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Dynamic network topology and market performance: A case of the Chinese stock market

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Abstract

After the subprime mortgage crisis, plenty of abnormal market performance indicates that financial markets can be regarded as complex systems and it's time to break through some classical models. To tackle the issue, we propose novel complex networks methods to identify financial crises and explain some performance of the Chinese stock market. Firstly, we use the daily closing prices to construct the dynamical complex networks and their minimum spanning tree (MST) maps. Secondly, we characterize topological evolution of dynamical MSTs by employing normalized tree length, node degree distribution, centrality measures, node strength distribution and edge survival ratios. Furthermore, empirical analyses show that: (i) the normalized tree length can be used to identify financial crises, it declines sharply in the run-up to, and during the financial crisis, and increases rapidly afterwards; (ii) the normalized tree length is positively correlated with market return and negatively correlated with market tail risk and volatility; (iii) the closeness centrality of most stocks is significantly negatively correlated with individual returns and positively correlated with individual volatility; (iv) the node degree and node strength in most of MSTs follow the power-law distribution; (v) the edge survival ratio analysis indicates that the dependence structure of the Chinese stock market is relatively stable.

KEYWORDS

Chinese stock market, complex network, financial crises, market performance, minimum spanning tree

1 | INTRODUCTION

After the global financial crisis triggered by the subprime mortgage crisis in 2008, plenty of abnormal market performance indicates that the traditional financial and economic modelling theory needs to be modified greatly, especially when financial markets experience extreme risk (Bouchaud, 2008; Farmer & Foley, 2009; Wen, Xu, Ouyang, & Kou, 2019; Ye, Hu, He, Ouyang, & Wen, 2020). Some facts have come to light that traditional models do not go very far in explaining the statistical features of real markets, especially their susceptibility to sudden, large price movements, and the in-depth analysis shows that the complex network model can well reproduce these features (Buchanan, 2009; Mantegna & Stanley, 2000). Part of the reason is because of the truth that financial markets can be regarded as complex systems (Cao, Zhang, & Li, 2017; Jefferies, Johnson, & Hui, 2003). Since the seminal work by Mantegna (1999), the complex network theory has been successfully implement in stock markets, and the empirical analysis of stock markets by means of complex networks has been the new world-wide focus (Qiu, Gu, Xiao, Yang, & Wu, 2018; Tse, Liu, & Lau, 2010; Tumminello, Lillo, & Mantegna, 2010).

As far as the stock network is concerned, it is rather natural to associate with each node and interaction edge yielding to a graph. Once the nodes are selected, there are usually two essential stages to build a stock network, the first stage is to define edges and the second is to filter noise. In the pioneering work (Mantegna, 1999), Mantegna proposed a classical Pearson correlation coefficient approach to define edges for a stock network. Thereafter, a great deal of papers calculated the Pearson correlation coefficients among log-return series of stocks to build edges (Boginski, Butenko, & Pardalos, 2005; Zhao, Wang, Wang, Bao, & Stanley, 2018). In addition to the use of Pearson correlation coefficient method to define linkages, some other methods such as partial correlation coefficient (Kenett, Huang, Vodenska, Havlin, & Stanley, 2015; Wang, Xie, & Stanley, 2018), Granger-Causality test (Billio, Getmansky, Lo, & Pelizzon, 2012; He, Zhou, Xia, Wen, & Huang, 2019; Wang, Xie, He, & Stanley, 2017; Yao, Lin, Lin, Zheng, & Liu, 2016), and Copula function (Wang & Xie, 2016) have been attracted more and more attention. A succeeding procedure of building a network that connects all pair of nodes results to a global coupling network, which contains a lot of noise information. Therefore, it is necessary to single out the important edges by filtering a complex global coupling network into a simpler relevant subnetwork. Very recently, some filtering methods such as the MST method (Huang, Yao, Zhuang, & Yuan, 2017; Lee, Youn, & Chang, 2012), the Planar Maximally Filtered Graph (PMFG) method (Tumminello, Aste, Matteo, & Mantegna, 2005; Zhao, Li, & Cai, 2016) and the correlation threshold method (Chen, Luo, Sun, & Wang, 2015; Xu, Wang, Zhu, & Zhang, 2018) have been successfully applied to stock networks. The MST method can extract the key information of the network on basis of reserving the simplest structure and therefore it is regarded as a superior method to excavate important nodes and analyse network evolution (Long, Guan, Shen, Song, & Cui, 2017).

Generally speaking, there are two classes of networks adopted in empirical analysis: one is static network and the other is dynamic network. Previous studies mainly focus on aggregating temporal networks into a static network, which consider a certain period as an entity, and the topology properties such as the hierarchical structure, the scale-free characteristic, the small world characteristic and the robustness are not time-varying (Caraiani, 2012; Zhang, Zhou, Jiang, & Wang, 2010). Obviously, the shortcoming of a static network is that the information about the time evolution of stock markets is ignored. In order to overcome the shortage, taking into account the temporal characteristics of stock markets, replacing a static network with a dynamic network has become the novel front of network science in recent years (Cao & Wen, 2019; Majapa & Gossel, 2016; Onnela, Chakraborti, Kaski, & Kertész, 2003; Schuenemann, Ribberink, & Katenka, 2020; Sensoy & Tabak, 2014; Zhang, Zhuang, & Lu, 2019; Zhang, Zhuang, Lu, & Wang, 2020; Zhang, Zhuang, Wang, & Lu,). Onnela et al. (2003) compared the topological difference of S&P 500 stock network between Black Monday and a normal day and found that the normalized tree length (NTL) decreased during the stock market crisis. Sensoy and Tabak (2014) constructed dynamic spanning trees to research the Asia Pacific stock markets and found that the most influential market is Hong Kong. Majapa and Gossel (2016) divided the full sample period into three sub-periods to investigate the topological evolution of the Johannesburg Stock exchange (JSE) network and found that the JSE network shrank during the global financial crisis in 2008. Zhang, Zhuang, Lu, and Wang (2020) constructed dynamic volatility spillover networks for the G20 stock markets to estimate the spatial correlation relationship and found that the spatial linkage of volatility spillover was time-varying. Zhang, Zhuang, Wang, and Lu () explored the time-varying risk spillovers and connectedness in the sectoral of the Chinese stock markets based on the tail risk network and found that stock markets undergo more systemic risks and exhibit more connections during market collapse.

To a large extent, the existing literature on theoretical studies of stock market is predominantly concerned with market performance, which can be described by the return, volatility and individual stocks or markets tail risk (Huang et al., 2017; Tan, Quek, & Ng, 2007). Literature dealing with the relationships between topological evolution of stock network and market performance appears to be scarce, such studies are however essential for us to understand the topology variation of stock networks and perform the risk management. To the best of our knowledge, the relationship between the topological evolution of dynamical networks and the market performance for the Chinese stock market has not been studied yet, and still remains as a challenging open problem.

Motivated by above discussion, in this paper, we employ the method of moving windows to scan through 882 stocks listed on the Chinese stock market from January 2006 to December 2017. Then 188 dynamical correlation-based networks and their MST maps are established. Next, the investigation of the relationships between the topological evolution of MSTs and the market performance is carried out. The contributions of this paper can be listed as follows.

1. With the help of the moving window correlation coefficient method, we construct time-varying networks instead of statics network by taking full considering of the dynamic characteristics of the stock markets.
2. The existing literatures are predominantly concerned with stock market performance. We investigate the relationships between the topological evolution of MSTs and the market performance.
3. The NTL can be viewed as an early warning indicator for market collapse. And our empirical results show that it can well identify the sub-prime mortgage crisis, the European debt crisis and the Chinese A-share market disaster.

The remainder of this paper is formulated as below. Section 2 gives an introduction to the methodology. Section 3 presents the dataset and empirical results. Finally, some conclusions are drawn in Section 4.

2 | METHODOLOGY

Dynamic networks created in this paper are based on a rolling window approach, the Pearson correlation coefficient and MST method. In order to measure the topology properties of networks, we will introduce the definitions of NTL, node degree, node strength, betweenness centrality, closeness centrality, node degree and strength distribution, and edge survival ratios. We also present some measures about market performance, such as return, volatility, tail risk and so on.

2.1 | Dynamic network construction

The evolution of the relationship between stocks can be characterized by dynamic network, which is constructed by the following three steps.

2.1.1 | Step 1. Use a rolling window to divide the closing price

The rolling window approach is widely used to construct dynamic networks (An et al., 2020; An et al., 2020). In this stage, we use a fixed-length rolling window to divide the closing price into a series of windows that evolve over time. We assume the length of the sample is T trading days. z and δ represent window length and rolling forward days, respectively. Thus, the total number of $Z(Z = 1 + (T - z)/\delta)$ windows can be easily obtained. Exactly, if the first window starts at day $t_1^1 = 1$ and ends at $t_2^1 = z$, then the second window starts at day $t_1^2 = 1 + \delta$ and ends at $t_2^2 = z + \delta$, the third window starts at day $t_1^3 = 1 + 2\delta$ and ends at $t_2^3 = z + 2\delta$, and so on.

2.1.2 | Step 2. Construct a distance matrix based on the Pearson correlation coefficient

For stock i and day t, let $X_i^m(t)$ be the closing price at mth window, the log-return of stock i can be defined as below

$$R_i^m(t) = \ln X_i^m(t) - \ln X_i^m(t-1). \tag{1}$$

Then the Pearson correlation coefficient between return series of stocks i and j can be given as

$$c_{i,j}^m = \frac{\left\langle R_i^m R_j^m \right\rangle - \left\langle R_i^m \right\rangle \left\langle R_j^m \right\rangle}{\sqrt{\left(\left\langle \left(R_i^m\right)^2 \right\rangle - \left\langle R_i^m \right\rangle^2\right)\left(\left\langle \left(R_j^m\right)^2 \right\rangle - \left\langle R_j^m \right\rangle^2\right)}}, \tag{2}$$

where $\langle \cdot \rangle$ denotes the statistical mean. The correlation coefficient $c_{i,j}^m$ satisfies $-1 \le c_{i,j}^m \le 1$. Particularly, if $i = j$, then $c_{i,j}^m = 1$.

According to Mantegna (1999), in order to define the edges, we convert the cross-correlation matrix $C^m = \left(c_{i,j}^m\right)$ into a distance matrix, denoted by

$$d_{i,j}^m = \sqrt{2\left(1 - c_{i,j}^m\right)}, \tag{3}$$

where $d_{i,j}^m$ is the distance metric between nodes i and j. It is worth noting that $d_{i,j}^m$ must fulfil the three basic properties of metric distance: (a) nonnegativity, $d_{i,j}^m \ge 0$ and $d_{i,j}^m = 0$ if and only if $i = j$; (b) symmetry, $d_{i,j}^m = d_{j,i}^m$ hold for all i and j; (c) triangular inequality, $d_{i,j}^m \le d_{i,k}^m + d_{k,j}^m$ hold for all k.

2.1.3 | Step 3. Construct the dynamical MST network

Based on complex network theory, we connect all pair of nodes according to the distance matrix $D^m = \left(d_{i,j}^m\right)$. Then, we can obtain a full network, where the node is the stock, the weighted edge is the distance obtained by the Pearson correlation coefficient of stock returns between each pair of stocks. The MST method based on Kruskal algorithm

(Kruskal, 1956) is then adopted to filter out the noise information. The implementation of MST usually follows four steps:

1. Make a list for $N \times (N - 1)/2$ edges and sort them according to the distance from small to large.
2. Create an empty map. Add the edge corresponding to the first component in the list to the empty map.
3. Add the edge corresponding to the next component in the list to the map, and if the map is still a tree, then the edge is retained, if not, the edge is discarded.
4. Repeat step 3 until all components are exhausted.

As the fact that the procedure of building network is performed Z times during the whole sample period, and therefore one can obtain Z successive MST networks.

2.2 | Network topology properties

In this section, we analyse the topological structure of dynamical MST networks. Firstly, the NTL are used to investigate the evolution of the structure of the entire stock market. Secondly, several indicators, which are commonly used in MST networks analysis, including node degree, node strength, betweenness centrality and closeness centrality are calculated to measure the influence of a stock node. Then we make use of the node degree distribution and the node strength distribution to explore the heterogeneity of the network structure. Finally, the survival ratio is utilized to describe the robustness of the network.

2.2.1 | Normalized tree length

The NTL is applied to assessing the closeness among the nodes of network (Onnela et al., 2003), and it is given by

$$L^m = \frac{1}{N-1} \sum_{d_{i,j}^m \in E^m} d_{i,j}^m, \tag{4}$$

where $m = 1, 2, ..., Z$, and E^m is the edge set of the mth MST.

2.2.2 | Node degree and node strength

The number of nodes which adjacent to node i is called as node degree k_i^m (Gong, Liu, Xiong, & Zhang, 2019; Onnela et al., 2003). It is defined as

$$k_i^m = \sum_{j=1}^{N} A_{i,j}^m, \tag{5}$$

where $A_{i,j}^m$ is the adjacency matric of the mth MST.

Let s_i^m be node strength, that is, the sum of the correlation coefficients of node i with all its adjacent nodes. It is defined as below

$$s_i^m = \sum_{j \in N^m(i)} w_{i,j}^m, \tag{6}$$

where $N^m(i)$ denotes the neighbours of node i, $w_{i,j}^m$ represents the cross-correlation coefficient between nodes i and j. This measure can be used to evaluate nodes that play an important role as a hub in the network (Sun, Wang, Yao, Li, & Li, 2020).

2.2.3 | Betweenness centrality

According to Huang and Wang (2018) and Barthélemy (2004), the betweenness centrality b_i^m can be characterized by

$$b_i^m = \frac{1}{(N-1)(N-2)} \sum_{j \neq e \neq i \in V^m} \frac{n_{j,e}^m(i)}{n_{j,e}^m}, \tag{7}$$

which is used to evaluate the intermediary role played by node i in transferring information in the network, where V^m is the node set of the mth MST, $n_{j,e}^m(i)$ indicates through node i, the amounts of shortest links form node j to node e, and $n_{j,e}^m$ denotes the number of the shortest links from node j to node e.

2.2.4 | Closeness centrality

Closeness centrality c_i^m is measured by calculating the reciprocal of the sum of distances from node i to all other nodes (Costenbader & Valente, 2003; Ji, Bouri, & Roubaud, 2018). Generally, the higher value of the closeness centrality the stronger connection appears in the central nodes. Its formula is

$$c_i^m = \frac{1}{\sum_{j=1}^{N} l_{i,j}^m}, \tag{8}$$

where $l_{i,j}^m$ denotes the minimum distance from nodes i to j.

2.2.5 | Node degree distribution

Node degree distribution $P(k)$ denotes the probability that a randomly selected node is connected to k edges. This measure describes the heterogeneity of the network structure. It has been proved that the node degree of numerous actual networks follows power-law distribution (Axtell, 2001; Wang & Chen, 2003), and $P(k)$ can be expressed as

$$P(k) \propto k^{-\gamma}, \tag{9}$$

where γ is a constant parameter that can be estimated by maximum likelihood. The power-law node degree distribution means that some hubs exist in the network. These hubs are related to most of other nodes and contain more information about the time series.

According to Clauset, Shalizi, and Newman (2009), the Kolmogorov–Smirnov (K-S) goodness-of-fit test will be employed to assess the rationality of the estimated distribution. This test can generate a p-value, and if the p-value is greater than 0.1, then the power-law hypothesis will be accepted, otherwise rejected. By the way, the node strength distribution can be examined by the same method.

2.2.6 | Survival ratio

The so-called survival ratio, also as the ratio of surviving edges, are usually applied to describe the robustness of the network (Onnela et al., 2003). Generally speaking, the survival ratios include single-step survival ratio and Multi-step survival ratio. One can defined the single-step survival ratio $\varphi(m)$ as below

$$\varphi(m) = \frac{1}{N-1}\left|E^m \cap E^{m-1}\right|, \tag{10}$$

where $\cap$ represents the intersection operator, and $|\cdots|$ gives the number of elements in the set. Multi-step survival ratio $\varphi(m, k)$ is defined as below

$$\varphi(m,k) = \frac{1}{N-1}\left|E^m \cap E^{m-1} \cap \cdots \cap E^{m-k}\right|, \tag{11}$$

where k is the number of steps. $\varphi(m, k)$ describe the short and long term stability of the network with respect to the small and large values of k. Obviously, the higher the survival ratio is, the more stable the network is.

2.3 | Market performance

Market performance can be described by the return, volatility and individual stocks or markets tail risk according to Huang et al. (2017).

As in Huang et al. (2017) and Wen, Wu, and Gong (2020), we can calculate the average return r^m of individual stocks or markets in the mth z-day window by

$$r^m = \frac{1}{z}\sum_t R^m(t), \tag{12}$$

where $R^m(t)$ is the log-return of a specific stock or market index at day t. Then the return volatility σ^m is given by

$$\sigma^m = \sqrt{\frac{\sum_t \left(R^m(t) - r^m\right)^2}{z}}. \tag{13}$$

Tail risk refers to the additional risk of fat-tailed return distributions associated to normal distributions. We employ the conditional value-at-risk (CVaR) to measure the return tail risk of individual stocks or markets (Rockfellar & Uryasev, 2000), and the CVaR with confidence level α is defined as follows

$$CVaR_\alpha(R^m) = E[R^m VaR_\alpha(R^m)], \tag{14}$$

in which $E[\cdot]$ represents conditional expectation, and VaR denotes the maximum loss on a portfolio over a certain period of time, it is a measure of risk generally applied in financial markets.

3 | DATA AND EMPIRICAL ANALYSIS

3.1 | Data

Our dataset comes from the China Stock Market and Accounting Research (CSMAR) database, and the empirical analysis makes full use of the data of daily closing prices of 2,795 companies listed in the Chinese A-share market from January 20, 2006 to December 29, 2017. The whole sample period covers 2,905 trading days. Due to the fact that some stocks were traded less than 2,905 days, just as shown in Hu, Gu, Wang, and Zhang (2019), the data can be processed as follows three steps to ensure the statistical reliability:

1. Remove stocks whose number of trading days are less than 80% of all trading days, and therefore 1,129 stocks are retained.
2. Remove stocks with successive missing closing prices over 100 days. There are totally 882 stocks left.
3. Perform the below procedure of filling in missing values. If $X_i(t+1)$, $X_i(t+2)$, ..., $X_i(t+s)$ $(s \geq 1)$ are

missing closing prices and $X_i(t)$ is a known price, then we denote $X_i(t+1) = X_i(t+2) = \cdots = X_i(t+s) = X_i(t)$; If $X_i(t+1)$, $X_i(t+2)$, ..., $X_i(t+s-1)$ $(s \geq 2)$ are missing closing prices and $X_i(t+s)$ is the first known price, then we denote $X_i(t+1) = X_i(t+2) = \cdots = X_i(t+s-1) = X_i(t+s)$.

Go through the above three steps, one can obtain a complete set of closing prices data for 882 stocks.

3.2 | Empirical analysis

3.2.1 | Analysis of the normalized tree length

This section employs moving window correlation coefficient to measure the dynamic correlations among stocks. To avoid numerous overlapping windows, we choose the window length of $z = 100$ days and the rolling step of $\delta = 15$ days. As a result, 188 windows (MSTs) are obtained. For each MST, its NTL is calculated and shown in Figure 1.

Figure 1 shows that the NTL decreased sharply in the run-up to, and during the sub-prime mortgage crisis, and its value dropped from 1.1019 to 0.7968. Since then, the NTL increased rapidly and returned to its initial level. However, the NTL decreased again as the European debt crisis broke out, and its value fluctuated up and down greatly as time elapses from 2009 to 2012. Afterwards, the NTL had undergone a steady growth period about from June 2012 to June 2014. In June 2015, the Chinese stock market suffered a serious disaster so that the NTL dropped sharply to 0.7301, which was the minimum over the whole sample period, and the value increased after the market recovery. Accordingly, the NTL declined sharply when stock market confronted extreme risk.

Furthermore, we investigate the relationships between topological evolution (for instance, NTL) of MSTs and market index performance. Here we choose the CSI 300 index as the representative to reflect the overall performance of the Chinese stock market. The variety of the CSI 300 index reflects the change of China's stock market to a great extent, and it is one of the representative stock indexes in China (Li, Li, & Liu, 2018). The CSI 300 index is extensively used in various types of financial applications, and is widely discussed in the literature (Wang, Murgulov, & Haman, 2015). To facilitate our analysis, we divide 188 MSTs into 10 equal groups by the following three steps. To begin with, we divide the CSI 300 index into a series of time-varying windows using the same rolling window as building dynamic networks. In the second place, the average return of the CSI 300 index of each window can be obtained. Lastly, according to the average return of the CSI 300 index within the corresponding time window, we can divide the average return of each window into 10 equal groups from the lowest return to the highest return. Thus, the corresponding MSTs are also divided into 10 groups. Afterwards, we calculate the number of networks corresponding to each group, and the results are shown in Figures 2 and 3.

Group 1 to group 10 represents from the lowest return level group to the highest return level group. As shown in Figure 2, we find that group 6 (with the average return of the CSI 300 index varies from −0.0001 to 0.0014) contains the largest number of MSTs in all groups. Moreover, groups with medium return levels contain greater number of MSTs than those with low or high return levels.

As is known to all, the longer the NTL the looser the network structure holds. The empirical analysis presents the average NTL (L) from group 1 ($L = 0.8164$) to group 10 ($L = 1.0177$), please see Figure 3. Obviously, the positive correlation between the average NTL and the market

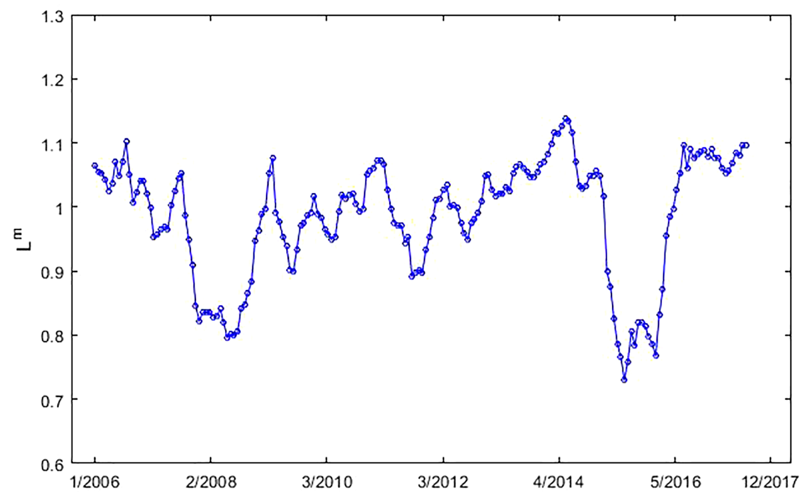

FIGURE 1 The normalized tree length in each period [Colour figure can be viewed at wileyonlinelibrary.com]

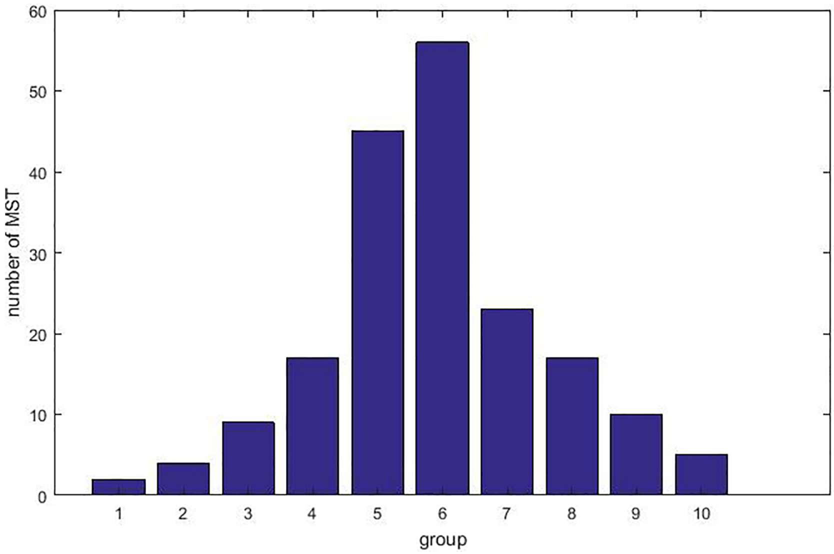

FIGURE 2 The number of minimum spanning trees belonging to each group classified according to the average return of the CSI 300 index within the corresponding time window [Colour figure can be viewed at wileyonlinelibrary.com]

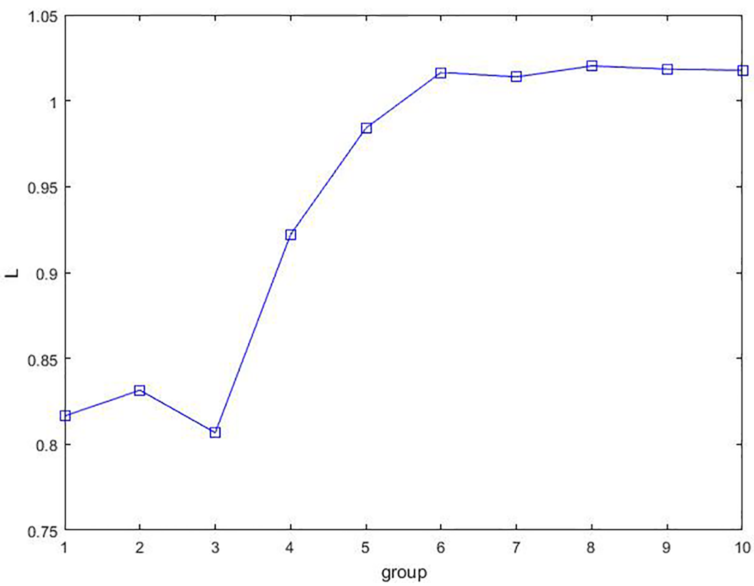

FIGURE 3 Average normalized tree length for each group classified according to the average return of the CSI 300 index within the corresponding time window [Colour figure can be viewed at wileyonlinelibrary.com]

return means that the higher the market return the looser the network structure holds.

In order to further investigate the relationship between the NTL and the market volatility, we divide the 188 MSTs into 10 equal groups according to the average return volatility of the CSI 300 index within the corresponding time window. The empirical results are shown in Figure 4 and 5.

Group 1 to group 10 represents from the lowest volatility level group to the highest volatility level group. From Figure 4, we can see that group 4 (with the return volatility of the CSI 300 index varies from 0.0134 to 0.0162) contains the largest number of MSTs in all groups. In addition, group 8 to group 10 (with the return volatility of the CSI 300 index varies from 0.0246 to 0.033) contains the smaller number of MSTs, which indicates that the stock markets have low or medium volatility in most of time windows.

Figure 5 displays the average NTL (L) for each group. The pattern of L shows a decreasing tendency from group 1 ($L = 1.07873$) to group 10 ($L = 0.80306$). That is to say, the NTL is negatively correlated with the market volatility. This means that the network structure turns to be denser when the market volatility is higher. In fact, a high level of volatility means a state of crisis, and the phenomenon of volatility clustering often exists during periods of crisis (Li, Hommel, & Paterlini, 2018). The volatility associated with the crisis causes the network to shrink and makes the NTL reduce, which implies that the volatility is easier to transmit. Figure 5 shows that the

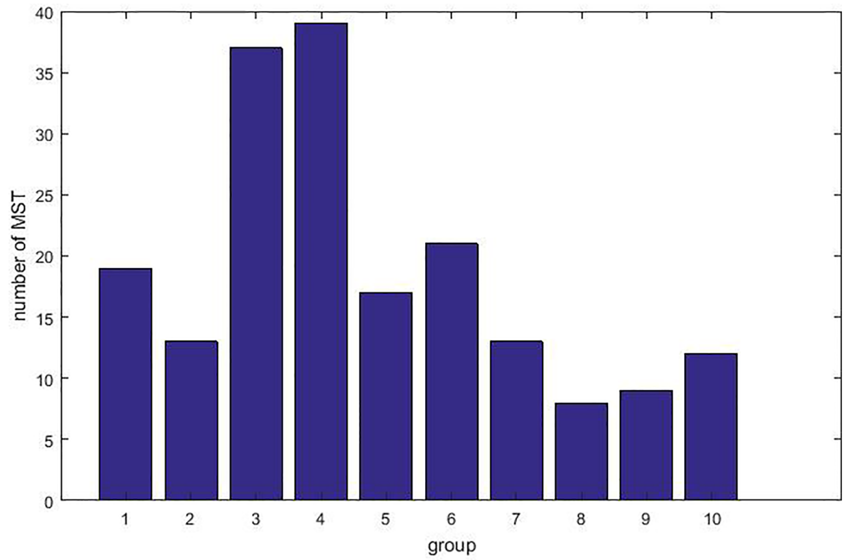

FIGURE 4 The quantity of minimum spanning trees in each group classified according to the return volatility of the CSI 300 index within the corresponding time window [Colour figure can be viewed at wileyonlinelibrary.com]

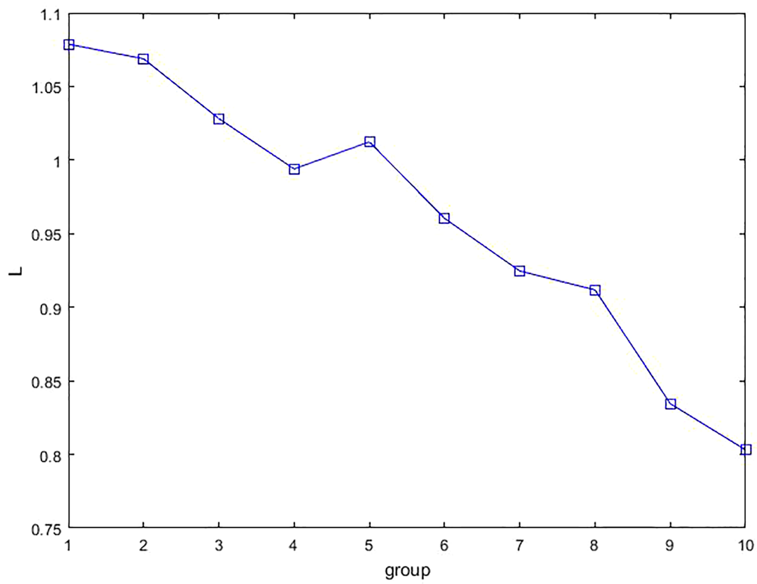

FIGURE 5 Average normalized tree length for each group classified according to the return volatility of the CSI 300 index within the corresponding time window [Colour figure can be viewed at wileyonlinelibrary.com]

empirical results of the NTL are in excellent agreement with those of Figure 1. In addition, the negative correlation between market volatility and NTL also means that with the increase of market volatility, most stock movements will tend to be consistent.

Also, according to the average tail risk level of the CSI 300 index within the corresponding time window, we divide 188 MSTs into 10 equal groups to investigate the relationship between market tail risk and NTL. The empirical results are presented in Figures 6 and 7.

The larger value of CVaR is, the lower tail risk of the market will be. Therefore, group 1 to group 10 represents from the highest tail risk level group to the lowest tail risk level group. As shown in Figure 6, we find that group 10 (with the value of CVaR varies from −1.8 to −1) and group 3 (with the value of CVaR varies from −7.4 to −6.6) contain the largest and smallest number of MSTs in all groups, respectively. Meanwhile, groups with high tail risk levels contain smaller number of MSTs than those with low tail risk levels.

Figure 7 presents the average NTL (L) for each group. The pattern of L shows an increasing tendency from group 1 ($L = 0.8166$) to group 10 ($L = 1.0621$). In other words, the market tail risk is negatively correlated with the NTL. This means that the network structure turns to be denser when the market tail risk increases. With the increasing tail risk, a great number of edges for the whole network are concentrated in a few highly centralized stocks, this means that a few nodes play an essential role in the entire network (Zhang, Zhuang, Wang, & Lu,). If these nodes encounter a risk shock or infection, the stability of the network structure will be very fragile and the

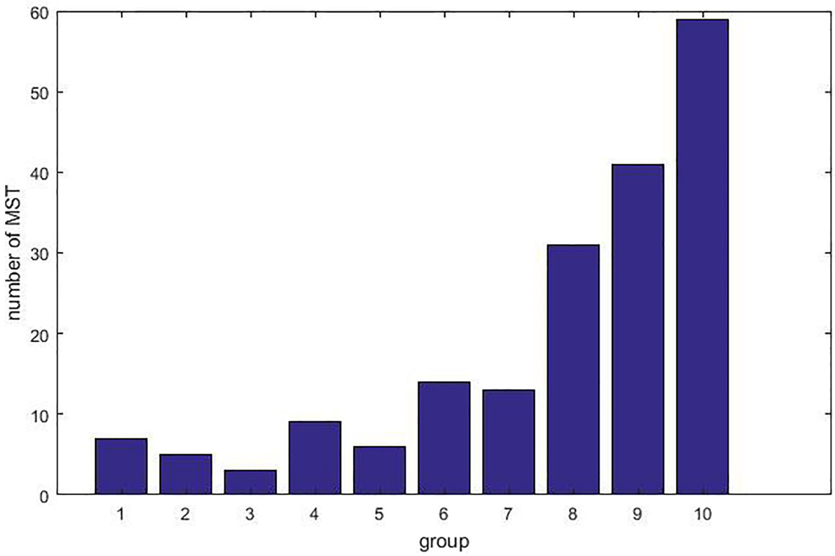

FIGURE 6 The quantity of minimum spanning trees in each group classified according to the return tail risk of the CSI 300 index within the corresponding time window [Colour figure can be viewed at wileyonlinelibrary.com]

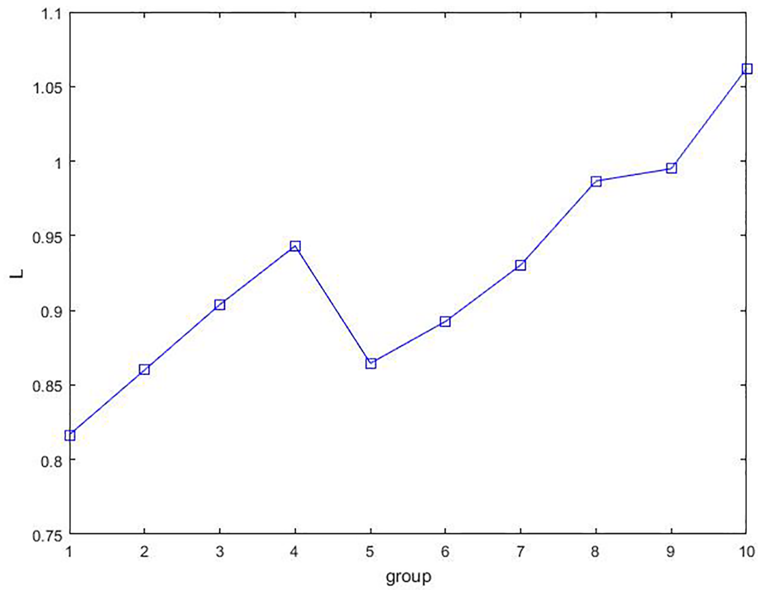

FIGURE 7 Average normalized tree length for each group classified according to the return tail risk of the CSI 300 index within the corresponding time window [Colour figure can be viewed at wileyonlinelibrary.com]

risk contagion effect of the whole network will increase significantly.

Based the above discussions, we can propose the NTL as an indicator to send early warning signal of financial crisis as the fact that it is positively correlated with the market return and negatively correlated with the market volatility and tail risk. Our findings may provide us some lights on identifying crisis and may have potential applications on employing suitable measures to manage stock market risk.

3.2.2 | Power-law analysis

Based on the method proposed by Clauset et al. (2009), for each MST, we investigate the node degree and strength distribution, and their *p*-value and exponents are displayed in Figures 8 and 9, respectively.

From Figure 8, one can see that the *p*-value fluctuates dramatically over time. In total, 124 (65.96% of 188) MSTs follow power-law node degree distribution, and the power-law exponents γ_1 vary from 2.58 to 3.5. This means that a few nodes in the MST occupy most of the edges, while the majority of nodes only have a small number of edges. In addition, (68.62% of 188) MSTs follow power-law node strength distribution, and their power-law exponents γ_2 vary from 2.66 to 4.72 in Figure 9. The empirical results indicate that the Chinese stock networks are heterogeneous networks in the majority of time windows, where a few nodes occupy most of the connections and have stronger connections with other

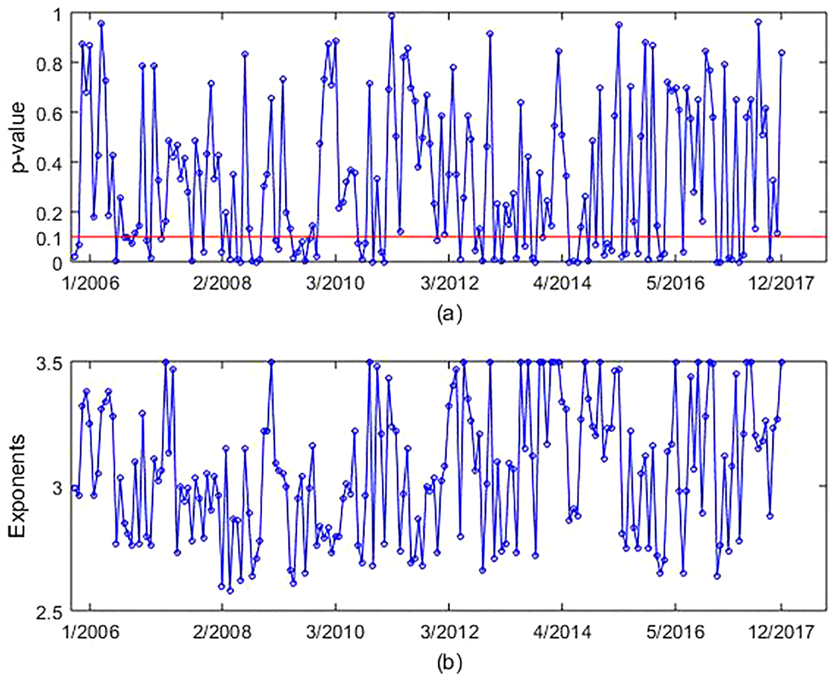

FIGURE 8 Time-varying *p*-value(a) and exponents(b) of node degree distribution [Colour figure can be viewed at wileyonlinelibrary.com]

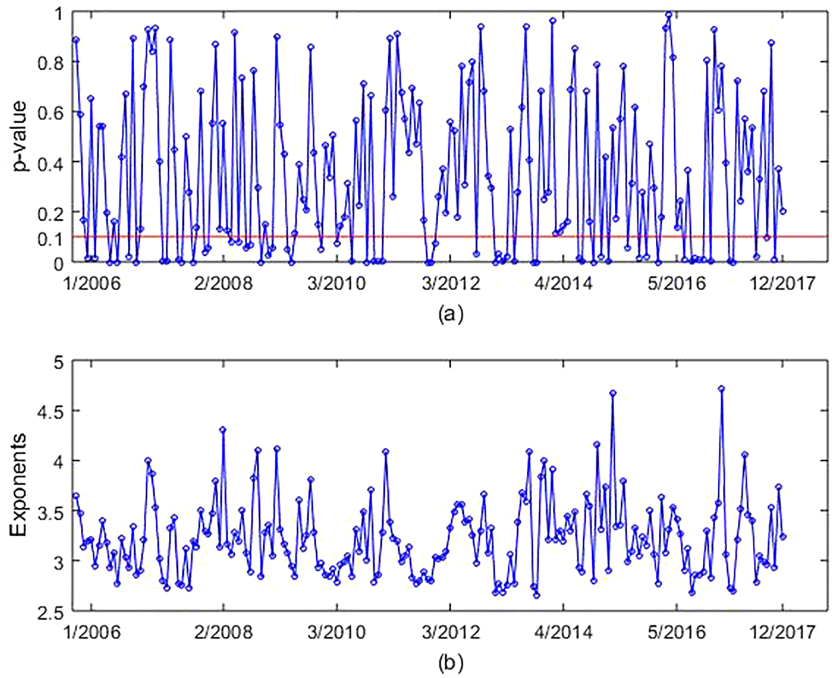

FIGURE 9 Time-varying *p*-value(a) and exponents(b) of node strength distribution [Colour figure can be viewed at wileyonlinelibrary.com]

nodes. Therefore, it is particularly important to dig out these influential nodes.

3.2.3 | Centrality analysis

Centrality measures can help us identify the influential nodes in the network. In other words, the more important nodes in the network always have larger value of the centrality measures. The highest centrality measures for each MST are shown in Figure 10.

Figure 10 presents the highest node degree, highest betweenness centrality, highest node strength and highest closeness centrality for each MST, and the corresponding values vary from 13 to 74, from 0.5664 to 0.9298, from 8.509 to 65.389 and from 1.0766×10^{-4} to 4.995×10^{-4}. Meanwhile, the corresponding stocks with the highest centrality measures also vary over

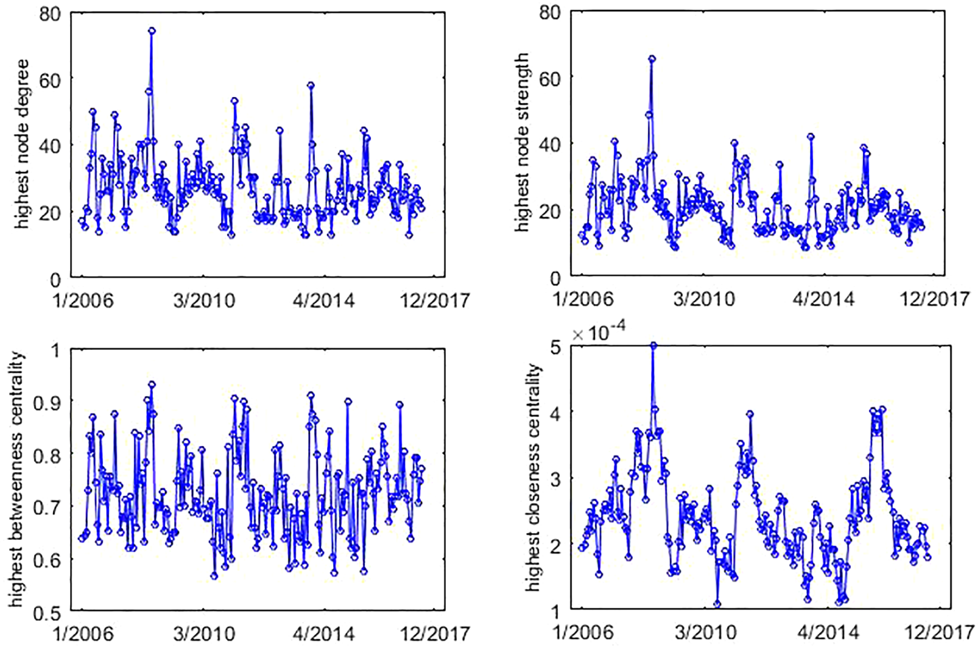

FIGURE 10 Highest centrality measures for each minimum spanning tree [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 1 Top 20 stocks based on the times they act as the central node in all minimum spanning trees

Highest node degree		Highest node strength		Highest betweenness centrality		Highest closeness centrality	
Stock ticker	Times	Stock ticker	Times	Stock ticker	Times	Stock ticker	Times
000756	9	000756	9	600308	8	600308	10
600308	7	600987	8	600103	7	600103	7
600987	7	600308	7	000912	6	000912	5
000797	5	000912	5	600218	5	600156	5
000912	5	600360	5	600360	5	600218	5
600360	5	600601	5	000089	4	600601	5
600601	5	000797	4	000528	4	000589	4
600621	5	000830	4	000589	4	000797	4
000830	4	600103	4	000797	4	600006	4
600103	4	600156	4	600006	4	600287	4
600156	4	600172	4	600156	4	600360	4
600172	4	600287	4	600287	4	600880	4
600287	4	600616	4	600601	4	600982	4
600616	4	600621	4	600880	4	000528	3
600846	4	000089	3	000422	3	000572	3
000089	3	000422	3	000572	3	600561	3
000422	3	000572	3	000707	3	600567	3
000572	3	000700	3	600561	3	600616	3
000589	3	600006	3	600616	3	600543	3
000700	3	600051	3	600811	3	600824	3

time. Throughout the sample period, there are totally 104, 97, 91 and 96 different stocks with the largest values of node degree, betweenness centrality, node strength and closeness centrality. Furthermore, we display the top 20 stocks based on the times they act as the central node with different highest centrality measures in all MSTs, and the results are shown in Table 1.

From Table 1, one can find that the top 20 stock lists for different highest centrality measures have some differences. However, several stocks appear simultaneously in the four different lists, their tickers are 600308, 000797, 000912, 600360, 600601, 600103, 600287, 600616 and 000572. According to the China Securities Regulatory Commission classification standard in 2017, these nine stocks belong to the manufacturing industry except 000797. Furthermore, manufacturing stocks occupy more than 60% of the top 20 stocks for each list. This indicates that manufacturing stocks act an important role in the MST network. This coincides with our experience. In fact, for a long time, China is called the "workshop of the world" by foreign countries because of the development and rapid growth of the manufacturing industry. Nowadays, the manufacturing industry has been the main pillar of national economic development and one of the largest contributors to China's GDP, which makes it the most important industry (Tian, Zheng, & Zeng, 2019; Wu, Zhang, & Zhang, 2019). Considering that China is still in the process of industrialization and urbanization, the manufacturing industry should be concerned by both regulators and investors.

It is interesting to know the correlations among these four different node centrality measures including node degree (k), node strength (s), betweenness centrality (b) and closeness centrality (c) by calculating the Pearson correlation coefficients. The False Discovery Rate (FDR) correction procedure is used to perform multiple hypothesis test correction, and significant correlations are then identified according to FDR q-value ≤ 0.05 (Benjamini & Hochberg, 1995). The results are shown in Table 2.

From Table 2, we find that the degree and the strength of 882 nodes (100% of 882) are significantly positively correlated, a similar correlation is hold for the strength and the betweenness centrality of 882 nodes (100% of 882). Meanwhile, the degree and the betweenness centrality of 880 nodes (99.77% of 882) are significantly positively correlated. In addition, there are significantly positive correlation also appear in the degree and the closeness centrality of 397 nodes (45.01% of 882), the strength and the closeness centrality of 619 nodes (70.18% of 882), the betweenness centrality and closeness centrality of 293 nodes (33.22% of 882). Accordingly, we conclude that these three centrality measures are highly positively correlated among them, including node degree, node strength and betweenness centrality. However, there is no highly positive correlation between the closeness centrality and other centrality measures.

Furthermore, correlations between topological evolution (node centrality measures) of MSTs and individual stock's performance can be examined directly. To prevent redundancy, only node degree and closeness centrality are selected for analysis. Similarly, the FDR correction procedure is performed for the subsequent tests to correctly assess the statistical significance.

We compute the Pearson correlation coefficients between node degree and corresponding stock's performance, and the distribution results are shown in Figure 11 and summarized in Table 3. We find that the node degree and the average return of 173 stocks (19.61% of 882) are significantly correlated, the node degree and the return volatility of 305 stocks (34.58% of 882) are significantly correlated. In addition, the node degree and return tail risk of 293 stocks (33.22% of 882) are significantly correlated. Therefore, only a small number of individual performance have significant relevance to the node degree.

Also, we can compute the correlation coefficients between node closeness centrality and corresponding stock's performance and show the results in Figure 12. It shows that the distribution of correlation coefficients in subfigures (a), (b), (c) has obvious positive and negative partitions. Table 4 summarizes the distribution results. Obviously, the node closeness centrality and the average

TABLE 2 Correlations among different node centrality measures

	ρ(k,s) number	ρ(k,b) number	ρ(k,c) number	ρ(s,b) number	ρ(s,c) number	ρ(b,c) number
0.80~1.00	873	263	0	251	0	0
0.60~0.79	8	404	5	418	7	1
0.40~0.59	1	181	62	180	132	35
0.20~0.39	0	30	271	29	379	190
0.00~0.19	0	4	376	4	314	462
−0.19~0.00	0	0	159	0	49	190
−0.39~−0.20	0	0	9	0	1	4
Significant positive	882	880	397	882	619	293
Significant negative	0	0	15	0	3	11

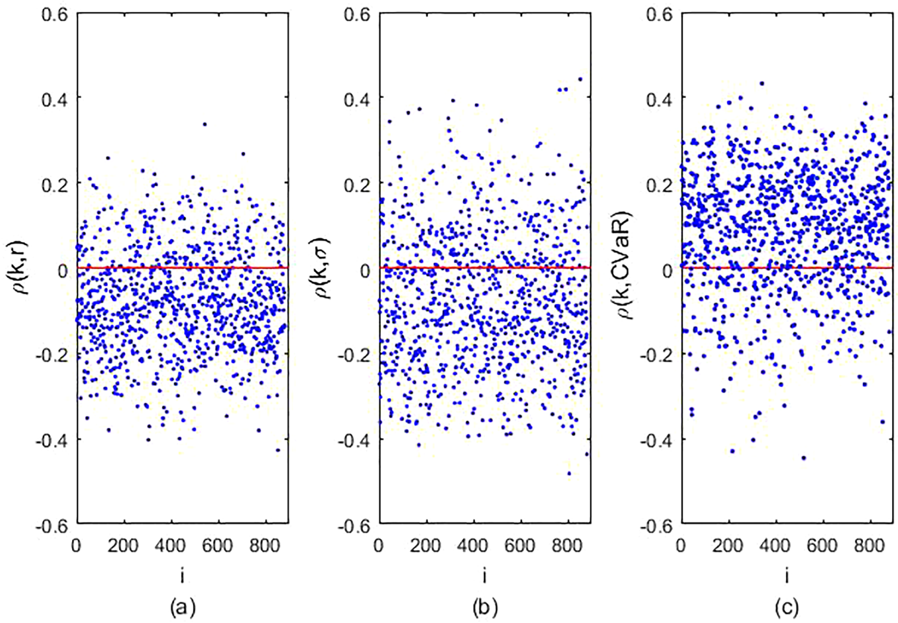

FIGURE 11 Correlation coefficients between node degree and corresponding stock's performance [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 3 Statistics of correlation coefficients between node degree and corresponding stock's performance

	p(k,r) number	p(k,σ) number	p(k,CVaR) number
0.40∼0.59	0	3	1
0.20∼0.39	7	39	195
0.00∼0.19	209	242	465
−0.19∼0.00	536	398	191
−0.39∼−0.20	128	197	27
−0.59∼−0.40	2	3	3
Significant positive	12	55	252
Significant negative	161	250	41

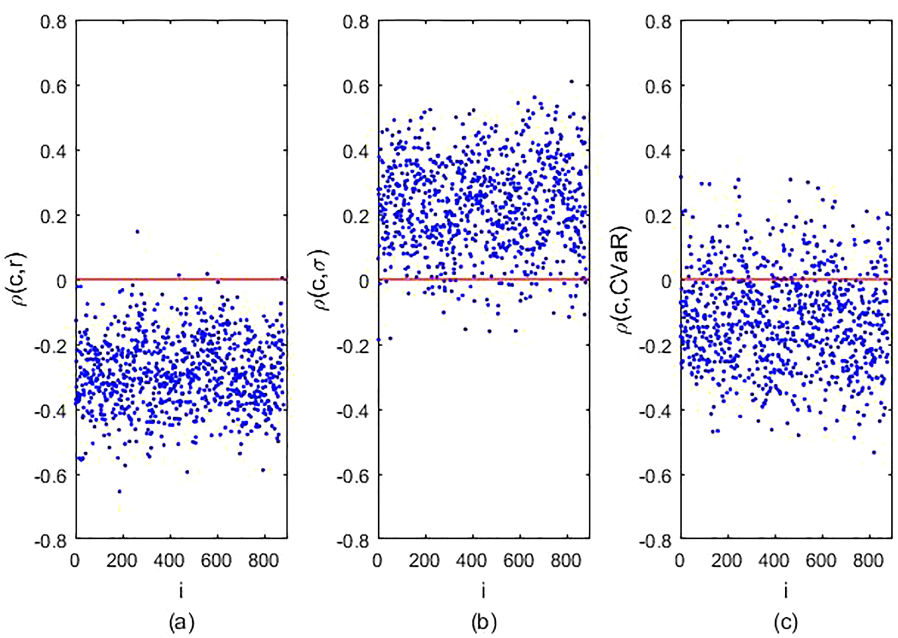

FIGURE 12 Correlation coefficients between node closeness centrality and corresponding stock's performance [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 4 Statistics of correlation coefficients between node closeness centrality and corresponding stock's performance

	p(c,r) number	p(c,σ) number	p(c,CVaR) number
0.60∼0.79	0	1	0
0.40∼0.59	0	95	0
0.20∼0.39	0	416	17
.00∼0.19	4	322	150
−0.19∼0.00	183	48	437
−0.39∼−0.20	559	0	257
−0.59∼−0.40	135	0	21
−0.79∼−0.60	1	0	0
Significant positive	1	615	26
Significant negative	799	5	359

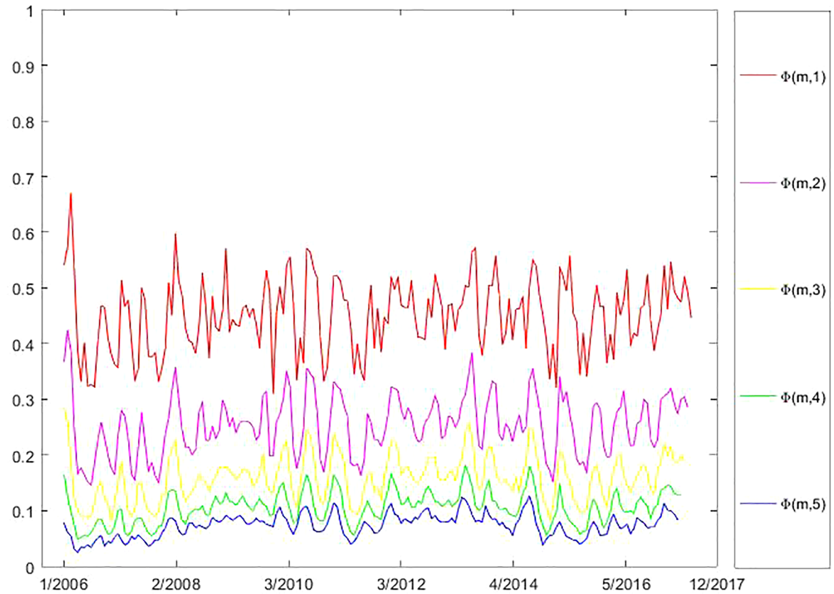

FIGURE 13 Time-varying survival ratios under different steps [Colour figure can be viewed at wileyonlinelibrary.com]

return of 799 stocks (90.59% of 882) are negatively correlated significantly, the node closeness centrality and the return volatility of 615 stocks (69.73% of 882) are significantly positively correlated, yet the similar correlation is hold for the node closeness centrality and the return tail risk of 359 stocks (40.70% of 882). Therefore, the node closeness centrality of most stocks is significantly negatively correlated with their average return and significantly positively correlated with their return volatility.

Overall, the manufacturing stocks play an important role in the MST network. There are highly positive correlation relationships among the node degree, node strength and betweenness centrality. In addition, the closeness centrality of most stocks is significantly negatively correlated with their individual returns and significantly positively correlated with their individual volatility. We can actually classify stocks according to the different correlation relationships between node centrality measures and corresponding stock's performance. Considering the return and risk play key roles during the process of portfolio investment, therefore, this classification can obviously give some valuable help for investors to construct a stock portfolio.

3.2.4 | Survival ratio analysis

In order to analyse the successive robustness of the MST topology, we calculate the time-varying survival ratios for 1, 2, 3, 4 and 5 steps, and the results are shown in Figure 13. It should be pointed out that for each case, $z = 100$ days and $\delta = 15$ days.

Just as shown in Figure 13, with the steps increase, the survival rate decreases significantly. We calculate the average survival rate for each step and find that the average value of the single-step survival ratio series reaches

0.451. This means that about 45% edges in the MST survive from window m to window $m+1$. Meanwhile, the average value of the five-step survival ratio series drops to 0.0525. In Figure 13, we have described survival ratio for five window width values, where we find no prominent dips indicating that no strong tree reconfiguration take place. Therefore, the dependence structure of the Chinese stock market is relatively stable.

4 | CONCLUSIONS

In this paper, we employ moving window method to build up dynamic cross-correlation matrices and MST networks for 882 stocks listed on the Chinese stock market from January 2006 to December 2017. The length of each window is 100 days, and the interval between adjacent windows is 15 days. We not only analyse the topological evolution of MSTs but also investigate the relationships between the topological evolution of MSTs and the market performance. Some basic findings and corresponding potential applications can be summarized as follows.

1. The NTL decreases sharply in the run-up to, and during the financial crisis, and increases rapidly afterwards. Moreover, the NTL is positively correlated with the market return and negatively correlated with the market volatility and tail risk. In a sense, we can propose the NTL as an indicator to send early warning signal of financial crisis, regulators should pay close attention to the changing trend of the NTL and take some measures to adjust the decision-makings once the market status is varying from a common period to a crisis period and vice versa.
2. In addition, 65.96 and 68.62% of MSTs follow power-law node degree and strength distribution, respectively, which indicates that the Chinese stock networks are heterogeneous networks in the majority of time windows. Based on the highest node centrality measures, we identify the 10 influential stocks and discover that most of them belong to the manufacturing industry. Thus, the policy makers and investors should focus on the influential stocks, especially the stocks belong to the manufacturing industry. On one hand, investors can rebalance their portfolio choices accordingly against the performance of the important stocks. On the other hand, monitoring the influential stocks is helpful for protecting the entire financial markets against risk contagion and keeping markets stable from the perspective of regulators.
3. There are highly positive correlation relationships among the node degree, node strength and betweenness centrality. We also find that the closeness centrality of most stocks is significantly negatively correlated with their individual returns and significantly positively correlated with their individual volatility. Such different correlations between the centrality indicators and the corresponding stocks performance contribute to classifying stocks and it can further guide risk management and portfolio management for investors.
4. The analysis of edge survival ratio indicates that about 45% edges in the MST survive between adjacent windows. At the same instant, a significant increase or decrease in the survival ratios of the MST is not discovered in the past few years, which implies that no strong tree reconfiguration take place. Therefore, the dependence structure of the Chinese stock market is relatively stable.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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