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Research Article

Structure Characteristics of the International Stock Market Complex Network in the Perspective of Whole and Part

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International stock market forms an abstract complex network through the fluctuation correlation of stock price index. Past studies of complex network almost focus on single country's stock market. Here we investigate the whole and partial characteristics of international stock market network (ISMN) (hereinafter referred to as ISMN). For the analysis on the whole network, we firstly determine the reasonable threshold as the basic of the following study. Robustness is applied to analyze the stability of the network and the result shows that ISMN has robustness against random attack but intentional attack breaks the connection integrity of ISMN rapidly. In the partial network, the sliding window method is used to analyze the dynamic evolution of the relationship between the Chinese (Shanghai) stock market and the international stock market. The connection between the Chinese stock market and foreign stock markets becomes increasingly closer, and the links between them show a significant enhancement especially after China joined the WTO. In general, we suggest that transnational investors pay more attention to some significant event of the stock market with large degree for better risk-circumvention.

1. Introduction

The international stock market network (ISMN) can be regarded as a complex network. In studies of securities markets to judge the method of constructing networks, scholars usually use correlation analysis to construct securities market networks, in which the nodes are stocks and the edges between nodes are the price fluctuation relationships of stocks.

Methods in designing networks include the minimum spanning tree (MST), planar maximally filtered graphs (PMFGs), and correlation threshold method. Mantegna was the first to use the correlation between stocks to build the stock market network [1]; he selected the main connections between the nodes and generated a tree graph to reveal the hierarchy of the network by adopting MST. Kim et al. also used the MST to study the topology of the network structure [2–5]. Tumminello et al. analyzed the portfolio of 300 most capitalized stocks traded at the New York Stock Exchange during the period 2001–2003 and used the statistical properties of the portfolio, such as the average path length to derive the PMFGs [6], which are based on MST but carry more information than the tree graphs. Boginski et al. all used the correlation threshold method to construct stock networks [7–11]. Clearly, the correlation method is widely used in building networks and is thus used in this paper. All aforementioned studies adopt the Pearson correlation coefficient; however, the statistical tests show that the sample data do not follow a normal distribution. Accordingly, we use Spearman rank correlation coefficient to describe the inherent relationships between stock indices.

Drawing from the conclusions of studies on stock market networks, Tse investigated all US stocks and found that the US stock network is scale free [9]. Gałązka studied the stock market of Poland by constructing a weighted complex network and MST [12]; the results showed that the Polish

stock market is scale free. Namaki et al. constructed the Iran stock network using the threshold method and found that the network is scale free under particular conditions [13]. Caraiani investigated the emerging European stock markets, incorporated fractal theory into the complex network theory, found that the network is scale free [14], and identified multifractal characteristics of clustering coefficient. Ma et al. investigated the dynamics of Chinese stock market from 2005 to 2012 by using sliding window and found that the Chinese stock market is scale free when it experiences a bear market [15]. Tan and Ding applied the visibility graphs to the US stock market and found that the degree distribution agrees with the scale-free property during the Global Financial Crisis in 2007 [16]. In general, the aforementioned studies all concentrated on single national stock network and the results show that most of the single national stock networks are scale free. However, the topology graph constructed in this paper shows that the ISMN composed of the nodes we selected is not scale free. Rare literature of complex network refers to the whole international stock market, and it is circumscribed for transnational investors. But this paper is based on the international stock market whose conclusion can be a reference to transnational investors.

The contribution of our study is as follows. First, our study has been conducted on the stability of ISMN under random and intentional attacks and found that ISMN has robustness against random attacks, which no one has studied before. Second, in all the aforementioned studies, static networks are constructed even if a stock market is a changing complex system; thus, we adopt the sliding window method to study the dynamic law of the ISMN and we come to an interesting finding: there exists enhancement in the links between the Chinese stock market and the foreign stock markets after China joined the WTO. The rest of the paper is organized as follows. Section 2 provides formulas for the statistical characteristics of a complex network and illuminates how the network is constructed. Section 3 presents an empirical analysis of the characteristics of an ISMN. Section 4 summarizes the results and deficiencies of this work.

2. Complex Network Model and Data

2.1. Complex Network Model. Normally, size and density are selected to describe the macrocharacteristics of a network, while the average path length and clustering coefficient are used to measure both indicators.

The distance between any two nodes, i and j, in the network is defined as the edges of the shortest path between them. A random sample of the maximum distance between two nodes is called the network diameter, which is denoted by D, $D = \max_{i,j} d_{ij}$.

The average path length of the network is

$$L = \frac{2}{N(N+1)} \sum_{i \geq j} d_{ij}. \tag{1}$$

In the formula, N is the number of nodes in the network, and the distance of the node itself is zero. The average path length represents the average distance between any two nodes and reflects the size of the network. The average path length is used to represent the transmission efficiency of the network.

Clustering coefficient analysis is conducted to assess if the nodes are closely interrelated and if the network is dense. If any one node, i, in the network is connected to other nodes via k_i edges, then k_i nodes are neighbor nodes of i and can each have up to $k_i(k_i - 1)/2$ edges. The ratio of the edges N_i that exist between node neighbor nodes of i, k_i, to the maximum edges that may exist as the clustering coefficient is denoted by C_i; that is,

$$C_i = \frac{2N_i}{k_i(k_i - 1)}. \tag{2}$$

The clustering coefficient of the entire network, C, is equal to the arithmetic mean of clustering coefficients of all the nodes in the network; that is,

$$C = \frac{1}{N} \sum_{i=1}^{N} C_i. \tag{3}$$

Obviously, $0 \leq C \leq 1$. When $C = 0$, all nodes in the network are isolated: that is, the network has no edges. However, when $C = 1$, any two nodes in the network are connected.

In many realistic complex networks, the connectivity probability between nodes is usually associated with the type of nodes. This selective connection between nodes is called assortativity. We can characterize assortativity in the network quantitatively by using an assortativity coefficient. The assortativity coefficient can be calculated in a variety of ways. In this study, we use the classic method proposed by Newman [17].

The nodes in the network are divided into N types. Let E_{ij} be the number of edges of the node types i and j ($i, j = 1, 2, \ldots, N$); let the elements in matrix E be E_{ij}; let normal matrix be $e = E/\|E\|$, where $\|E\|$ is equal to the sum of all elements in matrix. The assortativity coefficient is defined as

$$r = \frac{\operatorname{tr} e - \left\|e^2\right\|}{1 - \left\|e^2\right\|}, \tag{4}$$

where $\operatorname{tr} e$ is the trace of the matrix, which is the sum of diagonal elements in a matrix, and $\|e^2\|$ is the sum of all elements in the matrix. When $r = 0$, the different types of nodes show no connective preference. That is, the nodes are connected completely and randomly. When $r = 1$, these nodes are connected only to the nodes of the same type, and the network has complete assortativity. When $r < 0$, the nodes in the network are more likely to connect to nodes of a different type. Conversely, when $r > 0$, the nodes are more likely to connect to the nodes of the same type.

2.2. Data. For a dynamic research on the interactions and relationships between the stock markets in the world from January 1999 to December 2014, with 2369 observations being used, we use previous studies for reference and collect stock index data of 27 countries (regions). The data are extracted from "RESSET." We choose the 27 indices which include six continents except Africa. The 27 indices abbreviations

Table 1: The basic statistical properties of 27 index nodes' yield data sets.

Statistical parameter	Mean	Standard deviation	Skewness	Kurtosis	Jarque-Bera statistic	Probability of Jarque-Bera statistic
HSI	0.000325	0.019806	−0.32495	11.78236	7655.058	0
DAX	0.000257	0.019834	−0.44383	9.565421	4332.576	0
DJIA	0.000264	0.014655	−0.17922	8.998133	3563.927	0
NKY	0.000110	0.019304	−0.78716	9.250384	4100.921	0
BVSP	0.000830	0.025515	1.485915	37.20201	116338.6	0
IBEX	−0.000003	0.019567	−0.02564	7.953011	2421.804	0
JKSE	0.001021	0.020897	−0.51635	18.10679	22632.01	0
BEL20	−0.000041	0.017065	0.360482	15.92032	16529.15	0

are listed as follows: HSI, KOSPI, NKY, FSSTI, TWSE, PCOMP, FBMKLC, SENSEX, JKSE, SZZS, AS51, UKX, CAC, DAX, AEX, BEL20, IBEX, BUX, ATX, OMX, SMI, DJIA, S&P 500, S&P/TSX, MERVAL, BVSP, and MEXBOL. We construct ISMN under different threshold, in which the stock indices are nodes and the price fluctuation relationships of stock indices, as edges. ISMN describes the price fluctuation relationships of stock indices with the daily log-return of the nodes. The log-return of index i is

$$R_i(t) = \log\left(\frac{P_i(t)}{P_i(t-1)}\right), \tag{5}$$

where $R_i(t)$ is the yield rate of index i at time t and $P_i(t)$ is the closing price. Log-return is used as empirical analysis data to avoid the influence of exponential trend and can reduce nonstationarity of data.

Given the limited space, we select eight stock markets. The basic statistical characteristics of the return series are presented in Table 1.

As Table 1 shown, the Jarque-Bera statistic of the return series indicates that these series are not distributed normally. Most studies on complex networks are based on Pearson correlation coefficients to measure the relationship between nodes. However, Pearson correlation coefficients are more applicable to normal distribution series. Thus, we adopt the Spearman rank correlation coefficient in this study. Spearman rank correlation coefficient is based on the rank of random variable, so that, even in the case of nonlinear transformations, it is possible for a strictly monotonically increasing random variable to remain unchanged. It is also known as the rank correlation coefficient and can be used for nonlinear variables correlation measure [18].

The Spearman rank correlation coefficient, which is denoted by ρ, can be calculated by its ranking-difference collection d and has the following formula:

$$\rho = 1 - \frac{\sigma \sum_{i=1}^{N} d_i^2}{N\left(N^2 - 1\right)}. \tag{6}$$

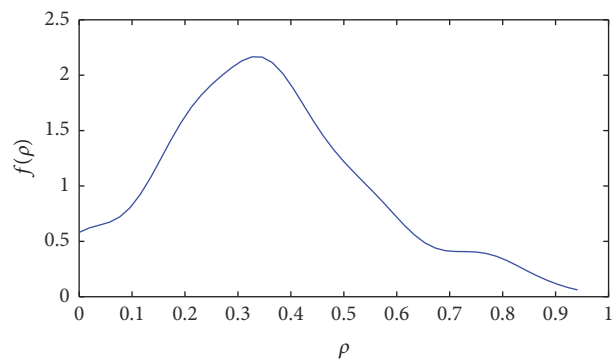

Figure 1: The probability density distribution correlation coefficients in ISMN. Most of the coefficients are between 0.1 and 0.6.

We can generate the adjacency matrix of the network by controlling the value of threshold θ

$$E = \begin{cases} e_{ij} = 1, & i \neq j \text{ and } \rho_{ij} \geq \theta, \\ e_{ij} = 0, & i = j \text{ or } \rho_{ij} < \theta, \end{cases} \tag{7}$$

where $\theta \in [0, 1]$. When $e_{ij} = 1$, an edge exists between two nodes; otherwise, an edge does not exist. We can obtain the undirected and unweighted complex ISMN based on the adjacency matrix.

3. Empirical Analysis

3.1. Properties of the Whole Network. In this section, we analyze the structure properties of ISMN on the whole. Topological graph and robustness based on average path length and clustering coefficient are studied to reveal the whole network's structure and stability. Figure 1 shows the probability density distribution correlation coefficients in ISMN.

We can see from Figure 1 that most of the coefficients are between 0.1 and 0.6. This phenomenon is because the indices are worldwide and the fundamentals of each index differ significantly from each other; thus, convergence between price trends is difficult to achieve. This figure is used to observe the distribution of the correlation coefficient.

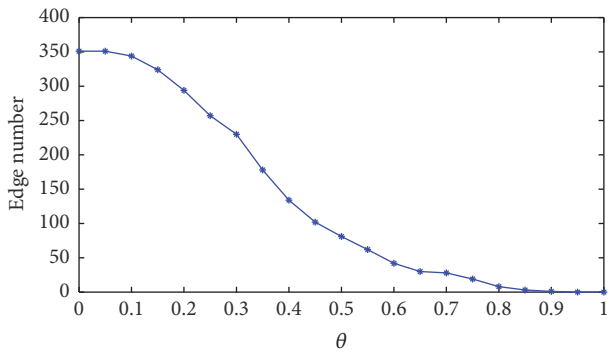

Figure 2: Number of edges at different threshold of the ISMN.

Rational threshold selection is a crucial step for constructing networks. If a selected threshold is too small, there would be false associations due to the random noise, resulting in the complete connected network; if the selected threshold is too large, the network will contain fewer vertexes, which could make some significant information filtered.

Figure 2 shows the number of edges at different threshold of the ISMN. We can find that the edge number declines with the increase of θ. To guarantee the rationality of density of ISMN, we choose the threshold which makes the edge number stay around the middle level (100–250), because under other circumstances, the networks are too dense or too sparse and are not suitable for analyses. In that case, the threshold is between 0.25 and 0.45 and the edge number declines rapidly in this interval, which implies that the contribution of these left indices is more significant than the filtered ones.

3.1.1. Average Path Lengths and Higher Clustering Coefficients. Average path length and clustering coefficient are the most essential properties. Short average path lengths and high clustering coefficient indicate the tightness of network and guarantee the small-world effect of complex network. Under different thresholds, average path length and clustering coefficient of the network are calculated according to formulas (1) and (3), respectively, in Figure 3.

As shown in Figure 3, we can observe that the average path length L increases with the increase of θ and clustering coefficient C declines with the increase of θ when $\theta < 0.4$. However, when $\theta > 0.4$, L and C show irregular fluctuation. This is because isolated nodes have occurred in the ISMN constructed when $\theta > 0.4$, the remaining nodes constitute a smaller subnet, the subnet gets sparser with the increase of θ, until θ comes to a larger value, and some nodes run away from the subnet and make up another smaller subnet. And this keeps circulating. To guarantee that all nodes are included in ISMN, we only study the network constructed when $\theta < 0.4$. In the following research on properties of the whole ISMN, we choose $\theta \in [0.25, 0.4]$ for study.

Compared with the basic statistical data of more than 20 kinds of networks reported in two previous studies (Albert and Barabási [19], Newman and Watts [20]), the data we calculated present lower average path lengths and higher clustering coefficients. And it follows the behavior $L \sim \ln N$. Thus, the ISMN has a small-world effect at low threshold values [21, 22]. If a real stock market network has small-world effect, the funding, information, and other elements are transmitted rapidly in the network. At the same time, when one or more markets in the network pose a risk, such risk can spread quickly, and the losses from such a risk can be reduced to a certain extent.

A shorter average path length L indicates that any two indices can be easily connected in the network and the fluctuations in some index prices can be easily transferred to other indices in the ISMN. When the network has a higher clustering coefficient, the network connectivity of the cluster, which is constituted of adjacent nodes of any of the stock indices, is good, and the fluctuations in a stock index price can be more easily spread among the clusters. In other words, the fluctuation in a single stock index price is more likely to spread among the stock indices with stronger correlation.

3.1.2. Topological Graph of the Network. The topological graph can reflect the whole structure and density of the network directly. Figures 4–7 are the topology diagrams at thresholds of 0.25, 0.3, 0.35, and 0.4, respectively. The numbers in parentheses are the degree of each node. Nodes with large degree in Figures 4–7 will be removed in the next section to study the robustness of ISMN.

A comparison of Figures 4–7 shows that the network is becoming increasingly sparse; thus, the higher the threshold value, the lower the degree of network connectivity. When $\theta = 0.25$ and 0.3, the entire ISMN is extremely dense with great connectivity. The network does not have one or a few hub nodes with very high degree which indicates that the network is not scale free. The Shanghai stock market is associated only with the Hong Kong stock market. In the next section, we adopt the sliding time-window approach to study this phenomenon further.

In Figures 6 and 7 we can find that two nodes (SHH and PH) are separate from the ISMN; only 25 nodes are left. Western countries in the right of Figure 7 are much more compact than those on the left, and their degrees are larger. That is why, we call the stock markets in Europe and America the center of global economy. However, the degrees of those Western countries are average; no hub node existed in ISMN which indicates that the network is not scale free.

3.1.3. Stability of the Network (Robustness). According to the complex network theory, robustness refers to the persistence of a system's characteristic behavior under perturbations or conditions of uncertainty [19]. Robustness is studied in many fields such as transportation and emergency logistics [23, 24]. The robustness of the international stock market refers to the stability of the network when the nodes suffer from random or intentional attack [25]. In this section, we simulate the random and intentional attack by stochastic and selective removal of nodes in the network. For stochastic removal, we repeat to remove node randomly for 1000 times. And for selective removal, we remove nodes in order of the degree of nodes (large ones first) with the reference of topological graph

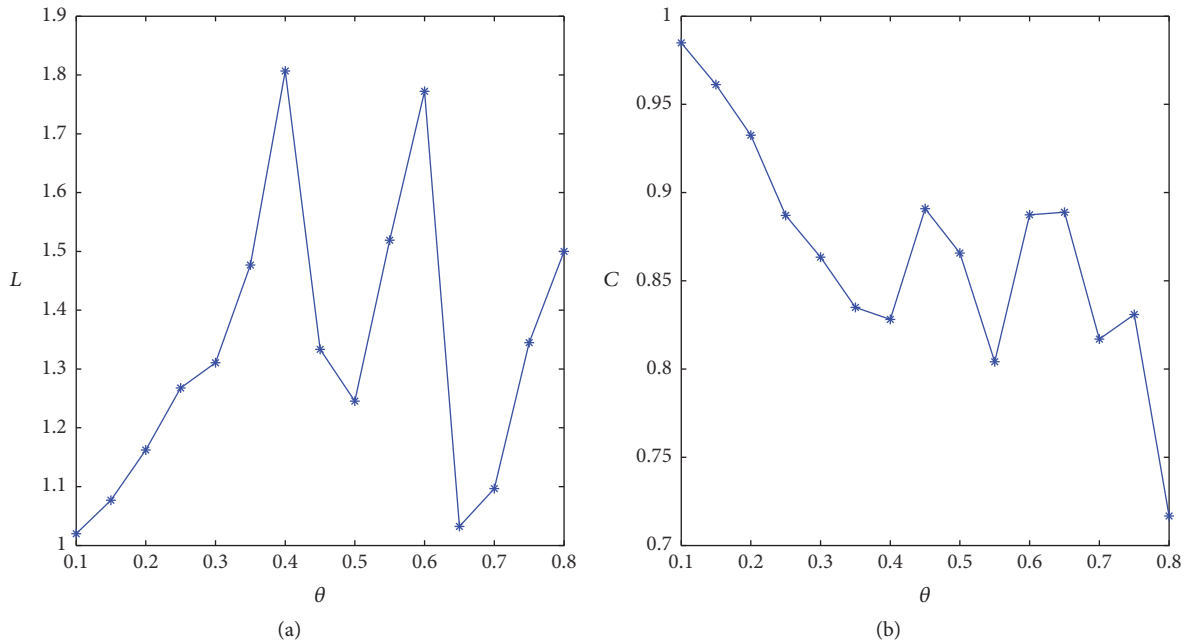

Figure 3: The average path length L and clustering coefficient C versus θ.

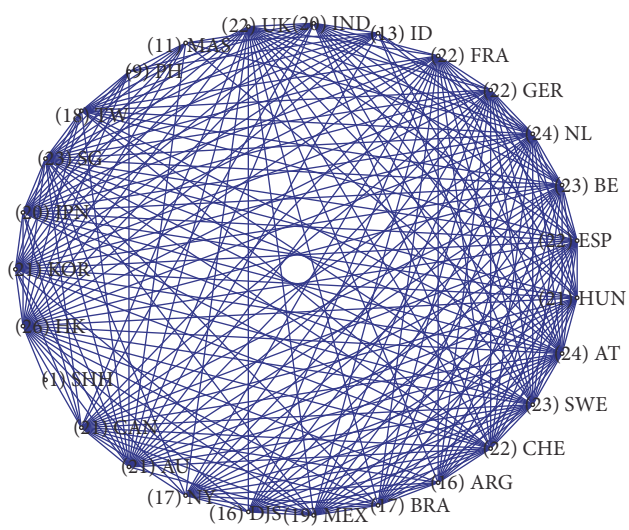

Figure 4: Topology graph of ISMN at $\theta = 0.25$.

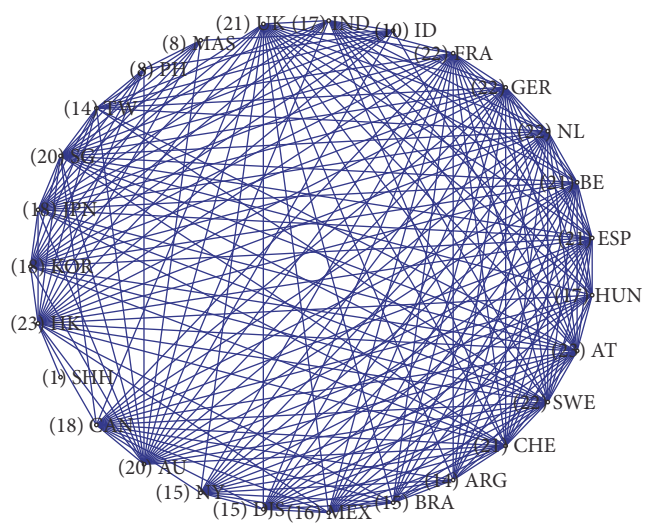

Figure 5: Topology graph of ISMN at $\theta = 0.3$.

above. Figures 8-9 show the relationship between clustering coefficient C (average path length L) and removal proportion f.

Figures 8(a)–8(d) show stability of stock correlation network when $\theta = 0.25, 0.3, 0.35$, and 0.4. We can find that the clustering coefficient C under stochastic removal in the four subgraphs almost stay the same, close to the horizontal line. On the contrary, the clustering coefficient C under selective removal presents obvious fluctuation and is all below the line of stochastic removal, which implies that the clustering coefficient under selective removal is smaller than that under stochastic removal.

For $\theta = 0.25$, 0.3, and 0.35, the clustering coefficient C under stochastic removal decreases with the increase of f when $f < 0.5$, which means that the clustering is getting weaker. And when $f > 0.5$, the clustering coefficient C climbs up and then declines. Because half the nodes with large degree are removed, the network is disconnected and the remaining subnet would make C larger. For $\theta = 0.4$, C presents a falling trend with oscillation. A minor removal proportion can make the network connectivity drop rapidly, while it needs to remove a large number of vertices to realize the same connectivity reduction extent under stochastic removal. For example, in Figure 8(a) when $f = 0.25$, C under

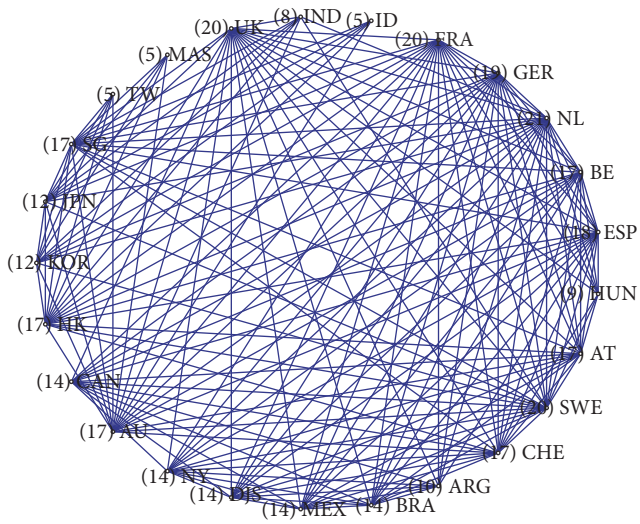

Figure 6: Topology graph of ISMN at $\theta = 0.35$.

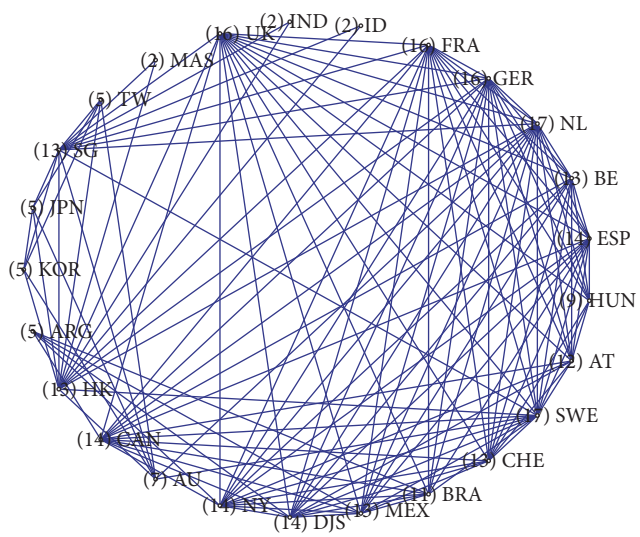

Figure 7: Topology graph of ISMN at $\theta = 0.4$.

selective removal is 0.8408, which is similar to the value under stochastic removal with $f = 0.75$.

The result of L versus f is similar to that of C versus f. In general, average path length L under selective removal is all larger than that of stochastic removal with the increase of f. In the first three pictures ($\theta = 0.25$, 0.3, and 0.35), trends of L under stochastic removal are almost straight lines, which implies that ISMN is robust against stochastic removal. However, L rises under selective removal when $f < 0.5$, which means that distances between nodes are farther and the network gets sparser. And when $f > 0.5$, the clustering coefficient C climbs up and then declines, because, with the removal of nodes, network gets farther away from uniformity. For $\theta = 0.4$, L declines with the increase of f under stochastic removal. The network becomes more fragile with the increase of the threshold but the average path length under selective removal is still larger than that under stochastic removal. That is to say, the ISMN presents weak robustness when threshold is relatively large.

In conclusion, the robustness against stochastic removal indicates that some stochastic events of international stock market will not have an essential influence on the whole price fluctuation correlation of the networks. However, intentional attack breaks the connection integrity rapidly and reduces the connective efficiency of ISMN which indicates that nodes with large degree make essential difference to ISMN. Those nodes not only ensure the transmission of information but also maintain the structural stability of ISMN. Hence, we must pay more attention to some significant event of the stock market with large degree such as the Western countries. For example, the UK left the EU on June 24 this year, and the Japanese, German, French, and American stock indices all fell sharply on that day. This attention will help transnational investors understand the dynamic price fluctuation correlation patterns among stock markets, and such understanding can be used for references in portfolio investments and risk managements.

3.2. Subnets and Single Nodes of the Network

3.2.1. Assortativity of ISMN. The study of average path length and clustering coefficient implies that the ISMN accords with the characteristics of complex network. The fluctuation of these indices is closely related and transfers rapidly. And then we classify the network into several subnets, detecting the preference of connection between different kinds of subnets, namely, assortativity.

In a real network, nodes have different connection choices and preferences. These preferences cause the connections between nodes to be related. Newman introduced the concepts of assortativity and disassortativity [17], which are based on the correlation of connections between the nodes in the network, to distinguish between the connection preferences of nodes. He used matching coefficients to describe the connections between the nodes quantitatively.

In this study, the sample, comprising 27 index stocks, was chosen according to the following criteria. First, the sample is divided into 14 developed countries and 13 developing countries according to the national development level. Second the sample is classified according to area, and hence, the sample is divided into 11 countries in the Asia-Pacific region and 16 countries in Europe and America. At different thresholds, the assortativity coefficient r is shown in Figure 1.

From Figure 10 we find that the assortativity coefficient when the sample is classified according to the national development level exhibits a lower degree of disassortativity at a low threshold, because the network is constructed at a lower threshold value, wherein the relationship between index prices is weaker. The network is based on the basic price trend, reflecting the overall feature of international stock market. The network reflects mainly the self-organization of a stock market and resembles a naturally formed complex system that lacks human participation. As a result, the network exhibits disassortativity to some extent. When the threshold increases from 0.3, the assortativity coefficient r exceeds 0. When the threshold varies from 0.3 to 0.5, r

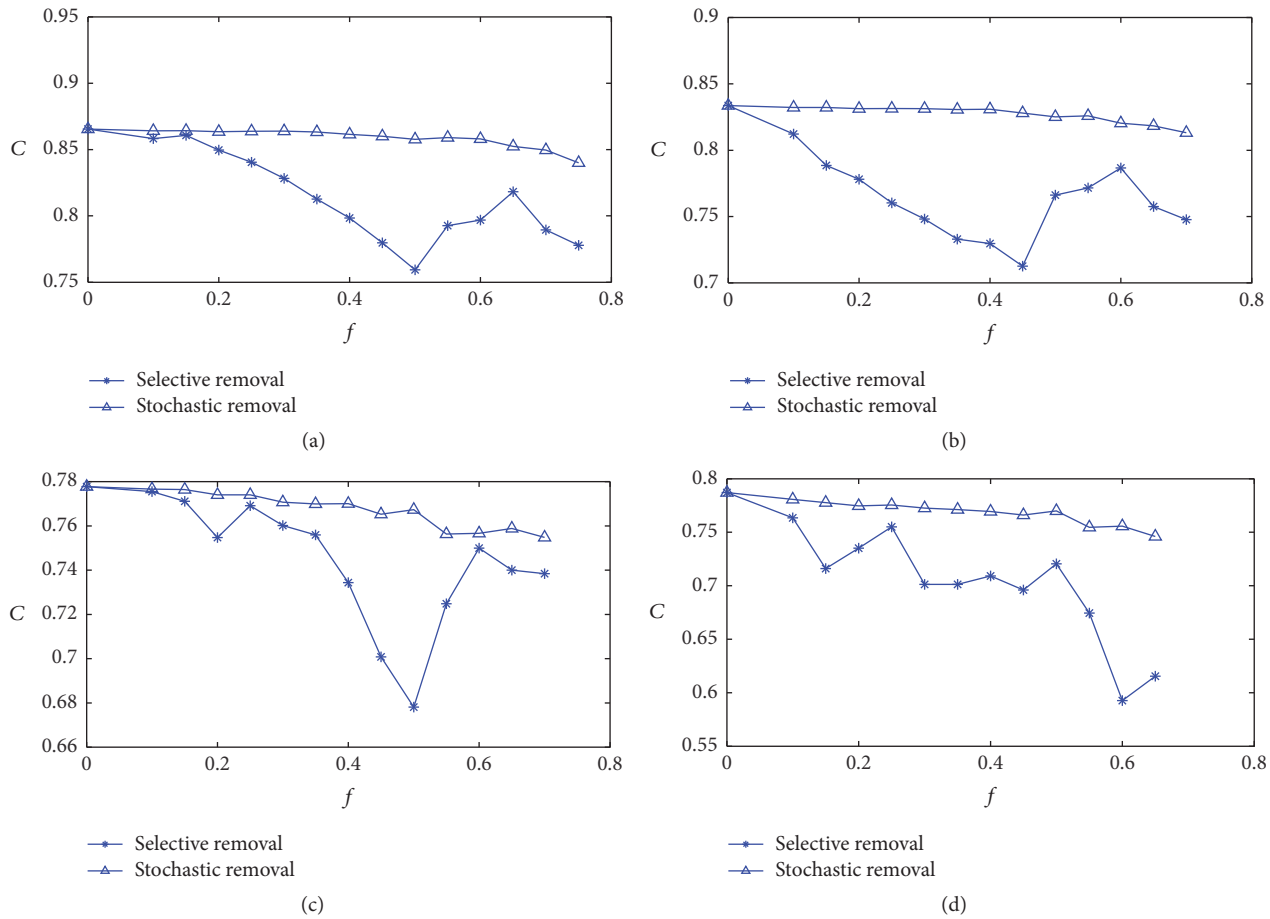

Figure 8: The clustering coefficient C versus f when (a) $\theta = 0.25$; (b) $\theta = 0.3$; (c) $\theta = 0.35$; (d) $\theta = 0.4$. With an increase of f, we find that the network becomes more and more weak to selective removal and is always robust against stochastic removal. If the thresholds equal other values in interval [0.25, 0.4], the general rules of topological stability are not changed. So we only demonstrate aforesaid four cases.

increases rapidly, and when the threshold is equal to 0.6, the assortativity coefficient reaches 0.45. The network is of considerable assortativity, as found in a previous study [26]. The stock indices in developed countries are more inclined to be connected to those of other developed countries at a high threshold, and the stock indices of developing countries are more likely to be connected to those of other developing countries. Clearly, the trends of stock indices of countries with similar economic levels are more consistent. This phenomenon is related to the macroeconomic situations and economic and financial policies of the countries.

The change in assortativity coefficient by region shows that the entire network presents strong assortativity, indicating that stock indices in the ISMN are more inclined to be connected to the indices in the same region. The assortativity coefficient also increases rapidly when the threshold exceeds 0.2. When the threshold is equal to 0.5, the assortativity coefficient, r, is 1; that is, the network is of complete assortativity. This result indicates that the stock indices in the countries in Europe and America are more inclined to be connected to each other. In the same way, stock indices in the countries in the Asia-Pacific region are also more likely to be connected to each other in the ISMN. Thus, the trend of the stock index is influenced by region to a large extent. Generally, assortativity by region is stronger than that by national development level, indicating that the trends of stock index prices in a region are more consistent in international stock markets.

3.2.2. Dynamic Evolution of Connection between Chinese and Foreign Stock Markets. In the following study, we use the sliding window method to analyze the time varying characteristics of the unweighted ISMN, which reflects the trend of the stock index relationship and the general structural features of ISMN under different threshold conditions.

As mentioned in Section 3.1, we find that when $\theta = 0.2$, the Shanghai stock market is only associated with the Hong Kong stock market. Given that we employ data covering a long time span beginning from 1999, we adopt the sliding time-window approach to shorten the time interval and allow for the study of the dynamic evolution of the association characteristics of the Chinese and foreign stock markets.

Within the study interval in this paper (16 years), we take 12 years as the size of a window, W, 1 year as the sliding distance in the sliding time-window approach, and acquire five data sets. The average of the correlation coefficient

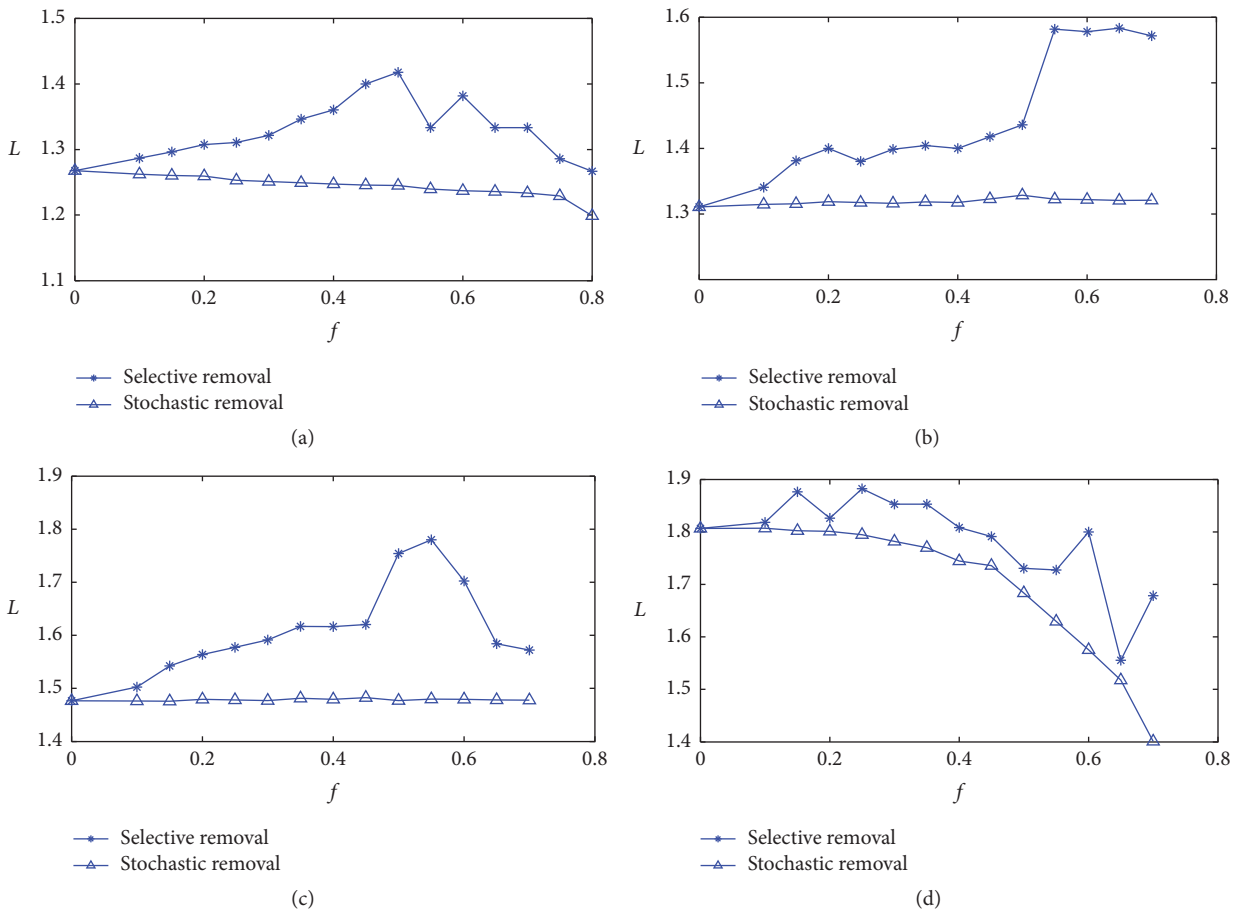

Figure 9: The average path length L versus f when (a) $\theta = 0.25$; (b) $\theta = 0.3$; (c) $\theta = 0.35$; (d) $\theta = 0.4$. With an increase of f, we find that the average path length L under selective removal is always larger than that under stochastic removal. These four subgraphs are all robust. If the thresholds equal other values in interval [0.25, 0.4], the general rules of topological stability are not changed. So we only demonstrate aforesaid four cases.

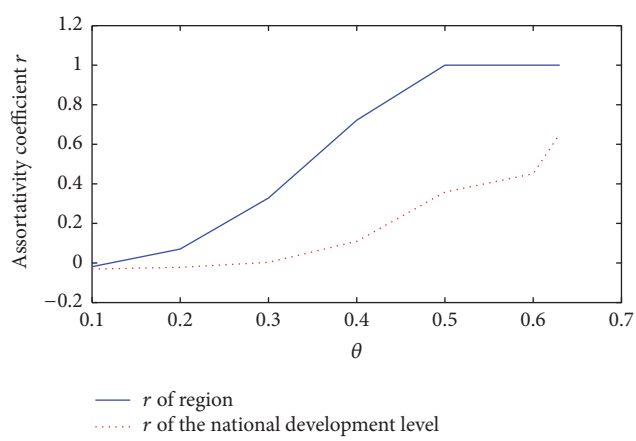

Figure 10: Assortativity coefficient, r at different thresholds for the different classification criteria.

between China and other countries from W1 to W5 is 0.193, so here we choose the $\theta = 0.193$ to construct the network. The network topology diagrams of the five data sets at $\theta = 0.193$ are shown in Figures 11–15.

As shown in Figures 11–15, the number of edges between the Shanghai stock market and foreign markets increases from one to seven in period range from W1 to W5. In other words, China's stock market is more closely linked with foreign stock markets. From W2 to W3, the number of edges between China's stock market and foreign stock markets increases from two to five, which can be explained by China accession with the WTO in 2001. The development of China's stock market may be considered to have begun in 1999. By 2001, after China joined the WTO, the opening up strategy of China's stock market has significantly progressed.

The domestic economic situation in China has resulted in the RMB convertibility on the capital account not being fully liberalized until now. Before 2013, Hong Kong, China's only offshore RMB center, handled 70% of the cross-border trade settlements in RMB. A popular argument asserts that foreign capital is impossible to trade openly and freely in China's A-share market up to now. Given that a convertible yuan currently remains unrealized, the following constraints to the capital account liberalization still exist: imperfect formation mechanisms of RMB exchange and interest rates, continuing inflation conditions, inadequate domestic financial market, and inactive microeconomic units. Even in Hong Kong, RMB

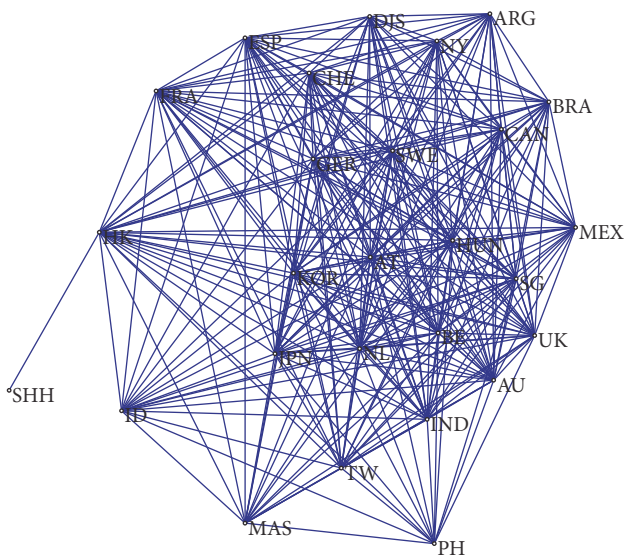

Figure 11: Topology graph of ISMN in 1999–2010.

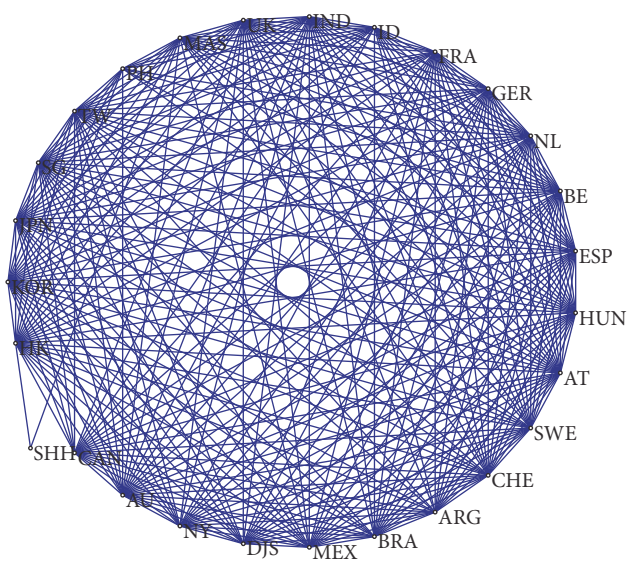

Figure 12: Topology graph of ISMN in 2000–2011.

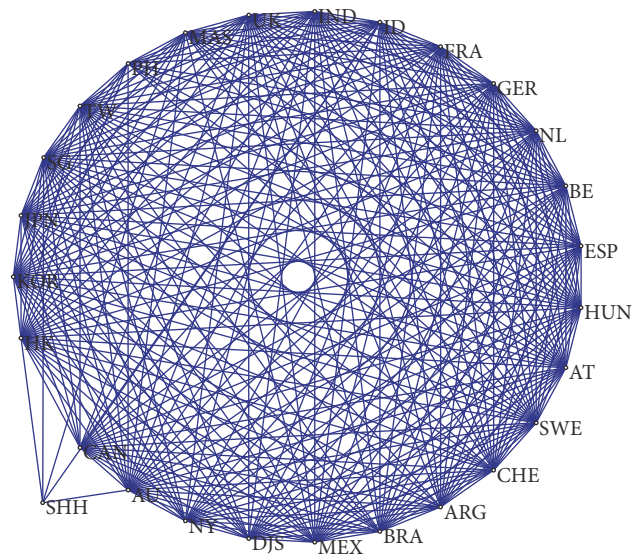

Figure 13: Topology graph of ISMN in 2001–2012.

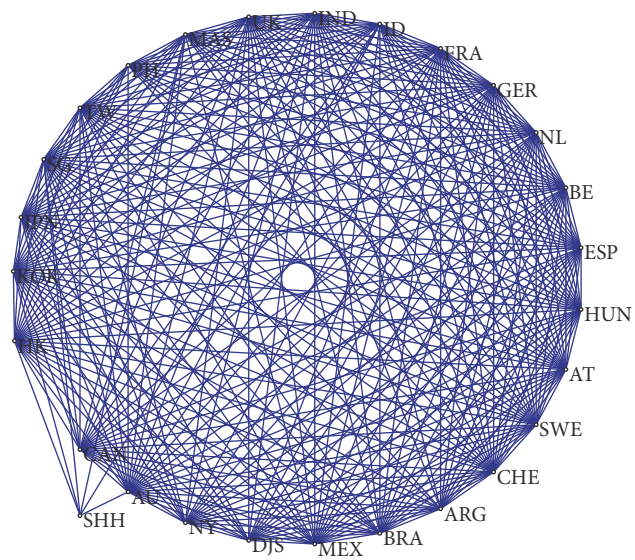

Figure 14: Topology graph of ISMN in 2002–2013.

could not be converted freely until November 2014 (before that, one person could have a maximum of RMB 20,000 exchanged). Therefore, active measures should be taken by the government to promote significantly the structural reforms of financial institutions and consequently enhance the national competitiveness of China in the financial industry.

4. Conclusions and Implications

This paper analyzes the structure characteristics of ISMN based on the whole network, subnet, and single node with the application of complex network theory. The above computational result and analysis show that it is consistent with the reality of the international stock market, illustrating the effectiveness of the method used in this paper.

(1) The analysis of network stability shows that the ISMN has robustness against random attack which indicates that some stochastic events of international stock market will not have an essential influence on the whole price fluctuation correlation of the networks. On contrast, intentional attack breaks the connection integrity of ISMN rapidly which indicates that nodes with large degree make essential difference to ISMN. Hence, we must pay more attention to some significant event of the stock market with large degree such as the Western countries. This attention will help transnational investors understand the dynamic price fluctuation correlation patterns among stock markets,

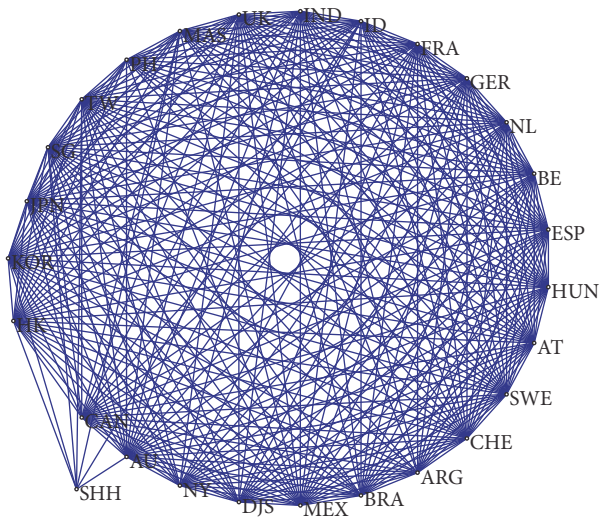

Figure 15: Topology graph of ISMN in 2003–2014.

and such an understanding can be used for references in portfolio investments and risk managements.

(2) The ISMN has assortativity under different development levels. That is, stock markets in developed countries are more inclined to be affected by stock markets of other developed countries, and stock markets of developing countries are also more likely to be affected by stock markets of other developing countries. This mechanism indicates that the stock indices of countries with similar economic levels are usually more consistent. The entire network presents strong assortativity when classified by regions, indicating that the stock indices in the ISMN are more likely to be connected to the indices in the same region. Overall, assortativity by region is stronger than that by national development level. The contagion between international stock markets is more influenced by regional than by national development level.

(3) The sliding window method is integrated with the complex network theory to establish a dynamic ISMN model. Chinese stock market is more closely linked with foreign stock markets, especially after China's accession to the WTO and the impact is rapid without any lag.

The result has significant contributions to the stock market in reality. We adopt the quantitative approach to testify that the funding, information, and other elements are transmitted rapidly in the network. When one or more markets pose a risk in the network, the risk can be spread quickly, and the losses from such risk can be reduced to a certain extent. The contagion is more likely to occur in the indices of same region. Hence, transnational investors should pay attention to the effect of international financial risks and develop response strategies in time.

In this paper and other literatures, threshold method was applied to control the component of ISMN, which may filter some information of the network more or less. For further study, we are going to construct the weighted network to exert effective information sufficiently.

Competing Interests

The authors declare that they have no competing interests.

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