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Research Article

Stock Market Temporal Complex Networks Construction, Robustness Analysis, and Systematic Risk Identification: A Case of CSI 300 Index

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The Chinese stock 300 index (CSI 300) is widely accepted as an overall reflection of the general movements and trends of the Chinese A-share markets. Among the methodologies used in stock market research, the complex network as the extension of graph theory presents an edged tool for analyzing internal structure and dynamic involutions. So, the stock data of the CSI 300 were chosen and divided into two time series, prepared for analysis via network theory. After stationary test and coefficients calculated for daily amplitudes of stock, two "year-round" complex networks were constructed, respectively. Furthermore, the network indexes, including out degree centrality, in degree centrality, and betweenness centrality, were analyzed by taking negative correlations among stocks into account. The first 20 stocks in the market networks, termed "major players," "gatekeeper," and "vulnerable players," were explored. On this basis, temporal networks were constructed and the algorithm to test robustness was designed. In addition, quantitative indexes of robustness and evaluation standards of network robustness were introduced and the systematic risks of the stock market were analyzed. This paper enriches the theory on temporal network robustness and provides an effective tool to prevent systematic stock market risks.

1. Introduction

Following its rapid growth and development, the Chinese economy has become the second largest economy in the world. However, the functionality of the underdeveloped financial market in China still contains room for improvement compared with the financial markets in other countries [1]. The stock market provides the most active window of capital in the financial system because of the more frequent events than Gaussian fluctuations, which reflect the features of loss, namely, initiating systemic financial risk [2–4].

Some scholars have investigated stock index futures with regard to three aspects, so as to evaluate market risks [5]. First of all, due to the high liquidity, high leverage, and bidirectional operation of futures markets, stock index futures are believed to improve the volatility of the spot market [6]. Secondly, stock index futures can help to enhance the depth and efficiency of the market, thus decreasing its volatility [7, 8]. Finally, the stability of the stock market is not very likely to be affected by transactions [9, 10]. By introducing the CSI 300 futures market on April 16, 2010, China attempted to enhance its financial system. In the CSI 300 futures market, investors can take short positions on futures to hedge against the risk in the Chinese stock market. It is generally believed that the futures market can signal a new era for China's financial market. Through the CSI 300 stock index, the performance and price fluctuation of the A-share index in China can be reflected. The index is designed to be a performance benchmark and a base for derivatives

innovation. At present, the CSI 300 stock index has been widely used to reflect the trends and movements in the Chinese A-share markets [11]. Increasing attention has been paid to the influence of the CSI 300 index futures on the underlying stock market. For instance, Cao et al. [5] investigated the correlation between the CSI 300 markets and the China securities index 300 (CSI 300) futures according to high-frequency data, using MF-DCCA. Suo et al. [12] used the recurrence interval analysis method to explore the risk estimation, memory effects, and scaling behavior of the CSI 300 in China. Qu et al. [13] carried out a comprehensive analysis of some popular time-series models to predict the RMVHR for the CSI 300 futures. Moreover, the out-of-sample dynamic hedging performance was evaluated by comparing this with the conventional hedging models through daily prices and the vector heterogeneous autoregressive model through intraday prices.

To date, the stock index has been widely studied through the theory of the complex network. There exist interactive individuals in technological, physical, biological, and social networks [14–16]. Therefore, the extension of graph theory, the complex network, and the edged tool have been used to analyze the dynamic involutions and internal structure of these networks [17–19].

Multilayer network theory is a development tool based on single network research, which provides a new perspective for grasping information within a colorful structure. A key aspect of multilayer network theory is that the underlying network structure can significantly influence the dynamic processes mediated by the edges [20]. Moreover, the authors adapted the implicit null model to fit the layered network, the main idea being to represent every layer through a slice [21–23]. A temporal network is a special multiplex network constructed on a timeline basis, which is of great importance to the process of risk dissemination. In the network, electronic or biological viruses and information or rumors are transmitted through electronic connections, social ties, and physical contact edges. The speed and extent of spreading are affected by the network structure owing to features such as degree correlations [24], degree distribution [25, 26], short path lengths [27], and community.

On this basis, this paper purposes two research questions: (i) what complex network indexes characterize the special stock in the market? (ii) How to quantify the risk or to say robustness in the stock market?

The contributions of this article to the existing research can be classified into the following aspects: first of all, the study establishes directed weighted stock networks using the CSI 300 index, considering the negative correlation between stocks; a multilayer time-series network was constructed. Secondly, the paper analyzes the systematic stock market risk according to the temporal network and designs an algorithm for measuring robustness. In addition, a quantitative index is provided. Finally, this article provides an effective tool for a systematic approach to risk in the stock market.

The remainder of this article is structured as follows: in Section 2, the literature pertaining to stock market risks and the application of temporal networks are reviewed; Section 3 details the data processing and the corresponding time-series tests; in Section 4, the complex network models are established, and their statistical characteristics are analyzed; Section 5 discusses the rationality criterion of stock market robustness in the context of the time complex network; finally, Section 6 concludes this paper. Figure 1 presents an overview of the research conducted for this study.

2. Literature Review

2.1. Stock Market Risk. Stock market risks are generally discussed from the perspectives of the correlations of individual stocks, or whole sectors and changes in the volatility of stock prices [28, 29], or in the context of financial restrictions [30, 31]. There are also some studies that explore technological risks, policy risks, and the social factors and economic policy behind stock risk. Apergis [32] studied the effect of policy and technological risks on US stock returns and emphasized the impact of economic policy uncertainty on stock returns, which rose to an all-time high after the 2007–2009 recession. Tsai [33] revealed the impact of economic policy uncertainty in China, Japan, Europe, and the United States on the risk of contagion in global stock market investments. Cao et al. [34] used a sample of A-shares listed in China from 2001 to 2012 to study the relationship between social trust and the risk of stock price collapse, finding that social trust as a social and economic factor is related to the latter risk. Regarding social factors, Li et al. [35] pointed out a correlation between stock price crash risks and social trust, based on the data of listed firms in China from 2001 to 2015.

In recent years, the distress risk anomaly in emerging markets has been investigated in many studies. For example, Gao et al. [36] investigated the significance of book-to-market, size, and momentum factors in capturing the financial distress risks of the stock market in China. Lai et al. [37] explained stock returns in the stock markets of Australia, Thailand, Singapore, Malaysia, Korea, Indonesia, and Hong Kong, finding that the four-factor financial crisis risk asset pricing model has received extensive empirical support in these markets. Eisdorfer et al. [38] studied several potential drivers of stock returns for distressed companies in 34 different countries and documented the exclusive risk anomalies in developed countries. Distress anomaly is more serious in countries with higher information transparency, lower arbitrage barriers, and stronger acquisition legislation. These findings demonstrate that all aspects of shareholder risk are of great importance to shape the stock returns of distressed firms. Gao et al. [39] studied the abnormal risk of distress in 38 countries over the past 20 years, finding this anomaly to be highly concentrated in low-market stocks in developed countries such as North America and Europe, instead of 17 emerging markets. The existing research predicts the stock return or the national attribute in order to explain the abnormal risk of distress, none of which studies the factors that capture the risk of stock financial distress.

The abovementioned research was mainly conducted using traditional measurement methods, such as the VAR model and the GARCH model, which have yielded different results without multifractality.

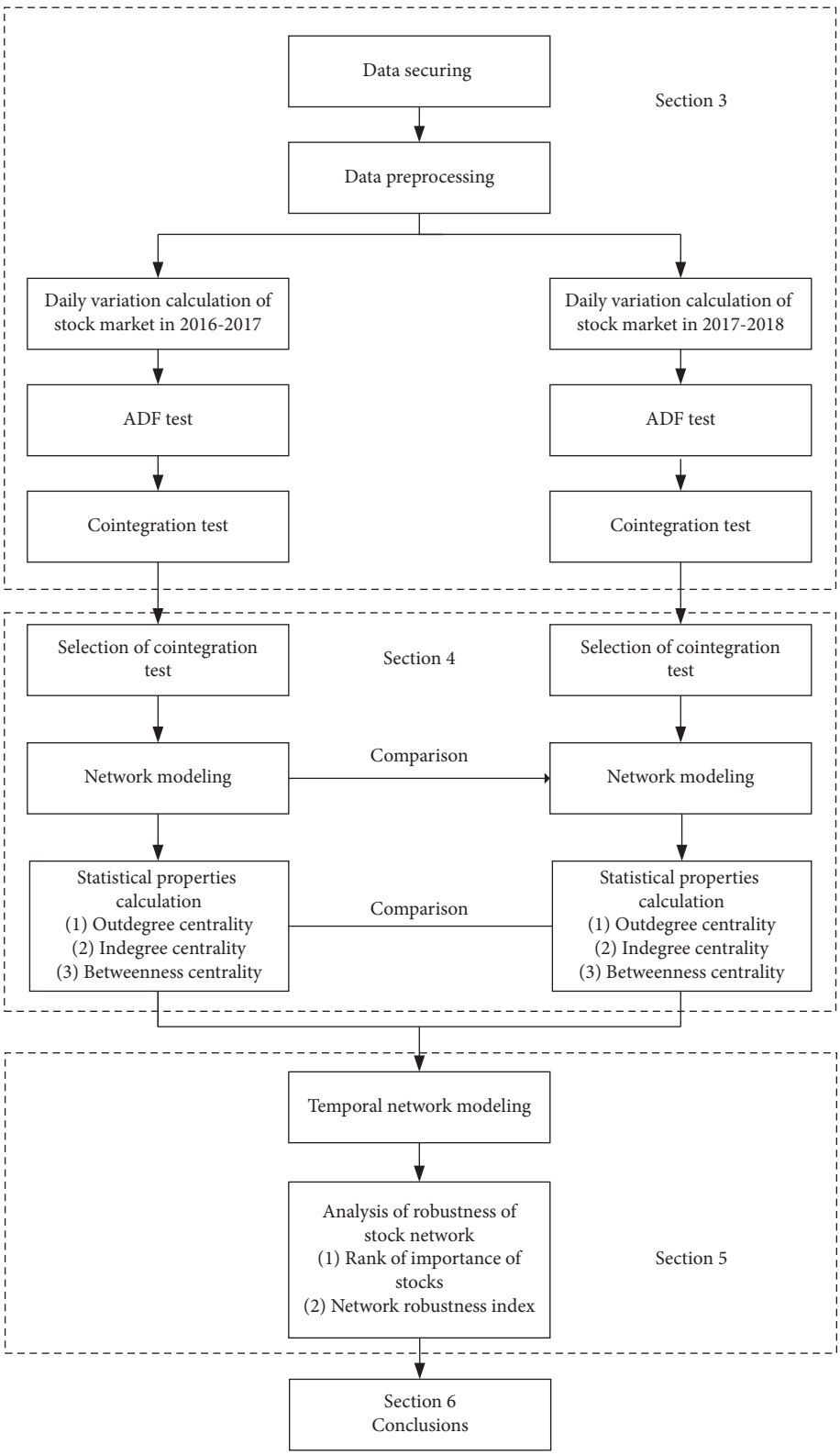

Figure 1: Research overview.

2.2. Temporal Network. Artificial intelligence generates data in a new form of complexity, bringing about the new era of big data [40], which is a huge challenge for researchers from different shielding agencies involved in extracting new structures or patterns from data with a large volume, high variety, and high speed. Over the past ten years, there have emerged increasing studies describing dynamic systems through complex networks based on time series [41].

In recent years, most studies have projected the time dimension by aggregating the connection between vertices and edges, even when the information about the time series of contacts or interactions was available [42].This method, temporal network, is to split the data into adjacent time windows in which contacts gather into edges. For instance, Karimi and Holme [43] explained the consequences of social influence, such as the spread of opinions and fads, in a temporal network by establishing threshold models. By exploring the diffusion of a supermarket, Deng et al. [44] found that the system evolves in a certain order that is not completely random. Moreover, the nodes are classified according to certain rules. Flores and Romance [45] recognized the nodes connected to a given complex network to be main topics in complex network analysis. Therefore, an eigenvector concentration model of a time network that evolves on a continuous time scale and sorts the nodes was proposed, according to the correlation of the nodes in the process of their occurrence in the network. For example, Everett et al. [46] used two-mode temporal data to measure the experience and knowledge held in social temporal networks. Li et al. [47] used the decision tree to find the node-level features that have a general impact on node transition over the temporal network.

In recent years, the temporal network method has been used to investigate the stock market in terms of stock risks. Huang et al. [48] put forward an algorithm—namely, a backward temporal diffusion process—to calculate the shortest temporal distance to the transmission source. Zhao et al. [49] characterized the time-evolving correlation-based networks of stock markets through the temporal network framework, in order to highlight the instability of the underlying market by portfolio selection in the evolution of the topology structure of the financial networks. Qu et al. [13] investigated the dynamic hedging performance of the high-frequency data of the CSI 300 index futures by designing the minimum-variance hedge ratio (RMVHR) approach. Lyócsa et al. [50] studied the connectedness of a sample of 40 stock markets across five continents using daily closing prices and return spillovers based on Granger causality based on the network model. Zhao et al. [51] utilized the temporal network framework to characterize the time-evolving correlation-based networks of stock markets.

All these studies focus on the critical value of the volatility, ignoring mechanism of the detail structure of the network influencing the risk propagation. This is the exact starting point of this paper.

3. Temporal Data Processing and Complex Networks Modeling

Stock data have a temporal property, which is mainly manifested on top price, floor price, closing price, and turnover. Annual cross section data also have a temporal property. Hence, the complex network established in the following subsections is a temporal complex one. Stocks on the CSI 300 index are those that are performing well in China's stock markets. They are thus not only a barometer of the stock market but also a symbol of economic status. Therefore, studying stocks in the CSI 300 index may be seen as significant.

Previous studies have generally constructed undirected networks with positive weights based on fluctuating stock data in a certain period. However, the influences among stocks are causal, to some extent. In this paper, directed networks were constructed to depict the collaborative relationships between stocks, and a multilayer temporal network was constructed based on several time series to describe the network's influential stocks from a long-term perspective.

3.1. Data Processing. In this paper, data from the CSI 300 index over 488 trading days from October 15, 2016, to October 15, 2018, were output from the "Choice Financial Terminals," including the opening price, top price, floor price, closing price, turnover, and volume of transaction of each stock during each trading day.

Two types of data anomalies were found during the data examination: missing data and zero transaction volume (or turnover). The missing data were due to the fact that the stock was not issued on the day or may have been issued but was not listed. For example, Merchants Highway was listed on December 25, 2017 [52], and data before were missing. Similarly, Huaneng Hydropower was listed on December 15, 2017 [53], and data before were missing. Caitong Security was listed on October 24, 2017 [54], and data before were missing. Zero transaction volume (or turnover) was caused by the suspension of stocks for major assets restructuring, the planning of nonpublic issue shares, major decision planning, and major cooperative projects. For example, the Midea Group planned an asset restructuring with the Cygnet Subsidiary and was suspended from September 10, 2018 [55]. Perfect World was planning to issue nonpublic shares and applied this to the Shenzhen Stock Exchange, so it was suspended as of June 4, 2018 [56]. Donghua Software and Tencent Cloud Computing were in the process of discussing key issues and planning to carry out extensive cooperation in the fields of medicine, the intelligent city, finance, and electricity, according to the latest communication, further promoting the update of strategic cooperation between the two parties. In addition, the dominant stockholder of Donghua Software was discussing with capital cooperation with Tencent-related companies, but this capital cooperation involved no changes to corporate control [57]. Donghua Software was suspended since May 14, 2018, after its application to the Shenzhen Stock Exchange [58]. Hence, this type of data exerted a certain disturbance and was deleted from the dataset. In the end, a total of 169 stocks were retained for the present study.

The CSI 300 index stocks can be discussed from multiple aspects, such as daily closing price, daily price change ratio, historical volatility, daily amplitude, and weekly amplitude of stocks. Among them, stock amplitude reflects the stock activity, denoting not only the industrial development of the stock market but also indicating the investment orientation and investors' attitudes. The amplitude analysis of stocks covers the daily, weekly, and monthly amplitude analyses. In

this paper, the daily amplitude (DA) of stocks was applied [59]. A low DA represents poor stock activity on the given day, the contrasting scenario indicating that the stocks are active.

If p_i^t is the share price of stock i on day t, therefore, $\max(p_i^t)$ "denotes the top price of stock i" on day t, and $\min(p_i^t)$ is the floor price of stock i on day t. If p_{si}^{t-1} is the closing price of stock i on the previous day, the calculation formula of its amplitude on day t (DA_i^t) is as follows:

$$\mathrm{DA}_i^t = \frac{\max(p_i^t) - \min(p_i^t)}{p_{si}^{t-1}}. \tag{1}$$

The daily amplitude data of each stock can be derived from equation (1). The DA data of certain stocks during 2016-2017 and 2017-2018 are shown in Figure 2.

In short, the data may be seen as stationary from the perspective of the sequence chart. The data were also tested using ADF in terms of the quantity angle.

3.2. ADF Test and Cointegration Test. With an unsteady time series, the traditional analysis method cannot assure the validity of the data. Conversely, the unit root test can create conditions for an unsteady time series. There are many unit root test methods, of which ADF was applied in the current study. If the DA data were to be deemed steady, they needed to meet the following condition:

(1) The mean, $E[\mathrm{DA}_i^t] = \mu$, is a constant unrelated with time t

(2) The variance, $D[\mathrm{DA}_i^t] = \sigma^2$, is a constant unrelated with time t

(3) The covariance, $\mathrm{Cov}[\mathrm{DA}_i^{t1}, \mathrm{DA}_i^{t2}]$, is a constant related with the time interval only, but it is unrelated with time t

The ADF test was applied to verify whether the DA met the above conditions. The verification results are shown in Table 1, obtained using Matlab 2017b.

The DA of other stocks also underwent the ADF test. In other words, the data of these 169 stocks in the study period were found to be steady sequences.

On this basis, the DA of all of the stocks could be seen as steady sequences and thereby meet the same-order conditions of the cointegration test. Hence, the correlation coefficient between two stocks was gained through the cointegration test.

Cointegration theory plays a vital role in economic circles. It is an econometric analysis method created by Johansen and is mainly applied to study the long-term equilibrium relationship among economic variables based on an unsteady time series [59]. The higher the absolute value of the cointegration coefficient, the stronger the correlation between two stocks; otherwise, the correlation is weaker. Selected cointegration coefficients are listed based on two stocks in the following section (as listed in Tables 2 and 3).

The program results show that the cointegration coefficients between the different pairs of stocks all passed the test. The following sections detail the construction of the complex networks based on the cointegration coefficient.

4. Complex Networks Modeling and Statistical Analysis

In this paper, stocks were denoted as nodes and the cointegration coefficients used as the weights of edges. Out degree centrality, in degree centrality, and betweenness centrality were chosen for the correlation analysis of network characteristics.

4.1. Stock Market Complex Networks Modeling. The above selected 169 stocks were viewed as nodes in the complex networks, and the cointegration relationships among the stocks were used as edges. The cointegration relationships between stocks i and j were determined in Section 3.2. The cointegration coefficient (a_{ij}) using stock i as a dependent variable and stock j as an independent variable was obtained, which corresponds to one directed side from node i to node j, with a weight of a_{ij}. In this way, a weighted directed graph $G(V, E, W)$ was plotted, where V represents the set of stocks, E the set of edges, and W the set of weights corresponding to the edges. This was determined by the following method. Since the cointegration coefficients a_{ij} and a_{ji} may not be equal, the rule for retaining edges was such that all directed edges of a_{ij} were retained if $|a_{ij}| > |a_{ji}|$; otherwise, all directed edges of a_{ji} were retained. The histograms of the frequency distribution of $|a_{ij}|$ after screening are shown in Figure 3.

It can be seen from Figure 3 that the absolute value of the cointegration coefficient during 2016-2017 is mainly concentrated in a relatively small region and generally presents a power-low distribution. The absolute value of the cointegration coefficient during 2017-2018 presents an approximately clock-shaped distribution pattern. There is no large frequency in regions with low and high absolute cointegration coefficient values. The number and proportions of the intervals corresponding to the two distribution tables are shown in Table 4.

Due to the positive relationship between the correlation of the pairs of stocks and the cointegration coefficient, the weight was determined as follows:

$$w_{ij} = \begin{cases} a_{ij}\left(\left|a_{ij}\right| > \mathrm{Con}\right), \\ 0\left(\left|a_{ij}\right| \le \mathrm{Con}\right), \end{cases} \tag{2}$$

where Con is the screened threshold. In Table 4, there are significantly different numbers of cointegration coefficients at different intervals. Here, the 70% quantile of two networks was selected as the screening base, according to the histogram results, and only 30% of the edges with great weights was retained. Finally, the threshold of absolute values of the cointegration coefficient during 2016-2017 was Con = 0.3117, and the threshold of the absolute value of the cointegration coefficient during 2017-2018 was Con = 0.4284. Stocks with strong correlations were chosen by this

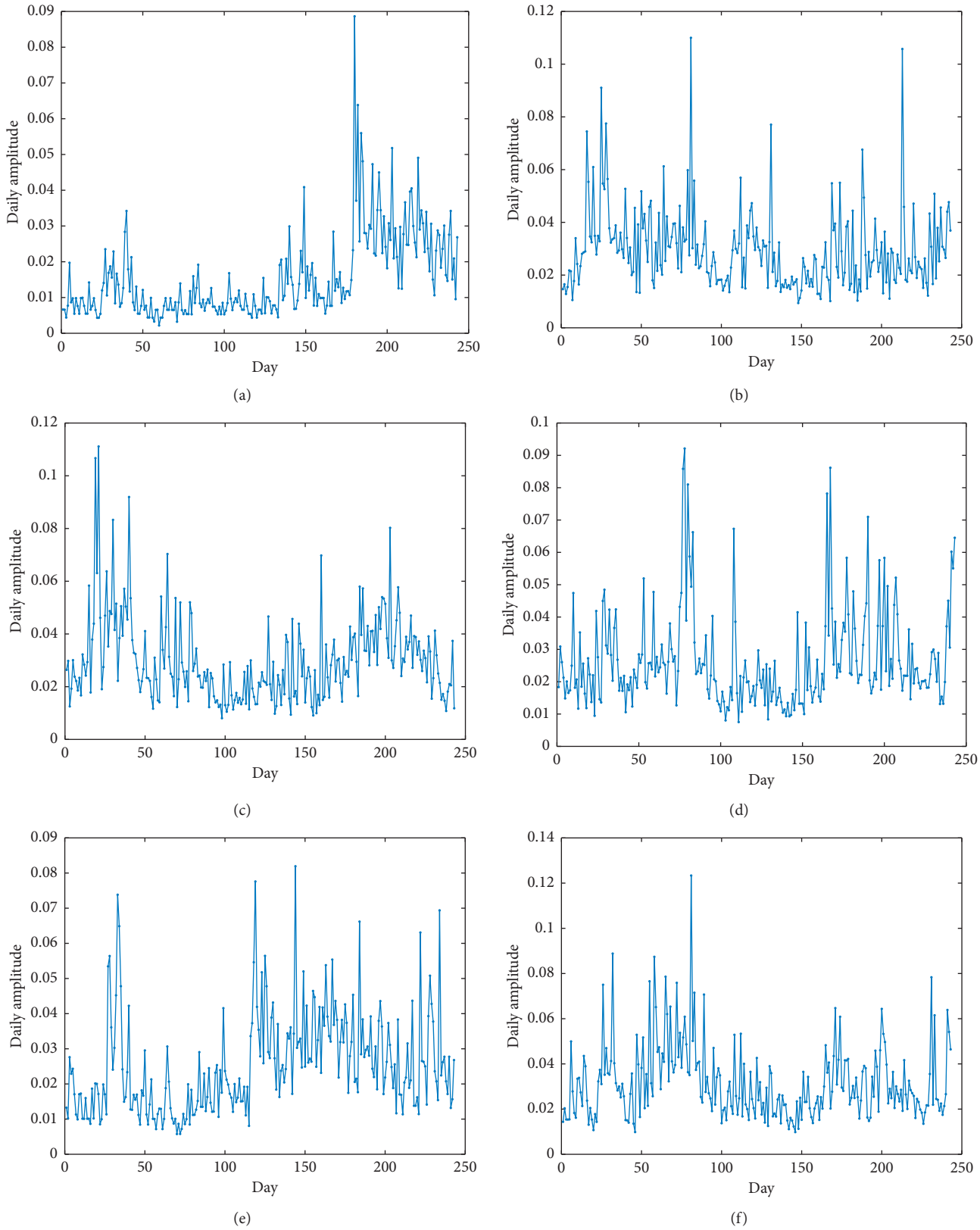

Figure 2: Display of daily amplitude of some stocks: (a) Ping An Bank during 2016-2017; (b) Ping An Bank during 2017-2018; (c) Shenzhen Zhongjin Lingnan Nonfemet during 2016-2017; (d) Shenzhen Zhongjin Lingnan Nonfemet during 2017-2018; (e) Overseas China Town A during 2016-2017; (f) Overseas China Town A during 2017-2018.

Table 1: ADF test of selected stocks during 2016-2017 and 2017-2018.

2016-2017			2017-2018		
Stock	D-F	*P* value	Stock	D-F	*P* value
Ping An Bank	25.2817	0.001	Ping An Bank	23.5691	0.001
Shenzhen Zhongjin Lingnan Nonfemet	27.0890	0.001	Shenzhen Zhongjin Lingnan Nonfemet	27.8371	0.001
Overseas China Town A	28.0743	0.001	Overseas China Town A	25.6870	0.001
Zoomlion Heavy Industry Science & Technology	22.0906	0.001	Zoomlion Heavy Industry Science & Technology	21.3686	0.001
Wei Chai Power	24.7719	0.001	Wei Chai Power	26.5893	0.001
Financial Street Holding	25.8204	0.001	Financial Street Holding	24.5114	0.001
Shandong Dong-Ee Jiao	26.0686	0.001	Shandong Dong-Ee Jiao	31.4732	0.001
Luzhou Lao Jiao	29.0036	0.001	Luzhou Lao Jiao	33.0492	0.001
Jilin Aodong Pharmaceutical	24.4411	0.001	Jilin Aodong Pharmaceutical	21.6696	0.001
Chongqing Changan Automobile	26.6082	0.001	Chongqing Changan Automobile	16.9782	0.001
Hubei Biocause Pharmaceutical	23.4925	0.001	Hubei Biocause Pharmaceutical	24.1930	0.001
Tongling Nonferrous Metals	24.5328	0.001	Tongling Nonferrous Metals	22.8132	0.001
HESTEEL	24.6379	0.001	HESTEEL	22.2333	0.001
BOE Technology	19.2278	0.001	BOE Technology	21.5965	0.001
Guoyuan Securities	20.5826	0.001	Guoyuan Securities	20.5943	0.001
Avic Aircraft	22.8011	0.001	Avic Aircraft	26.0381	0.001
GF Securities	22.7073	0.001	GF Securities	21.6436	0.001
Changjiang Securities	19.5375	0.001	Changjiang Securities	18.6640	0.001
CITIC Guoan Information Industry	20.3464	0.001	CITIC Guoan Information Industry	23.1893	0.001
Wuliangye	26.6843	0.001	Wuliangye	32.7552	0.001

Table 2: Cointegration coefficient of Ping An Bank with other selected stocks during 2016-2017.

Taking Ping An Bank as an independent variable	Cointegration coefficient	*P* value	Taking Ping An Bank as a dependent variable	Cointegration coefficient	*P* value
Shenzhen Zhongjin Lingnan Nonfemet	0.3800	0.001	Shenzhen Zhongjin Lingnan Nonfemet	0.2069	0.001
Overseas China Town A	0.2845	0.001	Overseas China Town A	0.1990	0.001
Zoomlion Heavy Industry Science & Technology	−0.0263	0.001	Zoomlion Heavy Industry Science & Technology	−0.0332	0.001
Wei Chai Power	0.1911	0.001	Wei Chai Power	0.1913	0.001
Financial Street Holding	0.0388	0.001	Financial Street Holding	0.0175	0.001
Shandong Dong-Ee Jiao	−0.0735	0.001	Shandong Dong-Ee Jiao	−0.0921	0.001
Luzhou Lao Jiao	0.0951	0.001	Luzhou Lao Jiao	0.0774	0.001
Jilin Aodong Pharmaceutical	0.0484	0.001	Jilin Aodong Pharmaceutical	0.0408	0.001
Chongqing Changan Automobile	0.0592	0.001	Chongqing Changan Automobile	0.1228	0.001
Hubei Biocause Pharmaceutical	0.9468	0.001	Hubei Biocause Pharmaceutical	0.2885	0.001
Tongling Nonferrous Metals	0.1386	0.001	Tongling Nonferrous Metals	0.0697	0.001
HESTEEL	0.1649	0.001	HESTEEL	0.0468	0.001
BOE Technology	−0.0866	0.001	BOE Technology	−0.0384	0.001
Guoyuan Securities	0.3485	0.001	Guoyuan Securities	0.1364	0.001
Avic Aircraft	0.0701	0.001	Avic Aircraft	0.0379	0.001
GF Securities	0.2499	0.001	GF Securities	0.3116	0.001
Changjiang Securities	0.1883	0.001	Changjiang Securities	0.1466	0.001
CITIC Guoan Information Industry	0.1263	0.001	CITIC Guoan Information Industry	0.0431	0.001
Wuliangye	0.1396	0.001	Wuliangye	0.1530	0.001
Henan Shuanghui Investment & Development	0.1728	0.001	Henan Shuanghui Investment & Development	0.3226	0.001

method to establish directed complex networks, thus enabling more accurate and explicit results. The two complex networks constructed are shown in Figures 4 and 5, respectively.

The size of the points (or names) in Figures 4 and 5 reflects the out degree of the points, that is, the influencing strength of the stock on other stocks. The different colors represent different communities. Both networks are divided into three respective communities: the bank security community, the industrial infrastructure community, and others. On the one hand, such a stable community division reflects the equilibrium state of economic relationships, which indirectly proves the certain coordinated relationships among stocks, to some extent. On the other hand, the

Table 3: Cointegration coefficient of Ping An Bank with other selected stocks during 2017-2018.

Taking Ping an bank as an independent variable	Cointegration coefficient	P value	Taking Ping an bank as a dependent variable	Cointegration coefficient	P value
Shenzhen Zhongjin Lingnan Nonfemet	0.2256	0.001	Shenzhen Zhongjin Lingnan Nonfemet	0.2370	0.001
Overseas China Town A	0.4112	0.001	Overseas China Town A	0.3500	0.001
Zoomlion Heavy Industry Science & Technology	0.1531	0.001	Zoomlion Heavy Industry Science & Technology	0.3943	0.001
Wei Chai Power	0.2849	0.001	Wei Chai Power	0.3529	0.001
Financial Street Holding	0.2593	0.001	Financial Street Holding	0.3746	0.001
Shandong Dong-Ee Jiao	0.0358	0.001	Shandong Dong-Ee Jiao	0.0966	0.001
Luzhou Lao Jiao	0.3454	0.001	Luzhou Lao Jiao	0.4204	0.001
Jilin Aodong Pharmaceutical	0.2238	0.001	Jilin Aodong Pharmaceutical	0.4819	0.001
Chongqing Changan Automobile	0.1454	0.001	Chongqing Changan Automobile	0.2494	0.001
Hubei Biocause Pharmaceutical	0.3767	0.001	Hubei Biocause Pharmaceutical	0.3035	0.001
Tongling Nonferrous Metals	0.1702	0.001	Tongling Nonferrous Metals	0.3043	0.001
HESTEEL	0.1881	0.001	HESTEEL	0.2488	0.001
BOE Technology	0.3214	0.001	BOE Technology	0.2195	0.001
Guoyuan Securities	0.2821	0.001	Guoyuan Securities	0.3623	0.001
Avic Aircraft	0.2119	0.001	Avic Aircraft	0.1579	0.001
GF Securities	0.3065	0.001	GF Securities	0.5227	0.001
Changjiang Securities	0.2526	0.001	Changjiang Securities	0.3744	0.001
CITIC Guoan Information Industry	0.2956	0.001	CITIC Guoan Information Industry	0.1725	0.001
Wuliangye	0.3000	0.001	Wuliangye	0.4482	0.001
Henan Shuanghui Investment & development	0.1772	0.001	Henan Shuanghui Investment & development	0.2126	0.001

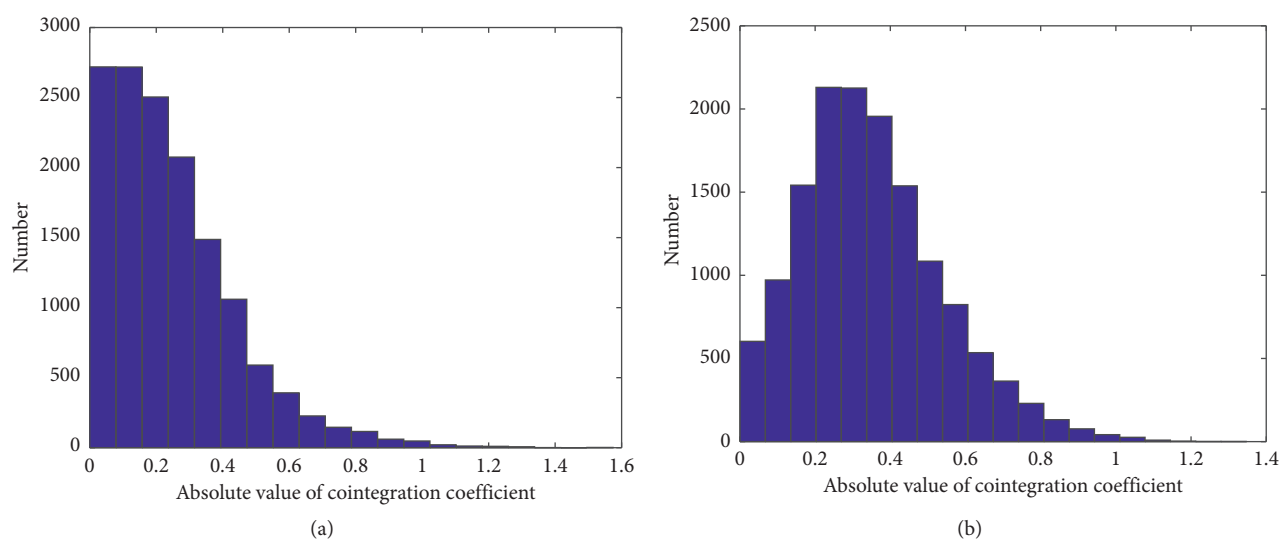

Figure 3: Distribution diagram of the absolute value of the cointegration coefficient during 2016-2017 (a) and 2017-2018 (b).

density of the edges is similar in the three communities of the complex CSI 300 network during 2016-2017. However, most edges in the complex CSI 300 network during 2017-2018 are concentrated in the bank security and industrial infrastructure communities, indicating the locally disharmonious correlations among the other industries during 2017-2018. The overall network situation is illustrated through network indexes in the following section.

4.2. Out Degree Centrality. Out degree centrality (k_i^{out}) was used to depict the number of sides from point i in the network to other nodes. In this paper, k_i^{out} reflects the influencing strength of stock i on other stocks, which is called "major players" in the stock market and can be calculated as follows:

$$k_i^{\text{out}} = \sum_{j=1}^{n} \varphi\left(\left|a_{ij}\right|\right), \tag{3}$$

where $\varphi(|a_{ij}|) = 1$ if $|a_{ij}| \neq 0$ or otherwise $\varphi(|a_{ij}|) = 0$. This index depicts the influence of each node in the network. The distribution of the out degree centrality reflects the overall

Table 4: Statistical chart of the absolute value of the cointegration coefficient during 2016-2017 and 2017-2018.

	2016-2017			2017-2018	
Interval	Number	Frequency (%)	Interval	Number	Frequency (%)
[0.0000, 0.0788)	2719	19.15	[0.0000, 0.0679)	603	4.25
[0.0788, 0.1575)	2718	19.15	[0.0679, 0.1357)	972	6.85
[0.1575, 0.2363)	2504	17.64	[0.1357, 0.2036)	1542	10.86
[0.2363, 0.3150)	2075	14.62	[0.2036, 0.2714)	2130	15.00
[0.3150, 0.3938)	1487	10.47	[0.2714, 0.3393)	2126	14.98
[0.3938, 0.4726)	1060	7.47	[0.3393, 0.4071)	1956	13.78
[0.4726, 0.5513)	590	4.16	[0.4071, 0.4750)	1538	10.83
[0.5513, 0.6301)	392	2.76	[0.4750, 0.5429)	1085	7.64
[0.6301, 0.7089)	227	1.60	[0.5429, 0.6107)	824	5.80
[0.7089, 0.7876)	146	1.03	[0.6107, 0.6786)	535	3.77
[0.7876, 0.8664)	116	0.82	[0.6786, 0.7464)	364	2.56
[0.8664, 0.9451)	61	0.43	[0.7464, 0.8143)	230	1.62
[0.9451, 1.0239)	48	0.34	[0.8143, 0.8821)	132	0.93
[1.0239, 1.1027)	21	0.15	[0.8821, 0.9500)	77	0.54
[1.1027, 1.1814)	12	0.08	[0.9500, 1.0179)	42	0.30
[1.1814, 1.2602)	10	0.07	[1.0179, 1.0857)	26	0.18
[1.2602, 1.3389)	7	0.05	[1.0857, 1.1536)	9	0.06
[1.3389, 1.4177)	1	0.01	[1.1536, 1.2214)	3	0.02
[1.4177, 1.4965)	0	0.00	[1.2214, 1.2893)	1	0.01
[1.4965, 1.5752]	2	0.01	[1.2893, 1.3571]	1	0.01

characteristics of the networks. The distribution diagrams of the out degree centrality during 2016-2017 and 2017-2018 were obtained using Matlab 2017b, as shown in Figure 6.

As can be seen from Figure 6, a high density occurs in a small degree region (degree centrality from 0 to 20) in the two distribution diagrams, indicating that significant stocks in the network occupy important positions. In order to mine out these special nodes, the top 20 stocks with a high out degree are listed in Table 5.

As can be seen from Table 5, most of the top 20 stocks located in the out degree centrality during the study period are financial securities, indicating that financial security stocks significantly influenced other stocks and the fluctuation of the stock market. The fluctuation of nodes with a high out degree centrality was quickly transmitted to most nodes in the network. Hence, this index measures the indicators that can influence other stocks, whereby stocks with a high out degree centrality are the sources of potential large-scale network risks.

4.3. In Degree Centrality. In degree centrality (k_j^{in}) was applied to depict the number of sides from node j in the network to other nodes. Here, k_j^{in} reflects the influences of other stocks on the stock j, which is called "vulnerable players," and can be calculated as follows:

$$k_j^{\text{in}} = \sum_{i=1}^{n} \varphi\left(\left|a_{ij}\right|\right), \tag{4}$$

where $\varphi(|a_{ij}|)$ in equation (4) is the same as above and describes the vulnerability of the stocks. A higher in degree centrality reflects a stronger vulnerability of the stock to most stocks. The distribution of the in degree centrality reflects the overall characteristics of the networks. The distribution diagrams of in degree centrality during 2016-2017 and 2017-2018 were obtained using Matlab 2017b (Figure 7).

Figure 7 indicates a high density occurring in a small degree region (degree centrality from 0 to 40) in the two distribution diagrams, indicating that significant stocks in the network occupy important positions. This is similar to the distribution diagrams of the out degree centrality. To specify these nodes, the top 20 stocks that had a high in degree are listed in Table 6.

Tables 5 and 6 show that the top 20 stocks in both the in degree and out degree centrality rankings during 2016-2017 and 2017-2018 are financial security stocks. This reflects the notion that financial security stocks influence other stocks and are, in turn, controlled by other stocks. However, some stocks are completely passive. For instance, the out degree centrality of Rongsheng Development and CITIC Guoan was 0 during 2017-2018. These stocks are at the margins of the stock network and their fluctuation at the occurrence of systematic network risks may not influence other stocks. Thus, these stocks can be said to be significantly controlled by other stocks, which are terminal bearers of network risks. The corresponding company thus has to pay attention to risk dispersion during the loss reduction brought about by network risks in daily management.

4.4. Betweenness Centrality. Betweenness centrality can indicate how many shortest paths cross a certain node. The current paper demonstrates that different stocks act as "moderators" or "gatekeepers" of information (and, correspondingly, may be unwilling to develop a requested feature).

If g_{st} is the number of shortest paths from node s to node t, n_{st}^{i} is the number of paths that pass node i in g_{st}. The betweenness centrality of node i can be expressed as follows:

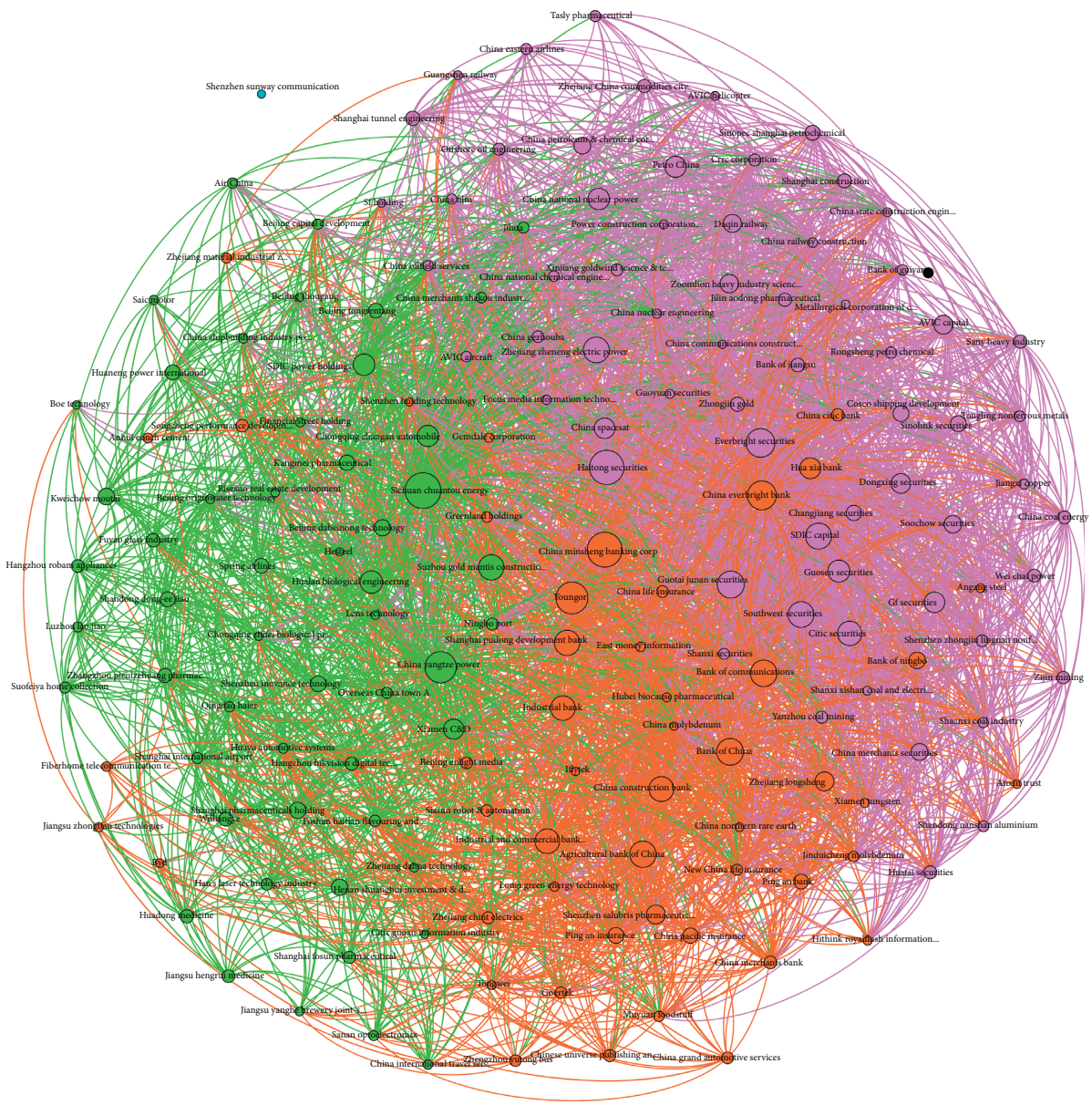

Figure 4: Complex network of CSI 300 during 2016-2017.

$$\mathrm{BC}_i = \sum_{s \neq i \neq t} \frac{n_{st}^i}{g_{st}}. \tag{5}$$

A higher BC_i (equation (5)) reflects a stronger bridging effect of node i in the network. In this paper, weight represents the closeness between points. The higher the closeness between nodes i and j, the lower the weight between them for calculating the betweenness centrality. Hence, the following conversion becomes necessary:

$$\widetilde{w_{ij}} = 2 - \frac{w_{ij} - \min\left(w_{ij}\right)}{\max\left(w_{ij}\right) - \min\left(w_{ij}\right)}, \tag{6}$$

where $\max(w_{ij})$ is the maximum weight of edges in the network, $\min(w_{ij})$ is the minimum weight of edges, and $\widetilde{w_{ij}}$ reflects the weights after conversion. The value of $\widetilde{w_{ij}}$ is negatively related with the correlation between two stocks. Such a conversion assures the weight in the interval of $[1, 2]$ and protects the significance of the betweenness calculation. Moreover, the data involved in this paper contain negative weights. The shortest path describes the shortest travelling path of fluctuation of one stock to another stock. Upon the occurrence of network risks, the government or other organizations should protect these stocks in a timely manner, which could then prevent the global loss of networks in the evolution of network risks. It shows different stocks act as moderators or gatekeepers of information. The relevant top 20 stocks with the highest betweenness centrality are listed in Table 7.

The top 20 stocks in terms of betweenness centrality shown in Table 7, including Jianfa Share, Overseas China Town A, and China Satellite, remained basically stable

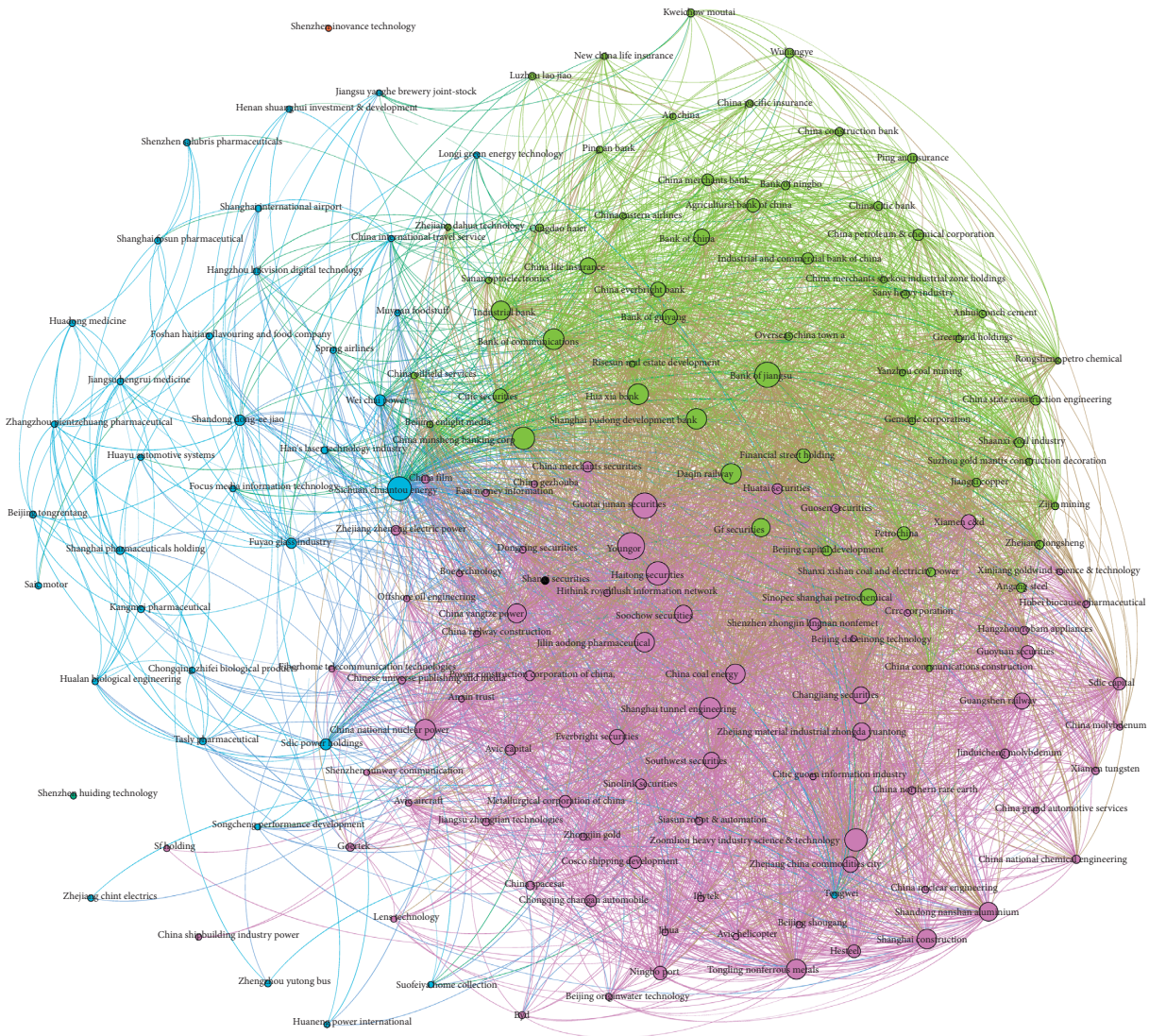

Figure 5: Complex network of CSI 300 during 2017-2018.

throughout the study period. Hence, they played a more prominent gatekeeper role in the financial network.

According to the results of the out degree centrality, in degree centrality, and betweenness centrality, some conclusions can be drawn:

(a) At the occurrence of collapse, the in-edges of nodes with a large out degree centrality and in degree centrality failed, exerting a domino effect on the outgoing edges. Based on the algorithmic principle, this paper finds that weights of the outgoing edges of nodes with a large out degree centrality and in degree centrality were mainly positive, meaning that the network collapsed in a short period. These findings prove that financial stocks are the backbone forces of stock networks, and that they are more important than other stocks to maintain the stability of the economic market. Any threats to these key financial stocks may spread over the whole network.

(b) The betweenness centrality results emerged as similar to algorithm principle, with a domino effect of collapse of the top 20 stocks. For instance, the intersection of SDIC Power Holdings, East Money, and Shanxi Securities reflected their role as bridges in the stock network. These stocks connect influential neighbouring nodes. Therefore, cutting the loss in time of these stocks at the point of network collapse could effectively prevent a follow-up loss. This may thus be termed the "defense force" of the stock network.

As a result, it is recommended that stock regulation departments, enterprises, and shareholders pay attention to the governance of the "major players," "gatekeepers," and "vulnerable players" in the stock network and prevent systematic stock market risks being incurred by these stocks.

5. Temporal Network and Robustness Analysis

5.1. Temporal Network Modeling. The out degree centrality, in degree centrality, and betweenness centrality of stocks during 2016-2017 and 2017-2018 were analyzed in this paper,

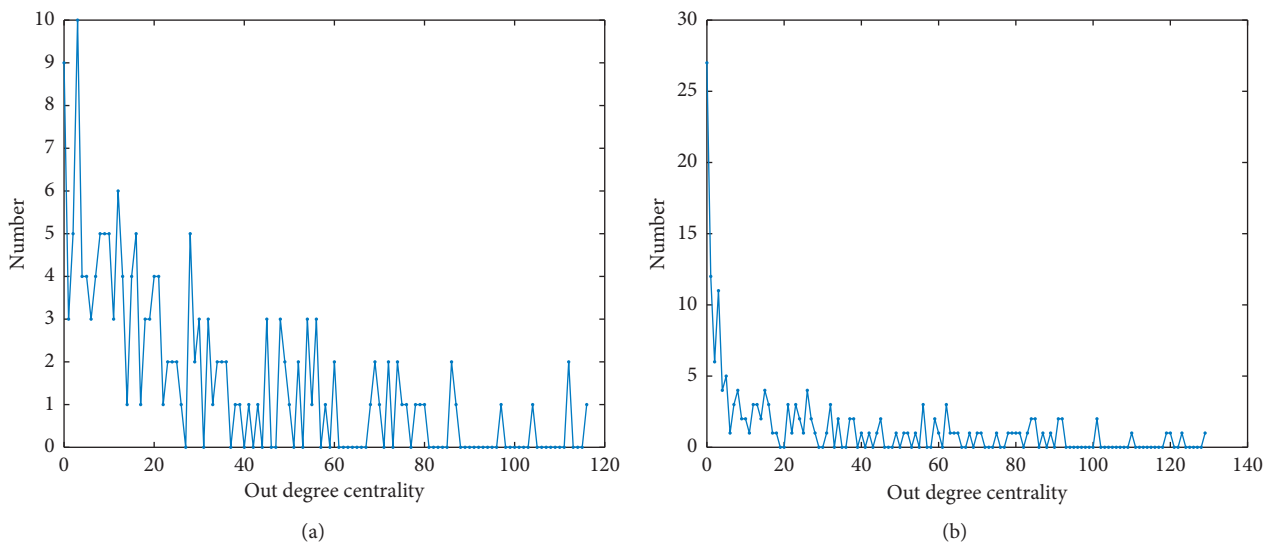

Figure 6: Distribution diagram of out degree centrality of CSI 300 network in 2016-2017 (a) and 2017-2018 (b).

Table 5: Top 20 out degree centrality stocks of CSI 300 network in 2016-2017 and 2017-2018.

2016-2017			2017-2018		
Id	Stock	Out degree centrality	Id	Stock	Out degree centrality
108	Sichuan Chuantou Energy	116	81	Youngor	129
63	China Minsheng Banking Corp	112	117	Haitong Securities	123
117	Haitong Securities	112	132	Guotai Junan Securities	120
81	Youngor	104	120	Bank of Jiangsu	119
119	China Yangtze Power	97	108	Sichuan Chuantou Energy	110
154	China Everbright Bank	87	4	Zoomlion Heavy Industry Science & Technology	101
30	Suzhou Gold Mantis Construction Decoration	86	63	China Minsheng Banking Corp	101
151	Everbright Securities	86	116	Shanghai Tunnel Engineering	92
136	Bank of Communications	80	136	Bank of Communications	92
132	Guotai Junan Securities	79	62	Hua Xia Bank	91
164	Bank of China	78	163	China national Nuclear Power	91
134	Agricultural Bank of China	76	59	Shanghai Pudong development Bank	89
70	SDIC Capital	75	123	Daqin railway	87
64	Zhejiang Zheneng Electric Power	74	6	Financial Street Holding	85
89	Southwest Securities	74	12	Tongling Nonferrous Metals	85
59	Shanghai Pudong development Bank	72	9	Jilin Aodong Pharmaceutical	84
76	China Northern rare Earth	72	159	China Coal Energy	84
161	China Construction Bank	70	80	Shanghai Construction	83
129	Industrial Bank	69	129	Industrial Bank	81
139	Industrial and Commercial Bank of China	69	119	China Yangtze Power	80

with certain differences found in terms of the stock ranking. Boccaletti et al. [60] introduced a basic multilayer network model and integrated structural characteristics of the multiplex network. Thus, two networks were effectively overlapped for a systematic analysis of stock importance. The temporal network was then analyzed from the multiplex perspective.

Firstly, a multiplex network was designed as follows: the upper layer was taken as the stock network during 2016-2017 and the lower layer as the stock network during 2017-2018. The same topics between adjacent layers were connected by lines. The multiplex network constructed is shown in Figure 8.

5.2. Robustness Analysis of Temporal Network. This section analyzes the potential "avalanche effect" in the temporal network according to the robustness of the network, with the

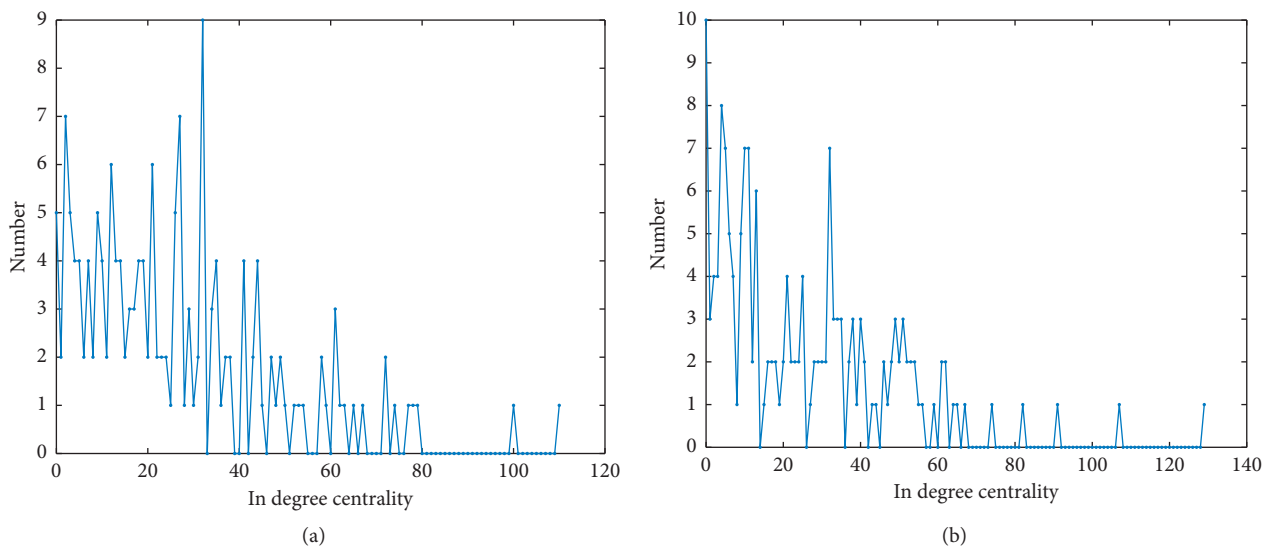

Figure 7: Distribution diagrams of in degree centrality of CSI 300 network in 2016-2017 (a) and 2017-2018 (b).

Table 6: Top 20 in degree centrality stocks of CSI 300 network during 2016-2017 and 2017-2018.

2016-2017			2017-2018		
Id	Stock	In degree centrality	Id	Stock	In degree centrality
117	Haitong Securities	110	81	Youngor	129
81	Youngor	100	117	Haitong Securities	107
15	Guoyuan Securities	79	136	Bank of Communications	91
51	East Money Information	78	32	Risesun Real Estate development	82
136	Bank of Communications	77	82	Yanzhou Coal mining	74
43	Shanxi Securities	74	131	Dongxing Securities	67
11	Hubei Biocause Pharmaceutical	72	19	CITIC Guoan Information Industry	65
30	Suzhou Gold Mantis Construction Decoration	72	92	Gemdale Corporation	64
143	China Nuclear Engineering	67	2	Shenzhen Zhongjin Lingnan Nonfemet	62
169	China Molybdenum	65	3	Overseas China Town A	62
152	China Communications Construction	63	26	China Merchants Shekou Industrial Zone Holdings	61
144	Metallurgical Corporation of China	62	43	Shanxi Securities	61
25	Shanxi Xishan Coal And Electricity Power	61	48	Guosen Securities	59
34	Iflytek	61	106	Greenland Holdings	56
130	China railway Construction	61	91	Beijing Capital development	55
147	Power Construction Corporation of China,	59	11	Hubei Biocause Pharmaceutical	54
58	Lens Technology	58	57	Beijing Enlight Media	54
103	Xiamen Tungsten	58	51	East Money Information	53
13	HESTEEL	54	88	Jiangxi Copper	53
149	Jihua	53	25	Shanxi Xishan Coal And Electricity Power	52

overall robustness of the network also investigated. The robustness analysis of the temporal network was based on a series of domino effects brought about by the reduction of nodes. If a stock network is rousting, the overall loss of the stock network caused by the disappearance of some seriously influenced stocks in the network is not very large. This reflects that the stock network is robust and has a strong resistance to interference, if the proportion of network loss after the node elimination is lower than 50% and such nodes account for 50% or higher of the total nodes. Otherwise, this stock network is vulnerable. However, the fluctuation of one node can never be transmitted to other nodes under extreme conditions

Table 7: Top 20 betweenness centrality stocks of CSI 300 network during 2016-2017 and 2017-2018.

2016-2017			2017-2018		
Id	Stock	Betweenness centrality	Id	Stock	Betweenness centrality
79	Xiamen C&D	479.7774	2	Shenzhen Zhongjin Lingnan Nonfemet	365.0909
89	Southwest Securities	249.2328	79	Xiamen C&D	287.7911
3	Overseas China Town A	229.713	78	China Spacesat	250.327
78	China Spacesat	223.3947	5	Wei Chai Power	236.3662
18	Changjiang Securities	212.8275	66	CITIC Securities	234.1923
168	Foshan Haitian Flavouring and Food Company	199.758	91	Beijing Capital development	170.5163
149	Jihua	161.4737	122	China Merchants Securities	143.3816
43	Shanxi Securities	160.9054	147	Power Construction Corporation of China,	138.1491
138	New China Life Insurance	157.7938	110	Qingdao Haier	136.6742
1	Ping An Bank	150.8605	140	Soochow Securities	98.52948
41	Hangzhou Hikvision Digital Technology	143.871	159	China Coal Energy	96.61944
132	Guotai Junan Securities	142.1785	148	Huatai Securities	95.98428
57	Beijing Enlight Media	135.3603	11	Hubei Biocause Pharmaceutical	94.59229
16	Avic Aircraft	127.645	3	Overseas China Town A	89.39425
141	China Pacific Insurance	126.0323	88	Jiangxi Copper	89.02667
82	Yanzhou Coal mining	125.4607	116	Shanghai Tunnel Engineering	80.96572
51	East Money Information	106.8625	75	Sinolink Securities	75.92961
9	Jilin Aodong Pharmaceutical	106.3568	15	Guoyuan Securities	74.45371
70	SDIC Capital	102.3938	135	Ping An Insurance	73.94458
130	China railway Construction	102.3834	18	Changjiang Securities	72.65543

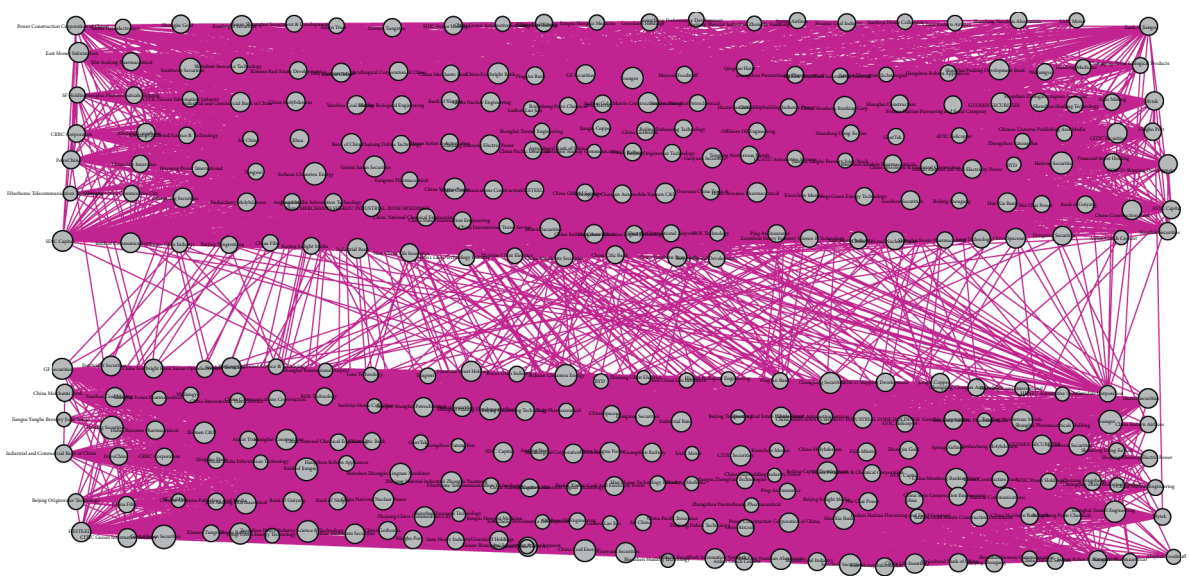

Figure 8: Temporal complex network.

because all of the nodes are isolated. Therefore, the robustness coefficient (ρ) of the network was defined as follows:

$$\rho = \frac{n_{\text{secure}} - n_{\text{isolated}}}{n - n_{\text{isolated}} + 1} = \frac{(n_{\text{secure}} - n_{\text{isolated}})/n}{1 - n_{\text{isolated}}/n + 1/n} = \frac{\rho_{\text{secure}} - \rho_{\text{isolated}}}{1 - \rho_{\text{isolated}} + (1/n)}, \tag{7}$$

where n_{isolated} denotes the number of isolated nodes, ρ_{secure} is the proportion of nodes with less than 50% of a destructive effect, and the corresponding ρ_{isolated} denotes the density of isolated nodes [61]. 1 exists for adjustment purposes, to prevent the denominator of 0. This definition integrates the network connection into the robustness coefficient well. The probability of controlling network loss that is lower than 50% upon a random attack is ρ.

Different from the traditional monolayer network, the multilayer network model applied in Section 4 considers the stock relationships in the study period from a time series perspective.

The following domino spreading algorithm was designed based on the ordinary spreading model:

Step 1: initialize the spreading time vector, t, and the spreading proportion vector, percent.

Step 2: choose the starting node, i (i circulates from 1 to n). The spreading set, $S_i = \{i\}$, the termination set $D_i = \{\varnothing\}$, and the healthy set, $H_i = \{j \mid 1 \le j \le n, j \ne i\}$, are established. The spreading time and spreading proportion are also determined at $t_i = 1$ and $\text{percent}_i = 1/n$, respectively.

Step 3: search the starting point of all nodes in S which are connected to node i in each layer of the network and the neighbouring set, ($S^i_{\text{neighbour}}$), with positive weights of connecting sides. $D_i = D_i + S_i$.

Step 4: if $S^i_{\text{neighbour}} \subseteq D_i$ and $|H_i| = 0$, go to Step 6; otherwise, go to Step 5.

Step 5: for $\forall j \in S^i_{\text{neighbour}}$, search the starting point of the connecting sides of node j in each layer of network and the neighbouring set, ($S^{i(j)}_{\text{neighbour}}$), with positive weights of connecting sides. If $S^{i(j)}_{\text{neighbour}} \subseteq D_i$, then $D_i = D_i + \{j\}$; otherwise, $S_i = S_i + \{j\} - \{i\}$. After all of the elements in $S^i_{\text{neighbour}}$ have been circulated, set $t_i = t_i + 1$ and $\text{percent}_i = (|S_i| + |D_i| - 1)/n$. $H_i = H_i - D_i - S_i$ and return to Step 3.

Step 6: if $S^i_{\text{neighbour}} = \varnothing$ and $t_i = 1$, let $t_i = n + 1$; otherwise, go to Step 7.

Step 7: $\text{percent}(i) = \text{percent}_i$ and $t(i) = t_i$. If $i \le n$, go to Step 2.

Step 8: output the spreading time, t, and the spreading proportion, percent.

In Steps 3 and 5, a Boolean retrieve was applied to search the neighbouring nodes of each node in the set S and $S^i_{\text{neighbour}}$ and to determine the potential communication target. Step 6 examines whether the spreading nodes in the initial state are isolated or have no positive weights on the outgoing edges. Under this circumstance, the passive nodes that are isolated in the initial state, or have no outgoing edges with a positive weight, cannot influence other nodes. Therefore, the nodes with the longest time are directly omitted from the algorithm. The simulated process of risk spreading based on a stock temporal network in Figure 9 is introduced in the following section.

The above algorithm considers two characteristics of stock networks: (1) the development of one stock is closely related with the amplitudes of other stocks; (2) the network collapse exerts a domino effect, as reflected by the spreading time and spreading proportion in the algorithm.

An example of a stock temporal network can be seen in Figure 9, and the process of spreading network risk is shown in Figures 10(a)–10(d), with the starting point at node 1.

The spreading set, (S_1), under each spreading time, (t_1), termination set (D_1), and the healthy set (H_1) and the spreading proportion of the final network (percent_1) after node 1 chosen as the risk spreading source in the network are shown in Table 8.

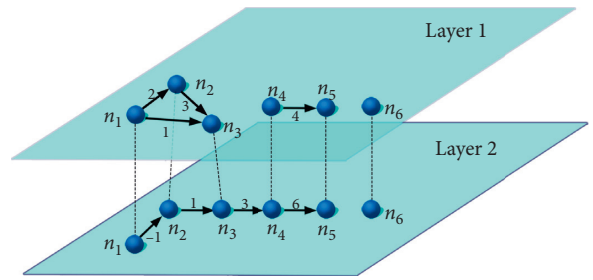

Figure 9: Initial status of 6 nodes in multiplex network with 2 layers.

As shown in Figures 9 and 10, if risk spreading was only to occur in layer 1, the process would end with $S_1 = \{2, 3\}$, $D_1 = \{\varnothing, 1\}$, and $H_1 = \{4, 5, 6\}$. However, layer 2 provides more information; namely, that in some cases, node 3 is linked with node 4. If that happens, the single layer (layer 1) cannot capture this chance of risk process. Similarly, due to the negative weight of the edge between nodes 1 and 2, that is, −1, without information from layer 1, the spreading process would end with $S_1 = \{1\}$, $D_1 = \{\varnothing\}$, and $H_1 = \{2, 3, 4, 5, 6\}$.

In short, the algorithm takes the worst network collapse into account. If the connecting side of two nodes in one layer is positive and the starting point of the side is collapsed (infected), the node at the other end will also, ultimately, be infected.

The Matlab simulation results are shown in Figure 11.

The red line in Figure 11 reflects that the collapse time of the network caused by most nodes is relatively small, indicating that these nodes might lie at the edges or core of the network. This has to be further determined according to the collapse proportion because the core nodes of the network would cause a more extensive collapse at the same time. Moreover, the collapse time of a few nodes is relatively high, and most of these nodes are isolated or powerless. The statistics on the top 20 stocks in terms of the collapse proportion are presented in Table 9.

Table 9 reveals that the top 20 stocks in terms of the collapse proportion fluctuate, essentially, at the same time. On the one hand, this explains the fact that these stocks can influence over 80% of the network's stocks in a short period. On the other hand, the importance of these stocks in the network varies to some extent. The difference in importance between China Yangtze Power in the first position and Shandong Dong-Ee Jiao in the 20th position reaches as high as 20%. In conclusion, the nodes in the stock market are significantly different, and the global stability of the network is almost controlled by a few stocks.

It finds from comparison of out degree centrality, in degree centrality, and betweenness centrality that the large-scale collapse of stock networks is mainly caused by financial stocks with a high out degree centrality and in degree centrality, such as those of the China Minsheng Banking Co., Ltd., Shanghai Pudong Development Bank, and Industrial Bank. Stocks with a high out degree centrality are more likely to establish positive correlations with other stocks. However, the in-sides of these stocks become ineffective when they are

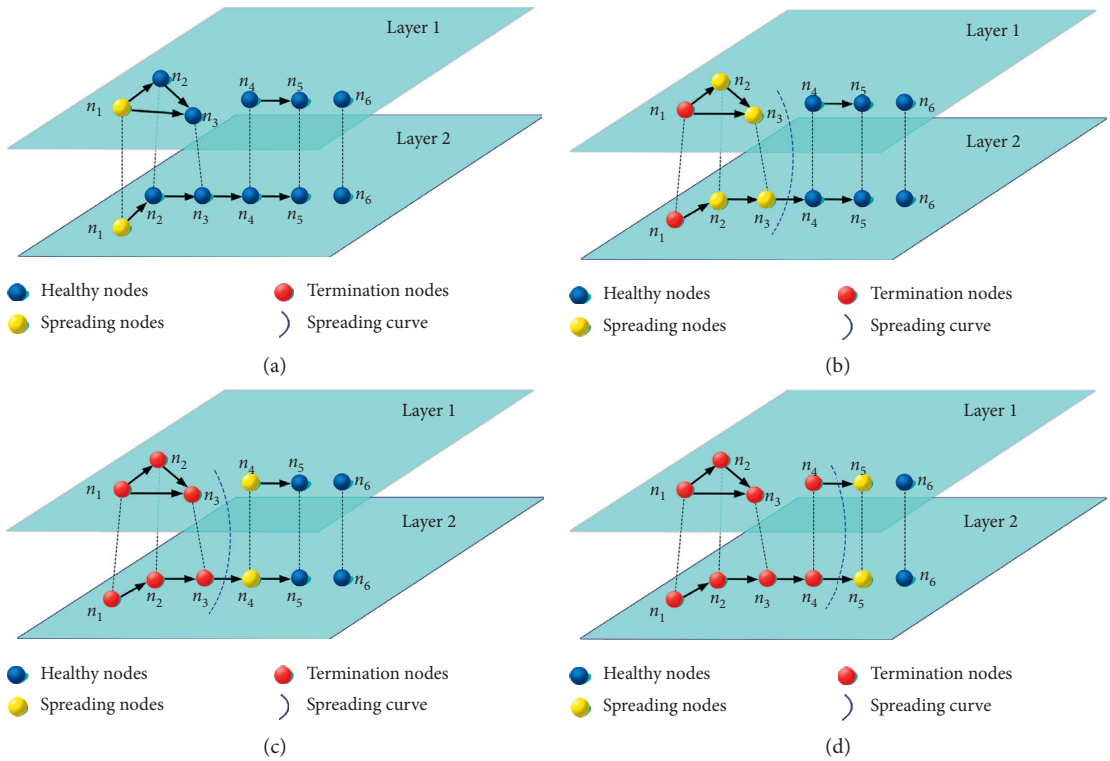

Figure 10: Example of risk spreading from node 1 with domino spreading algorithm: (a) spreading status with $t = 1$; (b) spreading status with $t = 2$; (c) spreading status with $t = 3$; (d) spreading status with $t = 4$.

Table 8: Risk spreading process from node 1.

	$t_1 = 1$	$t_1 = 2$	$t_1 = 3$	$t_1 = 4$
S_1	$\{1\}$	$\{2, 3\}$	$\{4\}$	$\{5\}$
D_1	$\{\varnothing\}$	$\{\varnothing, 1\}$	$\{\varnothing, 1, 2, 3\}$	$\{\varnothing, 1, 2, 3, 4\}$
H_1	$\{2, 3, 4, 5, 6\}$	$\{4, 5, 6\}$	$\{5, 6\}$	$\{6\}$
percent_1	1/6	1/2	2/3	5/6

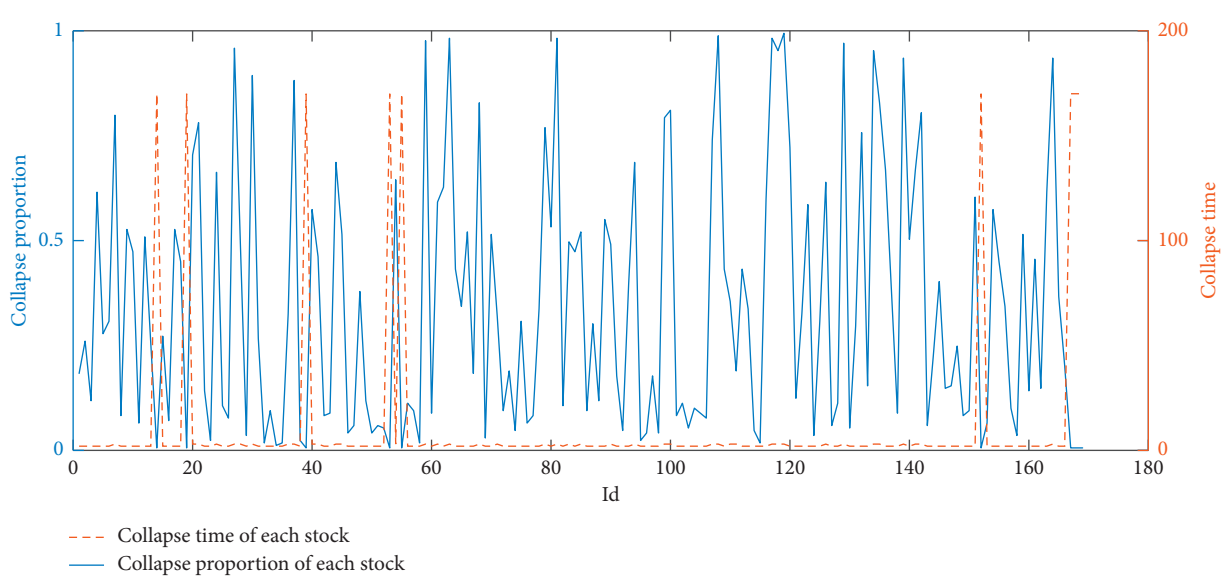

Figure 11: Collapse proportion and time originated from each stock.

Table 9: Top 20 stocks with disturbance power in collapse process.

Id	Stock	Collapse proportion	Collapse time
119	China Yangtze Power	0.9941	3
108	Sichuan Chuantou Energy	0.9882	3
63	China Minsheng Banking Corp	0.9822	3
81	Youngor	0.9822	3
117	Haitong Securities	0.9822	3
59	Shanghai Pudong development Bank	0.9763	3
129	Industrial Bank	0.9704	3
27	Hualan Biological Engineering	0.9586	3
118	SDIC Power Holdings	0.9527	3
134	Agricultural Bank of China	0.9527	3
139	Industrial and Commercial Bank of China	0.9349	3
164	Bank of China	0.9349	3
30	Suzhou Gold Mantis Construction Decoration	0.8935	3
37	Shenzhen Salubris Pharmaceuticals	0.8817	3
68	China Merchants Bank	0.8284	3
135	Ping An Insurance	0.8284	3
100	Kweichow Moutai	0.8107	3
142	Shanghai Pharmaceuticals Holding	0.8047	3
7	Shandong Dong-Ee Jiao	0.7988	3

collapsed, and the major domino effect occurs on the outsides. Based on the algorithmic principle, the weights of the out-sides of these stocks are mainly positive, so that they can induce a network collapse in a short period. Therefore, financial stocks can be seen as the core of the stock network, making it more important to maintain their stability in the economic market. In the worst-case scenario, any threats to these important financial stocks may spread over the whole network.

Moreover, the betweenness centrality and eigenvector centrality emerged as similar in the top 20 stocks, to some extent. For instance, the intersection of SDIC Power Holdings, East Money and Shanxi Securities reflects their role as bridges in the stock network. These stocks connect influential neighbouring nodes. Therefore, cutting the loss in time of these stocks at the point of network collapse can effectively prevent a follow-up loss. This may thus be termed the "defense force" of the stock network.

Finally, 116 nodes were seen to cause a collapse effect smaller than 50%, given that a two-layer temporal network was constructed in the current study, and the inner layer covered 0 isolated nodes. Therefore, $\rho_{\text{isolated}} = 0$, and the stability index of the network was $\rho = 0.6824 > 0.5$, indicating the high stability of the stock network.

Based on above analysis, the new algorithm developed here is arguably superior to the traditional infection model of complex networks in actual networks. Moreover, the situation of the negative weights of the sides between nodes in the stock network is here taken into account. The domino effect of collapse among different stocks was simulated from a multiplex perspective, thus obtaining the network loss caused by the collapse of each node. Finally, the backbone force and defense force of stock networks were analyzed, based on the data in previous sections.

6. Conclusions

In this paper, selected stock data drawn from the CSI 300 index were divided into two time series.

Next, the daily amplitudes of stock samples were calculated. The stationarity of the calculated data of each stock was tested using the ADF method. Finally, the cointegration coefficients between any two stocks were obtained by applying a cointegration test. The thresholds of the cointegration coefficients were acquired by combining the frequency distribution. Meanwhile, edges with a high weight were chosen in order to establish a weighted directed graph, which considered the negative correlations among stocks.

Distributions of out degree centrality and in degree centrality reflected the scale-free characteristics of the network. Only a few stocks were found to play important roles in the network and to control the stability of the stock network. The top 20 node stocks in the stock network, such as "major players," "gatekeeper," and "vulnerable players," were explored by analyzing the out degree centrality, in degree centrality, and betweenness centrality of the complex network.

On this basis, the temporal complex networks were constructed and an algorithm to test the robustness of these networks was designed. The quantitative indexes and evaluation standards of robustness were then proposed, and the systematic risk of the stock market was analyzed.

In summary, this paper has the following highlights:

(i) A robustness test algorithm for network stableness is designed

(ii) Quantitative indexes and evaluation standards of robustness are introduced

(iii) The methodology can be applied in other situations like social networks, to specify the strength among people or global supply chain networks

Apart from this research, some guidance is given for other situations for researchers to follow:

(i) The time slice is the year unit. It is chosen as the "year-round" feature of the stock market. In other situations, the features can be chosen as others like "month-round" and "season-round".

(ii) Generally, time series should be firstly stationary. ADF test is done for this. If the criterion is not fulfilled, the data should be differenced, and then the left jobs could be executed in the stream of Figure 1. Furthermore, the data can be analyzed in more than two layers of network, just replications of downstream of the single layer.

Also, US stock market or EU stock market could be done in the future for justifying the usage of methodology, and if real system risk dispersion data is obtained, the research could be enriched.

So, the research conclusions not only enrich the robustness theory of temporal networks but also provide an effective tool to prevent systematic stock market risks.

Data Availability

All data, the models used during the study that appear in the submitted article, and the original data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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