Physica A 492 (2018) 1016–1031

Contents lists available at ScienceDirect

Physica A

journal homepage: www.elsevier.com/locate/physa

Analysis of the impact of crude oil price fluctuations on China's stock market in different periods—Based on time series network model

Yang An, Mei Sun *, Cuixia Gao, Dun Han, Xiuming Li

Institute of Applied System Analysis, Jiangsu University, Zhenjiang 212013, Jiangsu, PR China

HIGHLIGHTS

- The directed and weighted networks of the impact of two price series are built.
- There is the time delay effect in the prices information transmission process.
- An approach combining information and complex network theory was used.
- The coupling degree is used to measure the unidirectional impact.
- The topological structure of two stock networks was analyzed in different periods.

ARTICLE INFO

Article history:
Received 20 May 2017
Received in revised form 1 November 2017
Available online 24 November 2017

Keywords:
Crude oil prices
China's blocks stock
Bivariate time series network model
Time delay
Coupling degree

ABSTRACT

This paper studies the influence of Brent oil price fluctuations on the stock prices of China's two distinct blocks, namely, the petrochemical block and the electric equipment and new energy block, applying the Shannon entropy of information theory. The co-movement trend of crude oil price and stock prices is divided into different fluctuation patterns with the coarse-graining method. Then, the bivariate time series network model is established for the two blocks stock in five different periods. By joint analysis of the network-oriented metrics, the key modes and underlying evolutionary mechanisms were identified. The results show that the both networks have different fluctuation characteristics in different periods. Their co-movement patterns are clustered in some key modes and conversion intermediaries. The study not only reveals the lag effect of crude oil price fluctuations on the stock in Chinese industry blocks but also verifies the necessity of research on special periods, and suggests that the government should use different energy policies to stabilize market volatility in different periods. A new way is provided to study the unidirectional influence between multiple variables or complex time series.

1. Introduction

The crude oil is an important factor in production. The fluctuations of crude oil prices impact not only profit changes in the crude industry, but also on other related industries. International crude oil prices have boomed and plummeted within 9 -150 dollars per barrel in the past few decades. The frequent fluctuations of crude oil prices increase the risk of market. During the two oil crisis, western economy underwent high inflation and economic recession, which draws significant attention of academia on crude oil price movements [1,2] and the relationship between crude oil prices and economy [3]. Huang

* Corresponding author.
E-mail address: sunm@ujs.edu.cn (M. Sun).

https://doi.org/10.1016/j.physa.2017.11.032
0378-4371/

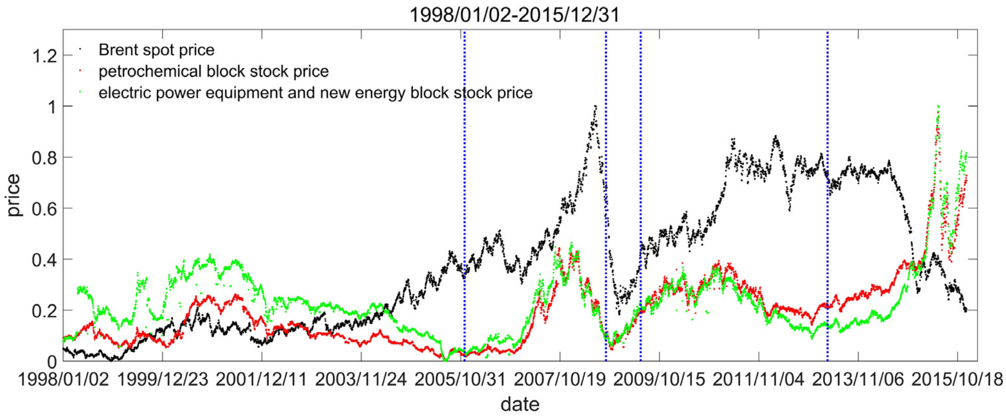

Fig. 1. The normalized prices of Brent crude oil and China's blocks stock.

et al. [4] found that an oil price volatility would better explain the impact on economic activity than the real interest rate. Rising oil prices will lead to higher energy-related industry costs, triggering economic downturns, lower output [5], lower consumer demand, and higher inflation. For a large oil consumer country like China, the dependence on the international crude oil market has increased year by year, from 17.22% in 1998 to 60.2% in 2015, the first time exceeded 60%. The sharp fluctuations of crude oil prices will have a huge impact on China's economy, including China's economic growth rate, price level, unemployment rate, consumer spending index and implementation of financial and monetary policy difficult [6–9].

As China's economic development is closely related to international relations, the domestic stock market is becoming more and more closely linked with the international financial market. In recent years, the fluctuation of international crude oil prices has a great impact on China's economy, with the increasing crude import dependency of China. As a barometer of China's economy, the stock market has a noticeable response to the fluctuation of crude oil prices. If the stock market is effective, the impact of oil price changes on the economy will be quickly and directly reflected in the stock market. China's stock market has developed rapidly in terms of the number of listed companies, the larger scale of market value and the non-ignorable role in the global financial market, but it is still an emerging capital market. If crude oil price volatility has different effects on stock returns of different industries [10], then changes of crude oil prices will affect the allocation of resources in different industries through capital markets. Hence, the study of the impact of crude oil price fluctuations on returns of different sectors of China's stock market is of great significance. Jones and Kaul [11] found that there exists a stable negative relationship between oil price changes and aggregate stock returns. Narayan et al. [12] established a predictive regression model to reveal the role of oil prices in predicting stock prices. Zhuang et al. [13] studied the relationship between ten industry indices and WTI crude oil prices based on multi-scale deviation correlation analysis. Park and Ratti [14] analyzed the impact of oil price fluctuations on the US and 13 European countries from 1986 to 2005. They found that the impact of oil prices on the real rate of return is much greater than the interest rate. Cong et al. [15] used the multivariate vector autoregressive method to study the interaction between oil price shocks and China's stock market.

The past literatures are mainly based on the econometric methods, such as statistical identification methods and vector autoregressive (VAR) [16–20], autoregressive conditional heteroskedasticity (ARCH) [21], cointegration [22] etc., focusing on the correlation relationship between two factors. There is little unilateral study about the effect of one factor on another. We are more concerned about the impact of crude oil price fluctuations on the stock market, rather than the impact of the stock market on crude oil price fluctuations, which indicates a process of information transmission from crude oil market to stock market.

The development of China's petrochemical industries is relatively backward and the international competitiveness is weak, with the impact of oil price on the industry being particularly remarkable [23]. New energy includes renewable energy sources, such as solar energy, wind energy and son on. As an alternative energy of crude oil, new energy also provides energy for the market. This paper examines the impact of Brent oil price fluctuations on the stock returns of China's petrochemical block and power equipment and new energy block from January 2, 1998 through to December 31, 2015. Fig. 1 shows the change of Brent oil price and the stock prices for the overall period. The two kinds of stock price trends are basically the same, while the trends of stock prices and oil price are just similar. There was a significant difference in local trend, for instance during 2007–2008 and during 2014–2015. The overall trend of oil prices and stock prices makes it difficult for us to find the laws. Fig. 2 on the other hand shows that the returns of Brent oil price and the Chinese industry sector stock fluctuates over time. The time series of the two kinds of variables contains a large length of data and a fluctuating relationship, leading or resulting the analysis of the impact of oil price fluctuations on the stock price into a complex system problem. Complex networks are an important means of revealing their internal mechanisms and are applicable to the analysis of nonlinear time series [24,25].

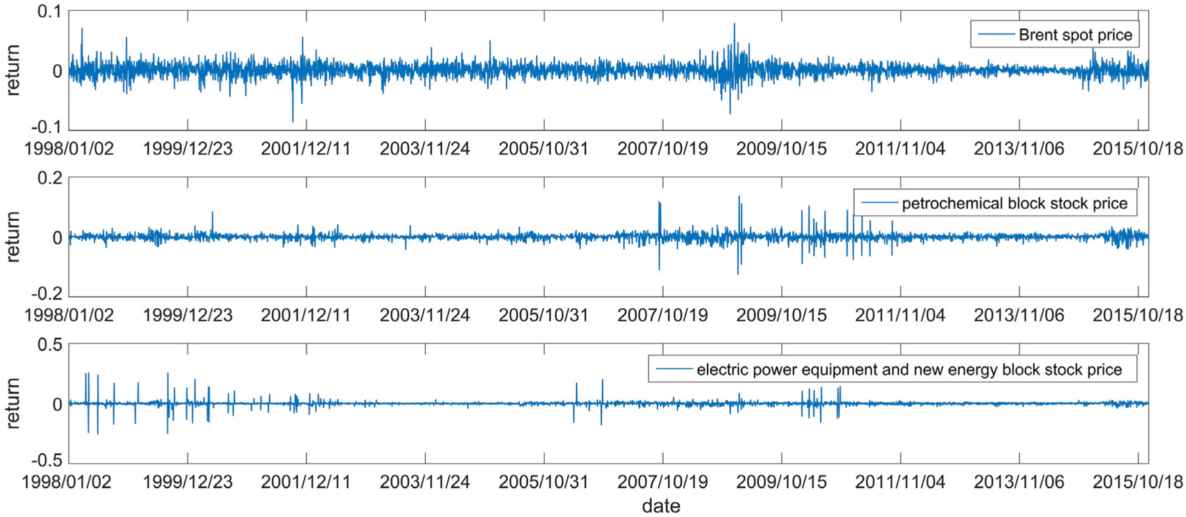

Fig. 2. Brent crude oil price returns and China's block stock price returns.

We proposed an approach combining information and complex network theory to explore the impact of crude oil price fluctuations on China's stock market. Main novel contributions in our studies are as follows: From the information theory perspective, the coupling degree we employ is used to analyzed the impact of crude oil price fluctuations on oil-related industry stock market in different periods and reveal some characteristics that econometric methods cannot show. The Shannon entropy in information theory is used to quantify the information transmission process from crude oil price to the stock market and the coupling degree identifies the unidirectional trend of stock price volatility with the shock of crude oil price. Time series can be mapped to the network topology according to complex network theory. The difference of co-movement between the fluctuation of crude oil price and stock price was discussed under different crude oil price fluctuation periods. The key information implicit in the time series is stripped by analyzing the nature of the network. The mechanism and the conversion periods of the co-movement of crude oil prices and China's block stock prices are different in different periods. There is a time delay effect in information transmission process. In addition, this study provides a practical method to identify the key points to regulate the market fluctuation.

The structure of this paper is as follows: Section 2 briefly introduces the data and methods. Section 3 builds the bivariate time series network models and investigates the properties of the networks. The final section summarizes the results of this paper.

2. Data and methods

2.1. Data

China's refined oil price has been basically linked with the international oil price after the domestic petroleum price formation mechanism reform after 1998. China's stock market has entered a standardized development stage since 1998. Domestic market, especially the stock market, is more sensitive to international crude oil price fluctuations . Thus, the study of the impact of international crude oil prices on China's industry blocks stock prices has a real significance. The Brent crude oil price system plays an important role in the pricing of crude oil, which covers more than 65% of the world's real crude oil. Therefore, Brent crude oil spot price and two block stock prices from 1998/1/2 to 2015/12/31 were chosen as the sample data. Brent crude oil spot price comes from the US Energy Information Administration (EIA). The corresponding price data of two oil-related industry blocks, namely, the petrochemical block and the electric equipment and new energy block, is collected from China's 27 industry blocks prices (http://q.stock.sohu.com/).

2.2. Period division

Historical data shows (Fig. 1) that the range of crude oil price fluctuations is large. By discussing the distribution of the different types of oil price fluctuations, the sample data are divided into the different fluctuations periods [26]. It can be easier to analyze the fluctuation characteristics of each period and reveal the intrinsic complexity by dividing different periods. Removing the missing date in the original data occupies a very small part of the sample, so it does not affect the trend of the sample data change, but also avoids the trend smoothing caused by the difference compensation data. The coarse-graining method can simplify the complicated data and express the fluctuating information more clearly.

Table 1
The period division of crude oil price.

No.	Period	State
I	1998/01/02–2005/11/24	Stable fluctuation period
II	2005/11/25–2008/09/18	Rapid rise period
II	2008/09/19–2009/06/01	Rapid decline period
II	2009/06/02–2013/03/26	Rapid rise period
II	2013/03/27–2015/12/30	Minor decline period

The crude oil prices with the data length N is represented as the time series $S_{oil}(t)$. The crude oil price fluctuations series is denoted as $\{\Delta S_{oil}(t) \mid \Delta S_{oil}(t) = S_{oil}(t+1) - S_{oil}(t)\}$, $t = 1, 2, \ldots, N-1$, where $S_{oil}(t+1)$ is the current price and $S_{oil}(t)$ is the previous price. The time-varying rate of price change is used to indicate the volatility of crude oil prices. We therefore make a comparative analysis of the fluctuation characteristics of crude oil price change with time in different periods. The mean value of the fluctuation is calculated as:

$$E_{\Delta}S_{oil} = \frac{\sum_{i=1}^{N-1} |\Delta S_{oil}(t)|}{N-1} \tag{1}$$

when $\Delta S_{oil}(t) > E_{\Delta}S_{oil}$, it means the oil price rises rapidly; when $E_{\Delta}S_{oil} \geq \Delta S_{oil}(t) > 0$, it means minor rise of the oil price; when $\Delta S_{oil}(t) = 0$, it means the oil price is stable; when $-E_{\Delta}S_{oil} \leq \Delta S_{oil}(t) < 0$, it means minor decline of the oil price, and when $\Delta S_{oil}(t) > -E_{\Delta}S_{oil}$, it means the oil price declines quickly, as shown in Eq. (2).

$$lr_i = \begin{cases} \mathrm{R}, & \Delta S_{oil}(t) > E_{\Delta}S_{oil} \\ \mathrm{r}, & E_{\Delta}S_{oil} \geq \Delta S_{oil}(t) > 0 \\ \mathrm{O}, & \Delta S_{oil}(t) = 0 \\ \mathrm{d}, & -E_{\Delta}S_{oil}(t) \leq \Delta S_{oil}(t) < 0 \\ \mathrm{D}, & \Delta S_{oil}(t) > -E_{\Delta}S_{oil} \end{cases} \tag{2}$$

The situation of crude oil price fluctuations is denoted by five kinds of symbols. Different types of fluctuation status are differentiated, including sharp rise (R), minor rise (r), stable fluctuation (O), minor decline (d) and sharp decline (D). Hence the fluctuations of crude oil prices can be expressed by a continuous sequence of different symbols as following:

$$Lr_i = \{lr_1, lr_2, \ldots, lr_{N-1}\}, lr_i \in (\mathrm{R}, \mathrm{r}, \mathrm{O}, \mathrm{d}, \mathrm{D}) \tag{3}$$

We make 6 months as a time interval about 125 data and calculate the probability of each symbol in each time interval. The five probability sequences SD, Sd, SO, Sr, SR of the symbols 'R, r, O, d, D' are get respectively. The change of each sequence over time is shown in Fig. 3(a). SRD = SD + SR, and Sdr = Sr + Sd are calculated to distinguish whether the fluctuation of crude oil prices is in sharp fluctuation period or stable fluctuation period, where SRD means the probability of sharp fluctuation, and Sdr means the probability of stable fluctuation. The process of SRD and Sdr evolution over time is shown in Fig. 3(b). From Fig. 3(b), we can clearly see that the probability of the sharp fluctuation is higher than the probability of the stable fluctuation on time data NO.2020 which corresponds to November 24, 2005. This means that the fluctuation state of crude oil price is changed on November 24, 2005. Therefore, the period from January 2, 1998 to November 24, 2005 is categorized as the stable fluctuation period of crude oil price. Similarly we can get the period from November 24, 2005 to March 26, 2013 is categorized as the sharp fluctuation period and the period from March 27, 2013 to December 30, 2015 is categorized as the stable fluctuation period. By calculating $SRr = Sr + SR$, $SDd = SD + Sd$, we can distinguish whether the fluctuation of the crude oil prices is into the rise or decline period, where SRr means the probability of the rise period, SDd means the probability of the decline period. The evolution process of SRr and SDd is shown in Fig. 3(c). From Fig. 3(c), we can get several decline and rise fluctuation periods to further divide the stable fluctuation and the sharp fluctuation periods we have obtained. In summary, the crude oil price fluctuations can be divided into five periods according to extent of the volatility, as listed in Table 1 . The five different fluctuation periods are separated by dotted lines as shown in Fig. 1. From Fig. 1, the peak and valley value of crude oil price are not the turning point of period division.

2.3. Coupling degree

There has been a lot of research on time series [26,27]. However, we are concerned about the trend of price fluctuations. The Shannon entropy is used to measure the fluctuation information transmission from crude oil prices to the stock market, and reveal whether the oil price fluctuation has a lag effect on the stock market. The inner composition alignment had been proposed to detect regulatory links from very short time series that facilitated the understanding of emerging structures in complex networks [28]. The temporal sequence is reconstructed by the phase space to obtain the ordinal patterns to represent the co-movement fluctuations of the crude oil prices and the block stock prices sequence. The time series $\{x_i\}$ and $\{y_i\}$ are reconstructed to generate the phase space by adjusting the parameters (τ, d). The time series $\{x_i\}$ and $\{y_i\}$,

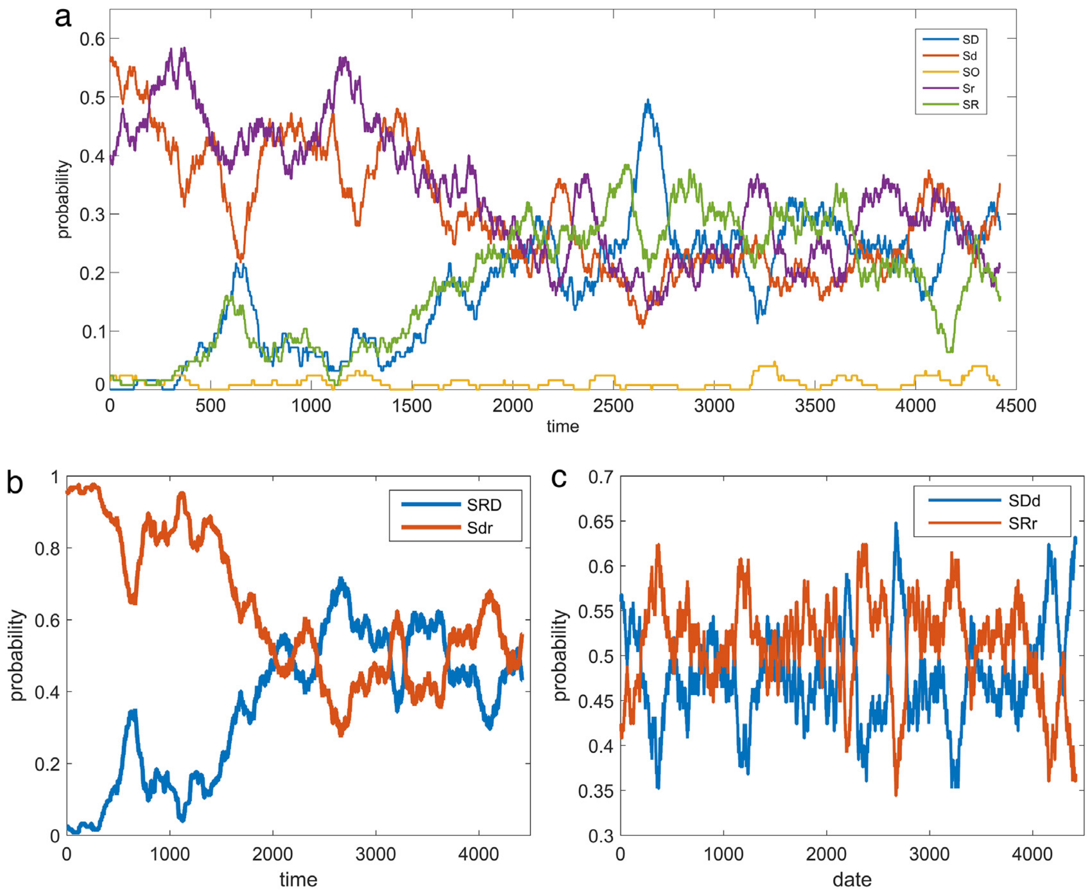

Fig. 3. (a) The probability evolution of the five states of crude oil price fluctuations; (b) the evolution of SRD and Sdr; (c) the evolution of SDd and SRr.

$i = 1, 2, \ldots, \omega$, are mapped to the trajectory matrices X and Y, respectively(see Eq. (4)):

$$X = \begin{pmatrix} X_1 \\ X_2 \\ \vdots \\ X_{\omega-(d-1)\tau} \end{pmatrix}, Y = \begin{pmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_{\omega-(d-1)\tau} \end{pmatrix} \tag{4}$$

where d denotes the embedding vector length and τ denotes the time delay. Each state vector $X_i = \{x, x, \ldots, x_{i+(d-1)\tau}\}$ has an ordinal pattern Π_i, which is also called the symbolic state vector. The ordinal pattern $\Pi_j^{(x)}$ refers to the order of each state variable X_i arranged in a non-decreasing order by comparison with neighboring values. The values of matrix X can be represented by the ordinal pattern matrix Π as depicted in Eq. (5). The entropy of the ordinal pattern is used to estimate the monotonicity of the new series [29].

$$\Pi = \begin{pmatrix} \Pi_1 \\ \Pi_2 \\ \vdots \\ \Pi_{\omega-(d-1)\tau} \end{pmatrix} \tag{5}$$

As a replacement, Π is substituted in the sequence $\{y_i\}$. The new state vector $Z_i = y_i(\Pi_i^{(x)})$ means the reorder of the state vector y_i relative to x_i. Let $Z = [Z_1, Z_1, \ldots, Z_{\omega-(d-1)\tau}]^\tau$. And the unique ordinal pattern Π is formed from Z.

The sequence has all different possible permutations $d!$, and the occurrence probability of each ordinal pattern is approximately represented by relative frequency $P(\Pi_j)$. The amount information of the ordinal pattern is measured by information entropy (see Eq. (6)). Shannon entropy of ordinal patterns Π_j is obtained by averaging the amount of all the patterns information (see Eq. (7)).

$$H = -\log[P(\Pi_j)] \tag{6}$$

$$H_d(x, y) = -\sum_{j=1}^{d!} P(\Pi_j)\log[P(\Pi_j)] \tag{7}$$

For two random sequences with enough data, all possible permutations of each ordinal pattern Π_i emerge with equal probability. The relative frequency of random sequences and Shannon entropy can be got by $P(\Pi_j) = \frac{1}{d!}$, $H_d = \log(d!)$.

The coupling degree is defined (see Eq. (8)) to quantitatively measure the series synchrony strength after removing the effect of the random sequence:

$$\sigma_d(x, y) = 1 - \frac{H_d(x, y)}{\log(d!)}. \tag{8}$$

The coupling degree is used to measure the information transmission from the sequence $\{x_i\}$ to the sequence $\{y_i\}$. In brief, a large value of the coupling degree represents a strong synchrony of two series. It means that the co-movement trend of the two sequences is similar.

2.4. Parameter selection

The original time series is divided into different small-scale fragments by a sliding window. The sliding window with length ω is moved to select the data each step at a time, and then for each data fragment the internal composition alignment is proposed to get the coupling degree of crude oil prices on block stock prices. The coupling degree is related to the sliding window length ω, the embedding vector d and the time delay τ. So it is necessary to select appropriate parameters, that is, the sliding window length ω, the embedding vector d and the time delay τ for each reconstructed data fragment. The logarithmic return $\{rate_x(t)\}$ of the crude oil prices $\{S_{oil}(t)\}$ is defined as:

$$rate_x(t) = \log S_{oil}(t + 1) - \log S_{oil}(t). \tag{9}$$

Similarly, $\{rate_{y1}(t)\}$ and $\{rate_{y2}(t)\}$ express respectively the logarithmic returns of petrochemical block and electric equipment and new energy block.

2.4.1. The selection of the sliding window length ω

For every sliding window, the Pearson correlation coefficients of the two time series is calculated. The correlation coefficient matrix $Q_{m\times n}$ related to the time series and the window length is designed, which reveals the relationship between the correlation coefficients of two time series and the length of the sliding window (Fig. 4). The correlation coefficients of the same window length over time are the column vectors $Q_{i,1}, Q_{i,2}, \ldots, Q_{i,n}(i = 1, 2, \ldots, m)$ of the matrix $Q_{m\times n}$. At the same point in time, the row vectors $Q_{1,j}, Q_{2,j}, \ldots, Q_{m,j}(j = 1, 2, \ldots, n)$ of the correlation coefficient matrix $Q_{m\times n}$ are obtained by finding the correlation coefficients of two time series at the same time under different window lengths.

It can be seen (from Fig. 4) that the fluctuation of the correlation coefficient between the crude oil prices and stock prices is not always stable. There are strong or weak correlation and positive or negative correlation changes between crude oil prices and stock prices with time. The correlation coefficient matrix $Q_{m\times n}$ contains all the changes information of the crude oil prices and stock prices for each day. If the sliding window is within the range of 1–10 days, the color of the correlation coefficient will be mutated disorderly. This is likely due to some occasional and stochastic factors and the hysteresis of the information that makes some changes not to immediately respond to changes in the stock market. When the sliding window is more than 20 days, the bandwidth of strong correlation becomes wider and wider with time than weak correlation. The strong correlation coefficient will offset some fluctuation information of the weak coefficient correlation. It will weaken the fluctuation changes, ignore or shield some market information and lose some key information. When the range of the sliding window is from 10 to 20 days, the correlation coefficient will be accurate to show the fluctuation information of two time series. The sliding window contains fluctuation information and excludes the occasional and random factors on the negative impact for the study. In order to obtain the fluctuation information as much as possible, this paper chooses 12 days as a sliding window. Most of the fluctuation information in the return series of crude oil prices and stock prices is captured over the short term.

2.4.2. Selection of parameters τ, d

According to the actual market situation and feasible conditions, the parameters τ and d are taken all the possible combinations and then put in order. For example, $(\tau, d)_1 = (1, 2), (\tau, d)_2 = (2, 2), \ldots, (\tau, d)_{30} = (6, 6)$, where $\{(\tau, d)|1 \le \tau \le 6, 2 \le d \le 6, \tau \in N_+, d \in N_+\}$. The coupling degree varies with the length of the window for each pair of combinations (τ, d) (shown in Fig. 5).

It can be concluded that the coupling degree decreases with the increase of the sliding window length w. It indicates that the coupling degree is suitable for measuring the co-movement relationship between the short term time series. For long-term sequences, it is necessary to divide them into short-term sequences to analyze, which can effectively capture more volatility information. Although the coupling degree increases with the time delay τ and the embedding vector length d, it is restricted by $\omega - (d - 1) \times \tau > 0$, and τ and d cannot be infinite. Considering the constraints and the actual situation, we can get the maximum coupling degree when $(\tau, d) = (3, 4)$ and $\omega = 12$. At this state, the synchrony level of the return sequence of the crude oil prices and the stock prices reaches 65%. That is, if it is delayed for three days to observe the market price fluctuations, more information in real market will be available.

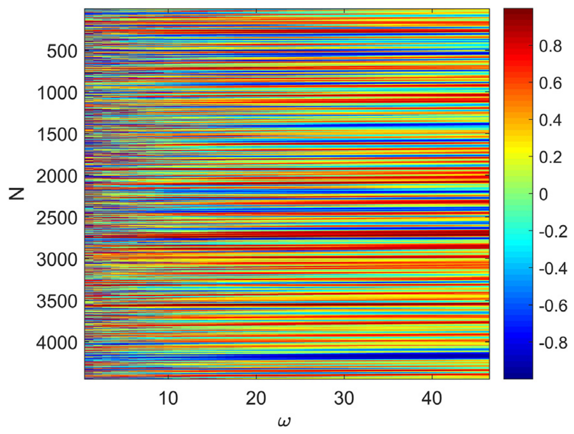

Fig. 4. Correlation coefficient changes over time and the sliding window length ω.

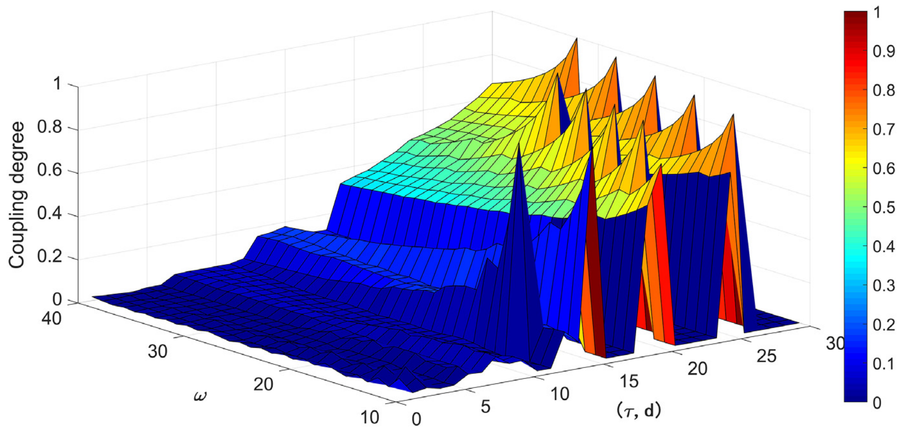

Fig. 5. The relationship between the parameters τ, d, the sliding window ω and the coupling degree.

2.4.3. Establishment of time series network models

The coarse-graining method is provided to analyze the characteristics of the co-movement. An et al. [30–32] used coarse-graining method to describe the relationship between two time series. In this paper, the coarse-graining method is used to define volatility modes of the coupling degree and show the dynamic linkage between crude oil prices and block stock prices. The coupling degree calculated at time delay $\tau = 1$ is equivalent to extract the information of original time series. The synchrony degree of crude oil prices fluctuation and the block stock prices fluctuation is measured through the coupling degree. The coupling state of the sample co-movement of is represented by a continuous symbols sequence $\{l\sigma_d(x, y)_i\}$. The coupling degree was defined as the symbols 'S', 'W' and 'U' based on the value of the coupling degree (see Eq. (10)).

$$l\sigma_d(x, y)_t = \begin{cases} S, \sigma_d(x, y)_t > E_{\sigma_d} + std/2 \\ W, E_{\sigma_d} + std/2 \geq \sigma_d(x, y)_t > E_{\sigma_d} - std/2 \\ U, E_{\sigma_d} - std/2 \geq \sigma_d(x, y)_t \geq 0 \end{cases} \tag{10}$$

E_{σ_d} is the median of the coupling degree sequence, and *std* is the standard deviation of the coupling degree sequence. The symbol 'S' denotes strong coupling strength, while 'W' denotes weakly coupling strength and 'U' denotes no-coupling connection. Normally, the trading days in crude oil market and stock market are both on weekdays, so the length of the sliding window is set to be 5 days. The coupling symbols sequence is divided into different small-scale states. The fluctuation state of the five consecutive days is denoted as a mode. The overlapped sliding windows (every 5 days) at 1-day intervals was used to unveil the transmission process from one mode to another, as shown in Tables 2 and 3. Each mode contains pre-fluctuating information and the effect of a new day's change on volatility. It retains the memory features and informative transitivity of time series.

We can get a sequence of common volatility modes of crude oil prices and the petrochemical block stock prices {UUWWW,UWWWW,WWWWU,· · · ,WWWWU}. Similarly, the sequence of common volatility modes of crude oil prices and the electric equipment and new energy block stock prices can also be obtained. In theory, there should be $3^5 = 243$ kinds

Table 2
The process of defining the fluctuation patterns of petrochemical block network.

NO.	The coupling degree	symbols		modes
1	0.3086	U		
2	0.3571	U		
3	0.4056	W		
4	0.4056	W		
5	0.4056	W	→	UUWWW
6	0.3571	W	→	UWWWW
7	0.3086	U	→	WWWWU
8	0.3571	U	→	WWWUU
9	0.3571	U	→	WWUUU
10	0.4239	W	→	WUUUW
...	...	...	→	...
4533	0.3571	U	→	WWWWU

Table 3
The process of defining the fluctuation patterns of electric equipment and new energy block network.

NO.	The coupling degree	symbols		modes
1	0.4723	S		
2	0.4056	W		
3	0.4056	W		
4	0.3571	U		
5	0.3571	U	→	SWWUU
6	0.4056	W	→	WWUUW
7	0.4056	W	→	WUUWW
8	0.3571	U	→	UUWWU
9	0.4056	W	→	UWWUW
10	0.4723	S	→	WWUWS
...	...	...	→	...
4533	0.4540	W	→	WWUWW

of different fluctuation modes, but only 98 and 97 kinds of fluctuation modes appeared in the two networks, respectively. In order to study the co-evolution of return of crude oil prices and two blocks stock prices, the complex network method is used. Each fluctuation mode is treated as a node. If there is a transformation between two volatility modes, there is a connection between two nodes. Weight between two nodes is the number of transformation between the volatility modes. The directed weighted network of crude oil prices and petrochemical block stock prices is built (Fig. 6). Many scholars have mapped time series to the network topology and used complex network method to analyze the time series [33]. The evolution characteristics of the complex time series can be found by analyzing the structure of the network. Based on the above, we obtain a sequence of the fluctuation patterns changing with the sliding window and the features of the fluctuation patterns over time.

3. Results

3.1. Identification of key patterns

The node strength is a comprehensive indicator of the importance of a node in the network. It does not only considers all the neighbors connected with the node, but also considers the close relationship between the neighbor nodes. A large value of the node strength represents a high possibility of its appearance in the network. It can be used to express the degree of correlation between crude oil prices and the blocks stock prices fluctuation modes. The node strength is related to the number of neighbor nodes and the weight of nodes. The strength of a node in a directed complex network can be divided into incoming and outgoing strength, which are defined as follows:

$$S_i^{in} = \sum_{j \in N_i} W_{ij}, S_i^{out} = \sum_{j \in N_i} W_{ji}. \tag{11}$$

where N_i is the set of all neighbors of the node i, W_{ij} is the weight from the node i to the node j, and W_{ji} is the weight from the node j to the node i. The weight is the frequency of the transmission between two kinds of fluctuation modes. The node strength includes in-weighted degree, representing the number of links that point to node i, whiles out-weighted degree, represents the number of links that point from node i to other nodes. The value of the node strength indicates the probability of this mode transforming to the other modes or the probability of keeping the existing state. The in-weighted degree indicates the probability that the mode will maintain the state at specific time. The out-weighted degree on the other hand indicates the probability that the mode will change into others. The greater the in-weighted degree of the node is, the more likely that the other nodes of the network will become this node is. This means it is easier to achieve this mode of the co-movement of crude oil prices and blocks stock prices. The greater the out-weight degree of the node is, the more likely

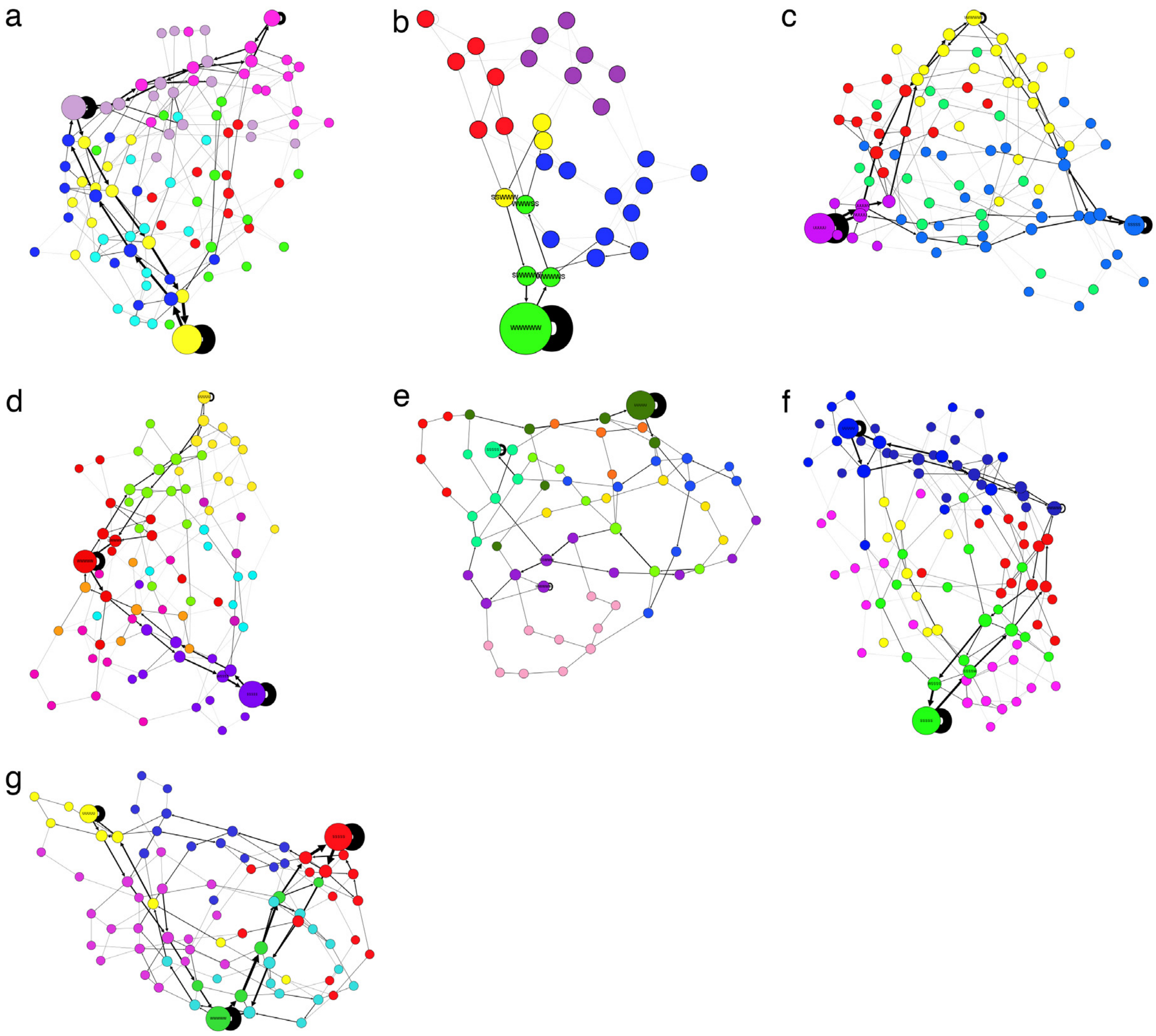

Fig. 6. The network graphs of the petrochemical block in different periods. (a) Global network; (b) Global network with time delay; (c) The network in period I; (d) The network in period II; (e) The network in period III; (f) The network in period IV; (g) The network in period V.

the nodes in the network will be transformed into other nodes is. This also means the more co-movement mode will be transformed into another state.

For a network with N nodes the degree distribution is the normalized histogram (see Eq. (12)) is given by

$$P_i = \frac{N_i}{N}. \tag{12}$$

where Ni is the number of degree-k nodes. Hence the number of degree-i nodes can be obtained from the degree distribution as $N_i = N \times P_i$.

The statistical distribution of the node strength was used to identify the major fluctuation modes in different periods. From the perspective of the global scale and sub-periods, Figs. 7 and 8 show the double logarithmic relationship between the node strength S_i and the distribution of the node strength P_i in the petrochemical block network and the electric equipment and new energy block network respectively. There is a 'long tail' effect exhibited in the figures. We estimate the double logarithmic relationship by a least squares linear regression. There are different R values for each least squares linear regression (see Tables 4 and 5). p1 denotes linear fitting coefficient. Double logarithm of the node strength and the distribution of the node strength shows a good linear relationship. The distribution of the petrochemical block network obeys the power-law in decline periods (period III and period V). The distribution of the electric equipment and new energy block network obeys more approximate power-law in sharp periods (period II, period III and period IV). That means that the node strength of most modes is very small in these networks and only a very small number of modes significantly affect

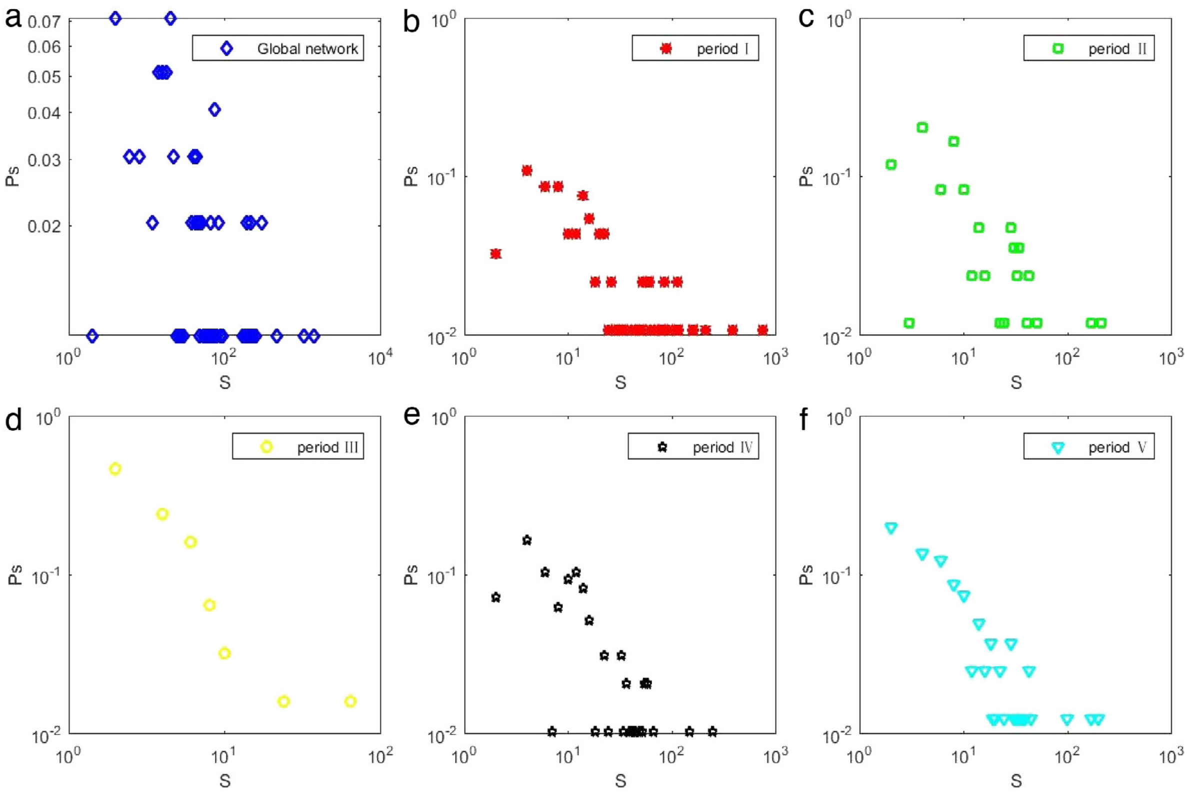

Fig. 7. The double logarithmic plot of the node strength and the number of nodes in the petrochemical block network.

Table 4
The fitting function of the strength distribution of the petrochemical block stock network.

Petrochemical block	Global network	I	II	III	IV	V
p1	−3.191	−2.460	−2.332	−1.351	−2.106	−1.972
R	0.2227	0.5233	0.3842	0.8800	0.5199	0.7273

Table 5
The fitting function of the strength distribution of the power equipment and new energy block stock network.

Electric equipment and new energy block	Global network	I	II	III	IV	V
p1	−2.384	−2.384	−2.143	−1.916	−1.980	−2.816
R	0.5395	0.5395	0.6004	0.6002	0.6978	0.1323

the fluctuation of the co-movement. These modes are the key modes for determining price synergies. There is different distribution of co-movement modes of two networks in different periods.

By calculating the number of nodes of the different cumulative node strength distribution, it is found that there are 10–13 nodes accounting for more than 50% of the total node strength, in which the probability of the fluctuation trend of crude oil prices and block stock prices is consistently more than 80% for 5 consecutive days and strong consistency accounting. There are about 30 nodes accounting for more than 80% of the total node strength. This indicates that the return of crude oil prices and block stock prices has a strong and continuous synchronization and consistency.

The modes of more than 50% cumulative node strength in the two networks are basically the same. The cumulative node strength of the modes 'SSSSS' ,'WWWWW' and 'UUUUU' in the two networks accounts for 30% of the total node strength. The weight of the self-transition is large, which means that the co-movement mode keeps this state for a long time after reaching this state and is not easy to translate into other modes. The impact of crude oil prices fluctuations on the stock prices fluctuations is continuity.

Figs. 9 shows the distribution of strong coupling mode 'SSSSS' in period I, period II, period III and period IV, respectively. The top of each figure shows the distribution of 5 consecutive days of strong coupling mode 'SSSSS' of petrochemical block stock network and the bottom is power equipment and new energy block stocks network. Although Fig. 9(b) and (d) are both rapid rise periods, there is no sustained high coupling mode during this a steep and high growth period in Fig. 9(b).

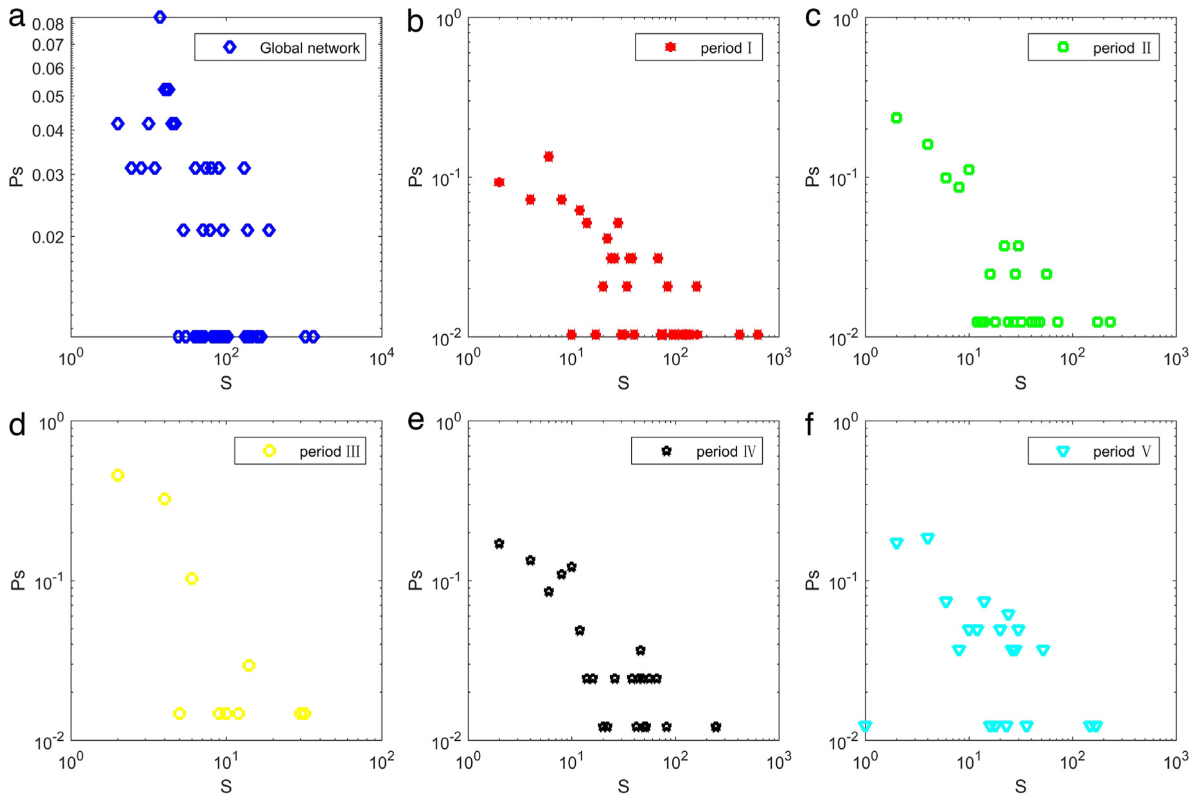

Fig. 8. The double logarithmic plot of the node strength and the number of nodes in the electric equipment and new energy block network.

This situation indicates that the continued high growth of the crude oil prices do not pass the information effectively to the stock market, although the time delay of the crude oil prices information is the most obvious at this time. Similarly, there is not the continued high coupling degree in a steep decline period as shown in Fig. 9(c). Stock prices do not fluctuate with the same trend as crude oil prices. Instead, there is high frequency with the same fluctuation trend of the stock prices and the crude oil prices in stable period (see Fig. 9(a)).

3.2. The conversion of co-movement modes

The shortest path is the path with the fewest number of links that connect nodes in the network. The average shortest path length can be used to describe the conversion time between the modes of the synergistic movement of two network. And it shows the evolutionary mechanism of co-movement of crude oil prices and block stock prices. The shortest path provides the reference for the prediction of the co-movement.

The average path length, the average of the shortest paths between all pairs of nodes in the network, is defined as:

$$L = \frac{2}{N(N-1)} \sum_{i \geq j} d_{ij} \tag{13}$$

If the network is an un-weighted network, the length of the shortest path d_{ij} is often called the distance between nodes i and j. If the network is a weighted network, d_{ij} means the sum of the weights on the shortest path of the two nodes.

The diameter of a network, which is the maximum shortest path between any two nodes in the network, denoted by D:

$$D = maxd_{ij} \tag{14}$$

The distribution of the shortest path in different periods is shown as Fig. 10. The maximum shortest paths of two un-weighted networks are both 9. When the networks are un-weighted, the distance between nodes is Gaussian distribution. The length of the shortest path length centers on 4–6. The average shortest path is about 4.8. When weight is taken into account, the shortest path length between nodes also follows a Gaussian distribution. The conversion cycle of the global network is 22–26 days. The transition cycle in stable fluctuation period is 2–3 days longer than in sharp fluctuation period which is around 14–16 days in sub-periods network.

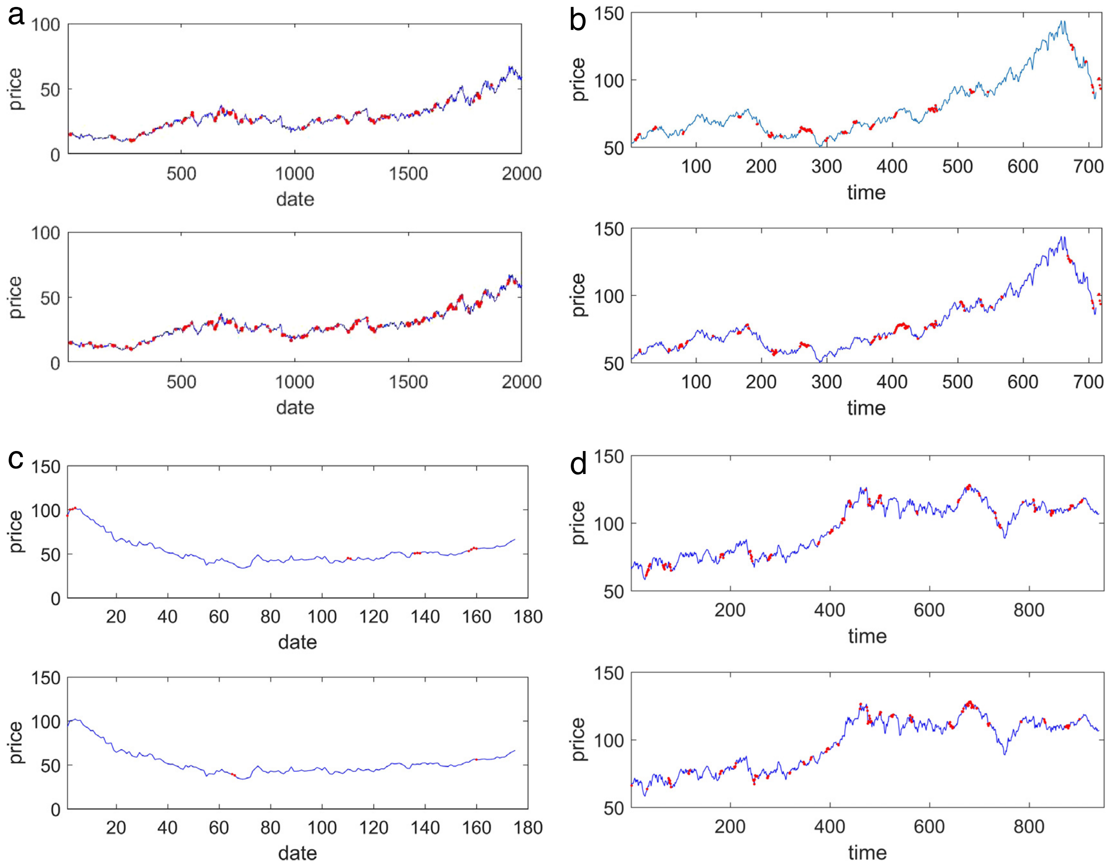

Fig. 9. The time distribution of strong coupling degree pattern 'SSSSS' in petrochemical block network above and electric equipment and new energy block network below in different periods. (a) Period I; (b) Period II; (c) Period III; (d) Period IV.

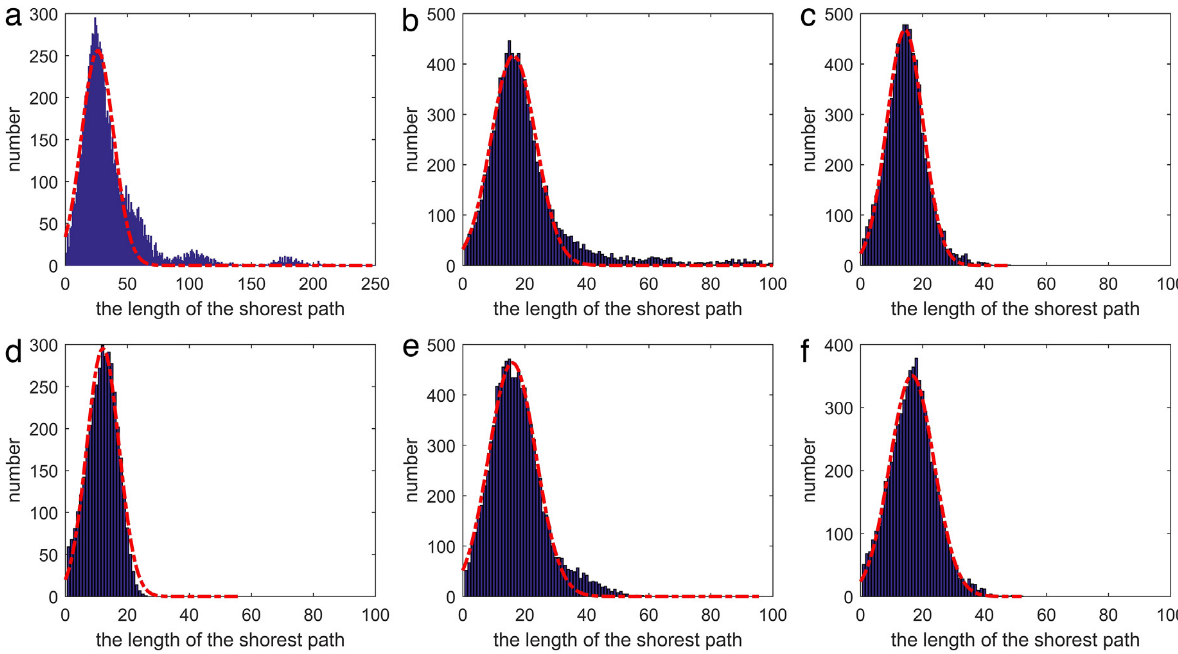

Fig. 10. The distribution of the shortest path in different periods.

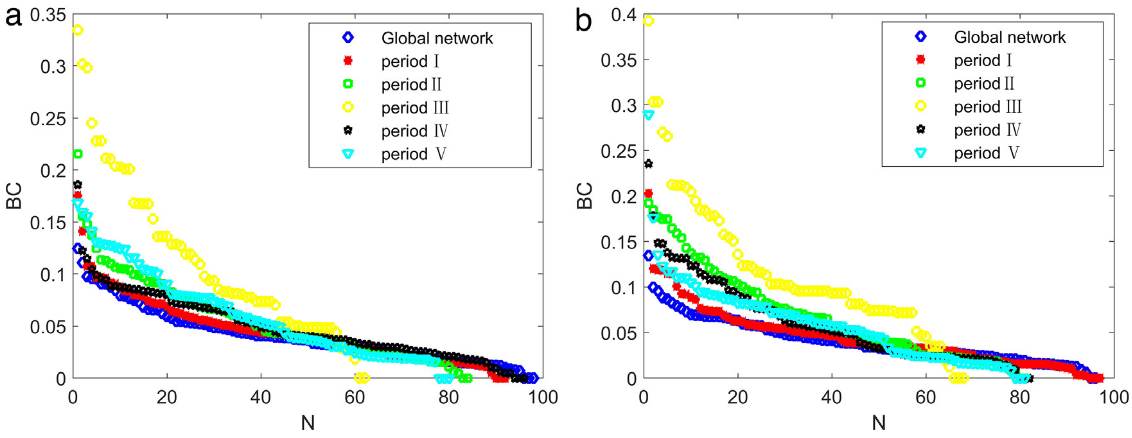

Fig. 11. Betweenness centrality of node in (a) the petrochemical block network and (b) the electric equipment and new energy block network in different periods.

3.3. Betweenness centrality

Betweenness centrality is usually used to study the hub level of each node in the network. The more the number of the shortest path through a node is, the more important the node is. Betweenness centrality reflects the intermediary status of a node and plays a key role in identifying high control nodes in the network. Betweenness centrality is defined as:

$$BC_i = \sum_{s \neq i \neq t} \frac{n_{st}^i}{g_{st}} \tag{15}$$

where denotes the number of the shortest paths from node s to node t, while n_{st}^i is the number of the shortest paths through node i of g_{st}.

The relationships between betweenness centrality and the number of nodes in the petrochemical block network and electric equipment and new energy block network are shown in Fig. 11. The figure (Fig. 11) reveals that only a few nodes have a high betweenness centrality, which means that the network is now in the transition period. These nodes can effectively predict the volatility mode in the next period.

There is also a difference in betweenness centrality of the nodes between the petrochemical block network and the electric power equipment and new energy block network. For the petrochemical block network, betweenness centrality in decline period is higher than that in rise period, and also higher in rise period than in stable fluctuation period. For the electric power equipment and new energy block network, betweenness centrality in the rapid fluctuations period is higher than that in the stable fluctuations period. The characteristic of the global network is very close to the network in stable fluctuation period. If we choose a long time period to analyze the co-movement of crude oil prices and the block stock prices, we will ignore some frequent violent fluctuations information caused by some non-market factors. This also confirms the necessity of dividing different periods to analyze the law of volatility evolution. The transformation modes of the two networks are different. In the rapid decline period, betweenness centrality of the nodes 'SSWWW' ,'UWSSW' and 'SWWWW' in petrochemical block network is large, however, the modes 'WWUUU' ,'UUUUW' and 'WUUUU' in electric equipment and new energy block network. The transformation between most of the modes in the petrochemical block network should go through the synchrony fluctuation modes of the crude oil prices and petrochemical block stock prices. Instead, most of the modes in the electric equipment and new energy block network transform through the divergent fluctuation modes of the crude oil prices and electric equipment and new energy block stock prices. The high betweenness centrality of the node indicates that it has a strong control capability for transformation between other node pairs in the network. The evolution time of the network is found by identifying the high betweenness centrality node. For example, policy adjustments can be made to stabilize market volatility at the time point of identifying the high betweenness centrality modes in a rapid decline period.

The relationship between the node strength and the betweenness centrality of the petrochemical block network and the electric power equipment and new energy block network is shown in Fig. 12. Most of the nodes center on the bottom left of the figures, that is, most nodes both have relatively small betweenness centrality and low node strength. In contrast, the node strength is stronger in stable fluctuation period than in other periods, but betweenness centrality is greater in decline periods than in other periods. And betweenness centrality of these nodes with large node strength is very small.

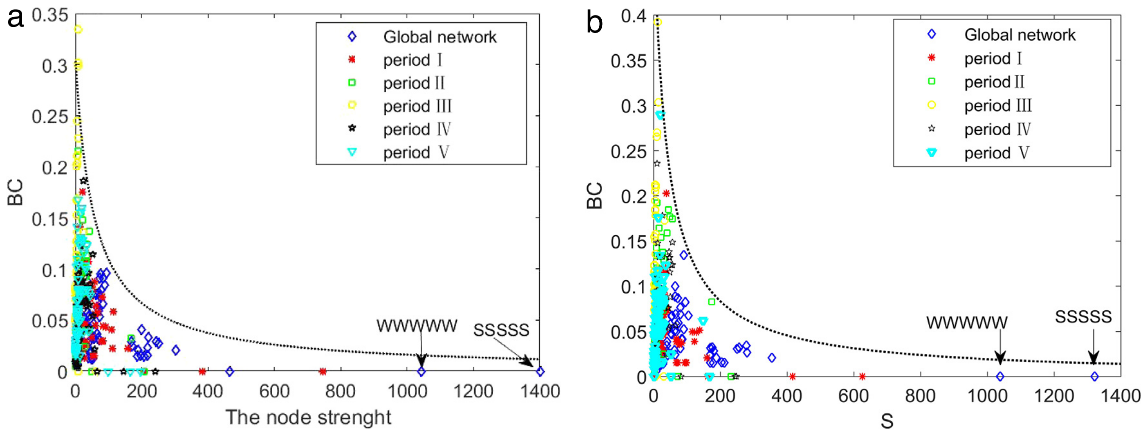

Fig. 12. Betweenness centrality of node in (a) the petrochemical block network and (b) the electric equipment and new energy block network in different periods.

Table 6
Comparison of two networks characteristics.

Characteristics	The number of nodes	The number of edges	Mode of maximum node strength	Probability	Average weighted degree
Network I	98	214	SSSSS	15%	46.204
Network II	31	60	WWWWW	62%	146.065

3.4. Comparative analysis of the network with time delay

The impact of the fluctuation of crude oil prices on the fluctuation of the block stock prices can be considered as the process that the information transmits from the crude oil prices fluctuation to the stock market and then the stock market reflect in the proceeds. Supposing there is the lag effect in the market information transmission process, we add the time delay in the original sequence to get respectively the coupling degree of the networks of the delay (Network II) comparing with no time delay networks (Network I) (see Fig. 6. (a) and (b)). Comparing with the characteristics of the two networks (see Table 6), the kinds of nodes in the network with time delay are only 31 and the modes of these nodes do not contain the symbol 'U'. It means that the modes of these nodes are all the synchrony relation. 62% of these modes are weak coupling relationship for five consecutive days, that is, block stock prices volatility has been consistent with the volatility of the crude oil prices. It also explains two prices are not synchronized in time series. It is found that there is the lag effect in the information transmission process from the crude oil price market to stock market.

4. Conclusions

In this paper, the prices of the international crude oil and two stock blocks closely related to petroleum industry from 1998/1/2 to 2015/12/31 were selected as a sample data to study the impact of the international crude oil prices volatility on China's block stock prices volatility. According to the characteristics of the crude oil prices fluctuations, the historical crude oil prices is built into 5 different fluctuation periods. It is revealed that the short-term sequence divided by the long-time series can better show the fluctuation characteristics.

In order to effectively extract the prices volatility information to reflect the real market volatility, the coupling degree is used to quantitatively measure fluctuation information transmission from the crude oil prices to two blocks stock prices based on the phase space reconstruction method. The coupling degree can indicate the synchrony relationship between time series.

The complex prices fluctuations are converted into symbolic sequences to reveal the impact of crude oil prices fluctuations on block stock prices fluctuations. Then the symbols sequence is converted into the different states by a sliding window, 5 days for a co-movement mode, 1 day for sliding step each time. Every mode represents a state about the coupling degree of two time series. We set the fluctuant patterns as nodes and the transformation relationship between patterns as edges. Directed weighted networks of the impact of the crude oil prices volatility on China's block stock market are built in different periods. The co-movement characteristics of crude oil prices fluctuation and block stock prices fluctuation are analyzed in the perspective of global period and sub-periods. The following results are obtained:

(1) The networks of the stock prices fluctuation with crude oil prices fluctuation are established in different periods, according to the fluctuation characteristic of crude oil prices. Characteristics of global network is similar to the network in stable fluctuation period. A Long time sequence should be divided into some short-term sequences to capture the fluctuations information and reveal the network evolution characteristics in rapid fluctuation periods.

(2) There is a 'long tail' effect in the node strength distribution of the petrochemical block network and the electric equipment and new energy block network in the global period and sub-periods. It is found that only a very small number of modes have a high node strength. These key nodes have significant influence on the co-movement and determine the common price fluctuation trend. The two networks have a high node strength in their own transformation modes, indicating that they will remain for a long time when the co-movement reaches 'SSSSS', 'WWWWW', or 'UUUUU' mode.

(3) It is found that the high coupling degree mode 'SSSSS' center on the period of relatively crude oil prices stable fluctuation. In the rapid and sustained rise period of crude oil prices, there is not a high synchrony between crude oil prices and the block stock prices due to stock market lag the information of crude oil prices fluctuations. When the fluctuations of crude oil prices are stable or small, the block stock prices will have a better synchrony degree. It indicates that the stock market has a stronger lag to the fluctuation of the crude oil prices in the fast and continuous fluctuation periods than in the stability or small fluctuation periods.

(4) It is found that only a few nodes have a high betweenness centrality. When betweenness centrality of a certain period is high, this network is now in the transition period. These nodes can effectively predict the next period of the fluctuation modes. Betweenness centrality of the petrochemical block network and the power equipment and new energy block network is slightly different. For both networks, the number of modes is seldom and betweenness centrality is large in decline periods. The performance of the transmission is more obvious in decline period than in other periods that indicating both networks have the larger volatility in decline period than other periods.

(5) The transformation time between modes is got by the shortest path length and the network diameter. It is found that the transition cycle of networks is 14–16 days in rapid fluctuation period , shorter than in stable fluctuation period.

(6) In contrast to the network with no delay time, more than 60% of the high coupling degree modes are weak coupling degree for 5 consecutive days in the network with time delay. It indicates that there is the time delay effect in information transmission process. The fluctuation of block stock prices have a high synchrony in the majority of time with crude oil prices fluctuation.

Acknowledgment

This research was supported by the National Nature Science Foundation of China (Grant No. 71473108).

References

[1] Y.J. Zhang, L. Zhang, Interpreting the crude oil price movements: Evidence from the Markov regime switching model, Appl. Energy 143 (2015) 96–109.
[2] Y.J. Zhang, T. Yao, Interpreting the movement of oil prices: driven by fundamentals or bubbles?, Econ. Model. 55 (2016) 226–240.
[3] P.K. Narayan, S. Sharma, W.C. Poon, J. Westerlund, Do oil prices predict economic growth? New global evidence, Energy Econ. 41 (2014) 137–146.
[4] B.N. Huang, M.J. Hwang, H.P. Peng, The asymmetry of the impact of oil price shocks on economic activities: An application of the multivariate threshold model, Energy Econ. 27 (2005) 455–476.
[5] M. Gisser, T.H. Goodwin, Crude oil and the macroeconomy: Tests of some popular notions: Note, J. Money Credit Bank 18 (1986) 95–103.
[6] Q. Zhang, The impact of international oil price fluctuation on China's economy, Energy Proc. 5 (2011) 1360–1364.
[7] Y. Wei, X. Guo, An empirical analysis of the relationship between oil prices and the Chinese macro-economy, Energy Econ. 56 (2016) 88–100.
[8] W. Tang, L. Wu, Z.X. Zhang, Oil price shocks and their short- and long-term effects on the Chinese economy, Ssrn. Electron. J. 32 (2009) S3–S14.
[9] L. Zhao, X. Zhang, S. Wang, S. Xu, The effects of oil price shocks on output and inflation in China, Energy Econ. 53 (2014) 101–110.
[10] E. Elyasiani, I. Mansur, B. Odusami, Oil price shocks and industry stock returns, Energy Econ. 33 (2011) 966–974.
[11] C.M. Jones, G. Kaul, Oil and the stock markets, J. Finance 51 (1996) 463–491.
[12] P.K. Narayan, R. Gupta, Has oil price predicted stock returns for over a century?, Energy Econ. 48 (2015) 18–23.
[13] X. Zhuang, Y. Wei, F. Ma, Multifractality, efficiency analysis of Chinese stock market and its cross-correlation with WTI crude oil price, Physica A 430 (2015) 101–113.
[14] J. Park, R.A. Ratti, Oil price shocks and stock markets in the U.S. and 13 European countries, Energy Econ. 30 (2008) 2587–2608.
[15] R.G. Cong, Y.M. Wei, J.L. Jiao, Y. Fan, Relationships between oil price shocks and stock market: An empirical analysis from China, Energy Policy 36 (2008) 3544–3553.
[16] S. Singhal, S. Ghosh, Returns and volatility linkages between international crude oil price, metal and other stock indices in India: Evidence from VAR-DCC-GARCH models, Resour. Policy 50 (2016) 276–288.
[17] E.M. Diaz, J.C. Molero, F.P.D. Gracia, Oil price volatility and stock returns in the G7 economies, Energy Econ. 54 (2016) 417–430.
[18] E. Bouri, Return and volatility linkages between oil prices and the Lebanese stock market in crisis periods, Energy 89 (2015) 365–371.
[19] G.M. Caporale, F.M. Ali, N. Spagnolo, Oil price uncertainty and sectoral stock returns in China: A time-varying approach, China Econ. Rev. 34 (2015) 311–321.
[20] R.G. Cong, Y.M. Wei, J.L. Jiao, Y. Fan, Relationships between oil price shocks and stock market: An empirical analysis from China, Energy Policy 36 (2008) 3544–3553.
[21] C. Zhang, X. Chen, The impact of global oil price shocks on China's stock returns: Evidence from the ARJI(-ht)-EGARCH model, Fuel Energy Abstracts 36 (2011) 6627–6633.
[22] S.F. Li, H.M. Zhu, K. Yu, Oil prices and stock market in China: A sector analysis using panel cointegration with multiple breaks, Energy Econ. 34 (2012) 1951–1958.
[23] S.Y. Wang, L.I. Dong, The spillover effects on petrochemical industrial concentration of international oil price, Energy Proc. 5 (2011) 2444–2448.
[24] J.F. Donges, R.V. Donner, J. Kurths, Testing time series irreversibility using complex network methods, Europhys. Lett. 102 (2012) 381–392.
[25] Z.K. Gao, Y.X. Yang, P.C. Fang, Y. Zou, C.Y. Xia, M. Du, Multiscale complex network for analyzing experimental multivariate time series, Europhys. Lett. 109 (2015).
[26] M.G. Wang, Y. Chen, L.X. Tian, S.M. Jiang, Z.H. Tian, R.J. Du, Fluctuation behavior analysis of international crude oil and gasoline price based on complex network perspective, Appl. Energ. 175 (2016) 109–127.
[27] Z. Wang, X. Liu, Y. Liu, J. Liang, V. Vinciotti, An extended Kalman filtering approach to modelling nonlinear dynamic gene regulatory networks via short gene expression time series, IEEE/ACM Trans. Comput. Biol. Bioinform. 6 (3) (2009) 410–419.

[28] Y. Liu, Z. Wang, X. Liu, State estimation for discrete-time Markovian jumping neural networks with mixed mode-dependent delays, Phys. Lett. A 372 (48) (2008) 7147–7155.
[29] X. Zhao, P. Shang, J. Wang, Measuring information interactions on the ordinal pattern of stock time series, Phys. Rev. E 87 (2013) 022805–022805.
[30] X.Y. Gao, H.Z. An, W. Fang, X. Huang, H.J. Li, W.Q. Zhong, Characteristics of the transmission of autoregressive sub-patterns in financial time series, Sci. Rep. 4 (2014) 6290–6290.
[31] X. Huang, H.Z. An, X.Y. Gao, X.Q. Hao, P.P. Liu, Multiresolution transmission of the correlation modes between bivariate time series based on complex network theory, Physica A 428 (2015) 493–506.
[32] H.Z. An, X.Y. Gao, W. Fang, X. Huang, Y.H. Ding, The role of fluctuating modes of autocorrelation in crude oil prices, Physica A 393 (2014) 382–390.
[33] T. Nakamura, T. Tanizawa, Networks with time structure from time series, Physica A 391 (2012) 4704–4710.