Energy 176 (2019) 281–291

Contents lists available at ScienceDirect

Energy

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

Identifying the peak point of systemic risk in international crude oil importing trade

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A R T I C L E   I N F O

Article history:
Received 31 May 2018
Received in revised form
21 March 2019
Accepted 22 March 2019
Available online 28 March 2019

A B S T R A C T

The fluctuations of international crude oil markets have caused significant attention around the world and aroused strong interest in the forecasting of the systemic risk in crude oil trade. Based on the oil imported values data of 34 major oil-importing countries from January 2005 to June 2017, we calculate the cross-correlation functions of time lags and construct a sequence of time-evolving oil import correlation networks according to the similarities between countries. The probability distribution of time lag shows that the time lag effect is not sensitive to positive correlations, but obvious for negative correlations. There is a longer time-lag effect in the years when positive correlations are stronger. Further, we use a percolation analysis to quantify the structural change in the correlation network. The key result is that abrupt percolation transition is leading spikes in systemic risk with advance of 3–11 months suggesting that this event could function as an alarm. Therefore, percolation transition in the correlation network of oil-importing countries can be used as a means to estimate signals about future systemic risk. The methodology and results presented in this paper bring a fresh perspective to the study of systemic risk in crude oil importing trade, and they facilitate risk early-warning research in other energy systems that also have interactions among their elements.

1. Introduction

Crude oil is an important energy source that is often called “black gold” and “the blood of modern industry”. It is non-renewable and rare, and thus strongly affects the economy and social development. As a strategic natural resource, oil remains the worlds leading fuel and accounts for one-third of global energy consumption [1].

The distribution of crude reserves oil is extremely uneven, and this creates a structural imbalance in the global supply and demand of crude oil that generates a widespread international crude oil market. Actually oil trade flows embody the relationship among different countries, which can form a complex network. The network model presents countries as nodes, trade relations as edges and trade volume as weight [2]. It offers a helpful tool for better analyzing the trading patterns by abstracting the trade system generated by the oil flows as a network [3]. This can be shown in Refs. [4–8]. An et al. constructed a directed network model of international oil trade to study the relationship between countries with common trade partners [4] and designed a weighted complex network model for examining the dynamics of the co-movement between crude oil features and spot prices [5]. Zhong et al. studied the evolution of communities of the world oil trade network by setting up un-weighted and weighted oil trade models using data from 2002 to 2011, and analyzed their evolutionary features and stabilities over the time [6]. Ji et al. identified the global oil trade

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https://doi.org/10.1016/j.energy.2019.03.127
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patterns using complex network theory, discovering that the global oil export core network displays the typical feature of complex network, that is scale-free distribution [7]. Zhang et al. studied the competition among oil importers using complex network theory, combined with several alternative measures of competition intensity, to analyze the evolution of the pattern and transmission of oil-trading competition [8]. Actually a detailed understanding of oil trading-based network is meaningful for governments because they are eager to increase their understanding of global oil trade in order to avoid the market risk.

Risks in supply, pricing, and geopolitics have caused price fluctuations and turmoil in the crude oil market. Kilian identified the underlying demand and supply shocks in the global crude oil market and estimated of how much each of the shocks contributed to the evolution of the real price of oil during the 1975–2007 period [9]. Hamilton found that historical oil shocks were a contributing factor in economic recessions [10]. The fluctuations in the crude oil market are caused by risk factors that are both systemic and non-systematic. Some studies have focused on such non-systematic risk factors as mismatches in supply and demand, capital speculation and exchange rates, but systemic risks bring the most powerful shocks to both the crude oil market and the global economy. Because of its uncontrollability and its ability to cause harm, it has been the focus of widespread concern in academia and among policy makers, especially since the 2008 financial crisis.

The systemic risk of crude oil importing trade system is the risk associated with the entire system, not the risk only related to an individual country. The issue of crude oil importing trade system is a global complex problem owing to the complex coupling relationships among the crude-oil-import countries. For example, the decisions of crude oil importers when they select exporters and imported values are not simply based on their own demand, for example, but are influenced by the behavior and decisions of other importers [11]. Incomplete information and market uncertainties would make it difficult for an importer in isolation to make optimal decisions. A sudden change, either increase or decrease of the oil imported value in one or several countries will lead to corresponding changes, either direct or indirect, in other countries. How much impact the imported value changes of one or several countries have on other oil-import countries, is determined by the complex coupling relationships among the different countries. In fact, various characteristic of the crude oil import market, such as systemic risk can be reflected by the coupling relationships among the crude oil importing countries. Thus understanding behavior correlations among oil importers is essential if we are to understand systemic risk. Network correlation study has long been used to quantify interactions, and the produced results are often useful. It has been applied to a wide variety of disciplines, including finance, biology, and climatology [12–29] but has seldom been used to understand systemic risk in the crude oil market. Recently, Wang et al. [30] built time-evolving interaction networks by using correlations among oil dependent countries, and proposed a formula, which is the linear combination of the topological indexes of the correlation networks, for measuring the evolution of systemic risk in crude oil importing system. Their study does not take into account how time lags delay the observable correlations among the imported values of different oil importing countries. However, time lag effect in fact exists among the correlation behavior of different oil importing countries. Thus we add the time lag influence to the oil import correlation network, where nodes are major oil importers and edges are correlations among the oil-import returns in different countries. Because understanding the structure and evolution of the early warning mechanism of systemic risk is important to governments and policy makers, our goal is to measure the correlation of oil-import behavior of different countries and forecast of the systemic risk in crude oil importing trade in a timely manner.

Systemic risk is often caused by dramatic changes in the structure of the system. In statistical physics and mathematics, percolation theory is an effective tool for understanding the resilience of connected network components to node breakdowns through structural properties [31,32]. It has been applied to many natural and human-made systems [29,31–36]. We here first combine the percolation method and network to identify the largest structural change occurred during the evolution of oil import correlation network, which is the signal about future systemic risk. The key result is that the abrupt percolation transition is leading spikes in systemic risk with advance of 3–11 months. The methodology is proved to be useful for forecasting the future systemic risk in international crude oil importing trade and potentially be used as a template to study other complex systems.

The paper is organized as follows. Section 2 describes the empirical data, the oil importing correlation network model, and the percolation analysis approach. Section 3 examines the time lag effect in the correlation network model and presents the results obtained from a percolation analysis that is comparable to the absorption ratio in the literature. Section 4 discusses the findings and presents conclusions.

2. Data and methodology

2.1. Data

All the data on crude oil imported values is derived from the United Nations Commodity Trade Database (UN Comtrade; http://comtrade.un.org). The data are recorded monthly from January 2005 to June 2017, 150 months. We rank the total oil imported values of each country. Due to limits and imperfect of data, we choose 34 major oil importers, where 61.8%, 20.6%, 5.9%, 5.9%, 2.9%, and 2.9% are from Europe, Asia, Oceania, South America, North America and Africa, respectively. There are 21 countries from Europe, including Germany, Netherlands, Italy, France, Spain, United Kingdom, Belgium, Poland, Greece, Sweden, Portugal, Finland, Lithuania, Austria, Czech Republic, Romania, Slovakia, Bulgaria, Switzerland, Croatia and Ireland. Seven countries are from Asia, including China, Japan, India, Korea, Singapore, Thailand and Philippines. Two countries are from Oceania, including Australia and New Zealand. Two countries are from South America, including Peru and Chile. One country, the United States of America, is from North America. One country, South Africa, is from Africa.

In probability theory and statistics, kurtosis is a measure of the "tailedness" of the probability distribution of a real-valued random variable. The kurtosis is the fourth standardized moment, defined as [37].

$$K(X) = \frac{E[X - E(X)]^4}{\sigma_X^4}, \tag{1}$$

where $E(X)$ is the average of the random variable X and σ is the standard deviation. The kurtosis of any univariate normal distribution is 3. It is common to compare the kurtosis of a distribution to this value. First, by Eq. (1) we calculate the kurtosis value based on the crude oil import value data of all countries at each time point. Fig. 1 shows the evolution of kurtosis values, and the proportions of $K(X)>3$ and $K(X)<3$. We find most of the time, $K(X)\neq 3$, which indicates that the distribution deviates significantly from the normal distribution. And $K(X)$ is greater than 3 for a long time. This is said to be leptokurtic, which means the distribution produces more outliers than the normal distribution [38]. Therefore, it is

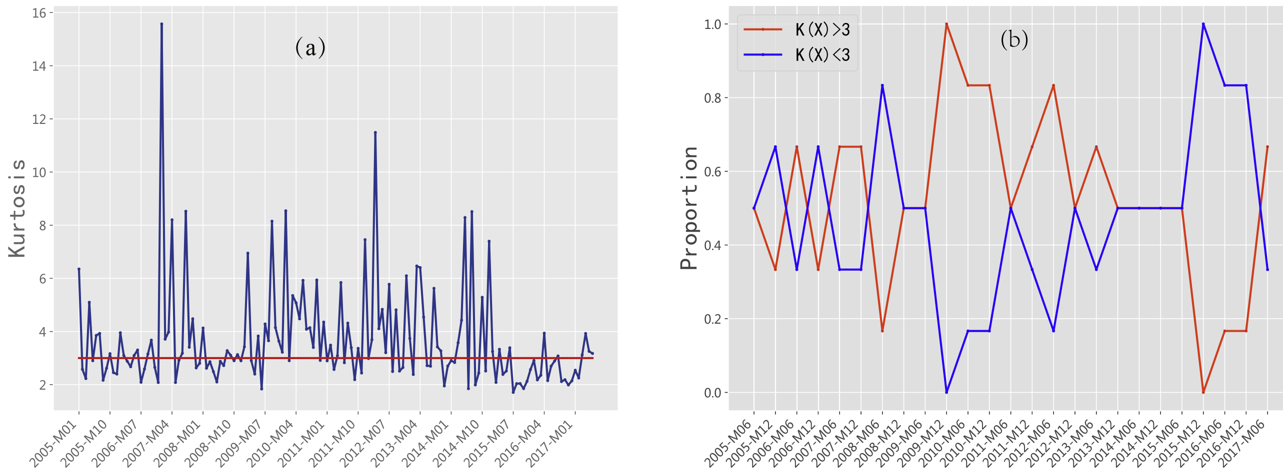

Fig. 1. (a) Evolution of kurtosis values; (b) Proportions of $K(X) > 3$ and $K(X) < 3$.

necessary to study the crude oil importing trade system under the condition of non-normal distribution.

2.2. The oil importing correlation network construction method

The nodes are the $N = 34$ major oil importing countries. For each country i, we denote $V_i(t)$ the monthly imported value at time t. The fluctuation at time t is defined

$$r_i(t) = \frac{V_i(t) - V_i(t-1)}{V_i(t-1)}. \tag{2}$$

The evolution of the fluctuation data is shown in Fig. 2.

Next we estimate the time-dependent correlation between each pair of the countries and construct a sequence of correlation networks. If we evaluate the correlation patterns over time through a time-series model from a holistic perspective, we will miss some important information because the correlation patterns are also a fluctuant process. Therefore we divide the holistic time series into different small-scale fragments using a moving window, and then construct a sequence of time-dependent correlation networks. Here, we assume that the length of the moving window is 24 months, the moving step is 1 month. The advantage of utilizing the moving window method is that the moving window have the feature of memory and transitivity. Thus the holistic fluctuation time series is divided into 120 segments with length 24. Within each window, we compute the correlation matrix $C(t)$, in which element $C_{i,j}$ is the weight of the link that connects country i and country j. First, the time-delayed cross-correlation function between the two time series $\{r_i(t)\}$ and $\{r_j(t)\}$ is calculated by Refs. [28,29],

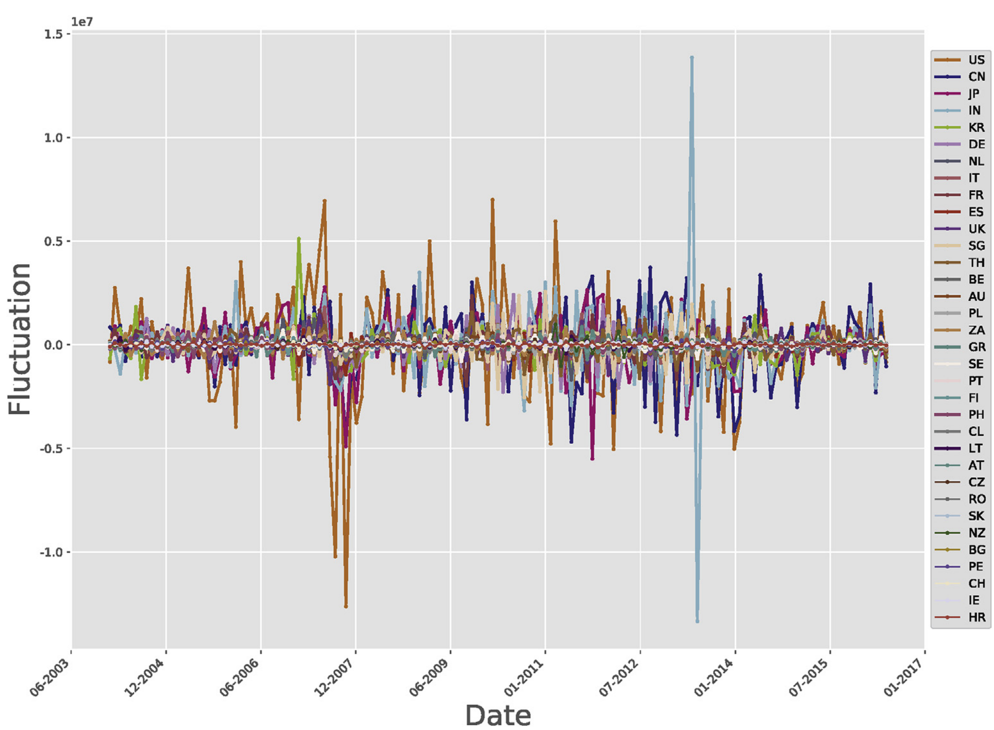

Fig. 2. Evolution of the fluctuation data.

$$C_{i,j}(\tau)=\frac{\langle r_i(t)r_j(t+\tau)\rangle-\langle r_i(t)\rangle\langle r_j(t+\tau)\rangle}{\sigma_{r_i(t)}\sigma_{r_j(t+\tau)}}, \tag{3}$$

where $\sigma_{r_i(t)}$ is the standard deviation of $\{r_i(t)\}$, $\tau\in[-\tau_{max},\tau_{max}]$ is the time lag, with $\tau_{max}=6$ months. Because of the time-reversal symmetry, $C_{i,j}(-\tau)=C_{j,i}(\tau)$. We identify the value of the highest peak of the absolute value of the cross-correlation function and denote the corresponding time lag of this peak to be $\tau^*_{i,j}$, and the weight of link connecting country i and country j to be $C_{i,j}=C_{i,j}(\tau^*_{i,j})$. The sign of $\tau^*_{i,j}$ indicates the direction of each link. That is, when the time lag $\tau^*_{i,j}>0$, the direction of the link is from i to j, which reflects the influence flow from i to j. When $\tau^*_{i,j}<0$, the direction of the link is from j to i, which means i is influenced by j. At each time point, there are $\frac{34*33}{2}$ time lags and they can be described by a probability distribution function (PDF) $P(\tau^*)$.

Thus the sequence of monthly shifting-correlation networks is constructed according to the similarities between nodes. More specifically, the nodes which are more similar (based on their oil-importing values variations) will be connected. The weighted adjacent matrix $A(t)$ of the correlation network at time t is defined as

$$A_{i,j}=\begin{cases}C_{i,j}, & |C_{i,j}|>\theta,\\ 0, & |C_{i,j}|\le\theta,\end{cases} \tag{4}$$

where $A_{i,j}$ is the weight of link connecting country i and country j, the critical threshold θ is the average of the absolute values of correlation matrix $C(t)$. Then we obtain 120 34-order directed and weighted networks for investigation that correspond to the time points from January 2007 to December 2016.

2.3. Percolation analysis

We examine the percolation phase transition by studying the evolution of clusters. At each time point, given $N=34$ isolated nodes, links are added one by one according to the weight, i.e., we first add the heaviest link and then continue in order of decreasing weight. During the evolution of the network, we measure the fraction of the giant component $G=\frac{p}{N}$, where p is the number of nodes in the largest component [31–36]. A component is a subset of network nodes in which each node has at least one path to another node in the subset [33]. During the growth process, the largest size change of the largest cluster is calculated by

$$\Delta=\max\{G(C_2)-G(C_1),G(C_3)-G(C_2),\cdots,G(C_{T+1})\\ -G(C_T),\cdots\}, \tag{5}$$

where C_T denotes the weight of the T-th added edge. The step with the largest jump is denoted C_c. The percolation transition in the network is Δ, and C_c is its transition point.

2.4. Absorption ratio

For the correlation matrix $C(t)$ at time t, we find $N=34$ eigenvalues λ_i in descending order. Here we use a measure of systemic risk called the absorption ratio, which is explained or "absorbed" by a fixed number of eigenvectors [39]. The absorption ratio captures the extent to which systems are unified or tightly coupled. When systems are tightly coupled, they are more fragile in the sense that negative shocks propagate more quickly and broadly than when systems are loosely linked. Reference [39] offers persuasive evidence that the absorption ratio effectively captures system fragility. We measure the systemic risk in the correlation network using the absorption ratio [11,21,30,39,40].

$$E_n=\sum_{i=1}^{n}\frac{\lambda_i}{N}, \tag{6}$$

where n is the number of the deviating eigenvalues. In this paper, they are chosen from the eigenvalues, which are greater than a critical value determined by the prediction of the Random Matrix Theory [21]. If an eigenvalue is greater than this critical value, it frequently contains valuable information about systemic dynamics [21]. The absorption ratio is a better approach because a perfectly integrated system can exhibit weak correlation. The larger E_n is, the higher the systemic risk is [15,40,41].

2.5. Empirical mode decomposition (EMD)

EMD is a method to extract the global structure and take into account fractal-like signals [42]. It is similar to other analysis methods, such as Fourier Transform and wavelet decomposition. We can use it to analyze natural signals, which are most often non-linear and non-stationary, and we can use it to decompose any complicated data set into a finite and small number of components called intrinsic mode functions (IMF) [43]. The first IMF usually has the most oscillating components (e.g., random noise) [44]. The equation is

$$I(n)=\sum_{m=1}^{M}IMF_m(n)+\mathrm{Res}_M(n), \tag{7}$$

where $I(n)$ is the multi-component signal, $IMF_m(n)$ is the m_{th} IMF, and $\mathrm{Res}_M(n)$ is the residue corresponding to M intrinsic modes. By using EMD method, we get a trend graph of a curve by removing the random noise.

2.6. Cross entropy

The cross-entropy measure has been used as an alternative to squared error. Cross-entropy characterizes the distance between the distribution of real data (probability p) and the predicted distribution of the model (probability q), often used as a loss function to estimate the degree of deviation between the series of predicted and actual values [45]. That is, the smaller the value of the cross entropy, the closer the two probability distributions are. Minimizing the cross entropy is the same as maximizing the likelihood [46].

The cross entropy for two discrete series p and q is defined as follows:

$$H(p,q)=-\sum_x p(x)\log q(x). \tag{8}$$

In this paper, p is the time series of absorption ratio E_n (the measure of systemic risk), q is the time series of lagged Δ obtained by percolation analysis. The minimum of $H(E_n,\Delta)$ corresponds to the greatest similarity of the two series.

3. Results and analysis

3.1. The correlation feature and probability distribution functions (PDFs) of time lag

We calculate the cross-correlation functions $C_{i,j}(\tau)$ between 34 countries using Eq. (3) and setting $\tau_{\max}=6$. months. From $C_{i,j}(\tau)$,

Table 1
Proportions of positive and negative correlations.

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
γ_p	65.7%	70.1%	77.2%	73.4%	62.1%	60.6%	56.1%	57.9%	60.4%	62.5%
γ_n	34.3%	29.9%	22.8%	26.6%	37.9%	39.4%	43.9%	42.1%	39.6%	37.5%

we obtain correlation $C_{i,j}$ between countries i and j. Table 1 lists proportions γ_p, γ_n of positive and negative correlations for different years and shows that the PDF of correlations is separated into positive and negative parts. During the first four years, the proportions of positive correlation increase and are higher in 2009 and 2010. Following 2011 the proportions of positive correlation progressively shrink. In contrast, the proportions of negative correlation gradually increase and attain high values in 2013 and 2014. In 2015 and 2016 the proportions of positive correlations continue to increase.

The different characters of positive and negative correlations can be further demonstrated by their PDF of time lag τ^*. Fig. 3 shows the PDF of the positive $P_p(\tau^*)$ and negative $P_n(\tau^*)$ correlations. The PDF of time delay has a maximum at $\tau^* = 0$ for positive correlations and $\tau^* \neq 0$ for negative correlations. This indicates that the time lag effect is clear for countries with negative fluctuation correlations but not for countries with positive fluctuation correlations. Combined this with Table 1, we see longer time-lag effects between countries with negative correlations that occur in years with higher proportion of positive correlations during the evolution, i.e., 2009, 2010, 2015 and 2016. When the proportion of positive correlations increases, the longer time-lag effect of the negative correlation grows more obvious.

3.2. Percolation analysis: identifying the peak point of systemic risk in oil importing trade

We use Eq. (5) to obtain the percolation transition for each oil import correlation network, and find that, usually between three and eleven months prior to the peak point of systemic risk, the correlation network has the largest Δ. We use this feature to forecast the peak point of systemic risk for the following year. Fig. 4 compares the evolution of the forecasting result and the absorption ratio. Fig. 4(a) shows the eight predicted time points obtained by percolation analysis. For a continuous warning within six months, we make the last one the standard. The remaining five time points are May 2008, May 2010, November 2012, December 2014, and October 2016. The last time point, October 2016 (blue), is out of the sample range. The absorption ratio obtained by Eq. (6) closely reflects the systemic risk of the correlation network, and Fig. 4(b) shows its evolution (blue curve). Using empirical mode decomposition (EMD), we remove the random noise from the blue curve and obtain the green curve, which reflects the trend of E_n. The trend of EMD curve shows that the blue curve reaches a maximum at December 2008, the first peak point, and then decreases to the second and the third peak points in April 2011 and February 2013. After bottoming, the blue curve moves upward and reaches the fourth peak point in September 2015. The time lead between the prediction and the peak point of systemic risk is in the interval of three to eleven months, which is shown in Table 2. There are four accurate alarms (orange points). The prediction point in October 2016 corresponds to the time point several months later. In 2017 the oil price trend is V-shaped and reaches the peak point in the middle of the year. This confirms our above findings.

Next, we concentrate on specific peak points of systemic risk in international oil importing trade to illustrate the evolving component structure. Using April 2011 as an illustrative example, in Fig. 5 we show the giant component G as a function of link strength C. We find that the largest jump of G occurs in May 2010, eleven months prior to the peak point in April 2011. The link connecting Thailand in Asia and Chile in South America was added in May 2010, and the giant component jumped from 0.353 to 0.706. For other time points the gap becomes smaller. This shows that the correlation influence from Asia has spread to South America. We find similar results at the other peak points: December 2008, February 2013 and September 2015. For the peak point of December 2008, the largest jump of G occurs in May 2008, seven months prior to it. The link connecting Greece and Lithuania in Europe was added in May 2008, and the giant component jumped from 0.382 to 0.676. The directed edge shows the influence flow in Europe, from south to north, and makes Europe the most highly correlated continent. For February 2013, the largest jump of G occurs in November 2012, three months prior to that. The link connecting Slovakia and Austria in Europe was added in November 2012, and the giant component jumped from 0.324 to 0.618. We also find that for the peak point of September 2015, the largest jump of G occurs in December 2014, nine months prior to that. The link connecting Sweden in Europe and Chile in South America was added in December 2014, and the giant component jumped from 0.529 to 0.824. This result indicates that the correlation tendency has spread from Europe to South America. Following the above, we can obtain information about the peak point of systemic risk in crude oil importing trade by investigating these abrupt transitions in the giant component G. We get that the largest gap occurs between three and eleven months prior to the peak point of systemic risk. Therefore, large Δ can be regarded as an alarm forecast that the peak point of systemic risk will develop in the following month.

In our manuscript, the “abrupt percolation” term is a concept from physical phase transitions, and not necessary related to abrupt changes in oil import values. It indicates discontinuous phase transition, which has attracted much attention recently in the context of interdependent networks [35,36]. While for randomly connected network system, it behaves a continuous percolation phase transition [28,32]. That is to say, if there is no interaction between the oil importers, the oil import correlation networks will not undergo an abrupt phase transition. The key result of our work is that the abrupt transitions occur 3–11 months prior to the peak point of systemic risk in oil importing trade. This is probably since the network percolation approach can capture in time the signals hidden behind the actual data, which reflects the interaction among the oil importing countries. This interdependence can cause system instability and even cascading failures.

3.3. The robustness analysis of prediction result

In order to investigate the robustness of the prediction result, we use Eq. (8) to obtain cross entropy to estimate the degree of deviation between the time series of E_n and lagged Δ. Fig. 6 shows the cross entropy of the two time series Δ and E_n, as a function of the interval Δ leading to E_n. Fig. 6(a) (orange point) shows that when the percolation transition sequence (from Dec. 2007 to Oct. 2008) leads the systemic risk sequence (from Jul. 2008 to May 2009) for 7 months, the cross entropy reaches minimum, which means the two time series have the least degree of deviation. The

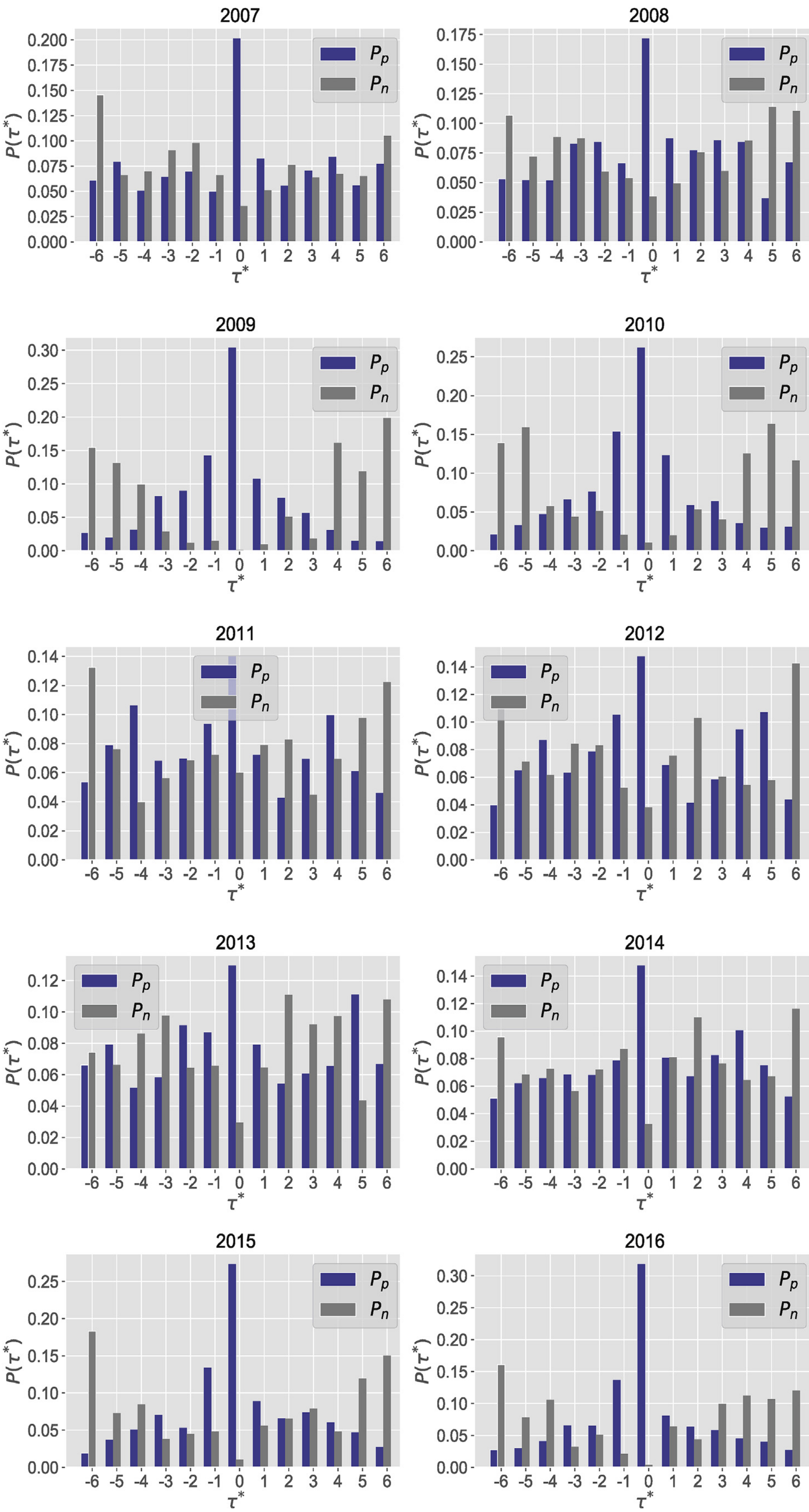

Fig. 3. Probability distribution function of time lag τ^* is shown for positive and negative correlations.

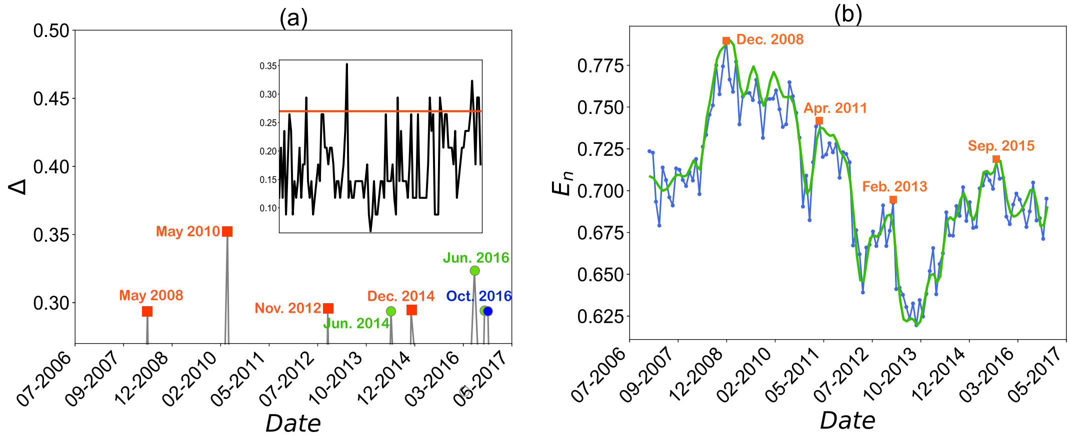

Fig. 4. Percolation forecasting result and absorption ratio based on oil imported value fluctuation dataset. We compare the largest gap of the largest cluster Δ during the oil importing correlation network evolution with a threshold $\Delta_c = 0.268$ (left panel) and the absorption rate (right panel) between January 2007 and December 2016. When Δ is bigger than Δ_c, which is 1.5 standard deviations, we give an alarm and predict that the peak point of systemic risk for oil importing trade will start in the following months. In the inset we show the full plot for the largest gap of the largest cluster Δ. The horizontal red line represents the critical value Δ_c. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 2
The time lead between the predictions and the peak points of systemic risk.

Δ	May 2008	May 2010	Nov. 2012	Dec. 2014	Oct. 2016
E_n	Dec. 2008	Apr. 2011	Feb. 2013	Sep. 2015	
Intervals (months)	7	11	3	9	

intermediate time points of the two time series respectively correspond to the predicted time point (May 2008) and the peak point (Dec. 2008) in systemic risk, as shown in Table 2. And for other time intervals Δ leading to E_n, there exist high cross entropy between the two time series. In Fig. 6(b), when the percolation

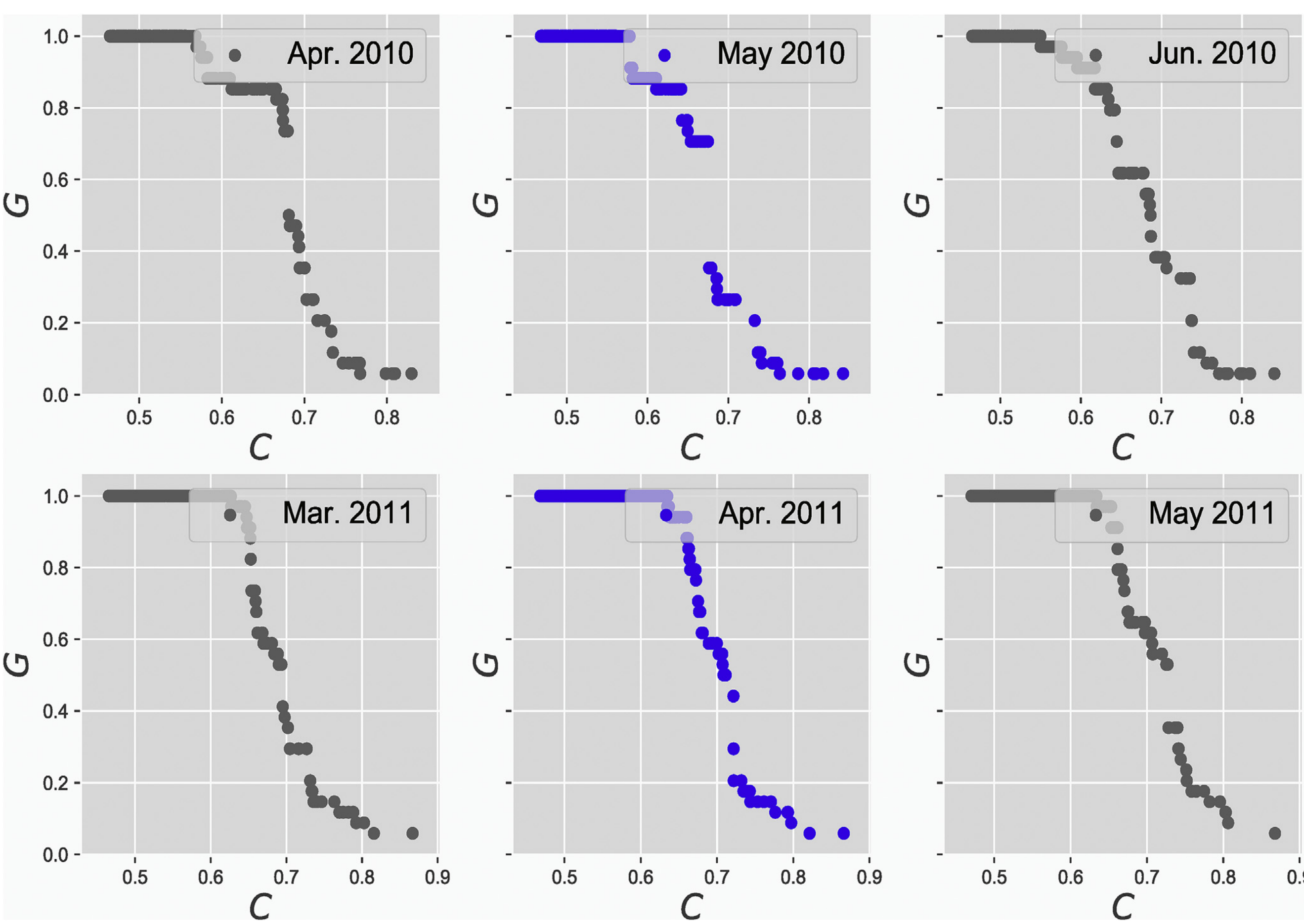

Fig. 5. The giant component G as a function of the link strength C. The largest jump of G occurs in May 2010, eleven months prior to the peak point in April 2011. When the link connecting Thailand in Asia and Chile in South America was added in May 2010, the giant component jumped from 0.353 to 0.706. The gap becomes smaller for other time points.

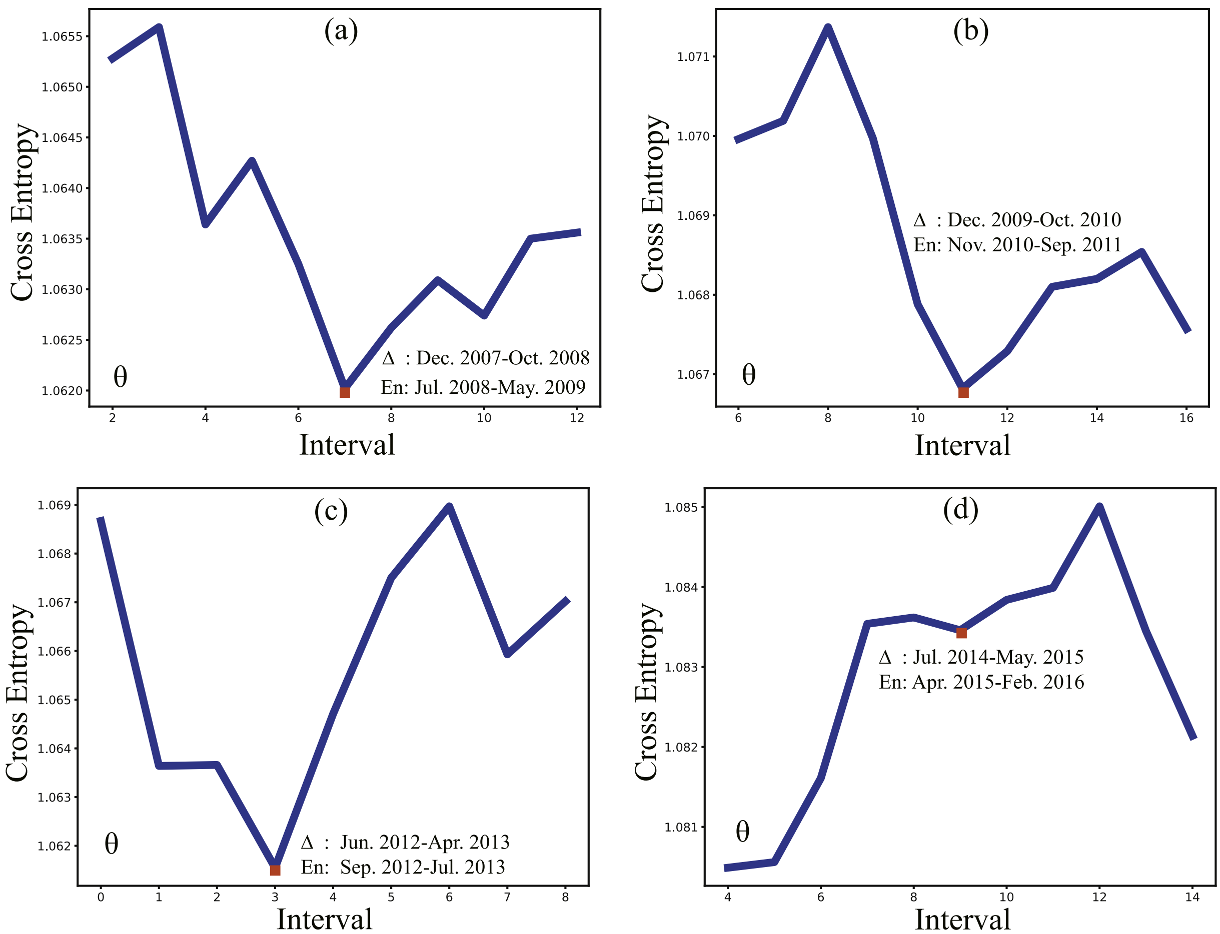

Fig. 6. The cross entropy of the two time series Δ and E_n as a function of the interval that Δ is leading to E_n. The minimum values (orange points) in (a), (b) and (c) respectively correspond to the cross entropy of the following time series: (a) Δ: Dec. 2007–Oct. 2008, E_n: Jul. 2008–May 2009; (b) Δ: Dec. 2009–Oct. 2010, E_n: Nov. 2010–Sep. 2011; (c) Δ: Jun. 2012–Apr. 2013, E_n: Sep. 2012–Jul. 2013. The intermediate time points of the above time series are consistent with those given in Table 2. However in (d), when the cross entropy of the two time series takes the minimum value, their intermediate time points do not coincide with the results in Table 2. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

transition sequence (from Dec. 2009 to Oct. 2010) leads the system risk sequence (from Nov. 2010 to Sep. 2011) for 11 months, the cross entropy of the two sequences reaches the minimum. The intermediate time points of the two time series are May 2010 and Apr. 2011. Fig. 6(c) shows that the cross entropy reaches the minimum, as the percolation transition sequence (from Jun. 2012 to Apr. 2013) is leading the system risk sequence (from Sep. 2012 to Jul. 2013) with advance of 3 months. The intermediate time points of the two time series are Nov. 2012 and Feb. 2013. The central time points appropriately correspond to the predictions and the peak points of systemic risk in Table 2. However in Fig. 6(d), when the cross entropy takes the minimum value, the intermediate time points of the corresponding two time series are inconsistent with those given in Table 2.

To investigate whether our findings are also valid when taking into account the influence of θ for constructing the correlation networks, we compare the cross entropy results under different thresholds: $\theta \pm 0.5\sigma$, $\theta \pm 1.2\sigma$ and $\theta \pm 1.5\sigma$, where σ and θ are the standard deviation and the average of the absolute values of the correlation matrix $C(t)$ respectively. The results of robustness testing are shown in Figs. 7–9. For the first prediction result in Table 2, regardless of the critical threshold, when the corresponding percolation transition sequence leads the system risk sequence for 7 months, the cross entropy result reaches a minimum, as shown in Fig. 7. For the second prediction in Table 2, Fig. 8 shows that adjusting the critical threshold has no effect on the prediction result. For the third prediction in Table 2, Fig. 9 shows that for different thresholds, the cross entropy reaches minimum when the percolation transition sequence (from Jun. 2012 to Apr. 2013) leads the systemic risk sequence (from Sep. 2012 to Jul. 2013) for 3 months. But when the critical threshold is taken as $\theta \pm 1.5\sigma$, the network connection is very sparse, the minimum deviation is not obvious. We conclude that the density of the network has an effect on the prediction results. However, for the fourth prediction result in Table 2, we find that for different critical thresholds, the corresponding percolation transition sequence and the systemic risk sequence show a high degree of deviation.

4. Discussion and conclusions

We have used the monthly crude oil import value data on 34 major oil importing countries from January 2005 to June 2017. We introduce the time lag effect and study the fluctuation correlations. The probability distribution function of correlations is separated into positive and negative sectors. The probability distribution functions of time lag indicate that the time lag effect is clear for countries with negative fluctuation correlations but not for countries with positive fluctuation correlations. When the proportion of positive correlations increases, the longer time-lag effect of the negative correlation grows more obvious.

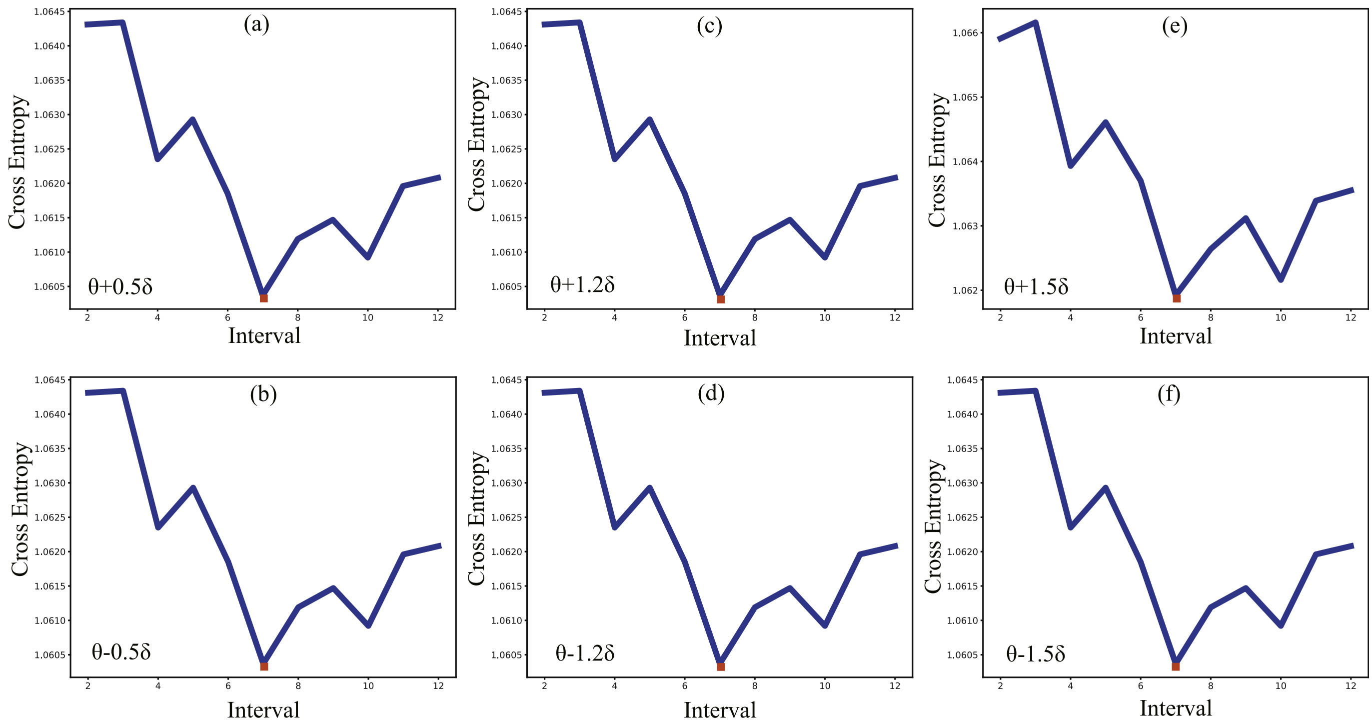

Fig. 7. The cross entropy results under different thresholds: (a) $\theta + 0.5\sigma$, (b) $\theta - 0.5\sigma$, (c) $\theta + 1.2\sigma$, (d) $\theta - 1.2\sigma$, (e) $\theta + 1.5\sigma$, (f) $\theta - 1.5\sigma$, where σ and θ are the standard deviation and the average of the absolute values of the correlation matrix $C(t)$ respectively. For different thresholds, the cross entropy reaches minimum when the percolation transition sequence (from Dec. 2007 to Oct. 2008) leads the systemic risk sequence (from Jul. 2008 to May 2009) for 7 months.

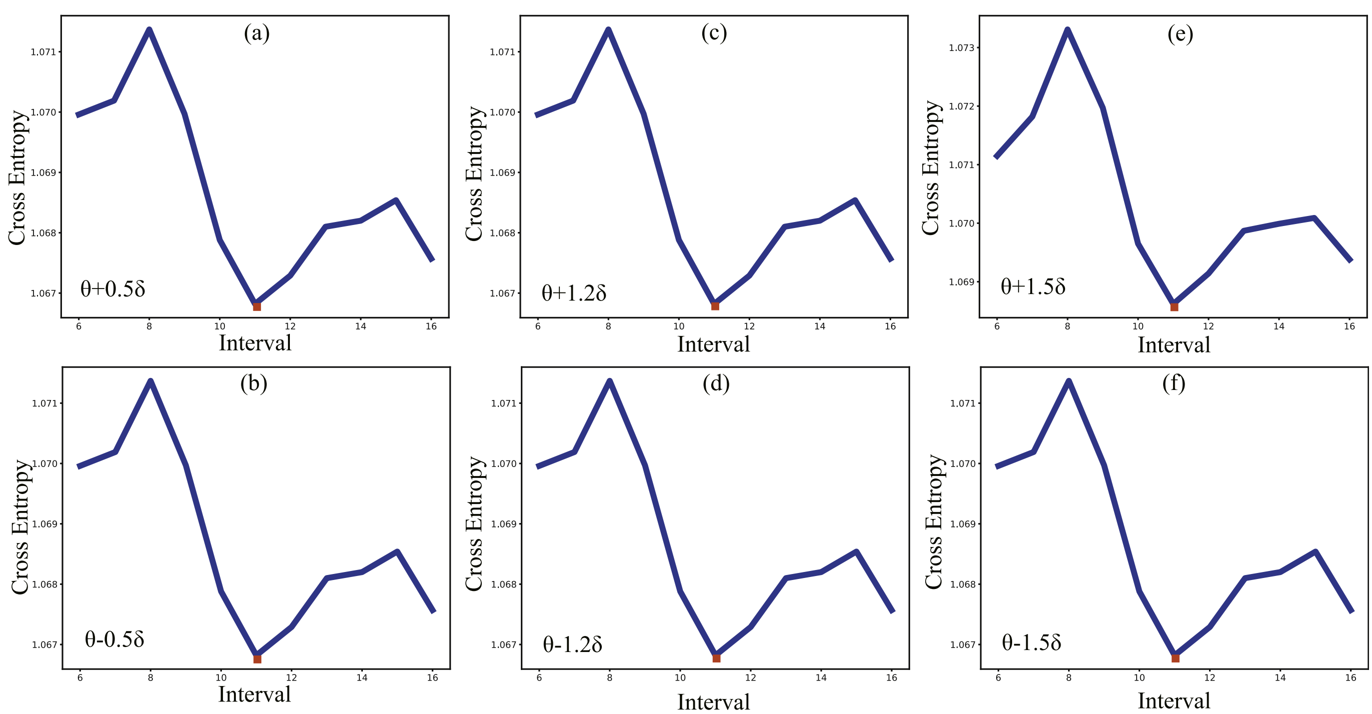

Fig. 8. The cross entropy results under different thresholds: (a) $\theta + 0.5\sigma$, (b) $\theta - 0.5\sigma$, (c) $\theta + 1.2\sigma$, (d) $\theta - 1.2\sigma$, (e) $\theta + 1.5\sigma$, (f) $\theta - 1.5\sigma$, where σ and θ are the standard deviation and the average of the absolute values of the correlation matrix $C(t)$ respectively. For different thresholds, the cross entropy reaches minimum when the percolation transition sequence (from Dec. 2009 to Oct. 2010) leads the systemic risk sequence (from Nov. 2010 to Sep 2011) for 11 months.

Based on the sequence of monthly shifting-correlation networks, we use the percolation method to develop an advance warning mechanism for systemic risk in the oil importing trade. We find that the structure of the network sharply changes and undergoes a first-order phase transition between three and eleven months prior to the peak point of systemic risk, which is measured

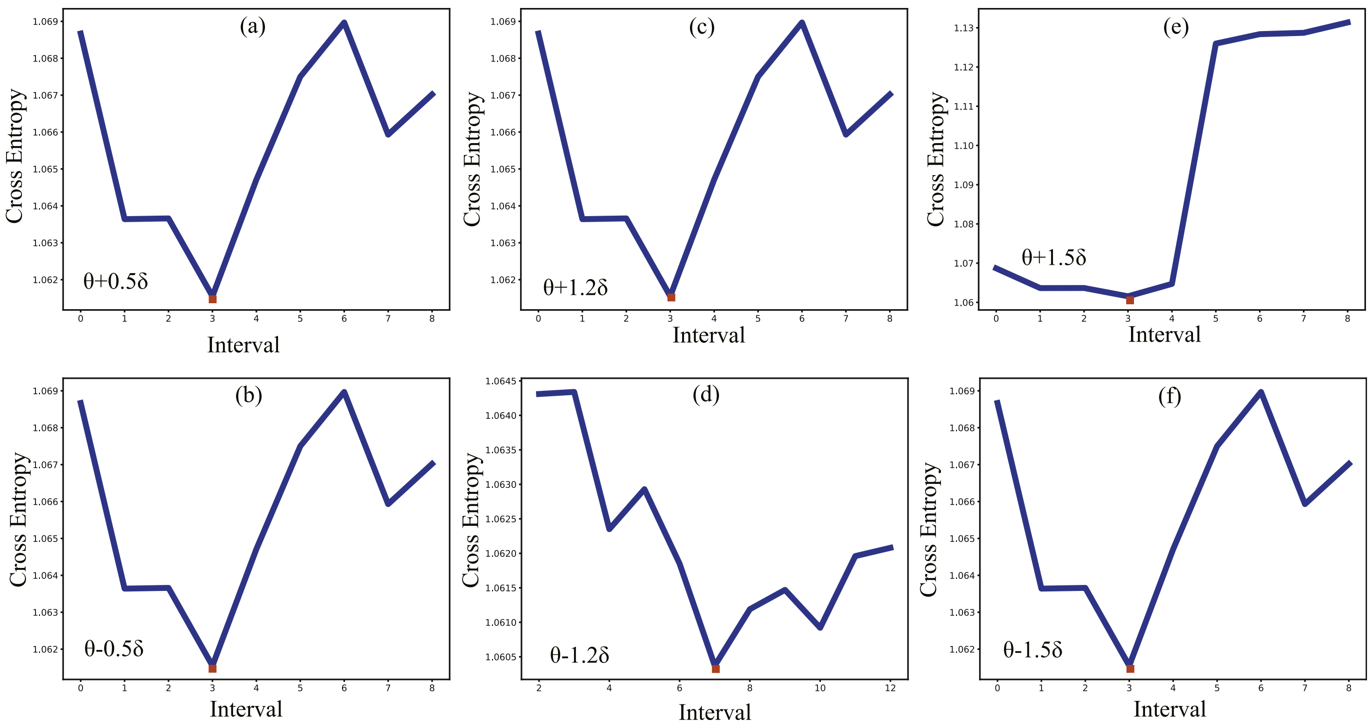

Fig. 9. The cross entropy results under different thresholds: (a) $\theta+0.5\sigma$, (b) $\theta-0.5\sigma$, (c) $\theta+1.2\sigma$, (d) $\theta-1.2\sigma$, (e) $\theta+1.5\sigma$, (f) $\theta-1.5\sigma$, where σ and θ are the standard deviation and the average of the absolute values of the correlation matrix $C(t)$ respectively. For different thresholds, the cross entropy reaches minimum when the percolation transition sequence (from Jun. 2012 to Apr. 2013) leads the systemic risk sequence (from Sep. 2012 to Jul. 2013) for 3 months. However, when the critical threshold is taken as $\theta+1.5\sigma$, the minimum deviation is not obvious. At this time, the average degree of the network is small, and the network connection is very sparse. We conclude that the density of the network has an effect on the prediction results.

using the absorption ratio. Thus the largest change in the giant component is an alarm that indicates that a peak point of systemic risk will occur within a few months. Using the percolation method, our forecasted time points are May 2008, May 2010, November 2012, December 2014 and October 2016. October 2016 is out of the sample data range. The peak points of systemic risk obtained through the absorption rate are December 2008, April 2011, February 2013 and September 2015. Further, cross entropy is applied to verify the robustness of the results. We also analyze and compare the structural changes in the network before and after the prediction time point and the peak point of systemic risk. We find the largest change in the size of the giant component in the correlation network of oil imported values fluctuation to be caused by the flow of influence among European countries and from Europe and Asia to South America.

To sum up, we have described the time-lag effect in the oil importing correlation network and used a percolation analysis to quantify the structural change. The key result is that abrupt percolation transition is leading spikes in systemic risk with advance of 3–11 months suggesting that this event could function as an alarm. Therefore, the percolation analysis in statistical physics can be used as an effective way for predicting signals about future systemic risk, and provides an important reference for oil trading countries and market analysis. Our work will help oil importers understand the varying structure of the oil importing correlation network and enable them to improve the security of the oil import market. Our new method can also be applied to other energy systems that have correlations among their elements. Although substantial progress in the study of oil trade networks has been recently achieved, a number of challenging problems remain. For example, we need a risk-warning mechanism that combines early warning information with an emergency response strategy. We also need a way of integrating the oil market, encouraging cooperation among oil importers and exporters, and improving world-wide systematic oil supply security. These issues are topics for future research.

Acknowledgement

This research was supported by National Natural Science Foundation of China (Grant Nos. 71690242, 11731014, 91546118, 71403105, 61403171, 71503132, 17BGL143, 71601112). The Boston University Center for Polymer Studies is supported by NSF Grants PHY-150500, CMMI-1125290, and CHE-1213217, and by DTRA Grant HDTRA 1-14-1-0017. The research is partially supported by Shanghai Pujiang Program (Grant No. 15PJC061), China Postdoctoral Science Foundation (Grant No. 2016M590973), Humanities and Social Science Talent Plan of Shaanxi, Shaanxi Postdoctoral Science Foundation (Grant No. 2017BSHEDZZ47).

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