SES), i.e., the financial institution's propensity to be undercapitalized when the system as a whole is undercapitalized, was also proposed as a systemic risk contribution measure in Ref. [5]. Billio et al. [22] proposed direct and unconditional econometric measures of connectedness based on principal components analysis and Granger-causality tests. These two measures of connectedness complement the conditional loss-probability-based measures (CoVaR, SES) in providing direct estimates of the statistical connectivity of a network of financial institutions' asset returns.

Second, we want to mention the literature on financial network models and systemic risk. The literature mainly focuses on empirical structure of interbank network and risk contagion. The investigated networks include interbank payment network [10,23], interbank exposure network [24–27] and bipartite bank-asset network [28–30]. Empirical studies showed that the connections between banks exhibit a power-law tail for US FedWire system, Austrian interbank market, Brazilian banking system, UK and Italian market [23,31,32]. The literature on risk contagion in networks is vast. Here we mention some of the closest works to our own research. Allen and Gale [33] suggested that a more interconnected architecture enhances the resilience of the financial system to the insolvency of any individual institution. However, other studies showed that the financial contagion exhibits a form of phase transition as interbank connections increase [8]. The size of the bank initially failing is the dominant factor whether contagion occurs, but for the extent of its propagation the characteristics of the network of interbank loans are most important [1]. In contrast to this literature, we consider the effects of local network structure of financial institutions on their systemic risk contribution.

Third, this paper contributes to a vast literature on network modeling analyses studying the correlations of stock prices. In the considered networks, the vertices are stocks and edges between vertices are price fluctuation relationships of stocks [34–41]. The resulting networks are usually very large and their analysis is rather complex. In much of the previous work, specific filtering processes were applied to reduce the complexity, such as the threshold method [34–36], Minimum Spanning Tree (MST) [37–40] and Planar Maximally Filtered Graph (PMFG) [41–43]. Kenett et al. [44] introduced the partial correlation network, including partial correlation threshold network and partial correlation planar graph which carry different information from the above correlation-based network. The empirical study showed that partial correlation network detects the prominent role of financial stocks in controlling the correlation structure of the market. A variety of dynamic analyses of the time-varying behavior of stocks has also been developed, where the interdependence between two stocks is studied using a rolling correlation analysis [45,46]. A common finding is that the topology of stock price cross-correlation network changes during the crisis. So, it is natural to investigate systemic risk from the perspective of the stock network. In the rolling correlation analyses, the size and drift of the estimation window are chosen arbitrarily, and the correlation coefficients tend to be biased when volatility increases. Wang et al. [47] investigated the dynamic cross-correlation structure of foreign exchange markets by a time-varying copula approach and the minimum spanning tree method. Trancoso [48] employed network analysis and dynamic correlations which were estimated by BEKK model, and constructed dynamic global economic network. Lyocsa et al. [49] estimated dynamic conditional correlations by applying the DCC MV-GARCH model proposed in Refs. [50,51]. The authors compared the topological properties of MSTs constructed using rolling correlations with MSTs constructed using dynamic conditional correlations, and found that the market dynamics can be better preserved by DCC.

3. Systemic risk contribution

3.1. CoVaR methodology

VaR has been used by regulators as an instrument to determine capital levels that need to be set aside by financial institutions against market risks. Given the returns r_i of a financial institution (or portfolio) and the confidence level p_1, $\mathrm{VaR}_i(p_1)$ is defined as the quantile of the order of p_1 of the return distribution:

$$\Pr(r_i \leq \mathrm{VaR}_i(p_1)) = p_1. \tag{1}$$

VaR focuses on the risk of individual institutions. It does not necessarily reflect the risk that the stability of the financial system as a whole is threatened. Adrian and Brunnermeier [3] proposed a measure for systemic risk, namely Conditional Value-at-Risk (CoVaR). Institution i's CoVaR relative to the system $\mathrm{CoVaR}_{s|i}(p_2)$ is defined as the VaR of financial system s conditional on the event of $r_i = \mathrm{VaR}_i(p_1)$:

$$\Pr(r_s \leq \mathrm{CoVaR}_{s|i}(p_2) | r_i = \mathrm{VaR}_i(p_1)). = p_2. \tag{2}$$

We denote institution i's systemic risk contribution by

$$\Delta\mathrm{CoVaR}_{s|i}(p_2) = \mathrm{CoVaR}_{s|r_i=\mathrm{VaR}_i(p_1)}(p_2) - \mathrm{CoVaR}_{s|r_i=\mathrm{Median}_i}(p_2). \tag{3}$$

$\Delta\mathrm{CoVaR}_{s|i}(p_2)$ is the difference between the CoVaR conditional on the distress of institution i and the CoVaR conditional on the normal state of the institution. It captures the marginal contribution of institution i to the overall systemic risk.

3.2. CoVaR estimation

The quantile regression methodology is generally used to estimate CoVaR [3,6]. One potential shortcoming of the quantile estimation procedure is that it cannot estimate the time-varying nature of systemic risk contribution. An alternative estimation approach using a bivariate diagonal GARCH model is proposed in Refs. [3,7]. These two methods produce quite similar estimates. The conditional probability (tail dependence) in formula (2) is related to copulas [52]. Hakwa et al. [53] connected CoVaR to the partial derivatives of copula through their conditional probability interpretation. The authors provided a closed formula for the calculation of CoVaR. The closed formula shows that CoVaR depends on the marginal return distribution of the financial system and the copula between the financial institution and the financial system. This paper estimates $\mathrm{CoVaR}^t_{s|i}(p_2)$ by using dynamic conditional correlation multivariate GARCH model (DCC-MVGARCH) [50,51].

Let P_i^t (P_s^t) be the closing price of stock i (financial index s) on day t. r_i^t (r_s^t) is the return of stock i (financial index s) given by $r_i^t = 100 \times (\ln P_i^t - \ln P_i^{t-1})$ ($r_s^t = 100 \times (\ln P_s^t - \ln P_s^{t-1})$). Suppose r_i^t and r_s^t obey the following distribution,

$$\mathbf{r^t} = (r_i^t, r_s^t)' | I_{t-1} \sim N(0, \mathbf{H}_t), \tag{4}$$

where $\mathbf{H}_t$ is a decompose variance–covariance matrix, $\mathbf{H}_t = \mathbf{D}_t \mathbf{R}_t \mathbf{D}_t$.

$$\mathbf{D}_t = \begin{pmatrix} \sigma_i^t & 0 \\ 0 & \sigma_s^t \end{pmatrix}, \tag{5}$$

where $\mathbf{D}_t$ is a diagonal matrix of time-varying standard deviations from univariate Gaussian-GARCH models. $\mathbf{R}_t$ is the time-varying correlation matrix:

$$\mathbf{R}_t = \begin{pmatrix} 1 & \rho_{i,s}^t \\ \rho_{s,i}^t & 1 \end{pmatrix}. \tag{6}$$

$\mathbf{R}_t$ can be expressed by

$$\mathbf{R}_t = \mathbf{Q}_t^{*-1}\mathbf{Q}_t\mathbf{Q}_t^{*-1}, \tag{7}$$

$$\mathbf{Q_t} = (1-\alpha-\beta)\bar{\mathbf{Q}} + \alpha(\boldsymbol{\varepsilon}_{t-\mathbf{1}}\boldsymbol{\varepsilon}'_{t-\mathbf{1}}) + \beta\mathbf{Q}_{t-\mathbf{1}}, \tag{8}$$

where $\mathbf{Q}_t = \begin{pmatrix} q_{i,i}^t & q_{i,s}^t \\ q_{s,i}^t & q_{s,s}^t \end{pmatrix}$, $\mathbf{Q}_t^* = \begin{pmatrix} \sqrt{q_{i,i}^t} & 0 \\ 0 & \sqrt{q_{s,s}^t} \end{pmatrix}$, $\bar{\mathbf{Q}}$ is the unconditional correlation matrix in dynamic correlation structure $\mathbf{Q}_t$, $\boldsymbol{\varepsilon}_{t-\mathbf{1}}$ are standardized residuals, α and β are DCC parameters estimated via maximum likelihood. The estimated dynamic conditional correlations $\rho_{i,s}^t$ are computed as

$$\rho_{i,s}^t = \frac{q_{i,s}^t}{\sqrt{q_{i,i}^t q_{s,s}^t}}. \tag{9}$$

According to the estimation results of DCC-MVGARCH, $\text{CoVaR}_{s|i}^t(p_2)$ has a closed-form expression under Gaussian framework [3]. By properties of the multivariate normal distribution, the distribution of the system return conditional on institution return is also normally distributed [3]:

$$r_s^t|r_i^t \sim N\left(\frac{r_i^t\sigma_s^t\rho_{i,s}^t}{\sigma_i^t}, (1-(\rho_{i,s}^t)^2)(\sigma_s^t)^2\right). \tag{10}$$

We can define $\text{CoVaR}_{s|i}^t(p_2)$ as the p_2%-VaR of the financial system given institution i is at its p_1%-VaR level. It is defined implicitly by

$$\Pr(r_s^t < \text{CoVaR}_{s|i}^t(p_2)|r_i^t = \text{VaR}_i^t(p_1)) = p_2. \tag{11}$$

After rearrangement, we get

$$\Pr\left(\left[\frac{r_s^t - r_i^t\rho_{i,s}^t\sigma_s^t/\sigma_i^t}{\sigma_s^t\sqrt{1-(\rho_{i,s}^t)^2}}\right] < \frac{\text{CoVaR}_{s|i}^t(p_2) - r_i^t\rho_{i,s}^t r_s^t/\sigma_i^t}{\sigma_s^t\sqrt{1-(\rho_{i,s}^t)^2}}\middle| r_i^t = \text{VaR}_i^t(p_1)\right) = p_2, \tag{12}$$

where $[\frac{r_s^t - r_i^t\rho_{i,s}^t\sigma_s^t/\sigma_i^t}{\sigma_s^t\sqrt{1-(\rho_{i,s}^t)^2}}] \sim N(0,1)$. Because $\text{VaR}_i^t(p_1) = \Phi^{-1}(p_1)\sigma_i^t$, we have

$$\text{CoVaR}_{s|i}^t(p_2) = \Phi^{-1}(p_2)\sigma_s^t\sqrt{1-(\rho_{i,s}^t)^2} + \Phi^{-1}(p_1)\rho_{i,s}^t\sigma_s^t. \tag{13}$$

Institution i can be viewed as in the median state when r_i^t equals its mean value. Because $\Phi^{-1}(50\%) = 0$, institution i's systemic risk contribution is given by

$$\Delta\text{CoVaR}_{s|i}^t(p_2) = \Phi^{-1}(p_1)\rho_{i,s}^t\sigma_s^t. \tag{14}$$

4. Dynamic financial network

4.1. Network construction

A network is defined as a collection of nodes connected by links. We consider a financial network where each financial institution is a network node. Each pair of financial institutions is connected with an edge, with weight equals to the dynamic conditional correlation (DCC) of their corresponding stock prices. We compute the dynamic conditional correlation $\rho_{i,j}^t$ between financial institution i and j on day t, where $i = 1, 2, \ldots, N;\ j = 1, 2, \ldots, N, i \neq j;\ t = 1, 2, \ldots, T$. This correlation can vary in the range $-1 \le \rho_{i,j}^t \le 1$, and if $i = j$, then $\rho_{i,j}^t = 1$. By replacing r_s^t with r_j^t, $\rho_{i,j}^t$ can be similarly computed as $\rho_{i,s}^t$ in the above section. The correlation $\rho_{i,j}^t$ forms a symmetric $N \times N$ matrix with diagonal elements equal to unity. We apply the correlation matrix to construct a financial network $G^t(V, E^t)$ on day t, where the node set is $V = \{1, 2, \ldots, N\}$, and the edge set is $E^t = \{e_{i,j}^t|e_{i,j}^t = \rho_{i,j}^t\}$. The correlation $\rho_{i,j}^t$ cannot be used as a distance between the two stocks because it does not satisfy axioms defining an Euclidean metric. We can convert the correlation by appropriate functions so that the axioms are satisfied. One of the appropriate function was defined in Ref. [54]:

$$d_{i,j}^t = \sqrt{2(1-\rho_{i,j}^t)}, \tag{15}$$

where the distance $d_{i,j}^t$ can lie in $0 \le d_{i,j}^t \le 2$. High correlations correspond to small values of $d_{i,j}^t$. $d_{i,j}^t$ satisfies the axioms of the Euclidean metric: (i) $d_{i,j}^t = 0$ if and only if $i = j$; (ii) $d_{i,j}^t = d_{j,i}^t$ and (iii) $d_{i,j}^t \le d_{i,k}^t + d_{k,j}^t$. Then the edge set of financial network $G^t(V, E^t)$ converts to $E^t = \{e^t_{i,j} | e^t_{i,j} = d^t_{i,j}\}$. $G^t(V, E^t)$ is a fully connected network which is not very interesting by itself. We construct a minimum spanning tree MST^t corresponding to $G^t(V, E^t)$. One of methods to construct the MST is called the Kruskal's algorithm and includes the following steps [55]:

- Step 1. Choose a pair of nodes with smallest distance and connect them with an edge.
- Step 2. Connect a pair with the second smallest distance.
- Step 3. Connect the nearest pair that is not connected by the same tree.

We repeat Step 3 until all financial institutions are connected in a unique tree. This procedure gives a connected and acyclic graph of N financial institutions with $N - 1$ edges.

4.2. Network topology structure

4.2.1. Node strength

According to Refs. [43,56], the node strength is defined as the sum of correlation coefficients of the given node i with all other nodes to which it is linked, i.e.,

$$S^t_i = \sum_{j \in \Omega_i} \rho^t_{i,j}, \tag{16}$$

where Ω_i is the set of nodes connected to node i in the MST^t. The node strength S^t_i is interpreted as the net influence for the financial institution i to affect other institutions in stock price changes. A node is more important and has greater influence on other nodes if its node strength is larger.

4.2.2. Node betweenness centrality

Betweenness centrality of the institution i in the MST^t is measured as

$$B^t_i = \sum_{j<k} g^i_{j,k} / g_{j,k}, \tag{17}$$

where $g_{j,k}$ is the number of shortest paths between j and k, $g^i_{j,k}$ is the number of shortest paths between j and k that institution i resides on.

Betweenness centrality builds on the notion that a node is central if it is needed to connect other pair of nodes. An institution with high betweenness centrality would have an important influence on other institutions as it can stop or distort the information that passes through it.

4.2.3. Node closeness centrality

Closeness centrality has an interpretation of independence in social networks in terms of communication control. We measure closeness centrality based on the distance of each institution to every other institutions in the MST^t. Closeness centrality of institution i is given by

$$F^t_i = \sum_{j \in V, j \neq i} l_{i,j}, \tag{18}$$

where $l_{i,j}$ denotes the length of the shortest path between institution i and j. This measure indicates the influence of a node on the entire network. An institution with low closeness centrality would depend less on other intermediary institutions to receive messages. In our work, this measure is related with the capacity of an institution to propagate contagion.

4.2.4. Node occupation layer

The node c with the maximum degree is the central node in the MST^t. The occupation layer of node i can be calculated as the shortest path length between i and c, and is denoted by $l^t_{i,c}$. The occupation layer of node c is set to zero. This measure reflects the extent of closeness to the central position in the network.

4.2.5. Node clustering coefficient

We cannot calculate node clustering coefficient in the MST^t as it does not have cyclic structures. The original network $G^t(V, E^t)$ with the edge weights equal to the DCC can be used to calculate the node clustering coefficient. Since $G^t(V, E^t)$ is a complete weighted undirected network, we choose the weighted clustering coefficient introduced in Ref. [57], where the clustering coefficient of the node i is defined as

$$C^t_i = \frac{1}{N(N-1)} \sum_{j,k} \left(|\rho^t_{i,j}| \times |\rho^t_{i,k}| \times |\rho^t_{j,k}| \right)^{\frac{1}{3}}, \quad i \neq j,\ i \neq k,\ j \neq k. \tag{19}$$

Table 1
ADF and Ljung–Box statistics.

	ADF statistic	$Q(5)$	$Q(10)$	$Q^2(5)$	$Q^2(10)$
ICBC	−26.0463 (0.000)	25.634 (0.000)	49.933 (0.000)	224.97 (0.000)	376.21 (0.000)
Index	−32.7525 (0.000)	5.2008 (0.392)	22.201 (0.014)	102.51 (0.000)	164.94 (0.000)

5. Empirical study

5.1. Data

According to the Guidelines for the Industry Classification of Listed Companies issued by China Securities Regulatory Commission (CSRC), there are 39 publicly traded financial institutions in Chinese stock market. These institutions are grouped into four financial sectors: commercial banks, security broker-dealers (including the investment banks), insurance companies, and other financial institutions such as trust companies. We choose CSRC financial business index to represent the financial system. We use daily price series for the 39 financial institutions and CSRC financial business index from January 2011 to June 2015 (1073 consecutive trading days). The data is taken from *Wind Info* which is the market leader in China's financial data services industry. The list of names of financial institutions and their stock codes are presented in the Appendix.

5.2. DCC estimation

Firstly, we compute the DCCs in the sample period between any two stock return series (or between stock return series and financial business index return series). There are 780 ($C_N^2 + N$, $N = 39$) pairs of return series in total. The DCC computation process for each pair of return series is as follows: (i) ADF unit-root, autocorrelation and ARCH effects tests to the return series, (ii) GARCH modeling for the series, and computing the standardized residual series, (iii) with DCC-MVGARCH model, estimate DCC by using the standardized residuals.

Because of space constraints, we only take the DCC computation between return series of Industrial and Commercial Bank of China (ICBC) and financial business index as an example to illustrate the process. Table 1 shows the statistics of ADF unit-root test, Ljung–Box Q autocorrelation test of series and its squared process. The ADF test was performed without a constant term and deterministic trend according to the data. It is obvious that the hypothesis of a unit root can be rejected for two return series. Thus the two series are all stationary. The Ljung–Box Q statistics calculated for 5 and 10 lags of ICBC return series and its squared process with 1% significance level indicate that they are both autocorrelated. The Ljung–Box Q statistics calculated for 5 and 10 lags of financial business index return series with 1% significance level indicate that there is no autocorrelation in it, but the corresponding statistics of its squared process indicate that the squared process is autocorrelated. Such results demonstrate that there is evidence of ARCH effects in the return series. We can build GARCH models for these series.

The estimation of AR-GARCH model for ICBC return series gives

$$r_i^t = 0.0144 - 0.0479 r_i^{t-1} + \varepsilon_i^t,$$

$$(\sigma_i^t)^2 = 0.0441 + 0.1181(\varepsilon_i^{t-1})^2 + 0.8526(\sigma_i^{t-1})^2.$$

The autocorrelation test for ε_i^t indicates that it is not autocorrelated. The Lagrange multiplier test for conditional heteroscedasticity shows no ARCH effects with test statistic $F = 1.4267$, the p value of which is 0.2326. Thus the model is adequate in describing the linear dependence in the return and volatility series. Likewise, the estimation result of GARCH model for financial business index is as follows:

$$r_s^t = 0.0374 + \varepsilon_s^t,$$

$$(\sigma_s^t)^2 = 0.0365 + 0.0474(\varepsilon_s^{t-1})^2 + 0.9412(\sigma_s^{t-1})^2.$$

The autocorrelation and ARCH effect tests for ε_s^t also indicate that the model is adequate. Then the standardized residuals are used to estimate parameters α and β in the DCC model, and we have $\alpha = 0.0322$, $\beta = 0.9081$. We implement estimations via UCSD_Garch toolbox for Matlab. We plot the DCCs $\rho_{i,s}^t$ between ICBC and financial business index return series in Fig. 1. The conditional correlations vary around a fixed mean level. The correlations are all positive with a range from 0.53 to 0.86. Its mean value and standard deviation are 0.73 and 0.04. The results suggest the positive co-movement between ICBC and financial system returns. The skewness and excess kurtosis are −0.76 and 1.8 respectively. It demonstrates that the correlation distribution is leptokurtic. We apply ADF unit-root test to the conditional correlation series. The ADF test statistic is −6.18 with a p value 0, indicating that the series is stationary and there are no apparent structural changes in the correlation process. We calculate the autocorrelation function (ACF) of correlation series. The results show that the sample ACFs are significantly positive from 1 to 11 days lag at the 5% level. The Ljung–Box statistics give $Q(5) = 3471.2$ and $Q(10) = 5058.8$. The p values of these two test statistics are all less than 0.0001. Thus, the conditional correlation has significant serial correlation. The conditional correlation at some time in the series is statistically positively correlated with the value at another time.

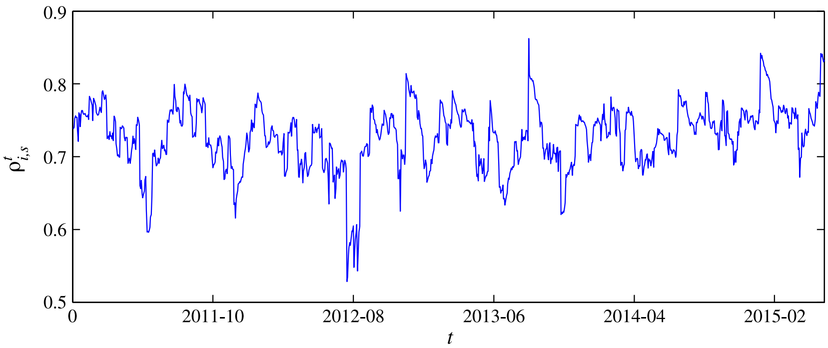

Fig. 1. DCCs between ICBC and financial business index return series from January 2011 to June 2015.

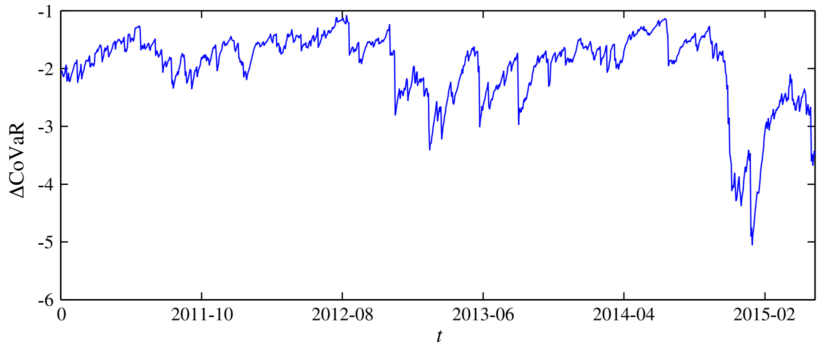

Fig. 2. Dynamic evolution of ICBC's systemic risk contribution from January 2011 to June 2015.

5.3. ΔCoVaR calculation

After estimating the DCCs between a financial institution and financial business index return series, we can calculate the daily systemic risk contribution of each financial institution according to formula (14). We take ICBC as an illustration example. Its time varying systemic risk contributions are given in Fig. 2 as $p_1 = 5\%$. According to the definition, it is obvious that the smaller the $\Delta \text{CoVaR}_{s|i}^{t}$, the larger the systemic risk contribution institution i has. The ΔCoVaR of ICBC fluctuates between a maximum of −1.08 and a minimum of −5.05. The mean and standard deviation values of ΔCoVaR are −1.97 and 0.64. There are three distinct local minimum points (13/10/2011, 6/3/2013 and 22/1/2015) with ΔCoVaR values of −2.35, −3.41 and −5.05, respectively. It shows that the local minimum values (local largest systemic risk contribution) are decreasing (increasing) as time evolves. Another interesting result is that the annual standard deviation values of ΔCoVaR for years 2011, 2012, 2013, 2014, and 2015 are 0.24, 0.29, 0.40, 0.70, and 0.71, respectively. It indicates that the ΔCoVaR are spread out over a wider range of values as time evolves, and the systemic risk contribution fluctuations become larger and larger. We also calculate the ACF of ΔCoVaR series. The results show that the sample ACFs are significantly positive from 1 to 39 days lag at the 5% level. The Ljung–Box statistics give $Q(5) = 4703.1$ and $Q(10) = 8509.9$. The p values of these two test statistics are all less than 0.0001. The results demonstrate that the systemic risk contribution series are persistent and predictable. The larger systemic risk contributions tend to be followed by larger systemic risk contributions.

Furthermore, we calculate the arithmetic mean of ΔCoVaR daily time-series for each institution, which we will denote by $\overline{\Delta \text{CoVaR}}$. We then rank each institution in order of decreasing absolute value of $\overline{\Delta \text{CoVaR}}$. The larger the absolute value of $\overline{\Delta \text{CoVaR}}$ is, the larger the systemic risk contribution is. Higher ranking of an institution means its systemic risk contribution is larger. The ranking list is shown in Table 2. The top five financial institutions are Shanghai Pudong Development Bank, Industrial Bank, Ping An Insurance (Group) Company Of China, Citic Securities Company, and China Merchants Bank. The bottom five financial institutions are Minsheng Holdings, Guanddong Golden Dragon Development, Anxin Trust, Sealang Securities, and Shanghai Aj Group. The four giant state-owned commercial banks: Agricultural Bank of China, China Construction Bank Corporation, Bank of China, and Industrial and Commercial Bank of China have ranking positions from 26th to 29th respectively. The average systemic risk contributions of small and medium-sized shareholding commercial banks are larger than those of giant-sized commercial banks. The average systemic risk contributions of institutions in the four financial sectors, namely commercial bank, security broker-dealers (including the investment banks), insurance companies and other financial institutions, are −2.2146, −2.0185, −2.2630 and −1.4458 respectively. The systemic risk contribution difference between commercial banks and insurance companies is small. By contrast, the security institutions' contributions are smaller. And other financial institutions such as trust companies' contributions are the smallest among the four sectors.

Table 2
Institution ranking based on systemic risk contribution. Higher ranking of an institution means its systemic risk contribution is larger.

Stock code	$\overline{\Delta\text{CoVaR}}$	Ranking	Stock code	$\overline{\Delta\text{CoVaR}}$	Ranking
000001	−2.2932	7	600837	−2.2953	6
000416	−1.0885	39	600999	−2.2346	16
000563	−1.7382	34	601009	−2.2762	10
000686	−2.0617	25	601099	−1.9588	30
000712	−1.2612	38	601166	−2.3667	2
000728	−2.1449	21	601169	−2.2410	15
000750	−1.5648	36	601288	−2.0314	26
000776	−2.2023	19	601318	−2.3390	3
000783	−2.1264	23	601328	−2.2925	8
002142	−2.2458	14	601377	−2.1157	24
002500	−1.8855	32	601398	−1.9723	29
600000	−2.4178	1	601601	−2.2306	17
600015	−2.2743	11	601628	−2.2195	18
600016	−2.2570	12	601688	−2.2523	13
600030	−2.3173	4	601788	−2.1647	20
600036	−2.3085	5	601818	−2.2797	9
600109	−1.9156	31	601939	−2.0251	27
600369	−1.7955	33	601988	−2.0115	28
600643	−1.5766	35	601998	−2.1415	22
600816	−1.3799	37			

Table 3
Stationary test results.

Variable	CoVaR	S	B	F	l	C	ln *Assets*	*leverage*	*ROA*
ADF_1	271.84 (0.000)	2552.60 (0.000)	2437.99 (0.000)	2646.70 (0.000)	3448.70 (0.000)	905.05 (0.000)	1.14 (1.000)	53.15 (0.986)	135.52 (0.000)
ADF_2	−11.26 (0.000)	−47.05 (0.000)	−45.29 (0.000)	−48.26 (0.000)	−56.13 (0.000)	−25.99 (0.000)	16.01 (1.000)	3.44 (0.999)	−4.38 (0.000)

Note: ADF_1 and ADF_2 represent statistics of ADF-Fisher Chi-square and ADF-Choi Z-stat respectively.

5.4. Network construction and topology structure

After calculating the DCCs between any two institutions' return series, we can construct the financial network $G^t(V, E)$ and the corresponding MST^t on day t. The resulted minimum spanning trees on the first day and last day of sample period are shown in Fig. 3. The correspondences between node labels (1–39) and financial institutions are presented in the Appendix. The relative position of a node in the two networks has significantly changed. Thus, its local network topology structures will have changed accordingly. For example, on the first day institutions with top five node degree are Shanghai Pudong Development Bank, Haitong Securities, Shaanxi International Trust, Guoyuan Securities Company, and Industrial Bank. However, on the last day institutions with the top five node degree are Shanghai Pudong Development Bank, Gf Securities, Haitong Securities, Sealang Securities, and Shaanxi International Trust.

Fig. 4 shows ICBC's dynamic evolution of local network topology structures. The ICBC's node degree ranges from 1 to 3, node strength ranges from 0.7026 to 2.7638, node betweenness centrality ranges from 0 to 718, node closeness centrality ranges from 141 to 414, node occupation layer ranges from 1 to 13 and node clustering coefficient ranges from 0.3875 to 0.6378.

5.5. Relationship between ΔCoVaR and network topology structure

We investigate effects of local network topology structure on the systemic risk contribution, using panel data of institutions' ΔCoVaR and topology structure variables. Previous research showed that institution size, leverage and profitability are important influence factors on institution's systemic risk contribution. We introduce natural logarithm of assets (ln *Assets*), leverage ratio (*leverage*, asset/equity) and return of asset (*ROA*) as additional independent variables. The data for additional variables are taken from quarterly reports, semiannual reports or annual reports of financial institutions, and has frequency of 3 months. We convert their quarterly frequency to daily frequency so as to match with other variables. To avoid spurious regression, we first conduct stationary tests on variables. Table 3 shows the test results.

The unit-root hypothesis can be rejected for all variables except ln *Assets* and *leverage*. Thus ln *Assets* and *leverage* are non-stationary variables. We replace them with their corresponding quarterly growth rate *Assets_growth* and *leverage_growth*. The stationary tests on *Assets_growth* and *leverage_growth* show that they are stationary. Then we apply Hausmen test for choosing between random effect and fixed effect model. The null hypothesis is that we should establish random effect model as follows.

$$\Delta CoVaR^t_{s|i} = \alpha + \mathbf{x_i^{t'}}\boldsymbol{\beta} + v_i + u_i^t,$$

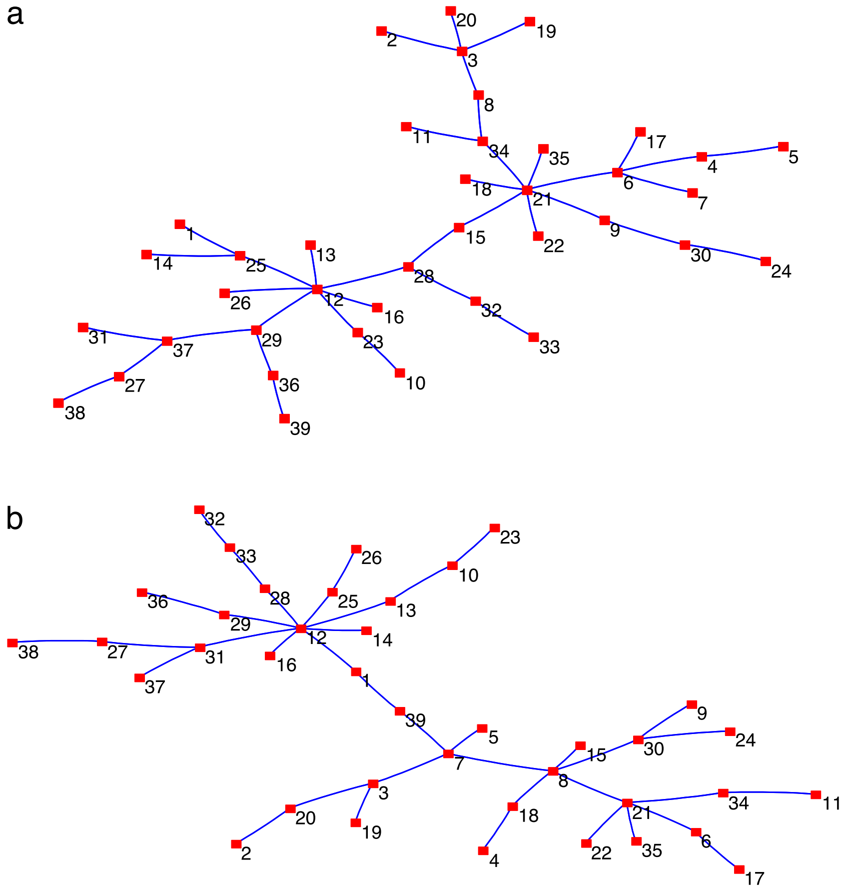

Fig. 3. The minimum spanning trees on (a) 4th January 2011, and (b) 5th June 2015.

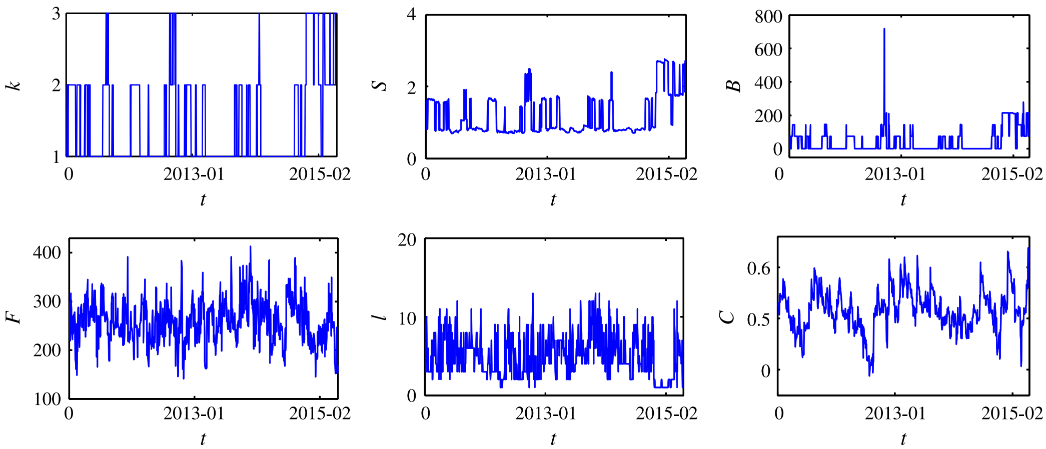

Fig. 4. Industrial and Commercial Bank of China's dynamic evolution of node degree (top-left), node strength (top-middle), node betweenness centrality (top-right), node closeness-centrality (bottom-left), node occupation layer (bottom-middle) and node clustering coefficient (bottom-right).

where $\mathbf{x}_\mathbf{i}^{\mathbf{t}'} = (S_i^t, B_i^t, F_i^t, l_i^t, C_i^t, Assets\_growth_i^t, leverage\_growth_i^t, ROA_i^t)'$, α is a constant term in the intercept, v_i is the random part in the intercept which represents individual random effect, $\boldsymbol{\beta}$ is a 8×1 coefficient vector, $i = 1, 2, \ldots, N$, $t = 1, 2, \ldots, T$. The Hausman statistic value for random effect model is 160.93 with p value 0.0000. The null hypothesis can be rejected. Thus we establish fixed effect model. Next we choose among variable coefficient model, variable intercept model and fixed parameter model by applying F-statistics test. The residual sum of squares of variable coefficient model, variable intercept model and fixed parameter model are $RSS_1 = 8743.40$, $RSS_2 = 12047.05$ and $RSS_3 = 14127.85$ respectively.

F statistics are as follows:

$$F_1 = \frac{(RSS_2 - RSS_1)/[(N-1)k]}{RSS_1/(NT - N(k+1))} \sim F[(N-1)k, N(T-k-1)],$$
$$F_2 = \frac{(RSS_3 - RSS_1)/[(N-1)(k+1)]}{RSS_1/(NT - N(k+1))} \sim F[(N-1)(k+1), N(T-k-1)],$$

where $N = 39$, $T = 1071$, $k = 8$, thus $F_1 = 51.6728$, $F_2 = 74.5803$. At the 5% level of significance, the critical values of $F[(N-1)k, N(T-k-1)]$ and $F[(N-1)(k+1), N(T-k-1)]$ are 1.1376 and 1.1296, respectively. Both F_1 and F_2 are larger than the corresponding critical value, so we determine to choose the following variable coefficient model.

$$\boldsymbol{\Delta}\mathbf{CoVaR}_{s|i} = \boldsymbol{\alpha}_\mathbf{i} + \mathbf{x_i}\boldsymbol{\beta}_\mathbf{i} + \mathbf{u_i},$$

where $i = 1, 2, \ldots, N$, $\boldsymbol{\Delta}\mathbf{CoVaR}_{s|i}$ is a $T \times 1$ vector of independent variables, $\mathbf{x_i}$ is a $T \times k$ matrix of dependent variables ($k = 8$), intercept $\boldsymbol{\alpha}_\mathbf{i}$ and $k \times 1$ coefficient vector $\boldsymbol{\beta}_\mathbf{i}$ differ among different institutions, $\mathbf{u_i}$ is the $T \times 1$ residual vector. The adjusted R-squared is 0.62 and F statistic value is 196.1370 with $p = 0.0000$. Table 4 shows the model estimation results.

The number of financial institutions whose corresponding node strength S in the financial network has a significant negative (positive) effect on its systemic risk contribution $\Delta CoVaR$ is 30(0). It indicates that in general the larger a financial institution's nodes strength in the network, the smaller $\Delta CoVaR$ is, and the larger its systemic risk contribution is. The number of financial institutions whose corresponding node betweenness centrality B in the financial network has a significant negative (positive) effect on its systemic risk contribution $\Delta CoVaR$ is 33(0). It indicates that in general the larger a financial institution's node betweenness centrality in the network, the smaller $\Delta CoVaR$ is, and the larger its systemic risk contribution is. The number of financial institutions whose corresponding node closeness centrality F in the financial network has a significant negative (positive) effect on its systemic risk contribution $\Delta CoVaR$ is 32(0). It indicates that the larger a financial institution's node closeness centrality in the network, the smaller $\Delta CoVaR$ is, and the larger its systemic risk contribution is. The number of financial institutions whose corresponding node occupation layer l in the financial network has a significant positive (negative) effect on its systemic risk contribution $\Delta CoVaR$ is 17(9). There are still 13 institutions whose node occupation layer has no significant effect on their systemic risk contributions. It indicates that the effect of node occupation layer on the systemic risk contribution has no consistent results. All of the financial institutions' node clustering coefficients C have significant negative effects on their systemic risk contributions. It demonstrates that the larger a financial institution's node clustering coefficient in the network, the smaller $\Delta CoVaR$ is, and the larger its systemic risk contribution is.

To test whether the results also hold for different sub-periods, we construct four different annual sub-periods of approximately the same length. The four sub-periods are years 2011, 2012, 2013, and 2014, respectively. There are enough observations to test the significance of the variables in these four periods. Table 5 presents summary results of the statistical significance of independent variables for sub-period panel data regressions. Regressions for the four sub-periods show similar results to the whole sample regressions. The robustness checks further confirm the relationships between network statistics and systemic risk contribution.

5.6. Further analysis

In the financial network, if a node's strength is larger, the stock return of its corresponding institution would have an greater impact in many other institutions, so the corresponding institution's systemic risk contribution is larger. If a node's betweenness centrality is higher, it is more central to the network by taking into account its role as intermediary in the network, thus the corresponding institution has a larger systemic risk contribution. An institution with high closeness centrality would depend more on other intermediary institutions to receive messages. Such institutions have larger systemic risk contributions. Node clustering coefficient reflects the edge density of its local network, and also reflects the return correlation strength among institutions in the local network. The empirical results show that the large edge density and strong return correlations in the local network lead to larger systemic risk contribution.

6. Conclusion

This paper investigate the effects of financial institutions' local network topology structure on their systemic risk contributions using data from the Chinese stock market. We first measure the systemic risk contribution with Conditional Value-at-Risk (CoVaR) which is estimated by applying dynamic conditional correlation multivariate GARCH model (DCC-MVGARCH). We observe that the average systemic risk contributions of small and medium-sized shareholding commercial banks are greater than those of giant-sized commercial banks. The financial sectors listed in systemic risk contribution order from the largest to smallest are insurance companies, commercial banks, security broker-dealers (including the investment banks) and other financial institutions.

We apply the dynamic conditional correlations between all pairs of stocks to construct dynamic financial networks. We observe the nodes' dynamic evolution of local topology structure. Finally, we relate systemic risk contribution with the financial institution's local topology structure in the financial network by panel data regression analyses. We show that in

Table 4
Model estimation results.

Stock code	$\beta_1(S)$	$\beta_2(B)$	$\beta_3(F)$	$\beta_4(l)$	$\beta_5(C)$	$\beta_6(A\_g)$	$\beta_7(l\_g)$	$\beta_8(ROA)$
000001	−0.3746** (−9.49)	−0.0007** (−8.43)	−0.0043** (−9.31)	0.0428** (6.19)	−6.5845** (−22.25)	−0.2727* (−2.36)	−1.3661** (−5.54)	0.6726** (4.09)
000416	0.0452 (0.22)	0.0010 (0.29)	−0.0006 (−1.39)	0.0096 (1.32)	−5.6065** (−17.51)	2.9621** (5.72)	−4.0868** (−8.58)	−0.0159** (−3.05)
000563	−0.3772** (−6.66)	−0.0014** (−7.63)	0.0003 (0.65)	−0.0262** (−3.78)	−6.7030** (−27.11)	0.0895* (1.97)	−0.2691 (−0.96)	0.0395** (8.96)
000686	−0.1140** (−2.95)	−0.0001 (−0.52)	−0.0004 (−0.75)	−0.0158* (−2.25)	−6.3640** (−19.20)	−0.3476* (−2.32)	−0.1387 (−1.25)	−0.1294** (−9.83)
000712	−0.8027** (−6.73)	−0.0065** (−7.66)	0.0004 (0.98)	−0.0229** (−3.24)	−6.2194** (−18.76)	−0.0634 (−1.52)	−0.0653 (−0.62)	−0.0537** (−9.10)
000728	−0.2260** (−5.72)	−0.0008** (−10.33)	−0.0021** (−3.68)	−0.0250** (−3.52)	−6.8566** (−25.87)	5.9051** (8.64)	−7.9012** (−9.69)	−0.2980** (−17.07)
000750	−0.2111** (−4.06)	−0.0012** (−10.02)	−0.0015** (−3.47)	−0.0180* (−2.56)	−4.7591** (−31.66)	0.0491** (9.39)	−1.3255** (−11.94)	−0.0183** (−3.53)
000776	−0.0618* (−2.27)	−0.0003** (−4.26)	−0.0042** (−7.36)	0.0077 (1.04)	−9.1926** (−29.12)	−0.5438** (−4.11)	0.5692** (3.76)	−0.8289** (−20.04)
000783	−0.1209** (−4.10)	−0.0012** (−13.37)	−0.0024** (−4.57)	0.0006 (0.08)	−6.7488** (−24.47)	−2.3301** (−8.16)	2.2623** (6.53)	−0.1504** (−8.29)
002142	0.0237 (0.72)	−0.0002** (−2.58)	−0.0038** (−8.63)	0.0540** (7.73)	−8.0107** (−22.52)	−0.1314 (−0.80)	−1.1291** (−4.37)	0.9684** (8.41)
002500	−0.1668** (−3.84)	−0.0010** (−5.98)	−0.0010* (−2.00)	−0.0057 (−0.79)	−6.1310** (−24.34)	0.6159 (1.42)	0.0110 (0.02)	−0.2463** (−14.69)
600000	−0.2848** (−4.94)	−0.0005** (−4.24)	−0.0043** (−8.13)	0.0292** (4.28)	−6.9005** (−23.13)	−0.6739** (−3.84)	2.3163** (7.84)	7.0514** (24.71)
600015	0.0532 (1.55)	−0.0003** (−3.61)	−0.0047** (−9.88)	0.0508** (7.56)	−8.0811** (−25.89)	1.3476** (6.64)	−0.3653* (−2.39)	0.3275* (2.01)
600016	−0.3921* (−6.54)	−0.0012* (−4.53)	−0.0036** (−7.88)	0.0465** (7.16)	−4.8425** (−15.15)	0.1672 (1.03)	6.6774** (19.18)	1.2151** (8.60)
600030	−0.0768** (−2.79)	−5.36E−05 (−0.79)	−0.0055** (−8.80)	−0.0346** (−3.85)	−4.9021** (−13.44)	0.8547** (5.34)	−3.3538** (−9.85)	−0.0628** (−4.42)
600036	−0.5330** (−11.99)	−0.0014** (−11.93)	−0.0049** (−10.45)	0.0489** (7.45)	−7.1395** (−20.16)	−1.0850** (−6.76)	−0.3862 (−1.94)	−0.8221** (−4.32)
600109	−0.3862** (−10.18)	−0.0024** (−15.20)	−0.0018** (−3.77)	0.0136* (1.95)	−5.6282** (−24.39)	−0.6043** (−6.14)	−1.1746** (−10.29)	−0.0357* (−2.56)
600369	−0.0757 (−1.86)	−0.0004* (−3.05)	−0.0012* (−2.57)	−0.0056 (−0.78)	−6.6626** (−34.18)	1.9425** (9.91)	−0.9984** (−5.51)	−0.2312** (−21.26)
600643	−0.1193 (−1.48)	−0.0017** (−3.42)	−0.0015** (−3.47)	−0.0097 (−1.35)	−6.5762** (−22.17)	−0.1413* (−2.43)	−1.0896** (−4.63)	0.1013** (7.78)
600816	−0.6960** (−8.02)	−0.0061** (−9.37)	0.0002 (0.46)	−0.0143* (−2.09)	−5.4287** (−18.23)	0.1032 (0.71)	1.4081** (6.34)	0.0053** (4.85)
600837	−0.0435 (−1.23)	−0.0001 (−1.49)	−0.0064** (−10.30)	0.0007 (0.08)	−6.7643** (−21.82)	−1.4389** (−7.15)	1.3697** (6.22)	−0.4618** (−19.70)
600999	−0.1470** (−5.28)	−0.0005** (−6.06)	−0.0023** (−4.11)	−0.0151* (−1.99)	−8.8469** (−27.17)	0.4342** (2.71)	0.4522* (2.88)	−0.6014** (−25.87)
601009	−0.2242** (−7.84)	−0.0004** (−4.77)	−0.0038** (−7.15)	0.0339** (4.65)	−8.2020** (−24.53)	−0.2655 (−1.72)	−5.0013** (−15.74)	1.3187** (7.66)
601099	−0.1336** (−3.62)	−0.0015** (−12.47)	−0.0011* (−2.16)	0.0069 (0.96)	−6.9003** (−23.13)	−0.4114** (−5.87)	−0.6781** (−6.85)	−0.0506** (−6.65)
601166	−0.3480** (−11.43)	−0.0006** (−8.12)	−0.0040** (−7.74)	0.0208** (3.01)	−7.5737** (−26.68)	−0.0337 (−0.26)	−0.4157 (−1.58)	−2.8007** (−12.61)
601169	−0.1997* (−4.43)	−0.0003** (−2.89)	−0.0042** (−9.36)	0.0522** (7.10)	−7.1013** (−21.50)	0.4270** (2.59)	0.3558 (1.41)	−1.8110** (−12.18)
601288	−0.2149** (−4.02)	−0.0014** (−5.39)	−0.0034** (−8.12)	0.0623** (9.57)	−7.5932** (−29.71)	−1.3887** (−5.49)	0.2446 (0.51)	−1.3236** (−7.50)
601318	−0.0366 (−0.91)	5.94E−05 (0.86)	−0.0040** (−7.09)	0.0143 (1.35)	−8.3838** (−22.47)	0.4838** (4.82)	−1.1297** (−7.10)	−1.0158** (−23.60)
601328	−0.5535** (−13.94)	−0.0010** (−8.57)	−0.0036** (−6.97)	0.0480** (7.17)	−5.3561** (−17.68)	−0.1095 (−0.47)	−4.1400** (−14.03)	0.2004 (0.92)

(continued on next page)

Table 4 (*continued*)

Stock code	$\beta_1(S)$	$\beta_2(B)$	$\beta_3(F)$	$\beta_4(l)$	$\beta_5(C)$	$\beta_6(A\_g)$	$\beta_7(l\_g)$	$\beta_8(ROA)$
601377	-0.2600^{**} (−7.81)	-0.0010^{**} (−7.26)	-0.0009^{*} (−1.65)	0.0089 (1.24)	-9.2377^{**} (−25.37)	0.1797 (1.03)	−0.1340 (−0.72)	-0.4116^{**} (−21.23)
601398	-0.5372^{**} (−10.60)	-0.0057^{**} (−17.34)	−0.0004 (−0.91)	0.0204^{**} (3.10)	-7.3628^{**} (−19.90)	−0.0450 (−0.19)	-1.5920^{**} (−4.55)	0.8254^{*} (2.35)
601601	0.0467 (1.54)	-0.0004^{**} (−5.54)	-0.0038^{**} (−7.24)	0.0035 (0.33)	-7.7098^{**} (−18.12)	-0.7720^{**} (−3.68)	0.9960^{**} (3.27)	-0.3795^{**} (−16.33)
601628	0.1631^{**} (3.86)	-0.0002^{*} (−3.41)	-0.0041^{**} (−7.73)	−0.0030 (−0.29)	-6.5099^{**} (−18.51)	0.1340 (0.44)	1.2761^{**} (4.22)	-0.5879^{**} (−17.63)
601688	-0.3069^{**} (−9.17)	-0.0002^{*} (−3.34)	-0.0031^{**} (−5.50)	0.0079 (−1.07)	-6.7583^{**} (−22.64)	9.5651^{**} (17.89)	-10.9600^{**} (−17.81)	-0.2335^{**} (−5.84)
601788	-0.1558^{**} (−4.98)	9.77E−05 (0.89)	-0.0027^{**} (−5.09)	-0.0189^{**} (−2.59)	-7.2538^{**} (−23.90)	-4.0404^{**} (−14.73)	3.5159^{**} (10.68)	-0.2151^{**} (−15.16)
601818	-0.3037^{**} (−8.95)	-0.0010^{**} (−8.65)	-0.0057^{**} (−13.39)	0.0443^{**} (6.11)	-6.7749^{**} (−22.06)	-1.0526^{**} (−5.74)	1.1080^{**} (3.94)	0.2535 (1.49)
601939	-0.9846^{**} (−21.66)	-0.0042^{**} (−13.32)	−0.0005 (−1.20)	0.0270^{**} (4.09)	-7.3362^{**} (−17.48)	-1.0565^{**} (−4.01)	-2.6659^{**} (−5.39)	−0.3824 (−1.84)
601988	-1.0370^{**} (−21.18)	-0.0045^{**} (−15.89)	-0.0019^{**} (−4.91)	0.0367^{**} (5.58)	-4.6945^{**} (−15.11)	-0.7330^{*} (−2.10)	-1.3898^{**} (−3.43)	−0.7851 (−1.76)
601998	−0.0318 (−0.51)	−0.0006 (−4.07)	-0.0037^{**} (−9.18)	0.0262^{**} (3.74)	-7.9525^{**} (−31.69)	-0.6038^{**} (−3.59)	-0.8780^{**} (−4.34)	1.4150^{**} (12.94)
Significant positive	0	0	0	17	0	11	11	11
Significant negative	30	33	32	9	39	17	19	24

Note: *A_g* and *l_g* represent variables *Assets_growth* and *leverage_growth* respectively, numbers in the parentheses are *t* statistic values.
* Represent 0.05 significance level.
** Represent 0.01 significance level.

Table 5
Summary results of the statistical significance of independent variables for sub-period panel data regressions.

Period	$\beta_1(S)$	$\beta_2(B)$	$\beta_3(F)$	$\beta_4(l)$	$\beta_5(C)$	$\beta_6(A\_g)$	$\beta_7(l\_g)$	$\beta_8(ROA)$
2011	29(1)	32(0)	31(0)	13(22)	39(0)	19(12)	17(8)	26(7)
2012	29(0)	33(0)	30(0)	8(15)	39(0)	17(10)	19(9)	24(8)
2013	30(0)	32(0)	31(0)	8(17)	39(0)	15(9)	20(11)	26(10)
2014	29(0)	34(0)	31(0)	9(16)	39(0)	15(9)	19(11)	25(10)

Note: The number of institutions with significant negative (positive) variable coefficient is out of (in) parentheses.

general a financial institution has a larger systemic risk contribution with a greater node strength, a larger node betweenness centrality, a larger node closeness centrality and a larger node clustering coefficient in the financial network.

In this paper, we mainly focus on the local network topology structure. A more comprehensive analysis might incorporate network measures with more balance sheet information which will provide a clearer view of systemic risk contribution.

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Appendix. Analyzed financial institutions

Node label	Stock code	Institution name	Node label	Stock code	Institution name
1	000001	Ping An Bank Co., Ltd.	21	600837	Haitong Securities Co., Ltd.
2	000416	Minsheng Holdings Co., Ltd.	22	600999	China Merchants Securities Co., Ltd.
3	000563	Shaanxi International Trust Co., Ltd.	23	601009	Bank of Nanjing Co., Ltd.
4	000686	Northeast Securities Co., Ltd.	24	601099	The Pacific Securities Co., Ltd.
5	000712	Guanddong Golden Dragon Development Inc.	25	601166	Industrial Bank Co., Ltd.

(*continued on next page*)

Node label	Stock code	Institution name	Node label	Stock code	Institution name
6	000728	Guoyuan Securities Company Limited	26	601169	Bank of Beijing Co., Ltd.
7	000750	Sealang Securities Co., Ltd.	27	601288	Agricultural Bank of China Limited
8	000776	Gf Securities Co., Ltd.	28	601318	Ping An Insurance (Group) Company of China, Ltd.
9	000783	Changjiang Securities Company Limited	29	601328	Bank of Communications Co., Ltd.
10	002142	Bank of Ningbo Co., Ltd.	30	601377	Industrial Securities Co., Ltd.
11	002500	Shanxi Securities Co., Ltd.	31	601398	Industrial And Commercial Bank of China Limited
12	600000	Shanghai Pudong Development Bank Co., Ltd.	32	601601	China Pacific Insurance (Group) Co., Ltd.
13	600015	Hua Xia Bank Co., Limited	33	601628	China Life Insurance (Group) Co., Ltd.
14	600016	China Minsheng Banking Corp.,Ltd.	34	601688	Huatai Securities Co., Ltd.
15	600030	Citic Securities Company Limited	35	601788	Everbright Securities Company Limited
16	600036	China Merchants Bank Co., Ltd.	36	601818	China Everbright Bank Company Limited
17	600109	Sinolink Securities Co., Ltd.	37	601939	China Construction Bank Corporation
18	600369	Southwest Securities Co., Ltd.	38	601988	Bank of China Limited
19	600643	Shanghai Aj Group Co., Ltd.	39	601998	China Citic Bank Corporation Limited
20	600816	Anxin Trust Co., Ltd.			

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