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Study on international energy market and geopolitical risk contagion based on complex network

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ABSTRACT

At present, the global political and economic situation is changing with geopolitical risks occurring frequently, and the commodity market represented by energy fluctuates violently. In order to deeply investigate the risk contagion status and interactive contagion mechanism between international energy market and geopolitics under the impact of extreme events, this paper selects crude oil spot prices and geopolitical risk index of major international oil-producing countries from January 2006 to December 2021, and analyzes the tail risk cross-contagion effects, dynamic effects and cyclical characteristics between international energy-geopolitics two-layer networks based on complex networks. Empirical research finds that risk spillover effect of traditional energy markets is more significant than that of clean energy markets. Russia acts as the main risk spillover of international crude oil market under extreme shocks, and geopolitical conflicts will exacerbate risk contagion between international energy markets. The analysis of energy-geopolitics two-layer network finds that the international energy market generates net risk spillover effect on geopolitics. In addition, the interconnectedness network study found that the United States, Russia and China are systemically important economies in the energy market under the complex geopolitical landscape. The risk contagion effect among systemically important economies finds that Russia's geopolitical risks have stronger impact on China's crude oil price. The cycle characteristics analysis of international crude oil market and geopolitical dynamic network finds that the short-term risk contagion effect is more obvious. The machine learning analysis found that the international crude oil-geopolitical connectedness can effectively warn the tail risk of the crude oil market, which provides basis for preventing cross-contagion risks from the perspective of system connectedness.

1. Introduction

In modern society, the smooth operation of economy depends on the secure and stable energy supply. The outbreak and recurrence of the COVID-19 epidemic since 2020 has caused global economic downturn. Large-scale work and production shutdowns have led to significant drop in energy demand and sharp drop in energy price. The ensuing Russia-Ukraine conflict, however, has led to sharp rise in energy price. At this stage, the international political situation is unstable and uncertain, with highly volatile energy market. General Secretary Xi Jinping of China remarked in early 2022 during his investigation that "energy security is a global and strategic issue linked to the nation's economic and social development." The 2022 Government Work Report of China highlights the importance of energy as the driving force of economic and social development. However, the current global economy is still heavily dependent on fossil fuels. Exposure to risks in the energy industry is becoming more frequent due to environmental degradation caused by the over-exploitation and burning of fossil fuels. In addition, under the current trend of strengthening economic integration, the external effects of energy market fluctuations among countries will also be strengthened, causing "black swan" events in the field of geopolitics. At the same time, frequent geopolitical events such as international military conflicts, political turmoil, and terrorist attacks (Blattman and Miguel, 2010) have also had a huge impact on the international energy market. For example, during geopolitical conflicts such as the 9/11 attacks, the wars in Afghanistan and Iraq, and the current Russia-Ukraine conflict, the international energy prices all showed a trend of dramatic fluctuations. At present, China has been deeply integrated into the world

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economy, it is significant to study the correlation between geopolitics and changes in global energy supply and demand to ensure energy security.

According to BP's 2021 report, despite the increasing application of renewable energy, fossil fuels account for 83.1% of energy consumption in 2020 and petroleum still occupies the largest share in the energy consumption structure. As the crucial strategic reserve resource, the oil's unique geographical property determines that the violent fluctuations in the market are closely related to geopolitics. Extreme occurrences, such as terrorist attacks, considerably increase the likelihood of fluctuating oil prices (Wen et al., 2021). Hence, the heightened geopolitical turbulence is often taken as the primary reason for drastic fluctuations in the price of crude oil (Liu et al., 2019). For example, before Iraq invaded Kuwait, the price of oil was $20 a barrel, while three months later the price rose to $40 a barrel. Since the Russian-Ukrainian conflict broke out, the spot price of WTI crude oil rose rapidly from $96.28 per barrel to $128.26 per barrel in less than ten trading days. Increasing geopolitical risks force oil-producing countries to cut oil supplies (Demirer et al., 2019) and impact energy financial markets through investor sentiment. In addition, concerning the relationship between geopolitical conflicts and oil resources, some studies have found that the seizure of oil resources is the cause of military violence (Cotet and Tsui, 2013), and the inability to get oil reserves is at the heart of many violent confrontations. Furthermore, the risk of social and political instability in oil-exporting economies is increased when oil prices fall sharply (Korotayev et al., 2018). As we can see, the relationship between geopolitics and global crude oil resources is intricate, which belongs to the puzzle of "chicken or egg". To avoid importing global risks, it is crucial to examine the intricate interactions between geopolitics and the international crude oil market. The status of tail risk contagion in the international energy market in face of extreme event shocks will therefore be examined in this paper, as well as the complex interconnectedness and dynamic characteristics between the international crude oil market and geopolitical risks from the perspective of complex networks.

As the world's main oil-producing nations are often involved in geopolitical conflicts, a varied energy system is able to mitigate oil-producing nations' supply risks and achieve carbon neutrality. (Gong et al., 2020). Moreover, under the impact of extreme events, the energy financial markets present non-linear fluctuations. Studies have found broad asymmetric correlations between conventional and renewable energy markets (Maghyereh et al., 2019). Therefore, our study will first examine the tail risk spillover effects between traditional energy and renewable energy financial markets in global energy markets before analyzing the intricate interconnectedness effects between geopolitical risk and the crude oil market. Then we focus on exploring the tail risk contagion mechanism among international crude oil markets composed of the world's major oil-producing countries, which provides basis for examining the complex connectedness effect between the international crude oil markets and geopolitics. After analyzing the complex connectedness effect between crude oil-geopolitics two-layer network, the time-varying characteristics of international crude oil-geopolitics connectedness are further explored using dynamic networks. Lastly, the machine learning method is employed to examine the early warning effect of the interconnectedness between crude oil and geopolitical risk networks on the tail risk of crude oil markets. The research on the international energy markets and geopolitical risk contagion from the perspective of complex network provides reference for countries to strengthen energy security, identify cross-contagion of risks, and effectively prevent systemic risks.

This paper constructs the research framework of international energy markets and geopolitical risk contagion from the complex network perspective. The innovation of our study is as follows: (1) The contagion of tail risks among international energy markets under the impact of extreme events is investigated by building the tail risk network between traditional energy and clean energy markets. (2) The interactive effects of the international crude oil market and geopolitical risks are further revealed through a two-layer international crude oil-geopolitical risk connectedness network. (3) In particular, to describe the dynamic characteristics of interconnectedness between international energy markets and geopolitics during extreme events, we analyze the dynamic effects and periodic laws of the international crude oil network, the geopolitical network, as well as the double-layer network from the perspective of dynamic network. (4) Based on the interconnectedness of the geopolitical risk network and the international crude oil market, machine learning is employed to provide early warning of tail risks.

2. Literature review

Energy is regarded as the driving force of global economic growth because it is the material basis for human survival and development (Acheampong et al., 2021). At the same time, as the countries' strategic reserves, energy security is closely related to international geopolitical relations. Oil plays the role of the foundation of the national economy, and its price fluctuations have received widespread attention (Herrera et al., 2019; Virbickaitė et al., 2020). Research on the energy-finance nexus has become more and more popular as the financial qualities of crude oil have improved. According to Li et al. (2015), using Google can improve the reliability of predicting oil prices. Oil price fluctuations is not only affected by monetary policy and liquidity, but also have an asymmetric effect on the global financial markets. As the state of the climate throughout the world worsens and several nations enact laws to reduce carbon emissions, clean energy has gradually emerged (Saeed et al., 2021), and its impact on macroeconomic growth has become increasingly evident. The new energy market and the crude oil market are closely related. Therefore, we will first analyze the spatial distribution of tail risks in energy markets under extreme event shocks, in particular the spillover effect of risks for traditional energy and renewable energy.

Because there is limited supply of energy, the price fluctuation and risk spillover in energy market are particularly vulnerable to the effect of geopolitics. Geopolitical risks are the risks linked with war, acts of terror, and friction between countries that impede international relations' regular, peaceful process (Caldara and Iacoviello, 2022). Most studies focus on the connectedness between geopolitical risks and the financial and energy markets in light of the present geopolitical unrest around the world. As extreme events, geopolitical conflicts can change investors' expectations, cause panic in the capital market, and then brings about prominent impact on fluctuations in the energy and financial markets. Meanwhile, geopolitical conflicts, which frequently occur in nations that produce crude oil, can impact international energy supply and cause significant price fluctuations in energy markets (Qin et al., 2020). In the context of frequent geopolitical events, it is crucial to analyze the interconnectedness impact among geopolitical risks and commodities markets (Bouoiyour et al., 2019).

As the world's predominant traditional energy source, the extreme volatility of crude oil markets is strongly associated with geopolitics. If geopolitical conflicts affect the oil supply, even without interruption of its supply, it can cause drastic fluctuations in oil prices (Noguera-Santaella, 2016). According to Plakandaras et al. (2019), geopolitical risk provides valuable information in predicting the risk of crude oil volatility. However, previous studies on the nexus between geopolitics and oil mainly explored the connectedness trend between them from the perspective of time series (Cotet and Tsui, 2013; Noguera-Santaella, 2016), and seldom investigated spatial interconnectedness between the geographic distribution of oil resource reserves and geopolitics from the perspective of spatial networks. In the clean energy sector, Yang et al. (2021) showed that there is no clear linear risk spillover from geopolitical risk to the markets for renewable energy. It can be seen that whether it is traditional energy or new energy, the current studies involved less about the nonlinear and complex connectedness between the geopolitical risk and energy markets, and mostly focused on utilizing econometric methods to examine the correlation between them from the perspective of time series (Song et al., 2019; Zheng et al., 2021).

To examine the spillover effects of risk under extreme event shocks from spatial perspective, scholars have begun to employ complex network tools for analysis (Diebold and Yilmaz, 2012; 2014; Gong et al., 2019b). Previous studies of network spillover effects on tail risks, however, have mainly centered on the financial field (Billio et al., 2012; Acharya et al., 2017). Indeed, from the standpoint of network connectedness, complex network tools facilitate the examination of tail risk spillover effects between existing and new energy markets (Wang et al., 2016; Wu et al., 2021). Tan et al. (2020) conducted research to evaluate the regional correlation spillover and dynamic effects that the European carbon market had on other financial markets. Nevertheless, these studies did not take into account the special characteristics of the energy market during extreme events. Under the impact of extreme events, the energy market presents typical characteristics of tail risk, which is specifically manifested in the peak and fat tail features of the distribution of energy price returns (Gong et al., 2019a). Geopolitical risk is closely related to energy price volatility due to its tail risk feature. Extreme events such as Geopolitical conflicts can affect crude oil supply and demand while spreading panic, which in turn affects crude oil prices (El-Gamal and Jaffe, 2018). Compared with the traditional risk spillover network based on variance decomposition, the tail risk network can compensate for the shortage of neglecting extreme risks in the traditional network measurement. As a result, this paper will firstly examine the tail risk contagion mechanism in energy markets under extreme event shocks using tail risk network, and then incorporate the statistical characteristics under extreme event shocks into the model to measure the complex interconnectedness of tail risk contagion more accurately between geopolitics and international energy markets.

Along with the frequent occurrence of geopolitical crises, the price of crude oil market fluctuates violently. The global geopolitical game has also become more intense as a result of the development of the crude oil market structure, and there is close relationship between geopolitical risks and global crude oil markets. But further study is still needed to determine the strength, direction, and information-transmission issues between them. The relationship between the volatility of the price of crude oil and geopolitics belongs to a multi-subject, interconnected, and complex systemic issue. Multilayer complex network tools can be utilized to analyze complex spillover effects characterized by heterogeneous attributes (Buldyrev et al., 2010). Hence, we employ the two-layer network tool to investigate the multi-agent complex connectedness effect between crude oil price volatility and geopolitics. The study of multi-layer networks is only in its infant stages at this point, and most of them pay attention to different types of financial institutions in the financial field (Poledna et al., 2015; Aldasoro and Alves, 2018). Moreover, the multi-layer network composed of the connectedness of different attributes adopted in this paper is less involved. Based on examining the tail risk spillover effect among international energy markets, this paper further constructs the international crude oil-geopolitics two-layer network analysis framework. Using the risk spillover profile of the two-layer network, we can then identify the mechanisms driving the risk contagion between international crude oil price volatility and geopolitics.

The connectedness effect between international crude oil markets and geopolitical risks is time-varying. Moreover, the multi-agent complex system between multi-layer networks is dynamic, and the tail risk network of international crude oil markets and geopolitical risk network under the impact of extreme events are also time-varying. In consequence, it is important to study dynamic crude oil-geopolitics two-layer networks. The dynamic network structure in different frequency domains is proposed to capture the cyclical nature of dynamic network changes (Baruník and Křehlík, 2018; Baruník and Ellington, 2020), given that economic activities do not affect the economic system to the same extent in different frequency domains. This paper constructs innovative dynamic networks in the frequency domain to examine the periodic patterns of international energy networks and geopolitical networks in order to reveal the dynamic and periodic changes of international crude oil markets and geopolitical risk contagion under the influence of extreme events. In addition, to investigate the dynamic effect of international crude oil-geopolitics interconnectedness, we examine the dynamic changes of the international crude oil-geopolitics two-layer network from the dynamic network perspective. On this basis, we adopt the machine learning method to investigate the early warning effect of the international crude oil-geopolitical interconnectedness on the tail risk of international oil markets. The research findings can help countries to prevent cross-risk contagion between crude oil markets and geopolitical relations.

3. Model framework

3.1. Tail risk spillover effects in international energy markets

At present, all countries regard carbon emission reduction as an important strategic goal. The continuous development of renewable energy is related to traditional energy security (Ji and Zhang, 2019). New energy stocks are usually used to hedge traditional energy risks. This section will study the risk contagion between traditional energy markets and new energy markets, as well as the effect of extreme events on the risk spillover effect between international energy markets. This paper will use the TENET model of Härdle et al. (2016) to construct the tail risk network connectedness among energy markets. The TENET model extends the bivariate CoVaR model and adopts a nonlinear correlation estimation method, which is more suitable for analyzing risk spillovers among multiple energy markets. At the same time, compared with the traditional CoVaR indicator that measures systemic risk, the TENET model not only introduces macro factors that affect tail risk spillover between energy markets for analysis, but also takes into account the risk contagion between one energy markets and all other energy markets in the model. Besides, geopolitical conflicts as extreme events can affect macro-state variables and the intensity of risk contagion among markets. The value-at-risk (VaR) of international energy markets is firstly estimated using macro-state variables and the log returns of each market to assess the possible losses from different event shocks to each energy market to measure systemic risk. Secondly, the single-index model for the generalized quantile regression framework is used to calculate the tail risk connectedness network.

$$X_{j,t} = g\left(\beta_{j|R_j}^{\mathrm{T}} R_{j,t}\right) + \varepsilon_{j,t} \tag{1}$$

$$\mathrm{CoVaR}^{\mathrm{TENET}} \equiv \widehat{g}\left(\beta_{j|R_j}^{\mathrm{T}} \widetilde{R}_{j,t}\right) \tag{2}$$

$$\widehat{D}_{j|\tilde{R}_j} \equiv \frac{\partial \widehat{g}\left(\widehat{\beta}_{j|\tilde{R}_j}^{\mathrm{T}} R_{j,t}\right)}{\partial R_{j,t}}\Big|_{R_{j,t}=\tilde{R}_{j,t}} = \widehat{g}'\left(\widehat{\beta}_{j|\tilde{R}_j}^{\mathrm{T}} \widetilde{R}_{j,t}\right)\widehat{\beta}_{j|\tilde{R}_j} \tag{3}$$

where $X_{j,t}$ represents the energy market's volatility at time t, $R_{j,t} \equiv \{X_{-j,t}, M_{t-1}\}$. $X_{-j,t} \equiv \{X_{1,t}, X_{2,t}, \ldots, X_{k,t}\}$ represents the introduced explanatory variables, which includes volatility of energy markets other than market j, where k is the quantity of energy markets. $M_{t\text{-}1}$ is the macro-state variable. $\beta_{j|R}$ includes the composition of $\beta_{j|-j}$ and $\beta_{j|M}$, $\beta_{j|-j}$ denotes the degree of spillover from other energy markets to j, and $\beta_{j|M}$ is the degree of influence of macroeconomic variables on market j. $\mathrm{CoVaR}^{\mathrm{TENET}}$ reflects the systemic risk of energy markets in extreme conditions and can be used to represent energy market tail risk.

By deriving $\mathrm{CoVaR}^{\mathrm{TENET}}$ to obtain $\widehat{D}_{j|\tilde{R}_j}$, the adjacency matrix A_s of the tail risk network can be calculated. As a result, the international energy market tail risk spillover network is developed using the adjacency matrix.

$$A_s = \begin{array}{c} \\ I_1 \\ I_2 \\ I_3 \\ \vdots \\ I_k \end{array} \begin{array}{c} \begin{array}{ccccc} I_1 & I_2 & I_3 & \cdots & I_k \end{array} \\ \begin{pmatrix} 0 & \left|\widehat{D}^s_{1|2}\right| & \left|\widehat{D}^s_{1|3}\right| & \cdots & \left|\widehat{D}^s_{1|k}\right| \\ \left|\widehat{D}^s_{2|1}\right| & 0 & \left|\widehat{D}^s_{2|3}\right| & \cdots & \left|\widehat{D}^s_{2|k}\right| \\ \left|\widehat{D}^s_{3|1}\right| & \left|\widehat{D}^s_{3|2}\right| & 0 & \cdots & \left|\widehat{D}^s_{3|k}\right| \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \left|\widehat{D}^s_{k|1}\right| & \left|\widehat{D}^s_{k|2}\right| & \left|\widehat{D}^s_{k|3}\right| & \cdots & 0 \end{pmatrix} \end{array} \quad (4)$$

According to the above risk spillover matrix, this paper calculated TC_s, which represents the total connectedness of international energy markets, where $TC_s = TC_s^{IN} = TC_s^{OUT} = \sum_{i=1}^{k}\sum_{j=1}^{k}\left|\widehat{D}^s_{j|i}\right|$. TC_s^{IN} and TC_s^{OUT} denote the total risk import and the total risk export in the energy markets. Then for the single energy market, we define the total risk import in energy market j as the risk export to j from other energy markets, denoted by $\sum_{i=1}^{k}\left|\widehat{D}^s_{j|i}\right|$. The total risk export in energy market j is defined as $\sum_{j=1}^{k}\left|\widehat{D}^s_{j|i}\right|$.

3.2. International crude oil markets and geopolitical risk spillover effects

Geopolitical conflicts are directly tied to crude oil markets, and there is a reciprocal relationship between geopolitical risk and crude oil price volatility. This section will examine the intensity, direction and other risk contagion patterns between geopolitics and crude oil markets. The fat-tail characteristics of the crude oil market are incorporated into the calculation of volatility, and then the variance decomposition spillover network method is used to examine the risk contagion effects between geopolitics and international crude oil markets. This is done with the consideration of tail characteristics exhibited by the international crude oil market in response to extreme event shocks. The distribution of energy market returns under the impact of extreme events exhibits the characteristics of leptokurtosis, fat-tail, and skewness, and presents volatility and heteroscedasticity effects. Thus, the above-mentioned atypical features need to be taken into account when characterizing the tail risks in energy markets. The stochastic volatility GARCH model can effectively fit the heteroskedasticity and long memory of time series. In addition, the EGARCH model may characterize the asymmetries of return volatility. In particular, the error term of asset returns is assumed to follow the skewed generalized error distribution (SGED) to more closely match the skewness, leptokurtosis, and fat-tail characteristics of energy market tail risk.

$$\begin{aligned} & y_t = \mu_t + \varepsilon_t, \varepsilon_t = \sqrt{h_t} z_t, \\ & \ln h_t^2 = \alpha_0 + \sum_{j=1}^{q}\beta_j \ln h_{t-j}^2 + \sum_{j=1}^{p}\alpha_j\left|\frac{\varepsilon_{t-i}}{h_{t-i}}\right| + \gamma_j\frac{\varepsilon_{t-i}}{h_{t-i}} \end{aligned} \quad (5)$$

where the EGARCH model does not have any restrictions on α_j, β_j. The asymmetric effect of information shocks is illustrated by introducing the parameter γ. The asset return error term z_t is assumed to adhere to the skewed generalized error distribution (SGED) with density function equation presented in Eq (6).

$$f(x|\mu,h,v,\lambda) = \frac{v}{2\theta h}\Gamma\left(\frac{1}{v}\right)^{-1}\exp\left(-\frac{1}{1+sign(x-\mu+\delta h)\lambda^v\theta^v h^v}|x-\mu+\delta h|\right) \quad (6)$$

where v represents the tail thickness parameter for the returns distribution and λ represents the skewness parameter, and $\theta = \Gamma(1/v)^{0.5}\Gamma(3/v)^{-0.5}S(\lambda)^{-1}$, $\delta = 2\lambda AS(\lambda)^{-1}$, $A = \Gamma(2/v)\Gamma(1/v)^{-0.5}\Gamma(3/v)^{-0.5}$, $S = \sqrt{1+3\lambda^2-4A\lambda^2}$.

After estimating crude oil market volatility under extreme event shocks, this research employs Antonakakis et al.'s (2019) TVP-VAR based variance decomposition network spillover approach to study the contagion effect between geopolitical risks and international crude oil markets. The variance contribution $d_{ij}(h)$ reflects the extent to which the energy market is influenced by itself or by other markets.

$$d_{ij}^H = \frac{\sigma_{ii}^{-1}\sum_{h=0}^{H-1}\left(\boldsymbol{e}_i'\mathbf{A}_h\Sigma\boldsymbol{e}_j\right)^2}{\sum_{h=0}^{H-1}\left(\boldsymbol{e}_i'\mathbf{A}_h\Sigma\mathbf{A}_h'\boldsymbol{e}_i\right)} \quad (7)$$

where $\sum$ is the covariance matrix of the disturbance vector $\boldsymbol{\varepsilon}_t$, σ_{ii} is the standard deviation of $\boldsymbol{\varepsilon}_t$. Besides, $i, j = 1 \ldots, N$, $i \neq j$. In Equation (7): H indicates the forecast time; h is the lag order of the interference vector.

The variance decomposition matrix $D_{ij}(h)$ is comprised of the elements $d_{ij}(h)$. $D_{ij}(h)$ can be utilized to characterize the risk contagion between the geopolitics and international crude oil market based on the variance contribution Eq. (7). The capacity of market i to take risk is shown by the sum of row i in $D_{ij}(h)$, which also shows the tail risk spillover from the other markets to market i. The sum of column j in $D_{ij}(h)$ shows both the capacity of market i to transfer risk and the extent of risk spillover from market j to all other markets. The difference between the capacity to transfer risk and the capacity to take risk is known as the net spillover level.

$$D_{ij}(h) = \begin{pmatrix} d_{11} & d_{12}\cdots d_{1N} \\ d_{21} & d_{22}\cdots d_{2N} \\ \vdots & \vdots \ddots \vdots \\ d_{N1} & d_{N1}\cdots d_{NN} \end{pmatrix} \quad (8)$$

3.3. Two-layer network of international crude oil and geopolitics

This section will construct an international crude oil-geopolitics two-layer network to find the complex risk contagion effects between geopolitical risks and crude oil markets in order to further analyze the risk spillover mechanism between the geopolitics and international crude oil market. Inter-layer degree correlation is a significant topological measure of the similarity between the layers of networks. The degree correlation of inter-layer shows the similarity of varying the same country's degree centrality indicator in the oil risk contagion network layer and the geopolitics network layer in the international crude-geopolitics two-layer network. The calculation is shown below.

$$\rho^{(a,b)} = \frac{\sum_i\left(Z_i^a - \widetilde{Z}^a\right)\left(Z_i^b - \widetilde{Z}^b\right)}{\sqrt{\sum_i\left(Z_i^a - \widetilde{Z}^a\right)^2\sum_j\left(Z_i^b - \widetilde{Z}^b\right)^2}} \quad (9)$$

where Z_i^a stands for the average rank of nodes in the network layer and $\widetilde{Z}$ stands for the rank of node i in the a-layer.

In the international crude-geopolitical two-layer connectedness network, the average global edge overlap index can depict inter-tier correlation. In the N-layer network ($N \geq 2$), nodes i and j may exist in more than one network layer, and the edge overlap is the ratio of the network layers in which nodes i and j are connected to the total number of network levels. For the two-layer network consisting of the crude oil network layer and the geopolitical risk network layer, N equals 2 and its overlapping edges (i, j) are denoted as o_{ij}. Based on this, we can calculate o_{ij} (the average global edge overlap index). $a_{ij}^{[\alpha]}$ is an α-layer adjacency matrix's element. K is the quantity of edges in a network layer.

$$o_{ij} = \frac{1}{N}\sum_{\alpha=1}^{N} a_{ij}^{[\alpha]} \quad (10)$$

$$\langle o \rangle = \frac{1}{N\sum_{i,j} a_{ij}}\sum_{ij} o_{ij} = \frac{1}{2NK}\sum_{ij} o_{ij} \quad (11)$$

Several centrality metrics are also employed to further examine the two-layer network in this article to find systemically important economies of international crude oil-geopolitics two-layer network. Strength centrality in a multi-layer network is the sum of a node's linked edge weights, which shows the nodes' direct effect. The PageRank centrality ranking of a node is determined by the quality and quantity of nodes pointing to it. The Katz centrality index denotes the variant of the eigenvector centrality index, assuming that the influence weight of nodes in the neighborhood of different distances is attenuated.

3.4. International energy market and geopolitical risk dynamics network

Based on the international crude oil-geopolitical risk two-layer network, this research continues to establish the dynamic network employing the risk spillover effects in the frequency domain framework established by Baruník and Ellington (2020). The frequency domain response at different frequencies, which correspond to different times of external shocks, is given by dynamic spectral decomposition of the matrix in Eq. (7). The high-dimensional dynamic network is obtained by measuring the time-varying adjacency matrix in various frequency domains. Transform the signal in the time domain with the Fourier transform to obtain the error variance decomposition in the frequency domain band of Eq. (12), where $[\boldsymbol{\theta}(u,d)]_{j,k}$ is the set of frequency domain solutions resulting from variance decomposition in the time domain. However, it is challenging to calculate the dimensionality of high-dimensional time-varying networks. The Bayesian estimating approach reduces the prior setting to increase the computing efficiency of the point estimate (Geraci and Gnabo, 2018).

$$[\boldsymbol{\theta}(u,d)]_{j,k} = \frac{\sigma_{kk}^{-1}\int_a^b \left|\boldsymbol{\Psi}(u)e^{-i\omega}\sum(u)\right|^2 d\omega}{\int_{-\pi}^{\pi}\left[\{\boldsymbol{\Psi}(u)e^{-i\omega}\}\sum(u)\{\boldsymbol{\Psi}(u)e^{+i\omega}\}^{\mathrm{T}}\right]_{j,j} d\omega} \tag{12}$$

3.5. Machine learning based tail risk warning for international crude oil market

Following the crisis that occurred between Russia and Ukraine, numerous nations' attention has been drawn to the interconnectedness of the risks associated with geopolitics and crude oil markets. The machine learning approach is utilized to forecast international crude oil market tail risk by way of the connectedness between geopolitics and international crude oil market. This is done to further investigate whether the connectedness between international crude oil markets and geopolitics can effectively warn the crude oil market of tail risks.

In terms of applying machine learning to the field of management, Gong et al. (2019c) proposed the LS-SVM-IPSO machine learning method for stock price volatility prediction. This paper continues this machine learning method by training and testing the level of tail risk in crude oil markets using the international crude oil-geopolitics two-layer connectedness network, the crude oil risk connectedness network, and the geopolitical connectedness network indicators to test whether the selected representative indicators are good at warning the tail risk.

LS-SVM denotes the support vector machine with quadratic loss function as the empirical risk. It replaces the inequality constraint with equation constraint and transforms the training of the model into linear solutions of the equation, which simplifies the computation process, shortens the training time and has more deterministic training results. Since the least squares-support vector machine (LS-SVM) technique has strong predictive power, the improved particle swarm optimization (IPSO) algorithm is used to optimize the parameters of the LS-SVM technique in the stock return volatility prediction process. In this study, we focus on the machine learning based LS-SVM method, in which the multi-region adaptive particle swarm algorithm is used for parameter estimation. Gong et al. (2019c) compares the individual AGARCH-nG model, the hybrid AGARCH-nG-ANN method, and the data mining based LS-SVM-IPSO methods for stock market forecasting performance. The empirical results validate the effectiveness and superiority of the method, showing that the LS-SVM-IPSO method outperforms non-Gaussian distributed AGARCH-type models and models integrated with artificial neural network methods. The optimized least squares-support vector machine has the most promising prediction performance with the lowest prediction error compared with other machine learning methods, while providing higher modelling accuracy, closer degree of approximation, and better generalization, making it an efficient and superior overall prediction method.

The sample set is separated into two parts by LS-SVM: a training sample set and a testing sample set. $x_i \in R^N$ represents the input of the sample, and $y_i \in R$ represents the output of the sample. For nonlinear systems, the nonlinear function can be expressed as a kernel space mapping function $\varphi(\cdot)$ and a weight vector $w \in R^N$ in the functional form $f(x) = w^{\mathrm{T}}\varphi(x)+b$. The following equation expresses the LS-SVM regression optimization problem.

$$\begin{aligned} &\min_{w,b,e} J(w,e) = \frac{1}{2}w^T w + \frac{C}{2}\sum\nolimits_{i=1}^{l} e_i^2 \\ &s.t.\ \ y_i = w^T\varphi(x_i) + b + e_i, i = 1, 2, ..., l \end{aligned} \tag{13}$$

where $e_i \in R$ denotes the error variable, b denotes the amount of deviation, and C represents the regularization parameter. Further, the Lagrangian function can be written in the following form, where $\alpha_i \in R$ is the Lagrangian multiplier.

$$L(w,b,e;\alpha) = J(w,e) - \sum\nolimits_{i=1}^{l}\alpha_i\left(w^T\varphi(x_i) + b + e_i - y_i\right) \tag{14}$$

4. Empirical research

4.1. Data

In the tail risk network of the international energy market, this paper selects the Oil Index (OIL) and Natural Gas Index (GAS) of the NYSE as the indicators of the traditional energy market. The NASDAQ-OMX Group's Green Economy Index family is utilized for the clean energy industry, which includes Biofuels (BIO), Geothermal Energy (GEO), Solar Energy (SOLAR), Wind Energy (WIND) and Fuel Cell (FUEL). We calculated the log returns of each energy market using daily closing prices. The data for each energy market covers the period from January 2017 to February 2022 and sourced from https://cn.investing.com/. According to Härdle et al. (2016) and Xu et al. (2021), the macro state variables of tail risk network in energy market include: (1) the implied volatility index VIX published by the Chicago Board Options Exchange; (2) short-term liquidity spread, and (3) the Standard & Poor's (S&P500) index returns.

The risk contagion effect among international energy markets is intensifying under the extreme event shock. The crude oil market, in particular, has shown dramatic fluctuations due to geopolitical events, as shown in Table 1. The geopolitical nature of crude oil means abnormal oil price variations is often an important influence on geopolitical conflicts. According to the monthly crude oil production statistics published on the UN Commodity Trade website (http://comtrade.un.org), in the international crude oil-geopolitics two-layer network, we have selected geopolitical risk index and crude oil spot prices for the top eight nations with the highest crude oil production. The eight countries are the United States (USA), China (CHN), Canada (CAN), Russia (RUS), Mexico (MEX), Norway (NOR), Saudi Arabia (SAU) and Iraq (IRQ), with monthly data covering the timeframe of January 2006 to December 2021. The eight oil-producing countries selected for this paper account for 62.50% of the world oil production and 60.99% of the world crude oil production in 2020. The data source of the geopolitical risk index comes from https://www.matteoiacoviello.com/gpr.htm website.

4.2. The tail risk spillover effect of international energy markets

The world's interactions have grown more complex during the past five years as a result of the regular occurrence of geopolitical events like

Table 1
Geopolitical conflict and crude oil price.

Time	Geopolitical conflict events	Brent crude oil spot price (USD/ barrel)	WTI crude oil spot price (USD/ barrel)
2001/09	9/11 attacks	25.62	26.20
2001/10	War in Afghanistan	20.54	22.17
2003/03	War in Iraq	30.61	33.51
2005/07	London bombing	57.52	59.00
2013/08	Syria crisis escalates	111.28	106.57
2014/03	The Crimea incident	107.48	100.80
2015/11	Paris terrorist attacks	44.27	42.44
2018/04	Syrian missile attack	72.11	66.25
2020/01	Tensions escalate between U.S. and Iran	63.65	57.52
2022/03	Russia-Ukraine conflict	117.25	108.50

the escalation of the Iran nuclear dispute, trade tensions between China and the US, the conflict in Syria, and the all-out conflict between Russia and Ukraine. The abrupt COVID-19 outbreak has also made the international political and economic environment more difficult. Fig. 1 shows the time-varying characteristics of the total connectedness (Total connectedness) and systemic risk level (Average λ) of the international energy market in order to indicate the risk contagion effect of the international energy market. As can be seen in the figure, the total connectedness of the international energy market has increased in 2017. Meanwhile, in this year, global geopolitical conflicts such as the escalation of tension between North Korea and the US, the independence referendum held in the Kurdish Autonomous Region of Iraq, and the Saudi anti-corruption campaign have occurred frequently. It is clear that geopolitical tensions go hand in hand with the degree of the international energy market's risk connectedness. The level of average λ has risen as a result of the emergence of Sino-US trade tension in 2018 and the escalation of trade tension in 2019. The average λ and total connectedness of the international energy market increased dramatically and reached its maximum level in April as a result of the global epidemic in 2020. With the macroeconomic recovery and economic stimulus plans of various countries after the epidemic, the degree of the international energy market's tail risk has declined. However, affected by geopolitical events such as the withdrawal of US troops from Iraq in 2021 and the Russo-Ukrainian war in 2022, the international energy market's total connectedness remains high. Based on the pattern shown in the level of tail risk in international energy markets, the volatility in international energy markets is closely influenced by geopolitical events.

Under the complicated geographical situation, the price of traditional energy fluctuates violently, and the development of clean energy is rapid. The dynamic characteristics of risk spillovers in the international energy market is depicted in Fig. 2. From the traditional energy and renewable energy markets, it can be determined that geopolitical events have a greater impact on the fossil fuel market, particularly the oil market. In 2017, the amount of risk spillover in the oil market increased as a result of a number of geopolitical events, including the crisis on the Korean Peninsula, the referendum on Kurdish independence, the referendum on Catalan independence, and the anti-corruption campaign in Saudi Arabia. At the same time, the escalation of Sino-US trade frictions in 2019, as well as US sanctions against Iran and Venezuela, also triggered a surge in the level of risk spillovers in the oil market. This is due to the fact that geopolitical conflicts will impact the production of oil by oil-producing nations, and the mismatch between oil demand and supply will generate volatile oil price changes and intensify the risk spillover effect. On the one hand, geopolitical risks usually affect the oil supply policies of oil-producing countries and lead to increased price volatility and uncertainty. On the other hand, geopolitical risks will affect economic activities to some extent, thus creating uncertainty in oil demand (Liu et al., 2019). At the same time, political unrest, military conflicts or extreme weather events have played important role in causing global energy prices to rise. Therefore, uncertainty from geopolitical conflicts can also generate great impact on the energy market by changing investors' psychological expectations and dampening investment activities and economic growth (Asif and Muneer, 2007).

With the emergence of COVID-19 at the beginning of 2020, the degree of risk spillover in the oil and gas markets skyrocketed and peaked. And the degree of risk contagion is far higher in the fossil fuel industry than in the market for renewable energy. This is because the global supply chain was broken during the epidemic, disrupting the supply of fossil fuels like oil and natural gas. Besides, the energy market experienced sluggish demand during the economic recession, which led to a sharp decline in the price of traditional fossil fuels like oil, which in turn increased the spillover effects of risk. This indicates that geopolitical crises might amplify risk spillover in international energy markets.

This study also uses nonlinear CoVaR to determine the dynamic variations in the systemic risk level in the international energy market. As can be observed, the conventional energy market is more severely affected by extreme events like epidemics than the clean energy market (Umar et al., 2022), and the traditional energy industry's change range of systemic risk is more substantial than that of the clean energy market. The outbreak of COVID-19 has led to the suspension of work and production in various countries and the disruption of supply chains, and the energy demand of the international community has dropped sharply. In addition, the conflict over oil pricing between Saudi Arabia and Russia has caused erratic price swings on the energy market. It demonstrates that, in order to avoid systemic risk contagion, it is very important to explore the connections among the risk contagion of the oil market and geopolitics.

4.3. Tail risk network of international energy markets

As illustrated in Fig. 3, the tail risk network of the international energy markets is constructed with different markets acting as the network's nodes and tail risk contagion intensity among energy markets acting as the network's edges in order to evaluate the spatial contagion impact of tail risk in the international energy market. In the international energy market's tail risk contagion network, there is strong risk contagion effect between the oil and natural gas market. However, the risk spillover effect among the clean energy and the traditional energy is

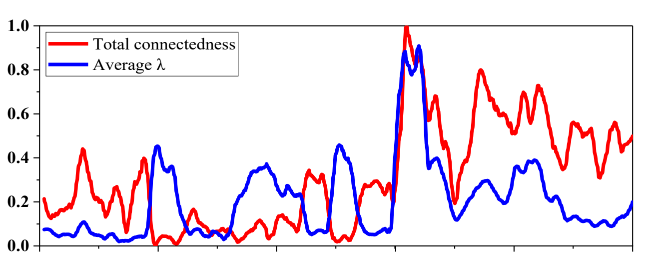

Fig. 1. Tail risk level of the international energy market.

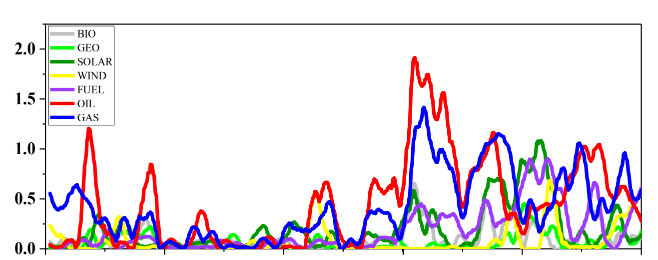

Fig. 2. Tail risk spillover of the international energy market.

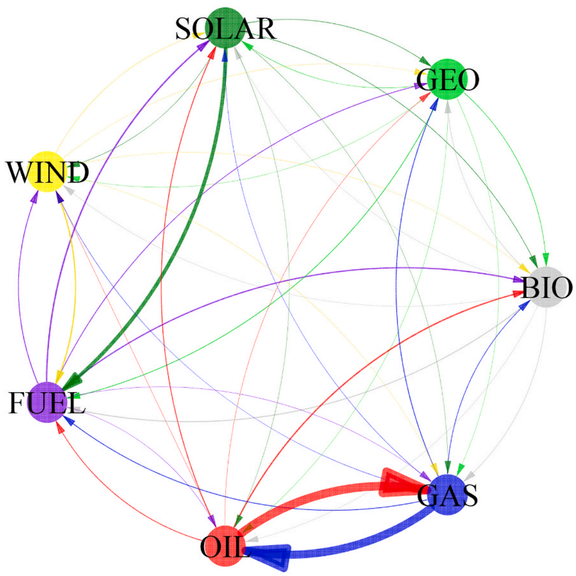

Fig. 3. Tail risk network of the international energy market.

relatively weak. Therefore, when the traditional energy market is shocked by extreme events and the tail risk level increases, investors can choose the clean energy market for hedging to diversify risks. Research findings provide evidence support for countries to vigorously develop clean energy as an alternative to traditional energy for preventing energy risks.

Oil market plays a crucial role in the tail risk contagion of the international energy market. and is shown to have the greatest intensity of risk contagion in the tail risk network of that market. It is also shown to be the major risk spillover party. Oil serves as the economic backbone of the country, thus oil shocks will generate big influence on the stock market (Broadstock et al., 2012). The spot price of oil is more susceptible for geopolitical disputes than the oil index. This paper establishes the tail risk network of the international crude oil market by using major oil-producing countries' crude oil volatility. The total connectedness of the international crude oil market is depicted in Fig. A. 1 of Appendix A due to space restrictions. The dynamic changes in risk export and risk import of the international crude oil market are shown in Fig. A. 2 and A. 3 of Appendix A. It is also found that risk spillover effects in crude oil markets is closely related to geopolitical conflicts.

This article continues to examine the spatial dimension of the direction and severity of risk contagion on the international crude oil market. The tail risk network of the international crude oil market is created, as illustrated in Fig. 4, using the main oil-producing nations as network nodes and the risk spillover link between the crude oil markets of the major oil-producing nations as network edges. It is found in the figure that the US has the highest risk spillover intensity among all countries, and Canada acts as the main risk importer of the US. Because the WTI in the United States is one of the three benchmark oil that are used in the market for oil around the world, it determines the significant position that US crude oil holds in this market. Moreover, the United States is Canada's largest oil trading country, which makes the crude oil market' tail risk spillover to the Canadian crude oil market. The crude oil market presents significant cross-border risk contagion phenomenon.

The tail risk network of the crude oil market in 2014 was chosen for comparative analysis when the geopolitical situation was tense to further investigate the law of risk contagion in the international oil market when it was influenced by geopolitical conflicts. This was done so that the pattern of risk contagion could be better explored. In 2014, geopolitical conflicts such as the conflict in Russia and Ukraine, the Iraqi civil war, the Palestinian-Israeli conflict, and the Syrian war followed one after another, resulting in sharp volatility in crude oil prices. In

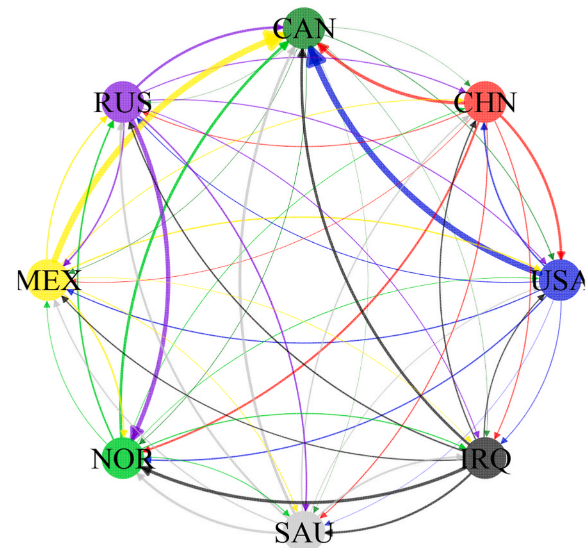

Fig. 4. Tail risk network of the international crude oil market.

Fig. 5, Russian oil market generates significant risk spillovers to the Canada's crude oil markets, China, US, and Norway. Compared with the connectedness network in the all period, the risk export level of the Iraqi crude oil market to the US and Canadian crude oil markets has also increased significantly. The comparison results show that geopolitical risk has dramatically enhanced the risk contagion in the international crude oil market. Geopolitical conflicts have become an important factor influencing risk contagion in the international crude oil market. To ensure energy security, countries should avoid the risk contagion of the crude oil market caused by geopolitical conflicts.

4.4. *The two-layer network of international crude oil and geopolitical risks*

There is a close relationship between geopolitical risks and the volatility of traditional energy markets. And there are many interaction pathways among geopolitical crises and crude oil markets. Traditional energy represented by crude oil is regarded as the strategic resource by governments of various countries, and competition for crude oil resources often becomes an inducement for geopolitical conflicts in some

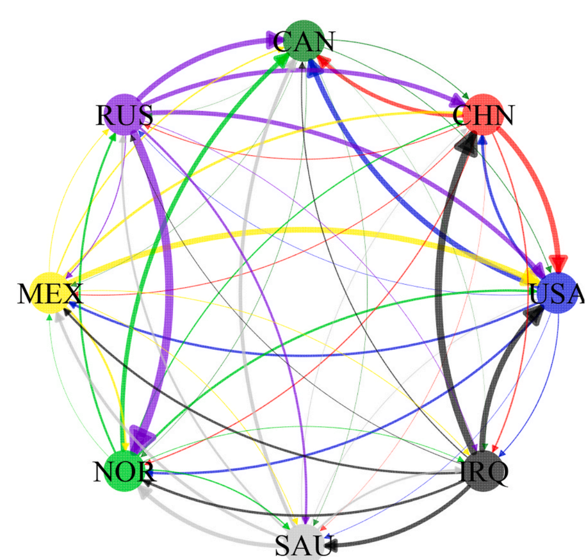

Fig. 5. Tail risk network of the international crude oil market in 2014.

countries. Moreover, violent fluctuations in crude oil prices will aggravate geopolitical risks through channels such as economic downward pressure or stock market shocks (Sharif et al., 2020). As geopolitical tensions intensify, crude oil supply will be reduced by the relevant crude oil producers. Additionally, geopolitical conflicts will impact the investment activity of neighboring nations and diminish their crude oil consumption. Frequent geopolitical turmoil can trigger changes in oil supply and demand. This is often acknowledged as a significant element influencing swings in crude oil prices (Liu et al., 2019). Geopolitical risk and crude oil price exhibit two-way nonlinear Granger causal relationship (Huang et al., 2021). Consequently, this section establishes a two-layer network analysis framework of international crude oil-geopolitical risk and investigates the complex interaction effect between the two from the perspective of spatial connectedness.

Major oil producer nations are used as the nodes of the two-tier network of global geopolitics and international crude oil. And the network edges are represented by the risk contagion effect among global geopolitical risks and the international crude oil market, as shown in Fig. 6. The lower-layer network represents crude oil market risk contagion relationships, while geopolitical risk contagion relationships represented by the upper-layer network. Network node colors and sizes in each network layer of global geopolitics and crude oil indicate their systemic importance. The strength of risk contagion is represented by the thickness of the edges in the two-layer network. By using the two-layer network built above, we can see the risk relationship between nodes more intuitively. It is impossible to overlook the cross-risk contagion between geopolitical risk and crude oil when there is cross-layer connectedness between the two-layer networks of international crude oil and geopolitics. Intra-layer risk contagion effect in the oil price fluctuation layer is much higher than that of the geopolitical risk network layer in the double-layer network. This is due to the fact that crude oil belongs to bulk commodity, not only its price fluctuations can be directly transmitted through trade channels between countries, but also the common pricing mechanism of crude oil (Ji and Fan, 2015). At the same time, the emergence of futures on crude oil and other types of financial derivatives has made the crude oil market's risk contagion even worse. As external shock, geopolitical risk mainly spreads across borders through the panic that affects market participants. This risk will affect the investment activities and economic growth of related countries, indirectly leading to the transnational contagion effect of the risk.

The structural characteristics of the international crude oil-geopolitics two-tier network can be measured by the topological

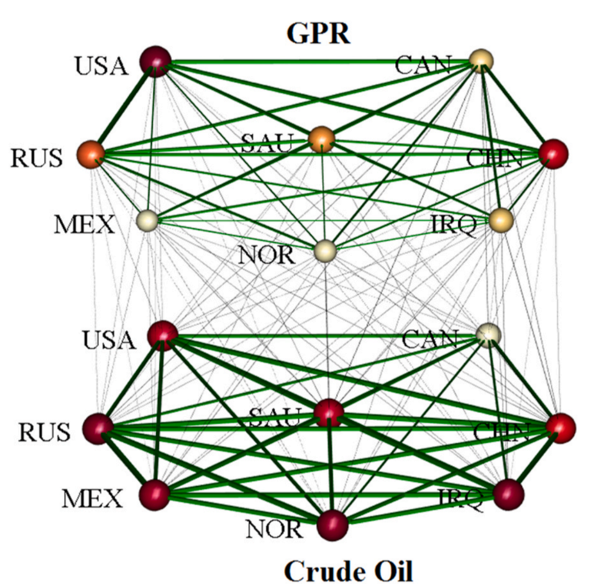

Fig. 6. Two-layer network of international crude oil and geopolitics.

indicators of the two-tier network. The geopolitical risk network layer's centrality index is substantially lower than that of the crude oil fluctuations network layer. The US and China have the highest eigenvector centrality indicators in the network in the geopolitical network, indicating that US and China play the key role in the contagion process of geopolitical risks and have a strong influence on the geopolitics of other countries. In the oil price volatility layer, it demonstrates that the major oil-producing countries across the world play a significant part in the process of risk contagion in the international market for crude oil. The US, China, and Russia all have high centrality rankings in the two-layer network of oil fluctuations and geopolitics. It means that these three countries are at the center of the intricate network of connectedness that exists between international crude oil and geopolitics. Mexico and Norway, both large crude oil producers, have risk spillover effect that is strong in the layer of the international oil volatility risk, but the risk contagion impact is smaller in the layer of the geopolitical risk network.

With the help of indicators such as edge overlap and strength centrality, PageRank, and Katz centrality, Table 2 explores the structural features in the geopolitics-international crude oil two-layer network from multiple dimensions. The connectedness among the geopolitical risk network layer and the crude oil network layer can be measured with the edge overlap metric. This metric is used to determine the strength of the relationship between the two network layers. The geopolitical risk network layer and the crude oil risk contagion network layer each have an edge overlap value of 0.61, and the average global edge overlap of the two-layer network is 90.86%. It demonstrates that the layer connectedness of the two-layer network comprising the international crude oil market and geopolitical risks is rather high, and that there is a two-way interaction impact among the layers of the geopolitical risks and oil price volatility. Table 2 not only lists the rankings of the two-layer network's three types of centrality indicators, but also compares those centrality indicators of the crude oil-geopolitics two-layer network, single-layer network, and aggregated network.

According to the comparison of centrality indicators in Table 2, it is found that the ranking of different centrality indicators in the same connectedness network is similar. For instance, using three different centrality indicators, the United States, China, and Russia all place among the top three nodes in the aggregation network. This suggests that the importance ranking of the international crude oil-geopolitics network nodes is not easily influenced by the method used to measure centrality. However, the ranking in different connectedness networks displays differences. For example, Iraq ranks low in terms of strength centrality in the geopolitical risk network but ranks third in the oil risk contagion layer. It shows that the properties of the network layer will affect the system importance ranking of nodes. The United States, China, and Russia have relatively high centrality indicators in the geopolitical risk network. In the oil tail risk contagion network, Iraq and Russia are more susceptible to contagion, though. Both are important countries for crude oil production and export, and changes in crude oil supply are key factors that causes volatility of oil prices. In the international crude oil-geopolitics double-layer network and aggregation network, the US, Russia and China still rank higher in centrality indicators.

In addition, this paper also uses the ring diagram to visually analyze the Authority centrality indicators of nodes in different networks. The top right corner of Fig. 7 designates the position of the different networks in the ring, from the inside to the outside, the geopolitical risk network, the aggregation network, the oil tail risk contagion network, and the two-tier network. The rings' changing color corresponds to the network's centrality index ranking. The similarity of node importance rankings in various networks was determined using the Pearson correlation coefficient, as indicated by the color difference between rings. In the ring diagram of the Authority centrality indicator, Canada ranks relatively low in the centrality indicators of all types of networks. Comparing the geopolitical risk layer and the crude oil price fluctuation layer in Fig. 7, it is found that there are differences in the system importance ranking of nodes in the two types of single-layer networks.

Table 2
The centrality of international crude oil and geopolitics two-layer network.

Country	Geopolitical risk			Crude oil price volatility			Double-layer network			Aggregate network		
	Strength	Page-Rank	Katz	Strength	Page-Rank	Katz	Strength	Page-Rank	Katz	Strength	Page-Rank	Katz
USA	0.96	1.00	1.00	1.43	0.97	0.96	3.12	1.00	0.87	2.39	1.00	0.94
CHN	0.80	0.90	0.92	1.53	0.95	0.94	3.25	0.97	1.00	2.34	0.95	0.96
CAN	0.82	0.72	0.66	0.81	0.70	0.70	2.68	0.91	0.59	1.64	0.72	0.68
RUS	0.86	0.82	0.83	1.53	0.99	0.99	3.15	0.92	0.96	2.40	0.96	1.00
MEX	0.53	0.63	0.57	1.58	1.00	0.98	2.93	0.85	0.96	2.11	0.87	0.88
NOR	0.46	0.61	0.60	1.23	0.94	1.00	2.51	0.87	0.65	1.69	0.84	0.56
SAU	0.67	0.77	0.78	1.56	0.97	0.96	3.07	0.90	0.99	2.23	0.91	0.92
IRQ	0.50	0.68	0.68	1.54	1.00	1.00	2.92	0.90	0.88	2.04	0.90	0.79

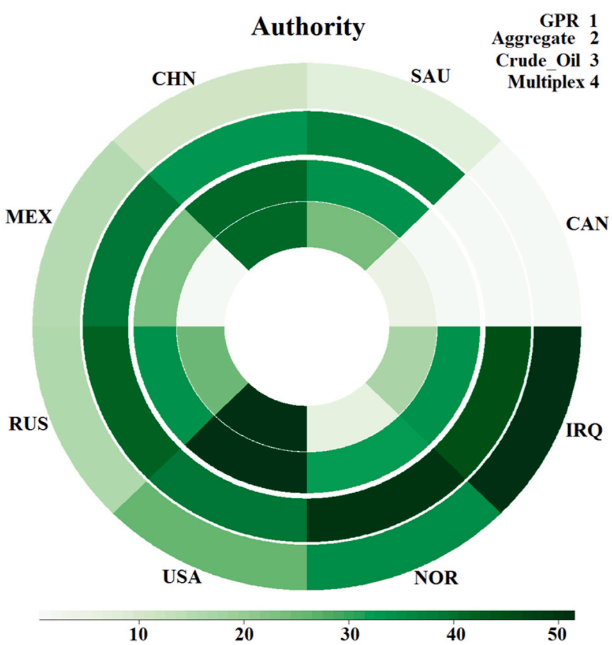

Fig. 7. Ring diagram of crude oil and geopolitics two-tier network.

The geopolitical risk network has lower overall centrality indicators compared to the oil tail risk contagion network, hence the properties of the network layer will have an impact on how important a system is ranked. The comparison between the aggregation network and the international crude oil-geopolitics double-layer network shows that different network construction methods may also have an impact on the ranking of centrality indicators. The main reason is that the projection process of the aggregation network will ignore the information of risk contagion, which may cause the deviation of centrality index calculation.

4.5. The spillover effect of international crude oil and geopolitics

The two-layer network risk spillover matrix shown in Table 3 is used to assess the risk contagion impact between geopolitical risk and the international crude oil market, along with the risk spillover effect inside the layer. In this table, the diagonal parts indicate the lag impact of the node itself, while the “From” represent the risk import and “To” represent risk export, respectively, and the “NET” shows difference between risk exports and imports. The primary diagonal results show that geopolitical risk has a longer lag than international crude oil volatility risk and is more likely to result in long-lasting shocks. Among these, geopolitical risks in Saudi Arabia, Mexico, and Norway exhibit a more pronounced lag. The “From” demonstrates that oil producing nations have a larger spillover risk in the crude oil network than in the geopolitical risk network. This is due to the crude oil volatility network’s intra-layer risk contagion impact is substantially bigger compared to the geopolitical risk layer. In particular, Iraq in the crude oil layer receives the highest level of risk import from other crude oil markets. The results obtained from the risk spillover matrix are the same as those from the two-layer network diagram. In terms of the “To” row, risk export from the international crude oil network layer remains much larger than the geopolitical risk network layer. The risk export level of China’s crude oil market is the highest in the international network for crude oil volatility. In terms of net spillover effects from the crude oil-geopolitics network, the geopolitical risk network layer is the risk receiver of the international crude oil fluctuation network layer, as evidenced by the fact that the net risk spillover of all nodes in the geopolitical risk network is negative. The contagion of risk transmits from the crude oil layer to the geopolitics network layer. The conclusion of international crude oil-geopolitics two-tier network risk spillover is a good answer to the question of “chicken or egg” between crude oil resources and geopolitics.

A detailed analysis of the risk contagion impact within and between layers may be done using the risk contagion matrix of the crude oil-geopolitics network. In terms of the layer’s risk contagion effect, the risk contagion intensity between Russia and the United States is at its highest in the geopolitical risk network layer. In the international crude oil market risk network, the intensity of risk contagion varies relatively little among crude oil markets. According to the two-layer network’s inter-layer interaction impact, the geopolitical risk posed by China’s swings in crude oil prices to Iraq shows the highest value (7.16). The nodes in the international crude oil network layer exhibit an overall greater risk contagion impact for the geopolitics layer nodes. If the complex interaction impact between the two-layer network is disregarded, it would lead to an underestimation of the intensity of risk contagion among geopolitics and oil markets.

Through the risk contagion of the geopolitics-crude two-layer network, we investigate the static relationship among the crude oil market and geopolitical risk over the sample period. But static networks reflect the average state of risk contagion among variables. Therefore, this section employs the net pairwise connectedness index to capture the dynamic features among geopolitical risks and oil price volatility. The net pairwise connectedness index aims to describe the evolution process of the magnitude and direction of risk contagion across markets. At the same time, dynamic connectedness can help us to further investigate how severe event shocks affect risk contagion mechanisms. Due to space reasons, this paper mainly selects the top three economies in the system importance of the two-tier network, namely the United States, China and Russia. Figs. 8–10 depict the three economies’ geopolitical risk in relation to the price of crude oil. For example, GPR(USA)—OIL(CHN) represents the net risk spillover effect between US geopolitical risk and Chinese oil price volatility.

In Fig. 8, except for the period from 2014 to 2017, when US geopolitical risk spillover on China and Russia crude oil was positive, the impact of China and Russia crude oil volatility on US geopolitical risk was greater in other times. During the international financial crisis, the geopolitical risks faced by the United States were significantly impacted by the ebb and flow of China’s oil prices. From 2018 to 2019, Sino-US

Table 3
Risk spillover effect of international crude oil and geopolitics two-layer network.

		GPR								OIL								From
		USA	CHN	CAN	RUS	MEX	NOR	SAU	IRQ	USA	CHN	CAN	RUS	MEX	NOR	SAU	IRQ	
GPR	USA	27.61	8.17	10.69	12.36	4.19	2.29	6.51	4.04	2.80	4.60	1.98	3.00	2.76	2.01	4.05	2.94	72.39
	CHN	9.77	30.83	8.76	8.01	5.86	2.67	5.42	2.86	2.55	3.29	3.21	3.07	3.00	3.73	3.99	2.99	69.17
	CAN	7.90	3.13	28.97	5.79	5.34	2.87	3.11	1.93	4.62	6.12	4.20	5.00	5.02	3.75	6.41	5.84	71.03
	RUS	10.44	7.74	8.35	36.96	2.31	2.50	4.08	1.80	3.83	3.58	3.44	2.71	2.83	1.99	3.67	3.75	63.04
	MEX	4.05	3.66	5.85	3.11	43.21	3.10	4.61	2.12	3.43	5.32	3.04	3.38	2.88	3.14	4.88	4.21	56.79
	NOR	3.29	4.40	5.06	6.14	3.09	41.37	3.58	1.99	3.78	5.54	3.87	3.70	3.63	3.07	4.27	3.22	58.63
	SAU	6.93	5.32	5.55	8.89	3.38	2.41	40.14	2.97	3.15	3.98	1.99	2.77	3.33	2.04	3.48	3.68	59.86
	IRQ	5.41	4.39	8.05	4.64	2.44	2.98	3.96	31.14	4.45	7.16	2.83	4.31	4.75	3.46	4.98	5.08	68.86
OIL	USA	0.90	1.49	2.49	1.55	0.98	2.39	1.23	1.07	15.86	13.52	5.52	9.74	12.42	7.11	10.93	12.79	84.14
	CHN	1.36	1.74	2.76	2.01	1.30	1.46	1.10	1.14	11.27	17.32	5.02	10.97	12.12	5.28	13.75	11.39	82.68
	CAN	1.39	1.69	5.63	3.33	1.72	3.53	2.01	0.89	9.15	9.03	28.63	6.64	8.04	4.95	6.30	7.06	71.37
	RUS	0.82	1.39	1.23	0.98	1.84	1.00	1.40	1.06	9.65	11.88	3.58	16.46	14.48	8.84	13.42	11.97	83.54
	MEX	0.86	1.42	1.89	1.15	1.25	1.68	1.04	0.84	11.52	11.98	4.45	13.60	16.25	7.85	12.14	12.06	83.75
	NOR	0.98	1.49	1.39	1.24	3.03	1.57	2.27	1.52	8.70	10.34	3.46	14.22	12.03	12.22	13.66	11.89	87.78
	SAU	1.07	1.83	1.75	1.03	2.10	1.11	1.68	1.08	9.89	13.83	4.22	12.73	11.98	6.70	16.53	12.45	83.47
	IRQ	0.88	1.79	1.37	1.04	1.47	1.30	1.46	0.93	10.87	13.09	3.85	11.77	12.97	7.82	14.46	14.90	85.10
To		56.06	49.65	70.84	61.26	40.30	32.87	43.47	26.23	99.65	123.26	54.67	107.61	112.26	71.74	120.38	111.34	TCI
NET		−16.32	−19.52	−0.19	−1.77	−16.49	−25.76	−16.39	−42.63	15.51	40.58	−16.69	24.07	28.51	−16.04	36.91	26.24	73.85

trade frictions triggered a strong risk spillover of Chinese and Russian oil price volatility to US geopolitical risks. As the epidemic swept the world in 2020, multiple shocks from the crude oil supply and demand mismatch caused the world oil market to swing wildly. Chinese and Russian oil price decline have had clear spillover effects on US geopolitical risk.

It is clear from looking at Fig. 9 that China's geopolitical risk is profoundly impacted by fluctuations of oil from Russia and the United States. Throughout the economic crisis, the unpredictability of Russia's crude oil market caused continual risk spillovers to China's geopolitics. In the early stages of the crisis, the risks presented by fluctuations in the US crude oil market and the threats posed by the geopolitical risk in China were mutually infectious to one another. After August 2008, the U.S. crude oil market's tail risk provided positive risk spillover to China's geopolitics. Moreover, the economic tensions between China and the US and the COVID-19 pandemic have been the triggers that have caused the contagion effect from Russia and the US crude oil market to China's geopolitics.

The net spillovers from Russian geopolitics and market volatility to China and US crude oil market are shown in Fig. 10. In general, the U.S. crude oil risk has a strong net spillover effect on Russia's geopolitics and lasts for a long time, especially during the COVID-19 pandemic and the global economic crisis. During 2012 to 2016, Russia's geopolitical risks had a greater impact on the volatility of China's crude oil market. Furthermore, the net pairwise connectedness index had an abnormal peak in March 2014, which was due to the Russia-Ukraine conflict, caused a surge in geopolitical risks in Russia. Since the US crude oil importers are mainly countries such as Canada, and the US has relatively high international oil pricing power, which makes the US crude oil market less affected by Russia's geopolitical risks in 2014.

4.6. International crude oil tail risk dynamic network and geopolitical dynamic network

The geopolitical connectedness network and the international crude oil market's tail risk connectedness network both exhibit dynamic, time-varying, and cyclical features when influenced by the macroeconomic cycle. As a result, this paper will further examine the dynamic changes of crude oil market tail risk network and geopolitical risk network and analyze the periodic characteristics of network dynamic changes from the perspective of frequency domain. The next part will explore the dynamic characteristics in the double-layer connectedness network.

Using the spectral representation approach of generalized variance decomposition, we can see time series diagrams of the international crude oil market dynamic network (Fig. 11) and the geopolitical risks dynamic network (Fig. 12) in different frequency domains. The average connectedness level in the high-frequency band is greater in Figs. 11 and 12, indicating that short-term shocks are predominantly responsible for the risk contagion impact of the geopolitical risk and the international crude oil market. When Figs. 11 and 12 are compared, it is clear that the geopolitical risk network's change range of connectedness in various frequency domains is much smaller compared to the international crude oil market. Additionally, geopolitical risks exhibit lower long-term and short-term risk contagion values when compared to the international crude oil market. The primary reason is because the financial characteristics of oil increase the volatile swings generated by speculation on the crude oil market. Furthermore, as strategic resource, crude oil is more vulnerable to the multiple impacts of indirect factors such as supply-demand imbalance and market sentiment, and the risk contagion effect is greater. This holds true in light of the prior conclusion. According to Fig. 11, the international crude oil market's short-term connectedness showed a downward trend while the market's long-term connectedness changed in an upward direction under the influence of extreme events like the subprime mortgage crisis in 2008, the Russia-Ukraine war in 2014, and the COVID-19 pandemic in 2020. So, under the impact of extraordinary occurrences, the short-term risk

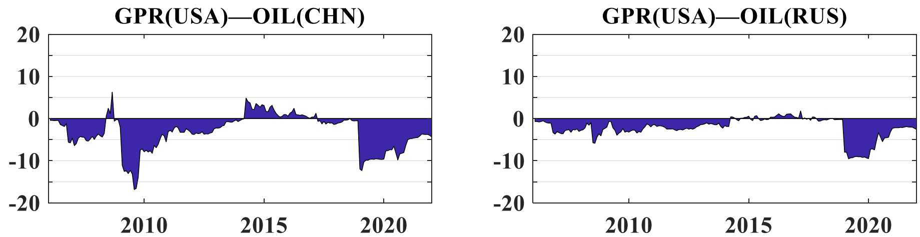

Fig. 8. Net spillover effects of U.S. geopolitical risk and oil price volatility.

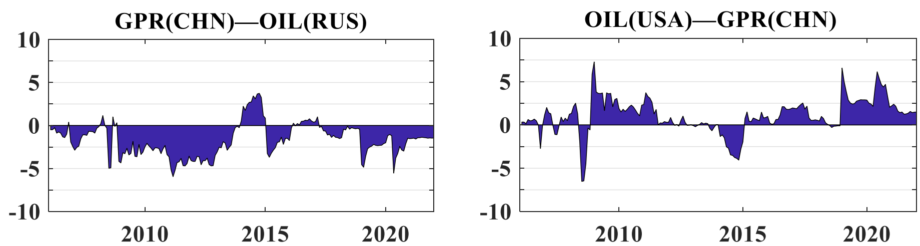

Fig. 9. Net spillover effect of China's geopolitical risk and oil price volatility.

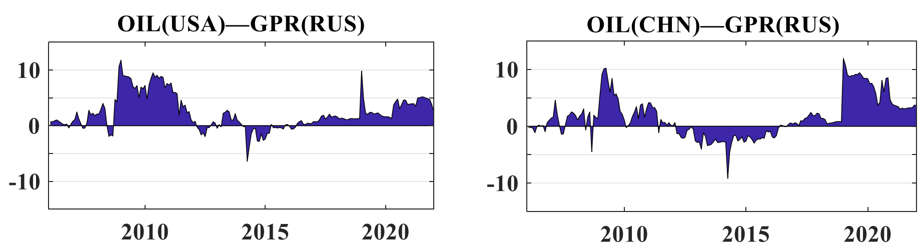

Fig. 10. Net spillover effect of Russia's geopolitical risk and oil price volatility.

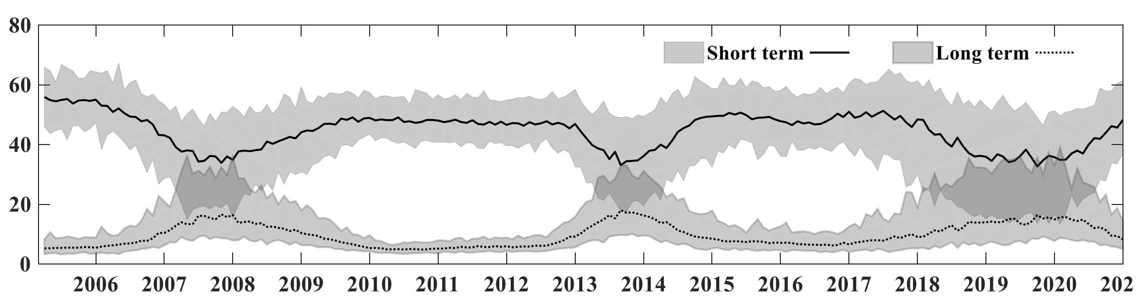

Fig. 11. Dynamic network of the international crude oil market in different frequency domains.

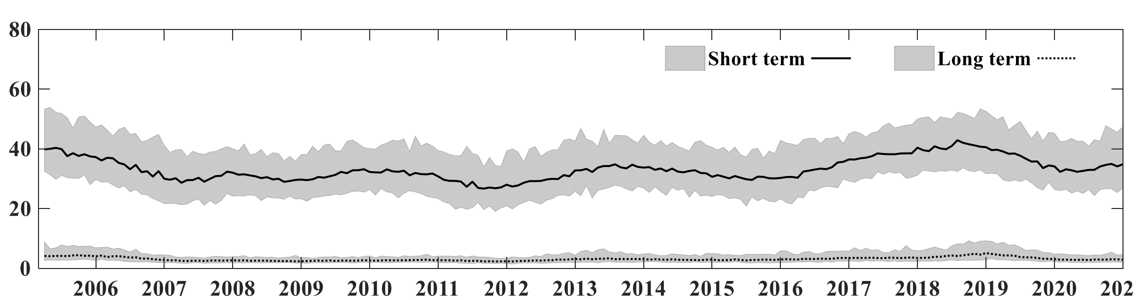

Fig. 12. Dynamic network of geopolitical risk in different frequency domains.

spillover on the crude oil market can easily be transformed into long-term risk spillover effect. In addition to avoiding short-term risk spillover effects in the international crude oil market and geopolitics, regulators should prevent the transformation of short-term risk spillover effects into long-term hazards under the influence of extraordinary events.

Following the clarification of the periodic characteristics of the crude oil market network and geopolitical connectedness network, the short-term and long-term impact networks of the two time periods with the greatest and lowest total connectedness in the crude oil and geopolitical networks are estimated, as depicted in Figs. 13–16. For example, Fig. 13 shows the period of geopolitical stability, that is, the time point when the total spillover effect of geopolitical risks was the lowest (2012/8). Fig. 14 presents the period of geopolitical shocks, that is, the time point when the risk spillover was the highest (2019/12). The upper layer in the figure is the short-term risk spillover network, and the lower layer is the long-term risk spillover network. The nodes' color and size reveal the weight of the eigenvector centrality. By contrasting Figs. 13 and 14, it can be shown that the periodic characteristics of the systemic relevance of nodes are not apparent during periods of geopolitical stability. In the period of geopolitical conflict in Fig. 14, although the importance of Norway in the short-term network has declined significantly, Canada and Iraq's systemic importance in the short-term layer is much larger than that in the long-term layer. During the period of geopolitical conflict, the systemic importance of nodes presents the characteristics of periodic heterogeneity. Overall, geopolitical concerns have considerably greater short-term spillover impacts than long-term ones.

By contrasting Figs. 15 and 16, we can see that the periodic characteristics of the importance ranking of nodes are not visible during the stable period of the international crude oil market, when the total spillover effect of the international crude oil tail risk network was the smallest (2011/6). During this period of turmoil on the international crude oil market, the maximum point of total risk spillover on crude oil market appeared in 2020. In the short-term layer, Norway and Russia's systemic significance has greatly grown, but the importance of crude oil markets such as China, Saudi Arabia, and Iraq in the short-term layer is significantly lower compared to those in the long-term layer. Therefore, the importance of nodes during the international crude oil market shocks presents the characteristics of cycle heterogeneity. Similarly, in the international crude oil market, short-term shocks account for the vast majority of tail risk spillovers. In conclusion, short-term risk spillovers are the primary source of risk contagion, and both geopolitical risk spillovers and crude oil market tail risks exhibit cyclical aspects. However, the systemic importance of networks during periods of shock exhibits periodic heterogeneity. As a result, to forestall the excessive risk contagion of crude oil fluctuations and geopolitical risks, the importance of short-term shocks should be taken into consideration, and the dynamic risk development of systemically important economies should be tracked in the short-term risk network.

4.7. Tail risk warning of international crude oil market based on machine learning

To explore the trend of international oil-geopolitics cross-risk changes at different times, we examine the dynamic change pattern of network connectedness over time using the topological indicators of the two-layer network (the average authority centrality and the eigenvector centrality in Fig. 17). During the 2008 subprime mortgage crisis, the 2016 US presidential election, and the 2020 COVID-19 pandemic, the network connectedness index increased dramatically. In 2008, affected by the global financial crisis, international oil prices collapsed, and the degree of international crude oil-geopolitical cross-risk contagion increased significantly. The high number of geopolitical events in 2014 and the US presidential election in 2016 caused severe fluctuations in international oil prices, which caused the international crude oil-

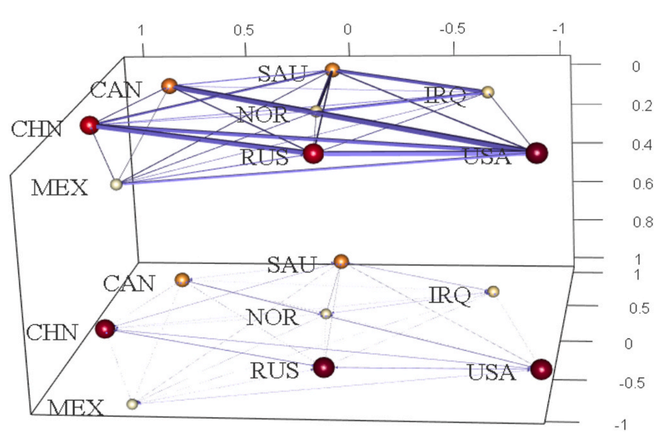

Fig. 13. Geopolitical risk networks in different frequency domains (2012/8).

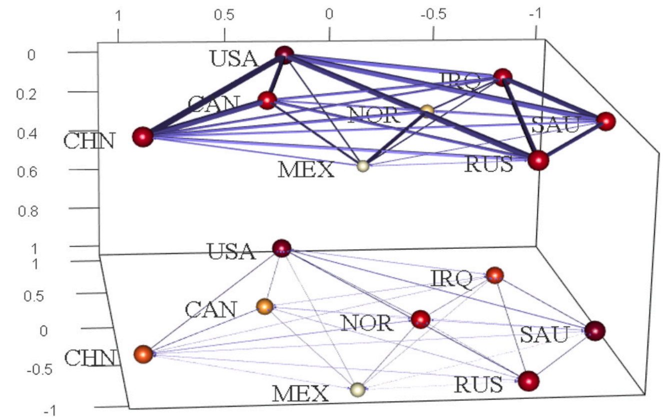

Fig. 14. Geopolitical risk networks in different frequency domains (2019/12).

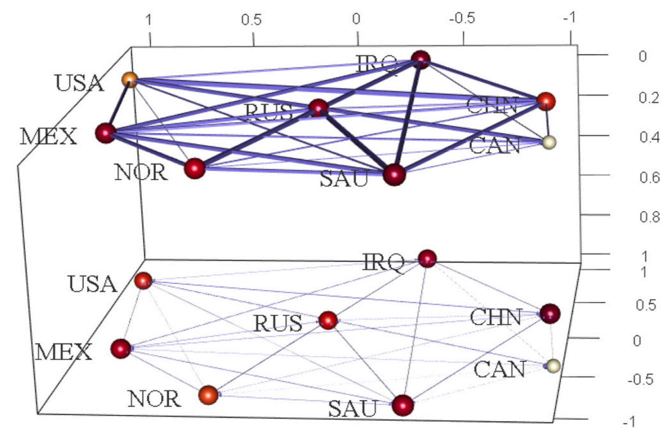

Fig. 15. Dynamic network of international crude oil market in different frequency domains (2011/6).

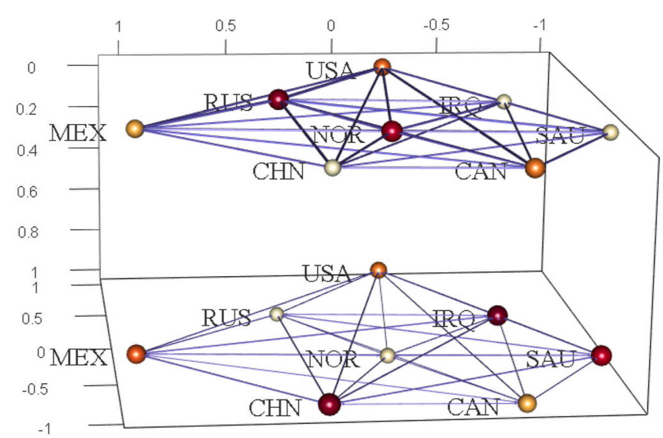

Fig. 16. Dynamic network of international crude oil market in different frequency domains (2020/9).

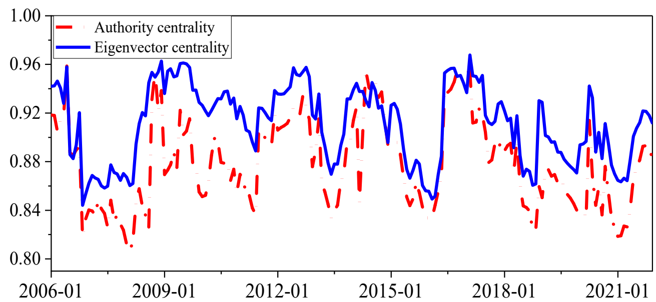

Fig. 17. Two-layer dynamic network of international crude oil and geopolitical risk.

geopolitics cross-risk level to rapidly grow to its pinnacle. It was not until early December 2016, when OPEC announced the first crude oil production reduction agreement since 2008, that the rising trend of international crude oil-geopolitics cross-risk levels began to reverse. Due to the abrupt emergence of the COVID-19 pandemic in 2020, the international crude oil-geopolitical cross-risk has risen to a high level once again. Through the crude oil-geopolitical connectedness, it is evident that geopolitical events will impact the tail risk level of the international crude oil market. As a result, this paper will investigate the early warning impact of crude oil-geopolitics connectedness on the international crude oil tail risk using machine learning methods.

Based on the dynamic effect of the international crude oil-geopolitics two-layer network, machine learning is utilized to study the early warning impact of the connectedness between international crude oil and geopolitics on the international crude oil market's tail risk. In the selection of machine learning input and output indicators, international crude oil market CoVaR values in section 4.2 are selected as the output indicators, and the input indicators contain the topology indicator values of the international crude-geopolitics connectedness network, the international crude oil network and the geopolitical relationship network calculated in sections 4.4 to 4.6. To further test whether the international crude oil-geopolitics connectedness can effectively warn tail risks of the international crude oil market, machine learning method is used to evaluate the rationality of the selected indicators.

Examining whether the chosen indicators can be incorporated into the crisis early warning indicator system is the main aim of the international crude oil market tail risk early warning simulation. The training set input and output data for crude oil tail risk machine learning contain the connectedness network topology data and tail risk values from March 2006 to December 2016, and the test set data for crude oil tail risk machine learning contain the connectedness network topology data and tail risk values from January 2017 to December 2021. Adopting machine learning methods to predict the level of tail risk in the crude oil market can examine whether the network connectedness performance can be included in the early warning index system. Fig. 18 shows the machine learning based tail risk warning for international crude oil. From the results of machine learning training and test errors, it can be judged that the crude oil market's tail risk early warning system can contain indicators like the degree of international crude oil-geopolitics network connectedness, which provides reference for building an extreme risk early warning system to guard the national energy security.

5. Conclusion

Under the current external environment where uncertain geographical relationships are increasing, energy security is becoming increasingly important to national strategies. It is significant to study the risk spillover among international energy markets and geopolitical risks under the influence of extraordinary events. This article begins by examining the direction and magnitude of tail risk contagion in the international energy market, concluding that the oil market has the most substantial risk spillover effect, and that its dynamic variations are strongly tied to geopolitical events. Then we examine the risk contagion channel of the tail risk in the international crude oil market. Considering the cross-contagion between international crude oil volatility and geopolitics, the cross-effect between international crude oil price volatility and geopolitical risks are further analyzed through the two-layer international crude-geopolitics network. On this premise, using frequency domain method to reveal the dynamic effects and periodic changes of risk contagion effects separately among geopolitical risk and the international crude oil market, as well as the dynamic variations of

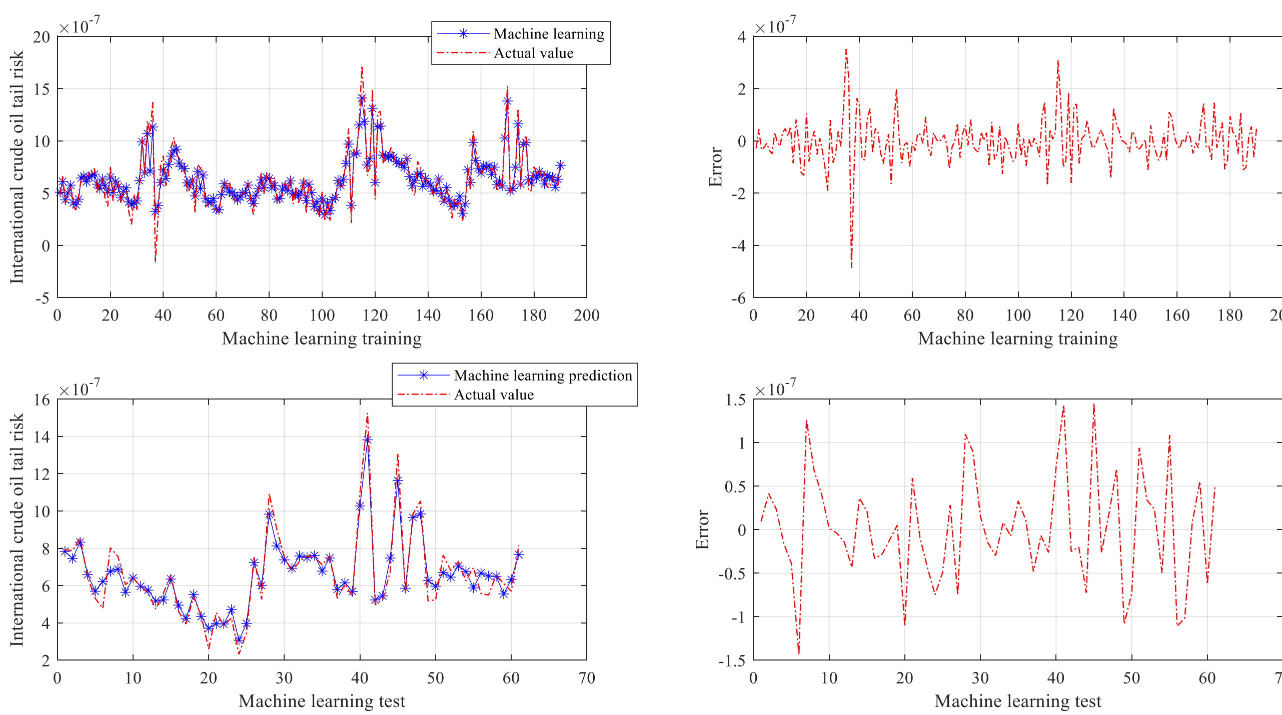

Fig. 18. Tail risk warning for international crude oil based on machine learning.

international crude-geopolitical connectedness. Finally, the early warning effect of the connectedness between crude oil and geopolitics on the tail risk of crude oil is investigated utilizing the machine learning technique.

In international energy markets, the dynamics of tail risk contagion levels are intricately linked to geopolitical conflicts. Traditional energy markets have higher level of tail risk spillover than clean energy markets. In addition, there is little risk spillover among traditional energy markets and clean energy markets. At the same time, traditional energy markets are more vulnerable to extreme events. As a result, clean energy markets tend to fluctuate less when faced with shocks from conventional energy crises. Clean energy financial derivatives provide convenience for investors to hedge or avoid traditional energy risks. Developing clean energy markets is important for countries to deal with the complex and changing geopolitical landscape. Meanwhile, under the global goals of "carbon neutrality" and "carbon peaking", governments should vigorously develop new energy sources and improve the diversified energy system.

In the international energy market, oil exhibits the greatest degree of risk spillover due to its important strategic status. The risk spillover impact of the fluctuations of the US crude oil to the Canadian market is the most glaring in the international crude oil tail risk network throughout the whole sample period. In addition, external shocks of different nature make the risk spillover in the crude oil market heterogeneous. Under the impact of the COVID-19 pandemic, the risk spillover level of the US crude oil market shows the highest. Under the extreme impact of the Iraqi civil war and the Russia-Ukraine conflict in 2014, the Iraqi and Russian crude oil markets, which are at the center of the geopolitical conflict, are the main risk contagion parties. An overly homogeneous crude oil import channel can lead to the country's crude oil market being less able to cope with input risks. Therefore, countries should form diversified crude oil import channels to better diversify the tail risk of offshore imports.

The cross-contagion risk is further examined using the crude oil-geopolitics two-layer network in light of the interaction mechanism between crude oil price changes and geopolitical risk. Overall, the analysis concludes that there is net risk spillover to geopolitics from international crude oil market. The analysis of two-layer network centrality indicators shows that the United States, China and Russia are systemically important economies. Dynamic contagion effects show that changes in oil prices in China and Russia exhibit stronger effect on American geopolitical risk, particularly around the time of the COVID-19 pandemic and the global financial crisis. And Russia's geopolitics creates significant risk spillovers to China's crude oil market. In order to prevent the cross-contagion between geopolitical risks and crude oil volatility risks, governments should promote the development and application of clean energy, and fundamentally reduce crude oil import dependence and the impact of external factors such as geopolitics.

Additionally, from the frequency domain viewpoint, periodic features of geopolitical risk, the dynamic network changes and the tail risk contagion in the international crude oil market are discussed. It is discovered that short-term risk spillover dominates the total risk spillover in both geopolitical and international crude oil markets. The geopolitical risk spillover effect between the international crude oil market exhibit periodic heterogeneity over the tumultuous time. Dynamic network analysis of international crude oil-geopolitics finds that geopolitical events influence the level of tail risk in the international crude oil market through the crude-geopolitics connectedness. Machine learning warning effects validate that indicators such as international crude-geopolitics network connectedness can be used to warn tail risks in the crude oil market. For these reasons, national regulators should pay attention to short-term emergency mechanisms for international crude oil market volatility and geopolitical conflicts so as to prevent short-term risk cross-contagion from evolving into long-term risk. On the other hand, it should deal with geopolitical relations to prevent crude oil-geopolitics cross-risks from being imported into the crude oil market and threatening national energy security.

Author statement

I have made substantial contributions to the conception or design of the work; or the acquisition, analysis, or interpretation of data for the work. I have drafted the work critically for important intellectual content. And I have approved the version to be published. I agree to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Besides, all persons who have made substantial contributions to the work reported in the manuscript.

Declaration of competing interest

The authors declare that we have no competing interests.

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Appendix A

Fig. A. 1 displays the time-varying characteristics of the total connectedness level of the global crude oil market to reflect the total risk level of the market. Intuitively, the dynamic shifts in the degree of total connectedness reflect the effects of extreme shocks, represented by geopolitical events, on crude oil markets. Due to the effects of geopolitical events like the Arab Spring, the "gunshots" in Norway, the riots in London, and the European financial crisis, the total connectedness level increased in 2011, this tendency can be attributed to these events as well as the European economic crisis. In 2014, geopolitical conflicts broke out successively, such as the conflict between Russia and Ukraine, the civil war in northern Iraq, and the conflict between Palestine and Israel. The international crude oil market has been in upheaval, prices have fluctuated sharply, and total connectedness has increased to its highest point as a result of frequent geopolitical events. Up until early 2015, when the geopolitical upheaval abated, the international crude oil market 's total connectedness level steadily decreased and stabilized. Subsequently, the 2018 trade disputes between the US and China again triggered a synchronized price decline in the international crude oil market, with the total connectedness level rising again. This is due to the fact that the trade disputes between the US and China will seriously affect investor sentiment. The risk aversion of investors caused turmoil in the equity market and other financial markets, which in turn affected the stability of crude oil and other markets for bulk commodities, resulting in a precipitous decline in oil prices. The total connectedness in the international crude oil market oscillated at higher levels as trade frictions between the US and China escalated in 2019. The outbreak of the COVID-19 pandemic in early 2020 once again led to a sharp rise in the total connectedness level of the international crude oil market. The effect of international geopolitical conflicts on the level of total connectedness for crude oil market is reflected over the course of the sample period. According to Liu and Gong (2020), rising crude oil volatility will also cause a rise in risk linkage and the size of risk contagion. It can be seen that there is a two-way interactive effect between international crude oil market fluctuations and geopolitical risks.

In order to further examine the dynamic impact of different geopolitical events on the international crude oil market, the time series diagrams of risk export and risk import in the crude oil market of eight countries are shown respectively. The dynamic changes of risk export and risk import in different crude oil markets are basically consistent with the changes in the total risk connectedness level of the international crude oil market. According to Fig. A.2, with the exception of the United States, the level of export risk on the international crude oil market climbed significantly in 2014 and reached a maximum in all other nations. Among them, the risk export of the markets for crude oil in Russia and Iraq changed the most drastically, emerging as the principal risk export parties throughout this time. As a result, the level of risk export between the two countries rises sharply and spreads to other countries. The COVID-19 epidemic caused risk export levels in crude oil markets worldwide to increase once more. The risk export on the American crude oil market increased far more than on other markets. The time-series plot of risk import on the international crude oil market is depicted in Fig. A.3. Throughout the study period, there are significant fluctuations in the Canadian risk import level, which peaks during the COVID-19 pandemic. The primary cause is that the Canadian crude oil market lacks pricing power, which leaves it susceptible to changes in the price of crude oil in other nations. In conclusion, risk contagion in the international crude oil market is closely tied to geopolitical risk. Geopolitical conflicts will raise the total risk level of the international crude oil market, and the countries where these conflicts take place are typically the main exporters of risk during this time.

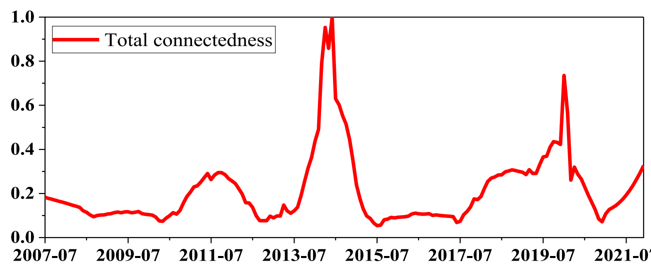

Fig. A.1. Total tail risk connectedness of international crude oil market.

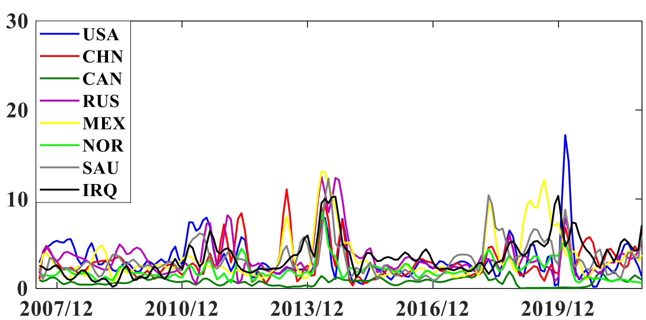

Fig. A.2. Risk export in the international crude oil market.

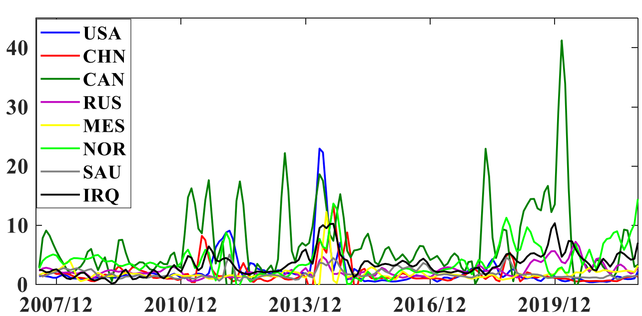

Fig. A.3. Risk import in the international crude oil market.

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