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Multidimensional risk spillovers among crude oil, the US and Chinese stock markets: Evidence during the COVID-19 epidemic

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ABSTRACT

This paper investigates the multidimensional risk spillovers among crude oil, the US and Chinese stock markets during the COVID-19 epidemic through a GARCHSK-Mixed Copula-CoVaR-Network method. Firstly, we find that during the COVID-19 period, the oil-stock risk spillovers are obviously stronger than those during the normal period. And there are significant risk spillovers from the US and Chinese stock markets to the oil markets. It is also discovered that the oil markets are greatly influenced by the second board stock markets, also known as the growth enterprise markets, especially during the COVID-19 outbreak. Furthermore, the bidirectional China-oil risk spillovers during the COVID-19 pandemic have rapidly increased. Besides, it is reported that the relationships across oil futures, main board and second board stock markets in the US and China are stable under different TSI levels and extreme events. Finally, the GARCHSK-Mixed Copula-CoVaR-Network outperforms the control groups in terms of marginal distribution and dependence structure. Our study not only offers new method and insight into the oil-stock relationship, but also has economic implications for investors and policymakers.

1. Introduction

Understanding the oil-stock relationship is a critical component to financial risk management, regulation policy planning, investing process and so on. Therefore, the oil-equity relationship has been a hot issue and received ample research attention [1–8]. Since Wuhan Municipal Health Commission reported a cluster of cases of pneumonia in Wuhan, Hubei Province, within seven months, the novel coronavirus (COVID-19) pandemic spread through the entire world.[2] As "economic weatherglass" and "industry blood", global stock and oil markets are hit hardest by the pandemic. Chinese and US stocks have suffered large swings, while Brent oil price slumped 71% dramatically and WTI oil futures price even slumped almost 300% on April 20, 2020, trading at around negative $37/barrel. As Adrian & Brunnermeier [9] say, crisis may induce systemic risk which is regarded as the adverse effects for the entire system. It is critical to estimate risk spillovers among markets during the crisis [10]. Therefore, it raises an important question: How do risk spillovers among stock markets and international oil owing to COVID-19 crisis?. Fig.1 demonstrates the number of deaths due to COVID-19.

The US and China have close relation with crude oil, because China is the largest crude oil buyer as well as US is the largest crude oil producer with 19% share of world total and main crude oil exporter.[3] Besides, according to WHO, the first cluster of COVID-19 confirmed cases was reported in China, in the meanwhile, both the number of COVID-19 confirmed cases and death cumulative total in US are so far the largest in the world. As the most impressive economies, these two countries have been shocked by COVID-19, with Chinese first quarter GDP shrank by 6.8% and US second quarter GDP shrank by an annualized 32.9%. Furthermore, the US and China have the largest stock markets in the world, which are likely uppermost concerned by investors, general public and policy

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[2] According to World Health Organization (WHO): https://www.who.int/news-room/detail/27-04-2020-who-timeline—covid-19.

[3] According to EIA: https://www.eia.gov/tools/faqs/faq.php?id=709&t=6.

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0360-5442/

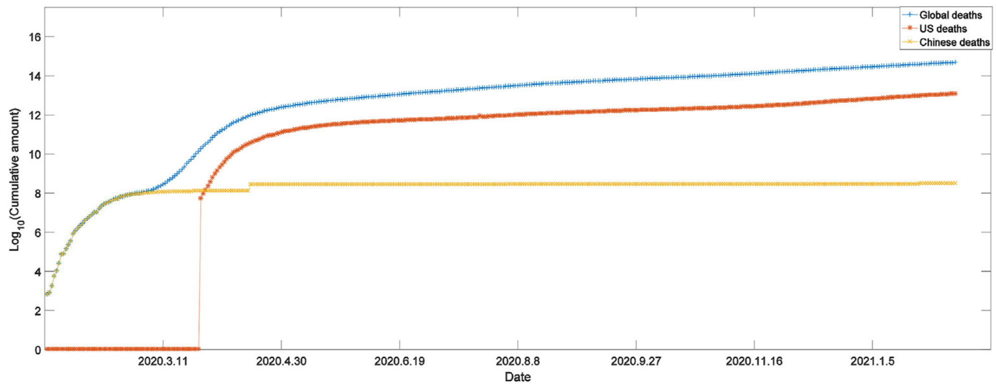

Fig. 1. Deaths due to COVID-19[16].

makers. Therefore, the stock markets of the US and China are representative during the COVID-19 pandemic.

Recently, what effects COVID-19 crisis cause on the world has been the notable focus in academia [11–17]. The COVID-19 crisis is often compared with subprime crisis of 2008, however, the former is the product of COVID-19, the latter is the product of US economic structural issues [12,13]. Thus, Harvey [14] emphasize two crises differentiation, and Damette & Stéphane [18] report that a series of policies responses to subprime crisis, are unable to deal with the COVID-19 crisis and even are likely to backfire. COVID-19 crisis is also compared with global wars, which demonstrates that it is an unprecedented epidemic which has more dangerous and contagious [15]. Furthermore, most countries have taken restrictions, such as lockdowns and quarantines, to cut down the channels of the COVID-19 disease spread. These containment measures have a massive impact on global businesses, job securities, and essential services [16].

Apart from relevant studies, our notable contributions and innovation are in the following aspects. Firstly, to the best of our knowledge, the multidimensional risk spillover effects across oil and stocks during the COVID-19 pandemic have been scarcely reported, but it has practical implications for regulatory decisions and assets allocation responses to COVID-19 crisis. Thus, based on data of international oil futures, main board stock and second board stock markets[4] in US and China during the COVID-19 pandemic, the oil-stock multidimensional risk spillovers are investigated. The research content includes: (1) the oil-stock risk spillovers (2) difference among WTI-stock, Brent-stock, as well as SC-stock relationships (3) the relationships between oil and main board markets and second board markets. The compelling reason why SC is employed to research the oil-stock spillovers is that since going public on March 22, 2018, the volume of SC has ranked the third place worldwide[5]. Contrary to WTI and Brent, SC is based on a medium sour crude oil instead of light sweet crude oil, and SC can be traded in Chinese yuan rather than dollar. It has realistic significance to study the difference between the relationships between stocks and SC as well as between stocks and the other oil futures. In the meanwhile, main board stock market provides reliable financial support for those large industrial enterprises that either use crude oil as raw materials or produce crude oil products, while second board stock market provides reliable financial support for high-growth & high-tech enterprises that have no direct connection with crude oil [19]. Therefore, the relationships between crude oil and main board stock markets as well as crude oil and second board stock markets are obviously distinct, which is ignored by relative literature.

Secondly, a GARCHSK-Mixed Copula-CoVaR-Network is proposed by four-phase modeling to measure multidimensional risk spillovers among financial markets. Based on nonlinear perspective, the method not only makes full use of both second moment (variance) and higher moments (skewness and kurtosis) information, but also measures both degree and structure of nonlinear and tail dependence. In the meanwhile, it can describe the dynamic multidimensional risk spillovers among oil and stock markets in the panoramic framework. The compelling reason why a General Autoregressive Conditional Volatility Skewness Kurtosis (GARCHSK) model is employed to construct the marginal distributions of returns is that based on the assumption that skewness and kurtosis are constant, GARCH class methods can only measure conditional variance [20,21], however, changeable financial market environment result in dynamic higher moments [22,23]. The modeling results under the GARCH class may be erroneous [24]. León et al. [20] propose a GARCHSK to structure for both conditional skewness and kurtosis. Therefore, we attempt to adopt a GARCHSK to describe the volatility of oil and stock markets in order to obtain more risk information. In addition, the potential reason why the network is used to measure the interconnections of variables lies in the fact that today's closely connected, global networks across financial markets have produced highly interdependent systems that we can be unable to understand and control well based on traditional methods and perspectives [25]. Therefore, network is employed to structure the multidimensional risk spillovers, between oil and stocks, oil and oil as well as stocks and stocks.

The specific work can be stated as follows: We begin by modeling the marginal distribution of the returns through a GARCHSK to obtain more univariate risk information, including time-varying variance, skewness and kurtosis. Then, a mixed Copula is employed to construct the nonlinear dependence structure between variables. Furthermore, Conditional Value at Risk (CoVaR) and Delta Conditional Value at Risk ($\triangle$CoVaR) are obtained to describe risk spillover between each pair of markets. Finally, based on the results measured by GARCHSK-Mixed Copula-CoVaR, we construct full-sample and dynamic networks to research multidimensional risk spillovers among international oil and stock markets during the COVID-19 pandemic.

The remainder of our work is organized as follows. Relative literature is briefly reviewed in Section 2. The methods are introduced in Section 3. We make a statistical description of data in Section 4. Section 5 describes and analyses the empirical results.

[4] Second board market are also known as growth enterprise market (GEM).

[5] According to EIA, https://www.eia.gov/petroleum/weekly/archive/2018/180425/includes/analysis_print.php.

Section 6 and Section 7 discusses and concludes our study, respectively.

2. Literature review

Crude oil price changes have a massive influence on listed enterprises' production, cost and profit, and then cause the changes of stocks prices [26–29]. In the meanwhile, the listed companies' achievement can lead to the changes economy. The supply and demand balance of international crude oil can be broken owing to changes in global economy, and further causes the fluctuations of crude oil prices [1,5,7]. Therefore, understanding oil-stock risk spillover is crucial for risk management and investing process.

The risk spillover between oil and stock is the focus in academia. Some scholars use linear methods, including multivariate Generalized Autoregressive Conditional Heteroscedasticity (multivariate GARCH), Complete Ensemble Empirical Mode Decomposition with Adaptive Noise-Granger causality (CEEMDAN-Granger causality), and generalized Forecast Error Variance Decomposition (generalized FEVD), to research the oil-stock risk spillover at the aggregate level or sector level [7,19,30].

Mohamed [19] examines the risk contagion from oil price volatility to stock markets. The empirical results verify that there is a great significant risk spillover from oil price to European sector stock market returns and fluctuations and that oil-stock spillover is unidirectional. Based on dynamic conditional correlation Generalized Autoregressive Conditional Heteroscedasticity (DCC-GARCH) model, Li et al. [6] investigate risk spillovers among oil spot, oil futures and energy stocks. It is discovered that the risk spillover between oil spot and futures is bidirectional, in the meanwhile, spillover between stock and oil futures is unidirectional. Lin et al. [7] research the risk contagion among oil, gold, as well as China and European stock markets under the CEEMDAN method and Granger causality test. It is found that there is bidirectional risk contagion among the oil, gold and stock markets in extreme events. Ashfaq et al. [28] report that the correlations between oil exporting countries' stock markets and petroleum are significantly stronger than the correlations between oil importing countries' stock markets and petroleum. Based on generalized FEVD method, Wang & Wang [30] observe that the pairwise spillovers between oil futures and sectoral stocks are heterogeneity and that some sectors, which oil products are either input or output for, are influenced more by oil price changes. Yu et al. [31] investigate the relationships between oil and stocks of US and China through multivariate Vector Autoregressive-Baba Engle Kraft Kroner-Generalized Autoregressive Conditional Heteroscedasticity (VAR-BEKK-GARCH). It is found that the WTI-US relationship is more volatile than WTI-China relationship in most cases.

However, the fact that the oil-stock relationship may be nonlinear has been verified by some scholars [1,3,4]. Thus, with the advantage of capturing nonlinear, asymmetric and tail dependence structure, Copula models have been widely employed in measuring the oil-stock relationship [1–4,32–35].

Kayalar et al. [3] evaluate the effects of oil price changes impacts on the global stocks under Copula methods. The empirical results verify that crude oil exporter' stock indices are higher oil price dependency. Maneejuk et al. [4] discover that the Thai-oil, Malaysian-oil and Indonesian-oil relationships are positive, while the relationships between oil and the other countries' stock markets are opposite. Furthermore, the relationships are unstable and dynamic. Melike & Bildirici [34] use Copula methods to explore the chaotic comovement between oil and stock returns. The empirical analysis denotes that oil prices' fluctuations have a massive influence on the stock returns. Uddin et al. [35] research risk spillover between the US stocks and oil through Copula and CoVaR. They discover oil symmetrical relationship with the US stock market under normal and extreme market environments. The other scholars also employ Copula family models to tinker with similar researches [1,2,32,33,36].

3. Methodology

3.1. GARCHSK

León et al. [20] propose a GARCHSK approach to structure for both conditional skewness and kurtosis. According to literature [20,22], AR(1)-GARCHSK is defined as follows:

$$\begin{aligned}
&Mean: \quad r_t = u_t + \varepsilon_t = \alpha_1 r_{t-1} + \varepsilon_t \\
&\varepsilon_t = h_t^{1/2} z_t; \quad \varepsilon_t \Big| I_{t-1} \sim D(0, h_t, s_t, k_t) \\
&Variance: \quad h_t = \beta_0 + \sum_{i=1}^{q_1} \beta_{1,i}\varepsilon_{t-i}^2 + \sum_{j=1}^{p_1} \beta_{2,j} h_{t-j} \\
&\text{Skewness}: \quad s_t = \gamma_0 + \sum_{i=1}^{q_2} \gamma_{1,i} z_{t-i}^3 + \sum_{j=1}^{p_2} \gamma_{2,j} s_{t-j} \\
&Kurtosis: \quad k_t = \delta_0 + \sum_{i=1}^{q_3} \delta_{1,i} z_{t-i}^4 + \sum_{j=1}^{p_3} \delta_{2,j} k_{t-j}
\end{aligned} \tag{1}$$

where I_{t-1} is an information set at $t-1$; $D(0, h_t, s_t, k_t)$ is an arbitrary distribution including conditional variance, skewness, and kurtosis. In addition, according to literature [20,22], $q_1 = q_2 = q_3 = p_1 = p_2 = p_3 = 1$. According to literature [22], let z_t subjects to Gram-Charlier expansion (GCE) distribution, which incorporates skewness and kurtosis as parameters into density function and is widely employed in higher moments methods modeling process [33,37]. Given nonnegativeness of its density function, León et al. [20] improve GCE function as follows:

$$GCE(z_t|I_{t-1}) = \frac{\varphi(z_t)\left(1 + \frac{s_t}{3!}\left(z_t^3 - 3z_t\right) + \frac{k_t - 3}{4!}\left(z_t^4 - 6z_t^2 + 3\right)\right)^2}{1 + \frac{s_t^2}{3!} + \frac{(k_t-3)^2}{4!}} \tag{2}$$

where $\varphi(\bullet)$ represents the probability density function corresponding to the standard normal distribution. In Eq. (1), conditional density function of ε_t is $h_t^{-1/2} GCE(z_t|I_{t-1})$. Without useless constant, logarithm likelihood function is described as follows:

$$l_t = -\frac{1}{2}\ln h_t - \frac{1}{2}z_t^2 + \ln\left(\psi^2(z_t)\right) - \ln\left(1 + \frac{s_t^2}{3!} + \frac{(k_t-3)^2}{4!}\right) \tag{3}$$

The standardized residuals z_t obtained by GARCHSK contain not only variance information, but also higher moments' information. Because of its potential advantages, we use the GARCHSK method to estimate the marginal distributions of each returns.

3.2. Mixed Copula

Because the relationships between financial markets are very complex tail relation with nonlinear characteristics [38], single Copula is unable to precisely describe the dependence structure [39]. Hu [40] propose a mixed Copula through combining several

[6] The data is downloaded from Johns Hopkins University's Center: https://coronavirus.jhu.edu/map.html.

single Copulas to measure the correlations between variables. The mixed Copula can describe both degree and structure of dependence, by association parameters and weight parameters [40]. Mixed Copula is defined as follows:

$$MC = \sum^{n} \omega_t * C_t \tag{4}$$

where $C_i,\ i = 1, 2, \cdots, n$ represent different single Copulas, corresponding to weights $\omega_i \geq 0, i = 1, 2, \cdots, n, \sum_{i=1}^{n} \omega_i = 1$, respectively.

Elliptical Copula family is unable to capture asymmetric tails, while Clayton and Gumbel Copulas, the members of Archimedean copula family, can describe lower and upper tails, respectively [38,39]. Besides, Frank Copula can describe both positive and negative dependence and has been proven its reliability [10]. Therefore, according to literature [39], Clayton, Gumbel, Frank Copulas are employed to construct a mixed Copula, and its cumulative distribution function can be stated as:

$$MC = \omega_{Clayton} C(u, v; \theta) + \omega_{\mathrm{Gumbel}} C(u, v; \alpha) + \omega_{Frank} C(u, v; \lambda) \tag{5}$$

where $C(u,\ v; \theta) C(u,\ v; \alpha),\ C(u,\ v; \lambda)$ denote cumulative distribution function of Clayton, Gumbel, Frank Copulas, separately. Besides, the association parameters $(\theta,\ \alpha,\ \lambda)$ denote the degree of dependence, and weight parameters $(\omega_{Clayton}, \omega_{\mathrm{Gumbel}}, \omega_{Frank})$ denote structure of dependence [40]. Elliptical and Archimedean Copula families are detailed in Ref. [41].

Maximum Likelihood estimation is used to estimate association parameters and weight parameters of mixed Copula, and its logarithmic likelihood function can be described as follows:

$$\begin{aligned} \ln L(x_1, x_2; \gamma) &= \sum_{t=1}^{T} \ln c_M (F_1(x_{1,t}; \gamma_1), F_2(x_{2,t}; \gamma_2); \gamma_c) \\ &= \sum_{t=1}^{T} \ln c_M(u, v; \gamma_c), \quad t = 1, 2, \cdots, T \end{aligned} \tag{6}$$

In Eq. (6), $F_1(x_1; \gamma_1)$ and $F_2(x_2; \gamma_2)$ are the marginal distributions of $x_{1,t}$ and $x_{2,t}$ respectively, where $u = F_1(x_1; \gamma_1) v = F_2(x_2; \gamma_2)$, $\gamma_c = (\omega_{Clayton}, \omega_{\mathrm{Gumbel}}, \omega_{Frank}, \theta, \alpha, \lambda)'$, $c_M(u,\ v; \gamma_c) = \frac{\partial MC(u,v;\gamma_c)}{\partial u \partial v}$,. $\gamma = (\gamma_1, \gamma_2, \gamma_c)'$ [7]

Considering the over-abundant estimated parameters and complicated procedures, Maximum Likelihood estimation is combined with expectation maximization and L-BFGS-B algorithms to calculate the logarithmic likelihood function and parameters.

3.3. CoVaR

Value-at-Risk (VaR), a well-known risk measure method, has been widely employed in many fields [10,41,42]. Recall that VaR of variable x_t is defined by α-quantile of the conditional distribution of x_t as follows:

$$\Pr(x_t \leq \mathrm{VaR}_t) = \alpha \tag{7}$$

According to definition of VaR, VaR under the GARCHSK family is stated as [42]:

$$\mathrm{VaR}_t(\alpha) = \mu_t + z_\alpha \sqrt{h_t} \tag{8}$$

where z_α denotes the α quantile for GCE distribution $D(0,\ h_t,\ s_t,\ k_t)$. However, VaR is unable to capture the systemic nature of risk because it only focuses on an individual institution's risk [33,39].

CoVaR is originally proposed by Adrian & Brunnermeier [9]. Then considering more severe distress events, Girardi & Erguen [43] modify the original CoVaR. CoVaR attempts to compute risk spillovers between financial institutions and has been attracted a great attention [10,32,43,44]. Assume that there are $x_{i,t}$ and $x_{j,t}$ with the same length N, where $t = 1, 2, \cdots, N$. Formally, the original CoVaR and modified CoVaR are defined as the β-quantiles of the following conditional distributions, separately:

$$\Pr\left(x_{i,t} \leq \mathrm{CoVaR}_{\beta,t}^{i|j} \middle| x_{j,t} = \mathrm{VaR}_{\alpha,t}^{j}\right) = \beta \tag{9}$$

$$\Pr\left(x_{i,t} \leq \mathrm{CoVaR}_{\beta,t}^{i|j} \middle| x_{j,t} \leq \mathrm{VaR}_{\alpha,t}^{j}\right) = \beta \tag{10}$$

The modified CoVaR proposed by Girardi & Erguen [43], has been approved its validity [10,32,33], therefore, the Eq. (10) is used to compute CoVaR.

Referring to literature [27,33], $\mathrm{CoVaR}_{\beta,t}^{i|j}$ under Copula is stated as[8]:

$$C\left(F_{1,t}\left(\mathrm{CoVaR}_{i,t}^{\alpha}\right), F_{2,t}\left(\mathrm{VaR}_{j,t}^{\beta}\right)\right) - \beta\alpha = 0 \tag{11}$$

where $F_{1,t}$ and $F_{2,t}$ denote the marginal distributions of $x_{i,t}$ and $x_{j,t}$ separately.

The contribution of risk spillover from $x_{2,t}$ to $x_{1,t}$ is further identified by introducing the measure of $\triangle$CoVaR [43], which is the percentage difference between the VaR for $x_{i,t}$ conditional on an extreme comovement of $x_{j,t}$ and the VaR for $x_{1,t}$ conditional on a median state of $x_{j,t}(x_{i,t} \neq x_{j,t})$. Therefore, referring to literature [27,33,43], we gain $\Delta\mathrm{CoVaR}_{i,t}^{i|j}$ under the following formula[9]:

$$\Delta\mathrm{CoVaR}_{i,t}^{i|j} = 100 \times \left(\mathrm{CoVaR}_{\beta,t}^{i|j} - \mathrm{CoVaR}_{\beta,t}^{i|j,\alpha=0.5}\right) / \mathrm{CoVaR}_{\beta,t}^{i|j,\alpha=0.5} \tag{12}$$

All in all, $\Delta\mathrm{CoVaR}_{1,t}^{1|2}$ measure the dynamic systemic risk contribution of $x_{j,t}$ to Refs. $x_{i,t}$ [44,49,50].

3.4. Network representation of CoVaR

In the previous relative researches, shcolars employ CoVaR to measure the each part of the system to the others [1,3,4,7,32], however, it ignores how many various parts are exposed to the whole system in the case of systemic risk [45]. Therefore, referring to Dastkhan [45,46], the network theory is applied to measure the interconnections of variables, based on absolute values of ΔCoVaR that are computed for pairwise of variables. Array A_t denotes the $\triangle$CoVaR with n markets in a specific period t, where $S_t^{i|j}$ represents $\Delta\mathrm{CoVaR}_{i,t}^{i|j}$:

[7] means that a row vector transposes a column vector.

[8] It is detailed in literature [10].

[9] Some scholars such as Karimalis & Nomikos [10] define $\Delta\mathrm{CoVaR}_{i,t}^{i|j} = \mathrm{CoVaR}_{\beta,t}^{i|j} - \mathrm{CoVaR}_{\beta,t}^{i|j,\alpha=0.5}$. In fact, the conclusions of these $\Delta\mathrm{CoVaR}_{i,t}^{i|j}$ are consistent. Furthermore, the value range of $\Delta\mathrm{CoVaR}_{i,t}^{i|j}(i \neq j)$ according to Eq (12) is not limited, which can exceed 100% under some extreme situations [32,33,69]. Besides, the $\mathrm{CoVaR}_{i,t}^{i|j}$ and $\Delta\mathrm{CoVaR}_{i,t}^{i|j}$ based on Copula are time varying without rolling window [41,44,49].

$$A_t = \left\{ \begin{array}{l} 0S_t^{1|2}S_t^{1|3}\cdots S_t^{1|n} \\ S_t^{2|1}0S_t^{2|3}\cdots S_t^{2|n} \\ S_t^{3|1}S_t^{3|2}0\cdots S_t^{3|n} \\ ::::: \\ S_t^{n|1}S_t^{n|2}S_t^{n|3}\cdots 0 \end{array} \right\} \quad (13)$$

ArrayA_t is considered as an adjacency matrix of financial network in period t. In Eq. (13), the rows denote that each market receives risk spillovers from the other markets, as well as the columns denote that each market emits risk spillovers to the other markets. In other words, the rows and columns of A_t represent values of Exposure-CoVaR and Contribution-CoVaR, separately. In addition, in order to classify the risk spillovers, Total spillovers index (TSI), Vulnerability index (VI) and Systemic importance index (SII) are used as main indices of network.

TSI is defined as the contribution of risk spillovers of all markets, in other words, it measures all spillovers inA_t. The TSI in period t can be stated as Eq. (14). The stronger contagion among markets, the higher value of TSI[10].

$$\mathrm{TSI}_t = \sum_{i=1,j=1}^{n} S_t^{i|j}(i \neq j) \quad (14)$$

VI is defined as the receiving total risk spillovers of market i from the other markets, showing how much market i is affected by the others. The VI of market i in period t can be stated as Eq. (15). The more sensitive to the changes in the other markets, the higher value of $\mathrm{VI}_{i,t}$.

$$\mathrm{VI}_{i,t} = \sum_{j=1}^{n} S_t^{i|j}(i \neq j) \quad (15)$$

SII is defined as the emitting total risk spillovers from market i to the other markets, showing how much the other markets are affected by market i. The SII of market i in period t can be stated as Eq. (16). The higher value of $\mathrm{SII}_{i,t}$, the more risk spillovers from market i to the other markets.

$$\mathrm{SII}_{i,t} = \sum_{j=1}^{n} S_t^{j|i}(i \neq j) \quad (16)$$

3.5. GARCHSK-Mixed Copula-CoVaR-network

Diebold & Yilmaz [47,48] propose some linear spillover index methods to measure the spillovers among assets, which have been widely employed in many fields. However, nonlinear and asymmetric tail comovements between markets have been reported in various researches [1–4,10,39,40] so these linear methods are hard to accurately describe the relationships among assets [57]. GARCHSK-Mixed Copula-CoVaR-Network is distinguished from spillover index methods of Diebold & Yilmaz [47,48] in the following aspects. It not only makes full use of both second moment and higher moments information, but also measures nonlinear and tail dependence. In the meanwhile, it can describe the dynamic multidimensional risk spillovers among oil and stock markets in the panoramic framework without rolling window. The detailed algorithm of GARCHSK-Mixed Copula-CoVaR-Network is described as follows[11]:

Phase 1. GARCHSK modeling. A GARCHSK is employed to each returns to obtain standardized residuals. Then, the marginal distributions are obtained by using the empirical cumulative distribution function (ECDF) to the residuals$z_t$measured by GARCHSK.
Phase 2. Mixed Copula modeling. Based on results obtained by GARCHSK, a mixed Copula composed of Clayton, Gumbel, Frank Copulas is used to measure the dependence structure between variables.
Phase 3. CoVaR modeling. Employing the results of GARCHSK-Mixed Copula above, we compute VaR, CoVaR, △CoVaR at the 95% confidence level. CoVaR and △CoVaR can denote the risk spillover between each pair of markets.
Phase 4. Network modeling. Based on the results measured by GARCHSK-Mixed Copula-CoVaR, we construct full-sample and dynamic networks to research the multidimensional risk spillovers across international oil and stock markets.[12]

4. Data and descriptive statistics

With price discovery and hedging functions, the crude oil futures market provides risk warnings and pricing guidance for spot market, which plays a critical role in crude oil pricing [51]. Furthermore, crude oil futures such as WTI and Brent are generally regarded as global oil benchmarks for the reason that the volume of trade in crude oil futures markets is estimated to account for more than half of world's total oil trade [52]. Many researches such as Kayalar et al. [3], Maneejuk et al. [4], Li et al. [5], Wang & Wang [30], An et al. [51], Zhu et al. [53] also adopt crude oil futures instead of spot as the representative of oil market to investigate the oil-stock risk spillovers. Therefore, we use oil futures rather than spot prices to investigate oil-stock spillovers.[13]

As benchmarks for international oil pricing, WTI oil futures and Brent oil futures are widely employed in relative studies [2–4,7]. In the meanwhile, SC has become the third largest trading volume crude oil futures.[14] Therefore, WTI, Brent and SC are adopted in the current paper, where the WTI prices are collected from the Energy

[10] The unit of$\Delta\mathrm{CoVaR}_{i,t}^{i|j}(i \neq j)$is percentage, so the unit of TSL is percentage. Distinguished from spillover index methods of Diebold & Yilmaz [47,48], $\Delta\mathrm{CoVaR}_{i,t}^{i|j}(i \neq j)$, which is obtained by the Eq (12), can exceed 100% under some extreme situations [32,33,69]. In other words, the value range of $\Delta\mathrm{CoVaR}_{i,t}^{i|j}(i \neq j)$is not limited. Therefore, it is common that TSI values which are the sum of $\Delta\mathrm{CoVaR}_{i,t}^{i|j}(i \neq j)$are much higher than 100%. Although $\Delta\mathrm{CoVaR}_{i,t}^{i|j}(i \neq j)$ which is represented by $S_t^{i|j}$ and spillover index methods of Diebold & Yilmaz [47,48] are the traditional methods to measure risk spillover between assets, the concepts of these methods are significantly different. In fact, some scholars based on LASSO-CoVaR such as Xu et al. [45] also employ our formula to construct TSL. Furthermore, the TSL can directly, intuitively and clearly show the difference between risk spillovers during the COVID-19 and pre-COVID-19 periods. In order to avoid the misread that values of total spillover indices should be between 0 and 100%, according to the literature [45], the symbol of % is not shown in the empirical results.

[11] MATLAB 2016a and R 4.0.2 software is employed in our work.

[12] $\mathrm{CoVaR}_{1,t}^{1|2}$ and $\Delta\mathrm{CoVaR}_{1,t}^{1|2}$ can describe the dynamic risk spillovers between assets according to Eq. (11) and Eq. (12) [44,49,50]. Therefore, based on dynamic risk spillovers between assets, dynamic networks and TSI are constructed according to Eq. (13)and Eq. (14) without rolling window. Then, we average dynamic △CoVaR ($S_t^{i|j}$) series to construct the full-sample (whole) risk spillovers network.

[13] In order to verify the validity of our work, oil spot prices are also used to investigate the oil-stock relationships during the COVID-19 outbreak. We find that the spot markets are more volatile than futures markets in most cases. Furthermore, it is reported that the main conclusions from oil spot markets are in coincidence with those from oil futures markets. These results are showed in robustness analysis section.

[14] According to EIA, https://www.eia.gov/petroleum/weekly/archive/2018/180425/includes/analysis_print.php.

Table 1
Summary descriptive statistics for returns.

	Mean	Median	Std.dev	Skewness	Kurtosis	JB	ADF	PP	KPSS
WTI	0.000	0.003	0.111	−5.453	86.394	76335.210***	−16.070***	−26.778***	0.067
Brent	0.000	0.002	0.042	−1.844	17.893	2540.593***	−15.598***	−15.594***	0.088
SC	0.000	0.000	0.031	−0.087	4.084	13.007***	−14.336***	−14.425***	0.043
DJIA	0.000	0.002	0.023	−0.852	12.337	972.102***	−10.496***	−20.902***	0.058
NASDAQ	0.002	0.004	0.022	−1.029	10.674	681.227***	−11.057***	−21.732***	0.059
CSI300	0.002	0.002	0.016	−0.664	10.006	548.655***	−15.094***	−15.140***	0.043
ChiNext	0.003	0.004	0.021	−0.661	4.432	41.012***	−16.049***	−16.063***	0.048

Note: *, **, *** mean the significance level of 10%, 5%, 1%, separately. J-B stands for the Jarque-Bera test of normality. ADF and PP represent the Dickey & Fuller [54] and Phillips-Perron [55] unit root test and KPSS represents the Kwiatkowski et al. [56] stationarity test.

Information Administration (EIA) (https://www.eia.gov/), while Brent and SC prices are collected from Wind database (https://www.wind.com.cn/). In addition, considering the fact that WTI and Brent are traded in dollars, we convert the Chinese yuan price of SC to dollar price.[15]

As traditional industrial “economic weatherglass”, Dow Jones Industrial Average (DJIA) is one of the most-watched and most-influential stock indices in the world. As role model of global Growth Enterprise Market (GEM), National Association of Securities Dealers Automated Quotations (NASDAQ) is famous for high-tech stocks. China Securities Index 300 (CSI300) is the most representative index in China, tracking the top 300 mainland listed firms in the Shanghai Stock Exchange and Shenzhen Stock Exchange, as well as the Growth Enterprise Market in China (ChiNext) has promoted a large number of Chinese small and medium enterprises growth healthily and steadily. Therefore, we respectively employ DJIA and CSI300 to represent the main board stock markets in the US and China, and respectively use NASDAQ and ChiNext to represent the second board stock markets in the US and China, where all data can be downloaded from Wind database (https://www.wind.com.cn/).[16]

A cluster of cases of novel pneumonia were reported by Wuhan Municipal Health Commission on December 31, 2019, and it is eventually identified as Coronavirus disease 2019 (COVID-19) by WHO. Therefore, the daily data from December 31, 2019 to February 9, 2021 is employed as the COVID-19 epidemic period, totaling 260 trading days, after eliminating the non-matching missing data.[17] The returns of all variables are computed using the logarithmic difference, and Table 1 demonstrates that each series has significant summit and fat tailed skewed characters that skewness is not equal to zero and kurtosis exceeds three. All returns are rejected following a normal distribution verified by Jarque−Bera statistics. The results of ADF and PP uniformly show that all returns have no unit root. The results of KPSS indicate that all markets are stationary.

5. Empirical analysis

5.1. GARCHSK-Mixed Copula-CoVaR estimation

We fit a GARCHSK model for each returns while the GARCH class models, including GARCH, TGARCH and EGARCH, are employed as control groups. Those estimation results are compared with GARCHSK in term of Log Likelihood, AIC and BIC, in order to choose an optimum method. In order to verify the validity of GARCHSK, referring to literature [32,66], the ARCH and Ljung-Box Q tests are used to exam whether these standardized residuals from GARCHSK satisfy the model assumptions. Furthermore, Copula is a multivariate distribution function whose marginal distributions are uniform distributions on the interval (0, 1) [57]. Therefore, according to literature [53], we obtain the marginal distributions of each market by using the empirical cumulative distribution function (ECDF) to the standardized residuals measured by GARCHSK, and then, Kolmogorov - Smirnov (K−S) test is used to exam whether the marginal distributions are useful for Copula modeling. Table 2 demonstrates the modeling results of GARCHSK.

Table 2 denotes that, for every variable, some higher moments parameters of GARCHSK are statistically significant, demonstrating that dynamic skewness and kurtosis exist in returns of oil and stocks. Fig. 2 shows the dynamic variance, skewness and kurtosis of three oil futures, where the results of the other variables are in coincidence with oil futures and not presented to conserve space. In addition, it is also found in Table 2 that GARCHSK outperforms GARCH class methods in terms of log likelihood, AIC and BIC.[18] Therefore, GARCHSK is the optimum method for measuring the volatility of oil and stocks. Furthermore, the results of ARCH and Ljung-Box Q tests do not reject the hypotheses of no conditional heteroscedasticity and not autocorrelated so it is clear that the residuals satisfy the model assumptions. Besides, the results of K−S test also show that these marginal distributions satisfy the Copula condition. Therefore, it is confirmed that the GARCHSK models are correctly specified.

Based on the above results, Clayton Copula, Gumbel Copula, Frank Copula are adopted to construct a mixed Copula. In the meanwhile, Archimedean Copulas are employed as control groups, those estimation results will be compared with mixed Copula in term of Log Likelihood, in order to choose an appropriate method for modeling the dependence.

It is discovered in Table 3 that mixed Copula is the best, which outperforms the other Copulas in term of log likelihood in most cases.[19] Table 3 also demonstrates that dependence patterns between markets are completely different in terms of degree and structure. These results verify the Maneejuk et al. [4]'opinion that with multiple movements features, the dependence structure across financial markets is volatile, so that it is hard to be accurately measured by single Copula. Besides, it is found that Clayton Copula takes the largest proportion in most dependence patterns. Many scholars consider that the negative effects of COVID-19 on the world are worse than world wars, financial crises and so on [11,12]. In such a complicated market environment, significant dependence

[15] Our research is investigated from the perspective of an international investor who is trading/investing in U.S. dollars.

[16] CSI300 and ChiNext indices are dollar-denominated.

[17] The period from December 31, 2019 to July 22, 2020 is also defined as the COVID-19 epidemic period to research the oil-stock relationships, and the results are in line with those in the current paper. These empirical results can be made available under request addressed to the authors.

[18] The estimation results of GARCH class can be made available under request addressed to authors.

[19] The results of single Copulas are not shown, because of space limitations.

Table 2
Modelling results of GARCHSK.

	WTI	Brent	SC	DJIA	NASDAQ	CSI300	ChiNext
	−0.4223***	−0.108**	0.162***	−0.166***	−0.117**	0.134**	−0.089*
	0.000***	0.000***	0.000***	0.000***	0.000***	0.000**	0.000
	0.196***	0.777***	0.417***	0.229***	0.189***	0.128***	0.026
	0.776***	0.128***	0.181***	0.492***	0.770***	0.678***	0.901***
	−0.261***	−0.287**	−0.011***	−0.269**	−0.672***	−0.149	0.002
	−0.421***	−0.006	−0.044***	0.032***	0.002	0.000	−0.002
	0.039***	−0.681**	0.999***	−0.764***	−0.649	−0.230	0.999***
	3.823***	3.737***	2.931	3.537***	0.994	3.317***	0.938*
	0.048***	0.196***	0.000	0.015**	0.000	0.031*	0.036
	0.025***	0.004	0.002	0.048	0.702***	0.038	0.683***
LL	689.873#	761.782#	653.278#	952.988#	948.041#	967.031#	875.525#
AIC	−1359.746#	−1503.564#	−1286.556#	−1885.975#	−1876.082#	−1914.061#	−1731.051#
BIC	−1324.178#	−1467.996#	−1250.987#	−1850.407#	−1840.514#	−1878.493#	−1695.483#
ARCH(8)	7.418	3.802	10.309	5.555	2.022	5.933	8.331
	8.432	11.074	9.702	11.538	9.277	6.456	6.777
	7.485	3.977	11.823	6.255	2.157	5.881	8.339
K−S	0.004	0.004	0.004	0.004	0.004	0.004	0.004

Note : *, **, *** mean the significance level of 10%, 5%, 1%, separately. LL denotes Log-Likelihood. The hypotheses of ARCH test and Ljung-Box Q test are that residuals are no conditional heteroscedasticity and no autocorrelated, respectively, where Q and Q^2 denote the Ljung-Box statistics for returns and squared returns, respectively. The hypothesis of K−S test is that the marginal distributions come from a uniform distribution on the interval (0, 1) [67,68]. # means GARCHSK outperform all control groups at a variable.

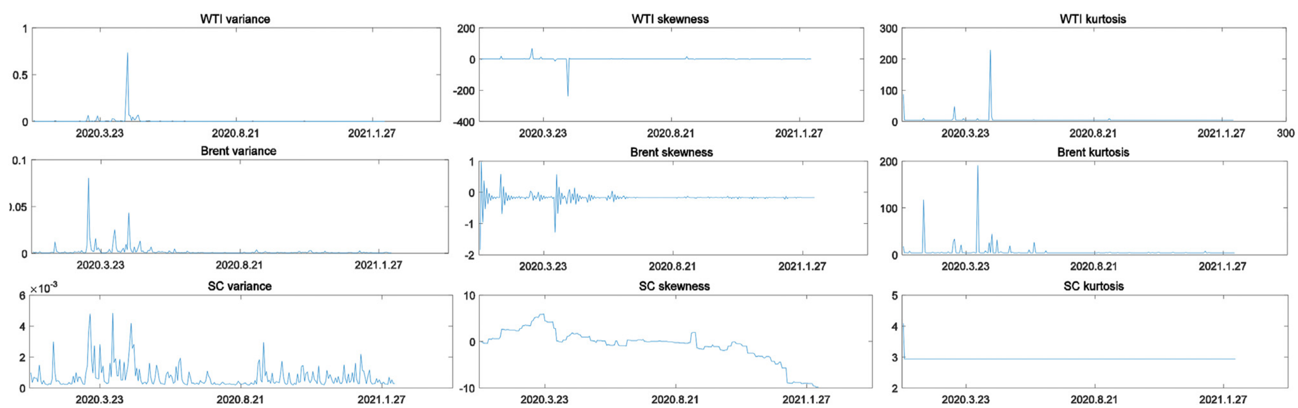

Fig. 2. Dynamic variance, Dynamic skewness, Dynamic kurtosis.

Table 3
Mixed Copula modeling results.

	ω_1	ω_2	ω_3	θ	α	λ	LL
WTI-Brent	0.478(0.002)	0.290(0.001)	0.231(0.001)	2.540(0.016)	3.157(0.006)	11.767(0.03)	155.104[a]
WTI-SC	0.623(0.001)	0.317(0.000)	0.060(0.001)	0.685(0.005)	1.700(0.003)	3.924(0.014)	33.600[a]
WTI-DJIA	0.978(0.005)	0.003(0.003)	0.020(0.001)	0.663(0.011)	1(0.007)	26.646(0.344)	28.250[a]
WTI-NASDAQ	0.997(0.008)	0.001(0.005)	0.002(0.002)	0.515(0.016)	1(0.010)	−5.035(0.204)	18.911
WTI-CSI300	0.997(0.006)	0.001(0.002)	0.001(0.002)	0.434(0.010)	1.048(0.006)	0.909(0.036)	14.249
WTI- ChiNext	0.996 (0.005)	0.002(0.003)	0.002(0.002)	0.342(0.007)	1(0.004)	0.387(0.025)	9.557
Brent-SC	0.700(0.002)	0.289(0.001)	0.011(0.002)	0.532(0.005)	1.513(0.003)	2.285(0.016)	21.999[a]
Brent-DJIA	0.628(0.006)	0.308(0.002)	0.064(0.004)	0.793(0.027)	1.510(0.047)	74.492(2.505)	42.687[a]
Brent-NASDAQ	0.880(0.005)	0.108(0.002)	0.012(0.002)	0.616(0.011)	2.265(0.017)	−3.79(0.120)	27.198[a]
Brent-CSI300	0.757(0.002)	0.223(0.001)	0.021(0.001)	0.499(0.004)	1.134(0.002)	1.018(0.012)	12.776[a]
Brent-ChiNext	0.989(0.004)	0.006(0.002)	0.005(0.001)	0.308(0.004)	1(0.002)	0.339(0.011)	7.751
SC-DJIA	0.574(0.001)	0.141(0.002)	0.284(0.000)	0.240(0.003)	1.185(0.002)	5.622(0.007)	15.131[a]
SC-NASDAQ	0.891(0.003)	0.007(0.003)	0.101(0.001)	0.218(0.004)	1.004(0.003)	15.575(0.043)	9.170[a]
SC-CSI300	0.845(0.003)	0.016(0.002)	0.139(0.001)	0.513(0.005)	1.225(0.003)	8.102(0.156)	24.159[a]
SC-ChiNext	0.717(0.003)	0.279(0.001)	0.004(0.002)	0.485(0.009)	1.195(0.005)	0.493(0.032)	13.600[a]
DJIA-NASDAQ	0.684(0.000)	0.301(0.000)	0.014(0.000)	2.365(0.000)	2.145(0.001)	33.853(0.039)	116.195[a]
DJIA-CSI300	0.451(0.000)	0.543(0.001)	0.006(0.002)	0.521(0.007)	1.338(0.004)	2.451(0.021)	19.859[a]
DJIA-ChiNext	0.413(0.000)	0.575(0.001)	0.012(0.002)	0.468(0.005)	1.212(0.003)	1.667(0.014)	11.825[a]
NASDAQ-CSI300	0.215(0.001)	0.779(0.003)	0.006(0.002)	0.451(0.008)	1.364(0.004)	2.691(0.022)	22.495[a]
NASDAQ-ChiNext	0.528(0.001)	0.459(0.000)	0.013(0.001)	0.217(0.003)	1.463(0.002)	−0.363(0.013)	14.244[a]
CSI300-ChiNext	0.648(0.003)	0.351(0.001)	0.001(0.004)	3.147(0.011)	2.605(0.008)	9.816(0.035)	153.793[a]

Note.
[a] denotes that mixed Copula is superior to the other Copulas in term of LL.

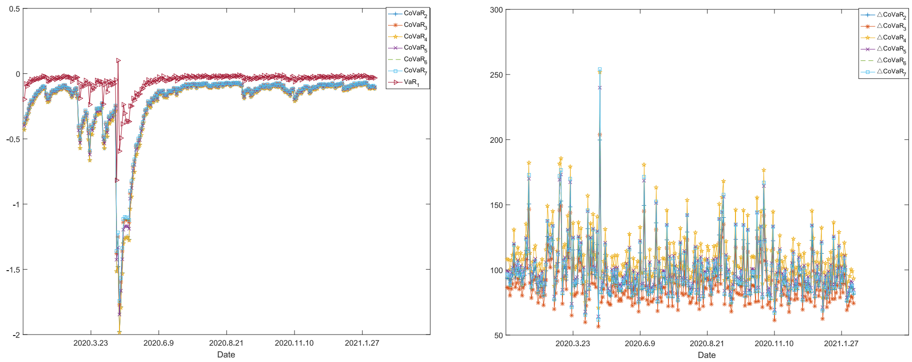

Fig. 3. VaR, CoVaR, △CoVaR for WTI

in the lower tails between financial markets is more likely to be discovered.

Employing the results of GARCHSK-Mixed Copula above, we compute VaR and CoVaR at the 95% confidence level ($\alpha = \beta = 5\%$). The left subgraphs of Figs.3–9 demonstrate time-varying VaR and CoVaR, and the right subgraphs of Figs.3–9 demonstrate time-varying △CoVaR. Left subgraphs show that CoVaR is obviously smaller than VaR. It is definite that CoVaR of variables estimates are higher in absolute risk value than VaR and that risk values are underestimated without considering the conditional on an extreme comovement of the other variables. The conclusion is in line with prior studies [27,33,43,44,49,50].

In right subgraphs of Figs.3–9, it is reported that all △CoVaR series are not zero means that there are two-way risk spillover effects between variables, which verify the prior studies' finding that regulators supervise risk of markets individually based on VaR, might not be the best policy for reducing systemic risk [9,43]. The subgraphs furthermore show that risk spillovers across markets are markedly different. The phenomenon may be accounted for the diverse nature of different markets.

5.2. Risk spillovers analysis

In order to analyze the multidimensional relationships among markets in the panoramic framework, we construct networks to research the full-sample and dynamic risk spillovers across oil and stock markets, based on the results measured by GARCHSK-Mixed Copula-CoVaR.

5.2.1. Full-sample (whole) risk spillover analysis[20]

The average dynamic △CoVaR ($S_t^{i|j}$) series are calculated to display the full-sample (whole) risk spillover from$x_{i,t}$to $x_{j,t}$ ($i \neq j$), respectively. Then these averages form an array, which is regarded as an adjacency matrix of full-sample network. The matrix is listed in Table 4. In Table 4, the off-diagonal column sums (labeled To) and row sums (labeled From) denote SII and VI, respectively. Besides, the TSI, sum of grand off-diagonal column sum (row sum), reveals in the lower right corner in Table 4. This table can provide an "input–output" matrix to denote the macro overview and whole network characteristics of multidimensional risk spillovers among markets during the COVID-19 epidemic. In the meanwhile, in order to make this study more in-depth concrete, the data from December 6, 2018 to December 30, 2019, totaling 250 trading days is chosen as the normal period, and the matrix is listed in Table 5.

Based on these matrices, we use network graphs for visualizing the multidimensional risk spillovers across markets.[21] Node sizes indicate assets' SII, which measure how much risk spillovers from a variable to the others; line (edge) sizes indicate the directional spillover of every pair. The higher value of risk spillover, the thicker line; arrow sizes indicate pairwise directional connectedness "to" and "from", where the higher value of unidirectional risk spillover, the bigger arrow size. Fig. 10 and Fig. 11 present the full-sample networks during the COVID-19 period and the normal period, respectively.

Tables 4 and 5 and Fig.10 and 11 demonstrate that the TSI and every market's SII during the epidemic period are obviously stronger than those during the normal period. COVID-19 pandemic, the gravest global crisis after the cold war, has already a huge influence on the international economy and development. According to a research report "The Pandemic and the Changing World" released by Boao Forum for Asia (BFA),[22] the pandemic may result in graver global economic recession than subprime crisis in 2008. The global stock and oil markets have also been hit hardest by the epidemic, through the global industrial and supply chains. Therefore, the TSI and every market's SII during the epidemic are stronger. The finding is in line with Sugimoto et al. [37]'s viewpoint that the contagion across financial markets becomes higher in the extreme events or crises.

Furthermore, in Tables 4 and 5 and Fig.10 and 11, it is discovered that distinguished from oil-stock relationships during the normal period, the risk spillovers from stocks to oil (total 802.603) are much stronger than those from oil to stocks (total 703.450) during the COVID-19 period. COVID-19 has severely damaged global economy [15,16], particularly oil importing coutries' economy, resulting into decline in oil demand. Although OPEC and their allies have struck a deal on a record cut in oil production and supply, the

[20] The way that we calculate TSI, VI and SII is in line with previous relative researches [1–5,9,10,32,33,42–46,49,50] that assume that all spillovers have the same weight. These studies calculate spillover indexes without considering the size of each market. In fact, the sizes of crude oil futures are difficult to compare with those of stock markets because crude oil futures markets are limited in crude oil while stock markets contain various industrial companies. In the meanwhile, different stock indexes contain different numbers of listed companies. For example, DJIA is a price-weighted index of 30 blue-chip U.S. companies, while NASDAQ contains more than 5000 listed companies. Another example, CSI300 is the most representative index in China, tracking the top 300 mainland listed firms, while ChiNext contains more than 800 listed companies. Therefore, the researches about the oil-stock relationships employ the way without considering the size of each market to study risk spillovers [1–5,9,10,32,33,42–46,49,50]. However, for further study, we also calculate TSI, VI and SII with considering the size of each market. The main conclusions of results are in coincidence with the current paper and can be made available under request addressed to the authors.

[21] We use Pajek software (http://mrvar.fdv.uni-lj.si/pajek/) to display large networks.

[22] This report is available on the link: http://english.boaoforum.org/u/cms/www2/202006/04165947ac6q.pdf.

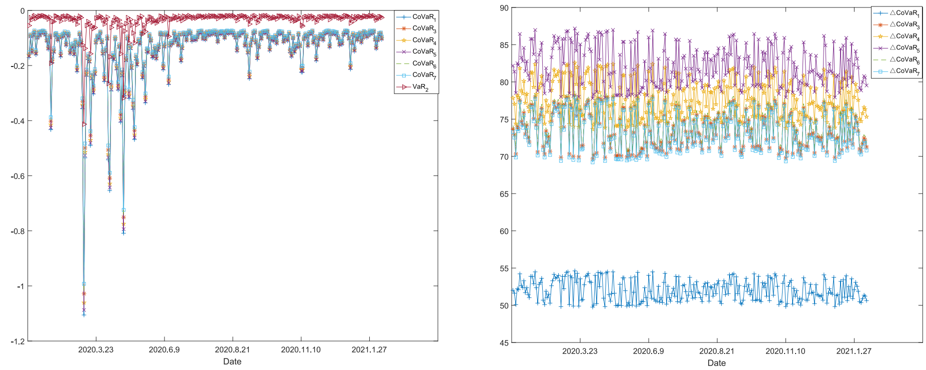

Fig. 4. VaR, CoVaR, △CoVaR for Brent.

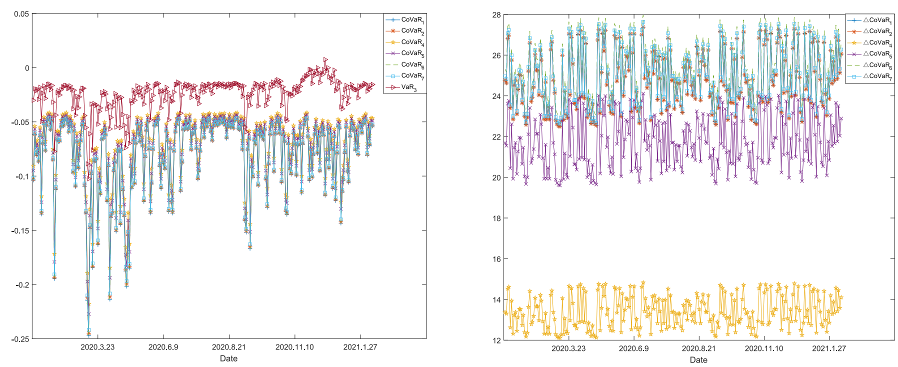

Fig. 5. VaR, CoVaR, △CoVaR for SC.

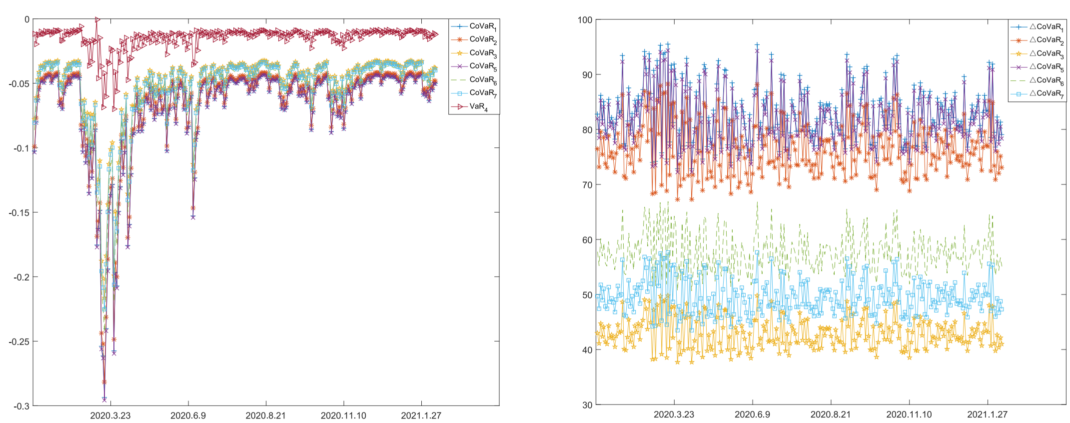

Fig. 6. VaR, CoVaR, △CoVaR for DJIA

oil prices reported severe contractions. Oil demand rely on global economic development [58]. As “economic weatherglass”, stock markets are more sensitive than oil response to the prosperity and recession of global economy [59], so that the investors in oil markets have to change investment actions according to the changes of stock markets.

In the meanwhile, in Tables 4 and 5 and Fig.10 and 11, it is found that oil futures receive high risk spillovers from second board stock markets, especially during the COVID-19 outbreak. It can be explained by the reason that soaring crude oil prices always occur during the boom years with bristling confidence of investors and consumers, thus, petroleum prices are positive relevant to the boom and recession of world economy [19]. With the outbreak of the information technology, high-growth & high-tech enterprises, listing in GEM, become a driver of the global economy and can be attributed to pro-cyclical sectors which synchronize with global economy [53]. Therefore, although most enterprises listed on the second markets do not directly need any input or output of related oil products, oil prices are greatly influenced by these second board markets.

In addition, tables and network graphs also demonstrate that the bidirectional China-oil risk spillovers during the COVID-19 pandemic have rapidly increased. On the one hand, as the largest crude oil buyer and emerging developing country, the changes of Chinese demand to the petroleum have a massive influence on the stability in the production and consumption of crude oil [28,30].

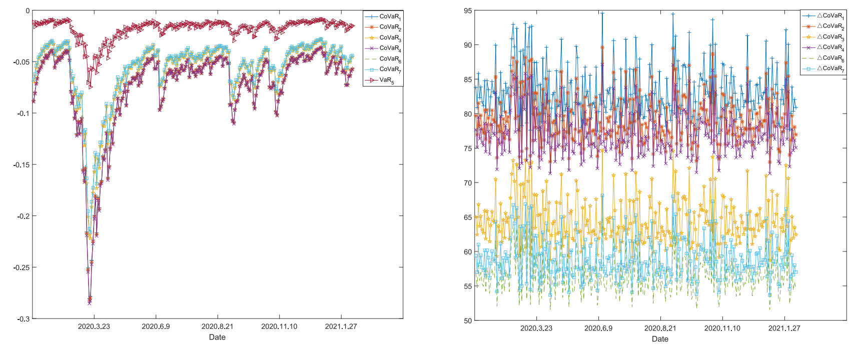

Fig. 7. VaR, CoVaR, △CoVaR for NASDAQ

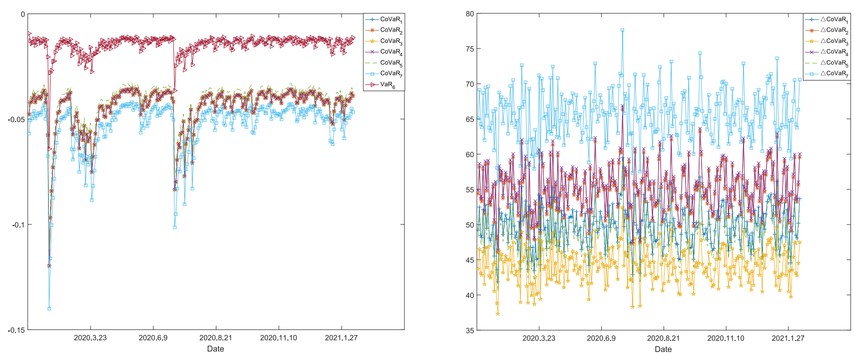

Fig. 8. VaR, CoVaR, △CoVaR for CSI300.

Fig. 9. VaR, CoVaR, △CoVaR for ChiNext. **Note:** VaR_1~ VaR_7 represent VaR of WTI, Brent, SC, DJIA, NASDAQ, CSI300, ChiNext, respectively. $CoVaR_1$~ $CoVaR_7$ represent the VaR for a variable conditional on an extreme comovement of WTI, Brent, SC, DJIA, NASDAQ, CSI300, ChiNext, respectively. △$CoVaR_1$~△$CoVaR_7$ represent the systemic risk contribution of WTI, Brent, SC, DJIA, NASDAQ, CSI300, ChiNext to a variable.

Table 4
The average of △CoVaR ($S_t^{i|j}$) during the COVID-19 period.

	WTI	Brent	SC	DJIA	NASDAQ	CSI300	ChiNext	From (VI)
WTI	0	95.640	88.787	111.225	101.761	97.014	99.941	594.368
Brent	52.008	0	73.606	77.7924	82.105	74.118	73.238	432.868
SC	24.785	24.781	0	13.388	21.712	25.328	24.981	134.974
DJIA	82.766	76.421	42.940	0	81.892	57.732	49.650	391.401
NASDAQ	83.304	79.197	64.601	77.2448	0	56.554	59.000	419.901
CSI300	49.669	55.000	44.097	55.416	48.740	0	65.677	318.595
ChiNext	41.420	43.895	40.140	43.700	36.098	49.120	0	254.372
To (SII)	333.952	374.928	354.171	378.766	372.307	359.866	372.487	TSL: 2546.477

Table 5
The average of △CoVaR (S_t^{ij}) during the normal period.

	WTI	Brent	SC	DJIA	NASDAQ	CSI300	ChiNext	From (VI)
WTI	0	86.137	52.506	66.740	45.766	64.807	8.849	324.805
Brent	16.916	0	34.243	29.317	29.619	31.958	9.019	151.072
SC	32.935	38.702	0	32.932	31.375	35.059	35.820	206.823
DJIA	37.284	43.918	25.226	0	64.957	29.410	29.241	230.037
NASDAQ	33.527	50.812	32.122	62.868	0	34.627	35.096	249.053
CSI300	61.923	49.650	40.220	20.924	34.653	0	66.208	273.577
ChiNext	14.203	13.387	39.157	35.013	35.824	37.075	0	174.659
To (SII)	196.788	282.607	223.474	247.795	242.195	232.936	184.233	TSL: 1610.027

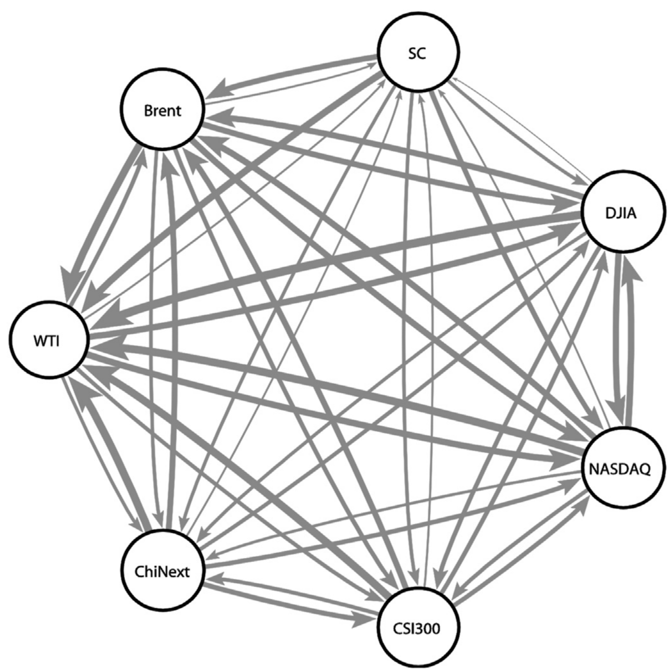

Fig. 10. Network during the COVID-19 period.

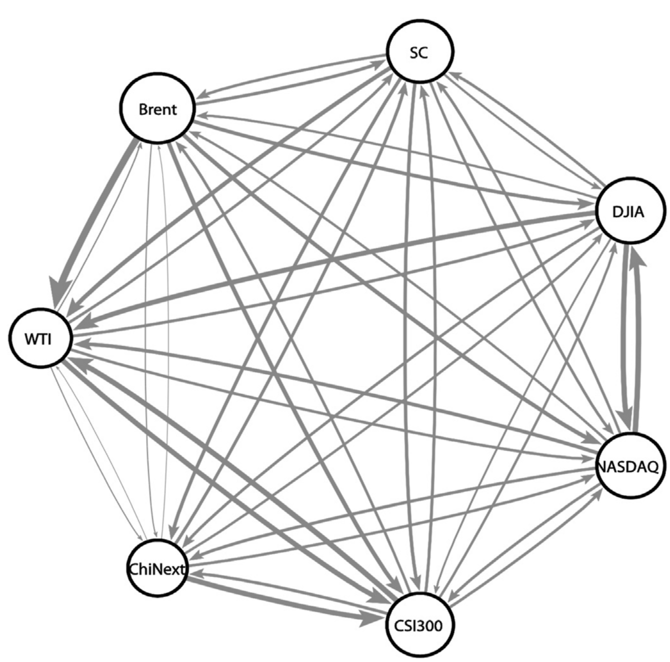

Fig. 11. Network during the normal period.

Besides, Chinese economy is hit by COVID-19 earliest, but Chinese economy begin to restore earliest with its GDP returns to growth with 3.2% in second quarter. On the other hand, sharp movement of oil prices affects entreprises' manufacture, social consumption, investors expection and government policy in China [19,60]. Thus, crude oil markets also have bigger risk spillovers to Chinese stocks than those in the normal period.

Further investigation of Tables 4 and 5 and Fig.10 and 11 indicates that SII of SC during the COVID-19 period is sharply increasing. With the quickening development of trading volume and internationalization, SC is increasingly playing an important role in the process of oil pricing. Then, SC is more representative of oil requirements in China than WTI and Brent, so that SC is vulnerable to the changes of Chinese economy and stocks. The phenomenon that VI of WTI is highest in Table 4 is also discovered. As the largest trading volume and highest internationalization crude oil futures, WTI is more vulnerable to the health of global economy as well as the supply and demand of petroleum than the other oil futures. The global economy recession and rapid decline in demand for crude oil worldwide are reported as a result of the COVID-19 outbreak, as well as OPEC and their allies failed to reach the valid agreement to trim supply before April. These negative information has the biggest impacted on WTI through the other financial markets.

5.2.2. *Dynamic risk spillover analysis*

Furthermore, time-varying risk spillovers during the COVID-19 pandemic are researched.[23] We begin the work by computing TSI_t. Fig. 12 denotes that the values of TSI_t during the COVID-19 period maintain at high levels, even the its lowest TSI (2315.460) is obviously stronger than full-sample TSI (1605.900) during the normal period. Besides, in Fig. 12, it is also found that the TSI series fluctuates within a high level rather than significant upward or downward trend. The phenomenon vertifies that the effects of COVID-19 on financial markets are long-lasting.

The results in Fig. 12 also show that the highest and lowest values of TSI are on March 20, 2020 and April 22, 2020, respectively. Therefore, we furthermore employ these days' data to form adjacency matrices and construct networks, in order to study the dynamic multidimensional risk spillovers. Table 6 and Fig. 13(a and b) denote the values of VI and SII as well as the networks on March 20, 2020 (corresponds to the lowest TSI) and April 22, 2020 (corresponds to the highest TSI), respectively. In Table 6 and Fig. 13(a and b), it is found that the main conclusions of risk spillovers characteristics and network structure both at highest and lowest spillover levels are in line with those in the full sample (see Table 4), which demonstrates that the relationships among oil futures, main board

[23] $CoVaR_{1,t}^{1|2}$ and $\Delta CoVaR_{1,t}^{1|2}$ can describe the dynamic risk spillovers between assets according to Eq. (11) and Eq. (12) [44,49,50]. Therefore, based on dynamic risk spillovers which can be detailed in Figss. 3–9, dynamic networks are constructed according to Eq. (13)and Eq. (14) without rolling window.

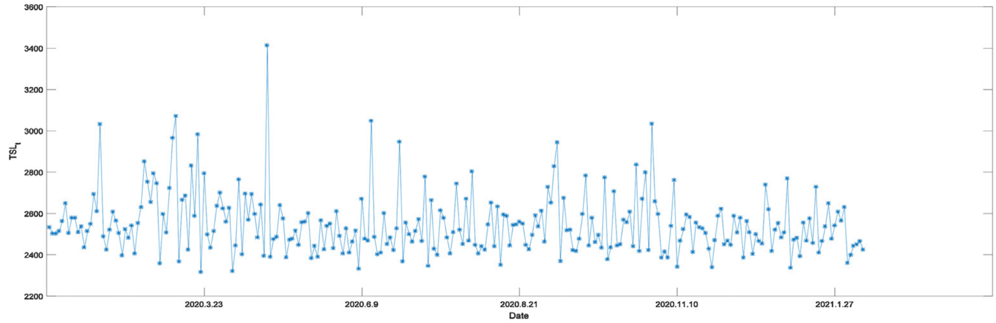

Fig. 12. TSI_t during the COVID-19 period.

Table 6
The values of VI and SII.

		WTI	Brent	SC	DJIA	NASDAQ	CSI300	ChiNext
2020/3/20	VI	433.588	411.434	124.680	384.128	412.913	289.943	258.774
	SII	323.368	342.134	321.494	338.725	333.183	325.867	330.689
2020/4/22	VI	1385.240	457.697	123.014	431.126	458.971	295.592	261.513
	SII	347.603	488.692	482.544	526.357	518.666	513.757	535.536

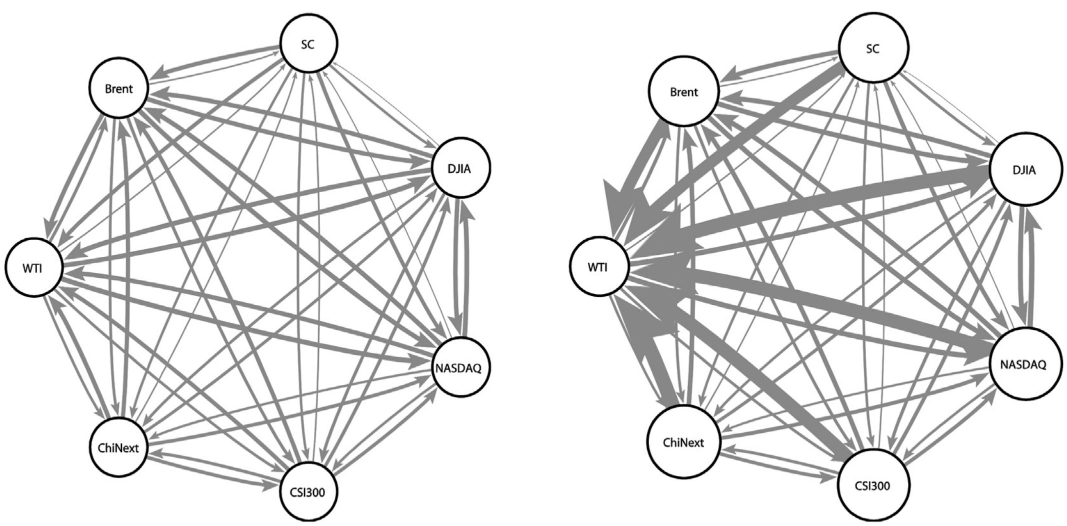

Fig. 13. a)The lowest TSI (TSL = 2315.460).(b) The highest TSI (TSL = 3413.154).

and second board markets in US and China are stable under both high and low TSI levels during the COVID-19 outbreak.

In order to further investigate time-varying risk spillovers among markets during the COVID-19 period, some time points corresponding to extreme events in Chinese stocks, US stocks and oil futures are also used to do more extensive studies. Chinese stock markets suffered one-day big drop on February 28, 2020 as a result of COVID-19 pandemic. Owing to rapidly increasing confirmed cases of COVID-19, US stocks tumbled and halted on March 9, 2020, described as “the worst one-day point decline ever for the Dow”. WTI oil futures price slumped almost 300% on April 20, 2020, trading at around negative $37/barrel, which is unprecedented price.[24] We construct matrices and networks corresponding to these events.

Table 7 and Fig.14–16 show the values of VI and SII as well as the networks on February 28, 2020, March 9, 2020, and April 20, 2020, respectively. These tables and graphs demonstrate that these effects of extreme events from different markets on TSI are various, where extreme event from US has the biggest influence on TSI, followed by extreme event from China, but the extreme event from oil futures has little influence on it. The phenomenon also verify our opinion that the stock markets lead the oil-stock risk spillovers during the COVID-19 period. Further investigation indicates that the main conclusions of risk spillovers characteristics and network structure under the extreme circumstances are in line with those in the full sample (see Table 4). Therefore, during the COVID-19 outbreak, the conclusions that risk spillovers characteristics and network structure among markets are stable under the extreme situations as well as extrme events have only impacted on the values of TSI can be obtained.

[24] According to EIA: https://www.eia.gov/dnav/pet/hist/RCLC1D.htm.

Table 7
The values of VI and SII.

		WTI	Brent	SC	DJIA	NASDAQ	CSI300	ChiNext
2020/2/28	VI	728.544	452.953	127.606	443.846	467.461	323.121	251.010
	SII	354.805	411.994	391.548	414.439	409.089	398.833	413.834
2020/3/9	VI	982.418	457.2616	124.027	405.804	439.768	297.430	258.344
	SII	338.574	430.508	418.177	452.601	442.772	434.580	447.842
2020/4/20	VI	755.977	411.077	128.449	352.640	409.198	333.130	251.514
	SII	322.236	390.010	369.635	404.038	389.062	374.363	392.642

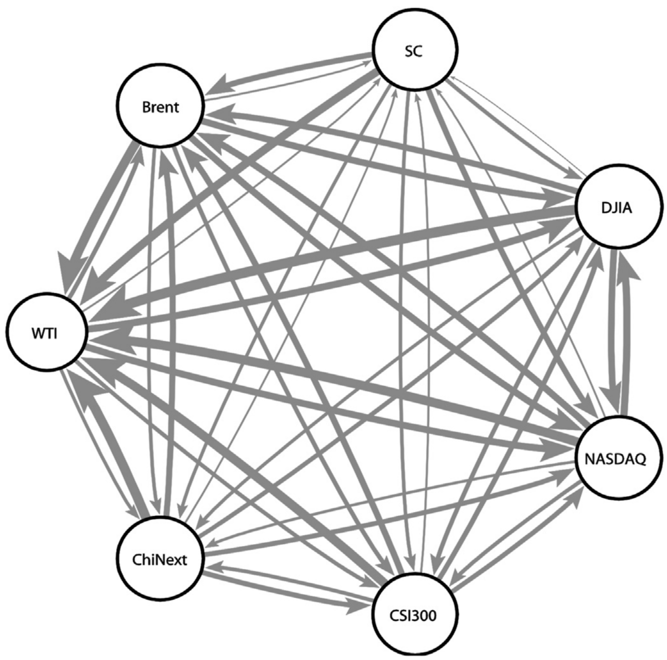

Fig. 14. Network on February 28, 2020 (TSI = 2794.542).

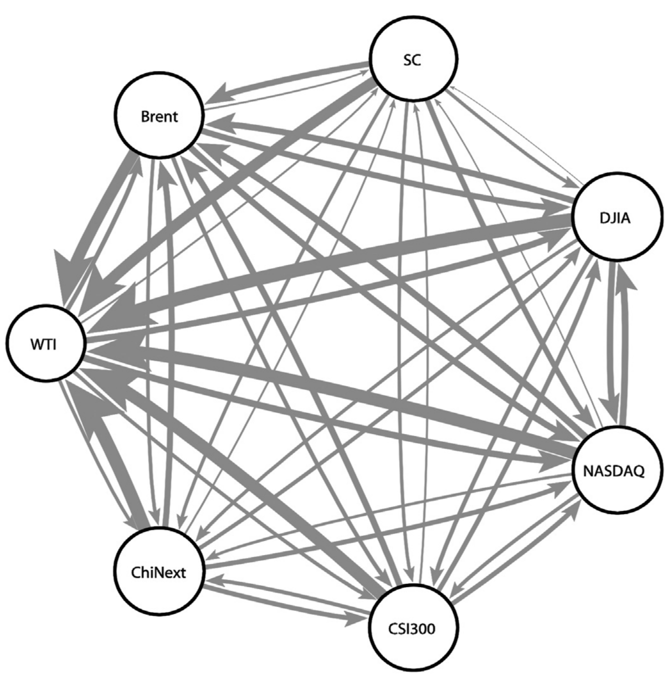

Fig. 15. Network on March 9, 2020 (TSI = 2965.053).

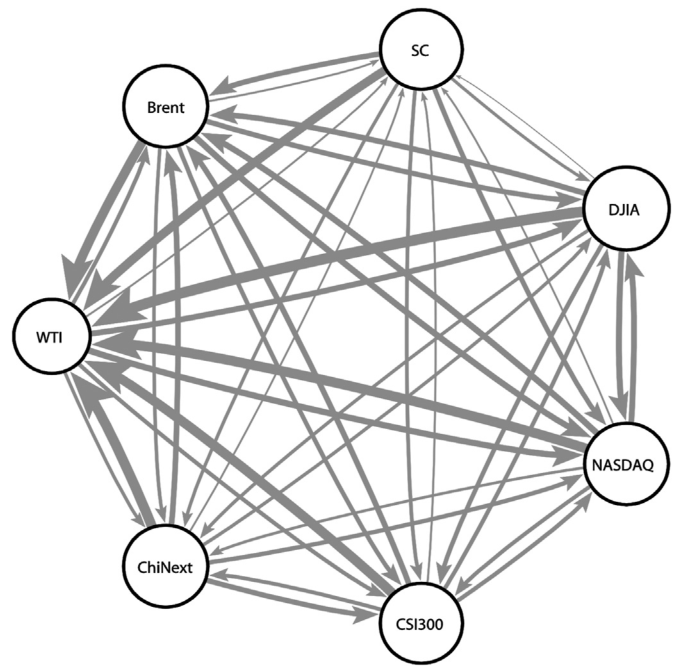

Fig. 16. Network on April 20, 2020 (TSI = 2641.986).

5.3. Robustness analysis

The robustness of risk spillovers among oil futures, main board and second board markets of the US and China during the COVID-19 period, is furthermore tested. Firstly, as the representative of crude oil, oil spot markets are employed to investigate the risk spillovers among markets. Besides, we reselect data process way to verify our empirical validity. Then, we also exam the risk spillovers weighted by the sizes of the markets. Because of space limitations, only full-sample risk spillovers results are shown.

We employ WTI spot, Brent spot, Daqing[25] spot prices as the representative of oil markets to investigate the oil-stock risk spillovers. Tables 8 and 9 and Fig.17 and 18[26] denote the full-sample risk spillovers results during the COVID-19 and normal periods. Compared with the results from oil futures, the TSL from oil spot markets is slightly stronger during the COVID-19 and normal periods. Then, the VI of Brent spot market is the strongest while the VI of WTI futures in section 5 is the strongest. It may be explained by the reason that WTI is the largest trading volume and highest internationalization crude oil futures while Brent spot market has

[25] SC has only futures without spot, while Daqing is often employed as the representative of Chinese crude oil spot market [51,70]. Therefore, we employ Daqing as Chinese spot market.

[26] There are some non-matching missing data between oil spot and oil futures, so that the phenomenon of same time frame but different amount of data is occurred.

Table 8
The average of △CoVaR during the COVID-19 period (oil spot prices).

	WTI	Brent	Daqing	DJIA	NASDAQ	CSI300	ChiNext	From (VI)
WTI	0	48.4818	51.332	57.336	56.30541	52.05787	43.44185	308.9543
Brent	119.178	0	116.523	119.788	117.892	115.030	116.811	705.223
Daqing	70.503	80.172	0	78.012	74.353	84.261	54.685	441.985
DJIA	59.223	60.987	56.866	0	64.799	37.418	29.170	308.464
NASDAQ	66.007	62.776	62.5441	61.790	0	56.797	60.105	370.019
CSI300	64.091	64.050	65.238	68.201	55.591	0	65.611	382.782
ChiNext	32.614	29.741	32.997	16.410	19.359	47.451	0	178.573
To (SII)	411.617	346.208	385.501	401.537	388.299	393.015	369.824	TSL: 2696.000

Table 9
The average of △CoVaR during the normal period (oil spot prices).

	WTI	Brent	Daqing	DJIA	NASDAQ	CSI300	ChiNext	From (VI)
WTI	0	82.947	67.024	63.572	48.358	53.451	14.139	329.492
Brent	28.335	0	26.956	19.835	26.669	16.088	10.971	128.855
Daqing	40.277	32.665	0	45.415	37.343	34.152	16.748	206.599
DJIA	55.065	46.715	54.749	0	63.042	52.084	47.394	319.049
NASDAQ	34.884	44.714	38.207	59.861	0	38.2883	37.739	253.693
CSI300	35.372	14.698	21.736	40.132	36.769	0	76.290	224.998
ChiNext	13.781	8.512	27.676	31.641	32.897	42.326	0	156.833
To (SII)	207.715	230.251	236.345	260.455	245.079	236.389	203.281	TSL: 1619.518

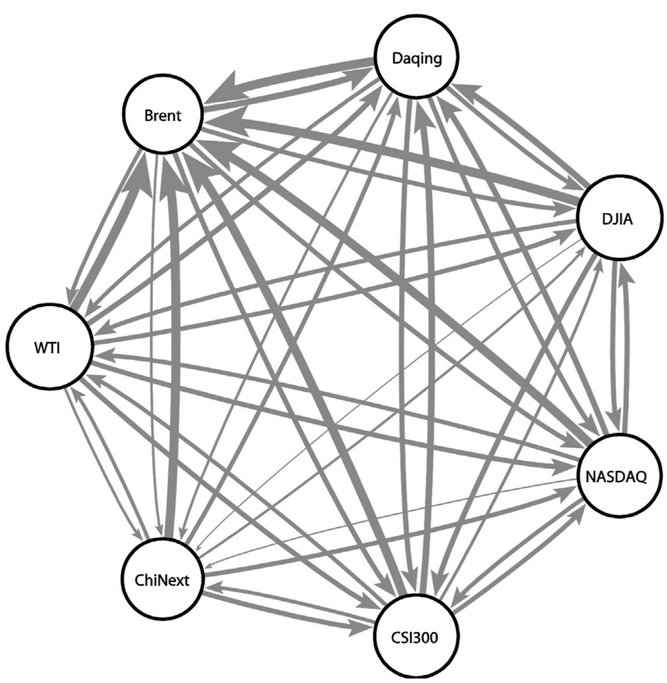

Fig. 17. Network during the COVID-19 period.

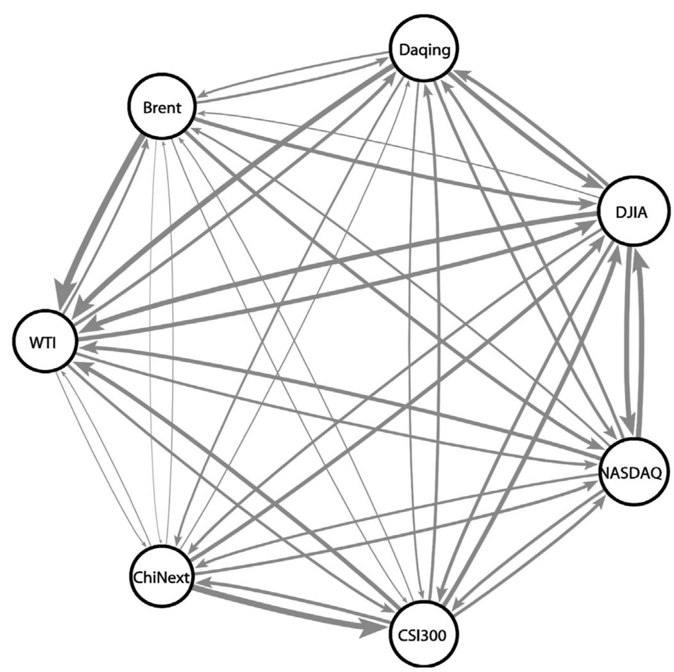

Fig. 18. Network during the normal period.

the largest trading volume in the crude oil spot trading. In fact, the Brent oil futures is as important as WTI oil futures in crude oil pricing [1,2,28,32]. Furthermore, the main conclusions Tables 8 and 9 and Fig.17 and 18 are in coincidence with section 5, which verify that empirical results in section 5 are reliable and robust.

Furthermore, owing to the difference of time zones and transaction rules, it is likely that markets in Asia are going to lead markets in the US, while lagged prices from the US are going to lead prices in Asia. In order to study influence from the “temporal proximity effect” which broadly states that part of the interconnectedness arises just because of non-synchronized trading hours [71,72] on the empirical results, we synchronize data based on the way from Výrost et al.[72].[27] The empirical results based on data synchronization are detailed in Tables 10 and 11 and Fig.19 and 20. It is no doubt that it significantly influences the results. However, the main conclusions are in coincidence with section 5, which verifies that empirical results are reliable and robust.

Besides, we also test the robustness of risk spillovers by changing α quantiles and COVID-19 period range, respectively. Fig.21 and 22 show the full-sample risk spillovers results during the

[27] Specific procedure can be detailed in literature [72].

Table 10
The average of △CoVaR in the COVID-19 period.

	WTI	Brent	SC	DJIA	NASDAQ	CSI300	ChiNext	From (VI)
WTI	0	91.248	94.926	95.512	95.630	11.759	17.912	406.986
Brent	52.008	0	74.132	88.721	95.482	104.649	101.168	516.161
SC	24.785	24.781	0	25.673	25.983	25.328	24.981	151.531
DJIA	82.766	76.421	42.940	0	81.892	57.732	49.650	391.401
NASDAQ	83.304	79.197	64.601	77.245	0	56.554	59.000	419.901
CSI300	49.669	54.995	44.097	106.012	99.802	0	65.677	420.253
ChiNext	41.420	43.895	40.140	49.984	60.755	49.120	0	285.312
To (SII)	333.952	370.536	360.836	443.147	459.544	305.141	318.388	TSL: 2591.544

Table 11
The average of △CoVaR in the COVID-19 period.

	WTI	Brent	SC	DJIA	NASDAQ	CSI300	ChiNext	From (VI)
WTI	0	53.595	8.3808	96.057	95.781	7.1424	2.100	263.056
Brent	16.916	0	19.529	38.835	30.638	22.789	10.930	139.638
SC	32.935	38.702	0	32.632	32.190	35.820	35.059	207.338
DJIA	37.284	43.918	25.226	0	64.957	29.241	29.410	230.037
NASDAQ	33.527	50.812	32.122	62.868	0	35.096	34.627	249.053
CSI300	14.203	13.387	39.157	10.556	12.592	0	37.075	126.970
ChiNext	61.923	49.650	40.220	26.633	62.236	66.208	0	306.869
To (SII)	196.788	250.064	164.635	267.581	298.395	196.296	149.201	TSL: 1522.960

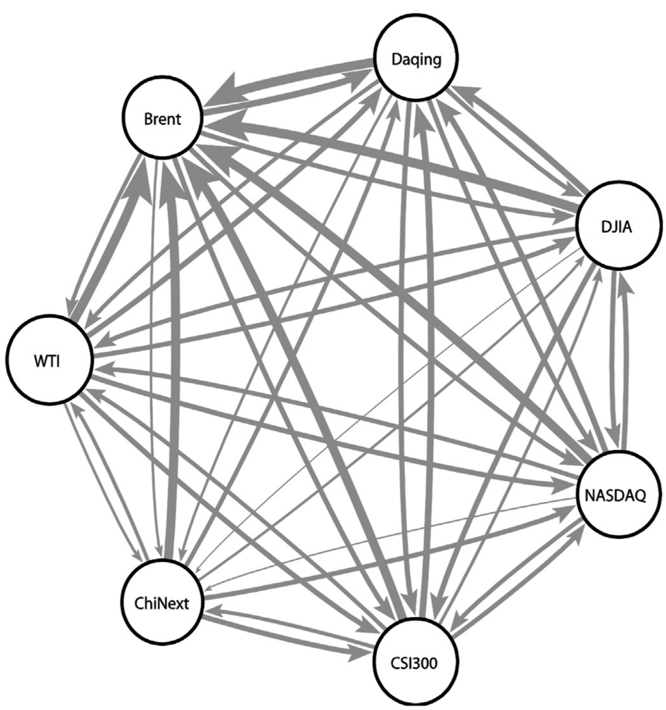

Fig. 19. Network during the COVID-19 period.

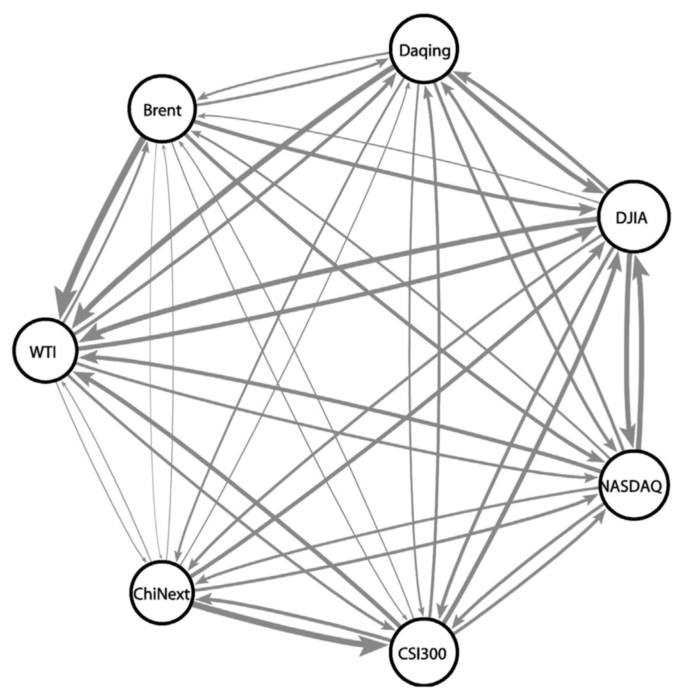

Fig. 20. Network during the normal period.

COVID-19 period when$\alpha$are 1% and 10%, respectively. Then, the WHO declared the first confirmed case of COVID-19 outside of China in Thailand, on January 13, 2020. Therefore, the daily data from January 13, 2020 to February 9, 2021 is employed as the data of COVID-19 period, these empirical results are shown in Fig. 23. These robustness results verify that the main conclusions are not affected by the changes αquantiles of CoVaR and COVID-19 period range.

6. Discussion

We propose a GARCHSK-Mixed Copula-CoVaR-Network to construct full-sample and dynamic networks for researching the multidimensional oil-stock risk spillovers during the COVID-19 pandemic. Around the research topic of oil-stock risk spillovers, we study not only the difference among WTI-stock, Brent-stock, and SC-stock relationships, but also the relationships between oil and main board markets and second board markets.

Based on full-sample risk spillover analysis, the result that risk spillovers among markets in the crisis period are obviously stronger than those in the normal period is in line with [17,61–63]. The

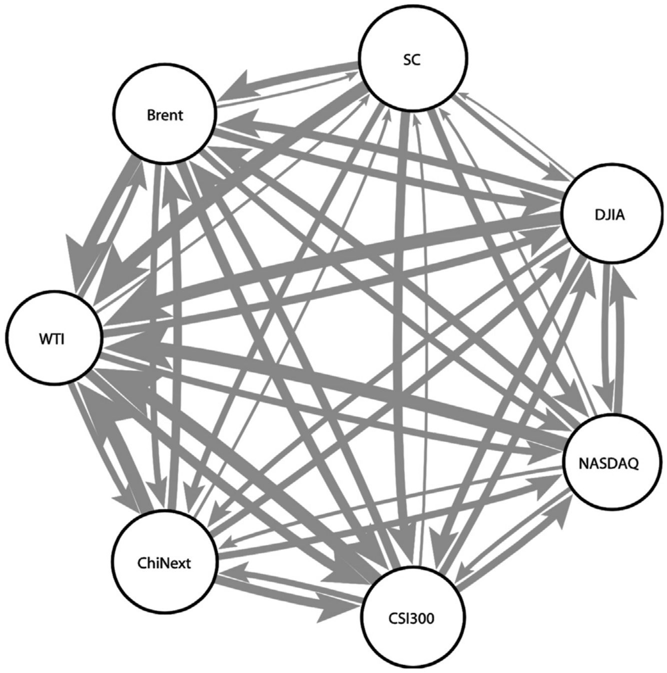

Fig. 21. Network(α = 1%) (TSI = 4232.076).

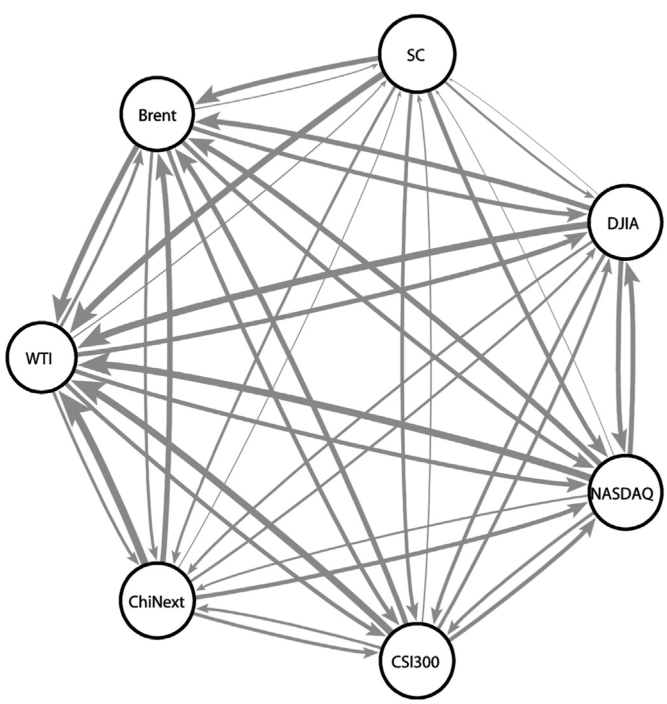

Fig. 22. Network (α = 10%) (TSI = 1976.052).

disease has also created the pandemic which is altering around the global financial markets. As Sugimoto et al. [37] say, the contagion across financial markets becomes higher in the extreme events or crises. However, unlike Mohamed [19] and Wang & Wang [30] who report that there is a greater significant risk spillover from oil price to stock markets, our conclusion is opposite. COVID-19 has severely damaged global economy [15,16]. It is explained that oil demand relies on global economic development [58], while stock markets are more sensitive than oil response to the prosperity and recession

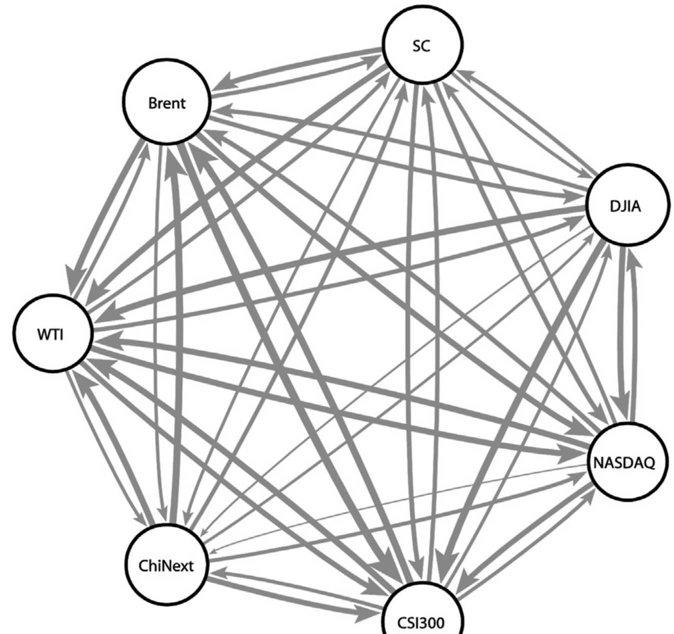

Fig. 23. Network (TSL = 2536.215).

of global economy [59]. Therefore, there are significant risk spillovers from the US and Chinese stock markets to the oil markets during the COVID-19 pandemic.

In addition, Yu et al. [31], Zhu et al. [53], Berna & Omid [64] discover the weak relationships between oil and Chinese stock markets, while we find that bidirectional risk spillovers between Chinese stock markets and international oil futures have rapidly increased. The phenomenon can be partly interpreted by Ashfaq et al. [28] who report that as the largest crude oil buyer, petroleum demand of China has a massive influence on the stability in the production and consumption of crude oil. Furthermore, the Chinese economy is the first to be hit by COVID-19 and also the first to restore. Therefore, there are strong risk spillovers from Chinese stocks to oil markets. The strong bidirectional risk spillovers between Chinese stocks oil can be also explained by Mohamed [19] who finds that sharp movement of oil prices affects list entreprises' efficiency in China. Oil markets suffered large swings owing to pandemic, resulting in a bigger risk spillover from oil to Chinese stocks. Distinguishing from relative literature [1–4,6,7,28,30,31,34,35], we also investigate the relationships between oil and GEM and discover that oil markets receive high risk spillovers from second board stock markets, especially during the COVID-19 outbreak. Besides, the conclusion that DJIA which emits strongest risk spillovers to the others is in line with [2,6,36].

Based on dynamic risk spillover analysis, the conclusion that the multidimensional relationships among oil futures, main board and second board markets in the US and China are stable under both high and low TSI levels and extreme situations can be in line with prior studies' finding that the effects of COVID-19 on financial markets are long-lasting [14,18,65]. Furthermore, it is reported in the current paper that extreme event from US has the biggest influence on TSI, followed by extreme event from China, but the extreme event from oil futures has little influence on it. The finding can be supported by Uddin et al. [35] who report that the US has the largest stock markets where 5000 companies are listed and influence the prices of the other countries' stocks and commodities.

7. Conclusions

We propose a GARCHSK-Mixed Copula-CoVaR-Network to construct full-sample and dynamic networks for researching the multidimensional risk spillovers among international oil futures, main board and second board markets in the US and China during the COVID-19 pandemic. The conclusions are as follows:

A GARCHSK-Mixed Copula-CoVaR-Network is proposed by four-phase modeling to measure multidimensional risk spillovers. The empirical results are as following: Firstly, for every variable, GARCHSK outperforms GARCH class methods while mixed Copula outperforms the other Copulas in most cases. In the meanwhile, Clayton Copula takes the largest proportion in most dependence patterns. Then, the △CoVaR under GARCHSK-Mixed Copula show that there are two-way risk spillover effects between assets.

Based on full-sample risk spillover analysis, these conclusions are summarized as follows: Firstly, TSI and every market's SII in the COVID-19 period are obviously stronger than those in the normal period. Besides, there are significant risk spillovers from the US and Chinese stock markets to the oil markets, during the COVID-19 outbreak. In addition, oil futures receive high risk spillovers from second board markets, especially during the COVID-19 outbreak. Moreover, bidirectional risk spillovers between Chinese stock markets and international oil futures have rapidly increased. Then, SII of SC in the COVID-19 period is sharply increasing.

Based on dynamic risk spillover analysis during the COVID-19 outbreak, these conclusions are obtained as follows: Firstly, the relationships among oil futures, main board and second board of stock markets in the US and China are stable under both high and low TSI levels. Secondly, these effects of extreme events from different markets on TSI are various, where extreme event from US has the biggest influence on TSI, followed by extreme event from China, but the extreme event in oil futures has little influence on it. In addition, risk spillovers characteristics and network structure across markets are stable under the extreme situations.

Our study not only offers new method and insight into the oil-stock relationship, but also has economic implications for policymakers and investors. For policymakers, it is necessary to consider financial markets as a whole because global networks across financial markets have highly produced interdependent systems. Furthermore, it is essential to introduce stricter and differentiating regulatory and institutional rules to control cross-market risk contagion during the COVID-19 pandemic, where stocks instead of oil should be received more attention. In addition, second board stock markets are supposed to be brought into the scope of regulation by regulators when confront with COVID-19 crisis. With the rapid development of information revolution, high-growth & high-tech enterprises have become a driver of the global economy, thus the effects of GEM on oil are highly-regarded.

For investors, risk spillovers in our work might be contributed to constructing effective portfolio schemes and improving investment efficiency. It is essential to reduce the weights of three oil futures and increase the weights of stocks in the portfolio. As the vulnerable markets which are greatly influenced by the stocks during the COVID-19 period, oil futures may bring more uncertainty to portfolio and worsen the portfolio performance of return and risk. Then, the second board markets have strong influence on the others so that the weights of NASDAQ and ChiNext should be increased more than main board stock markets in order to improve diversification benefits in the wake of COVID-19 crisis. Furthermore, it is unwise to only employ oil-stock portfolio for offsetting adverse price risk during the COVID-19 pandemic because of the result that the risk spillovers during the COVID-19 period are stronger than those during the pre-COVID-19 period. In order to improve the portfolio performance, it is essential to introduce other commodities such as gold into the oil-stock portfolio.

However, there are some limitations in our work, which should be admitted to add context to our conclusions and provide evidence for further research. Firstly, the study is limited in a single perspective that we use stock indices for research at the aggregate level without considering the heterogeneity of the risk spillovers between distinct stock sectors and crude oil. Another limitation of our work is that COVID-19 crisis is far from end so that the financial markets would be notorious changeable. Further follow-up studies are needed to confirm our conclusions.

Author statement

Pengfei Zhu: Writing-original draft, Investigation, Conceptualization, Methodology; Yong Tang: Supervision, Funding acquisition; Yu Wei: Supervision, Validation; Tuantuan Lu: Data curation, Software, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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