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Linkages between the international crude oil market and the Chinese stock market: A BEKK-GARCH-AFD approach

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ABSTRACT

The extant literature mainly utilized the wavelet tools and EMD-type methods to investigate linkages between different markets based on the frequency-domain information, confronting the difficulties of the wavelet basis selections and scale aliasing phenomenon. To overcome these disadvantages, the present study proposes a BEKK-GARCH-AFD approach based on the adaptive-Fourier-decomposition (AFD) to reveal the linkages between the international crude oil market and the Chinese stock market. According to the spillover effect between markets revealed by BEKK-GARCH, the proposed approach could further disclose the linkages between markets under external shocks with high-resolution information concerning market fluctuations provided by the AFD. Our empirical results demonstrate that the oil supply and demand shocks caused by external events (e.g., the strikes, the geopolitics, and the natural disasters) will put pressure on the Chinese stock market, while the combination of bullish and bearish events (e.g., the reduction of crude oil production and the shale oil boom) contributes to stabilizing the stock market.

1. Introduction

In addition to being a product that is scarce, strategic, economic, and geopolitical, the role of oil as a financial product has gained much popularity. An increasing number of investors have taken the oil assets (especially the oil futures) into their investment baskets, leading to the linkages between the oil market and the financial markets (especially the stock market) (Jiang and Yoon, 2020). The oil-stock links have been extensively reported by academia (Guo et al., 2021). Theoretically, a rapid increase in oil price will enlarge the inflation rate affecting production costs and actual consumption level (Reboredo and Ugolini, 2016), which may result in a decline in investment, especially the investment in the stock market. In turn, stock market conditions and investor sentiments could also exert significant effects on oil price (He, 2020).

China's oil import dependence has grown rapidly for its fast-developed economics (Zhang et al., 2020b). By the end of 2019, China's crude oil imports increased by 9.5%, causing a high degree of dependence on imports at over 72%. Thus, China's economy and its "barometer", the stock market, are sensitive to the international oil market with the decisiveness of three major crude oil prices internationally to oil product prices (Huang et al., 2018). Therefore, it is imperative to analyze the linkages between the international oil market and the stock markets, especially the Chinses stock market, for financial risk management and investment decision.

Up to the present, abundant literature has explored the linkages between the oil and stock markets considering the time-domain information with three groups of statistical models. The first refers to the vector autoregression (VAR) models, which are commonly used to capture the impact of oil shocks on the stock market (Wen et al., 2019), whereas they neglect the nonlinear features of complex relationships between real financial markets (Yu et al., 2020). The copulas can solve this problem by allowing nonlinearity, symmetric, asymmetric, and tail dependence (Jammazi and Reboredo, 2016; Liu et al., 2017; Sukcharoen et al., 2014) since they have more relaxed requirements for data (Sklar, 1959). However, they fail to determine the direction of spillovers between the markets (Ji et al., 2018; Uddin et al., 2020). The third is for the GARCH models, which have gained much popularity for considering the heteroscedasticity of the conditional variance of financial time series (Engle and Kroner, 1995). Additionally, one of them, namely BEKK-GARCH, overcomes the disadvantages of the copulas and determines the direction of the spillovers from one market to another accurately

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(Salisu and Oloko, 2015).

It is noted that most existing literature is conducted based on the assumption of a constant data generation process (DGP) (Mensi et al., 2015). However, given that the impact of the external events, there might exist structural breaks (Chen et al., 2014a; McMillan et al., 2021; Salisu and Oloko, 2015; Yu et al., 2020) potentially influencing the relationship between the two markets. Thus, some studies have also considered the oil-stock links by introducing the definition of structural breaks. A part of them first divide the sample period due to the structural breaks and then explore the changes in spillover effects between the oil market and the stock market in sub-samples. For example, Hou et al. (2019) discover differing patterns of bilateral spillovers between the fuel oil market and the stock market across multiple periods. On the contrary, the other studies first explore linkages between the two markets and then detect the structural breaks in the linkages. For instance, based on the work of Westerlund (2006), Li et al. (2012) provide evidence of structural breaks for the relationship between oil price and Chinese sectoral stocks.

Considering that the financial time series also possesses the frequency dimensional features, a branch of literature also concentrates on the oil and stock markets by applying frequency analysis such as the wavelet analysis and the EMD (Empirical Mode Decomposition), the most two famous methods to capture the frequency-domain information. Some literature has concentrated on the oil market through the combination of wavelet decomposition and the statistical methods (e.g., VAR, MARCH) (Chen et al., 2020, 2019). Moreover, several studies capture the oil-stock co-movements by employing the wavelet coherence analysis (Sun et al., 2020). Additionally, some scholars combine the EMD with different methods to investigate the interactions between markets, analyze price-driving factors and make price predictions (Zhu et al., 2019, 2017, 2018). On this basis, a portion of researchers work on the financial time series by EEMD (Ensemble Empirical Mode Decomposition, EEMD) and CEEMD (Complete Ensemble Empirical Mode Decomposition, CEEMD), which are the improvements of EMD (Lin et al., 2019; Zhang et al., 2020a).

Generally, although the above studies consider the time-domain and frequency-domain information, they all have certain limitations. To be specific, the commonly used statistical models fail to consider the frequency-domain information, while a challenge for wavelet analysis is how to select the wavelet basis and decomposition level, which can influence the visual presentation of the time-frequency analysis diagram (Xie et al., 2021). Although the EMD avoids this disadvantage, it presents the scale aliasing phenomenon (Hu et al., 2012). To improve this problem, Wu and Huang (2009) propose EEMD by adding noise to the original signal. However, it does not completely eliminate the phenomenon of scale aliasing in EMD, and the reconstructed signal by it restrains the residual noises (Wu and Huang, 2009). A further improved model, CEEMD, resolves the mode aliasing problem comprehensively and minimizes the error of reconstructed signals (Colominas et al., 2014). However, its computational complexity and cost might be enormous (Yeh et al., 2010). Besides, more important is that although being aware of the frequency domain information, most of the existing literature still ignores the existence of the structural breaks that consider frequency information.

To fill the existing gaps, the present study proposes a BEKK-GARCH-AFD approach that is based on adaptive-Fourier-decomposition (AFD), a novel signal decomposition model, to investigate the linkage between the international crude oil market and the Chinese stock market. Firstly, the BEKK-GARCH is employed to testify the existence of the risk spillovers between the international oil market and the Chinese stock market. Then, the AFD is utilized to construct the instantaneous time-frequency distribution that is employed for detecting the structural breaks given the frequency information of the market, which receives the risks transmitted from the other. Finally, the present study analyzes the fluctuation characteristics of the market that is a risk receiver under the detected structural breaks by considering the influence of the risk sender.

The main contributions of the current work are presented as follows. Firstly, the BEKK-GARCH-AFD can not only determine the spillover relationship between markets but also accurately grasp the specific time and the magnitude of the influence of one market on another market. Secondly, the proposed approach overcomes the disadvantages of the widely used statistical models and frequency analysis (e.g., the ignorance of frequency information, the necessity for base functions, or the scale aliasing phenomenon), and notices the structural breaks in the frequency domain (Dang et al., 2013). Thirdly, to our best knowledge, this paper is the first to analyze the oil-stock linkages under the structural breaks considering the frequency domain information and provide empirical evidence for them.

This study obtains some important findings. First, the empirical results demonstrate that there is a significant spillover effect from the international crude oil market to the Chinese stock market. Second, influenced by the fluctuation of the international oil market, there exist obvious structural breaks of the Chinese stock market, which results in volatile changes. The oil supply and demand shocks caused by external events (e.g., the strikes, the geopolitics, and the natural disasters) will lead to drastic fluctuations in the oil prices, which can thus put pressure on the Chinese stock market. Additionally, the combination of bullish and bearish events (e.g., the reduction of crude oil production and the shale oil boom) is significant for the balance of the oil market, which is conducive to stabilizing the Chinese stock market.

The remainder of this paper is organized as follows. Section 2 introduces the proposed approach. Section 3 deals with the data and performs the empirical analysis. Section 4 presents the conclusion.

2. Methodology

2.1. The framework of BEKK-GARCH-AFD

This paper proposes a BEKK-GARCH-AFD approach based on the BEKK-GARCH model and the AFD to investigate the linkages between the international crude oil market and the Chinese stock market. The proposed approach attempts to capture the risk transmission between the international crude oil market and the Chinese stock market, and struggles for detecting the structural breaks of the risk receiver in the frequency domain. Specifically, the BEKK-GARCH model is first employed to determine the direction of the risk spillovers between the two markets, aiming to identify the risk receiver. On this basis, the AFD algorithm is applied to decompose the data series of the risk receiver. Subsequently, based on the AFD, the instantaneous time-frequency distribution of the data series of the risk receiver is reconstructed. Then, according to the instantaneous time-frequency distribution, the structural breaks of the market can be detected. Finally, this paper analyzes the extent of the influence of the risk sender on the risk receiver under the external shocks. As shown in Fig. 1, the block diagram of the BEKK-GARCH-AFD method is displayed.

The steps of the proposed approach are presented as follows:

Step 1: Within the sample interval, the existence of risk spillovers between the international crude oil market and the Chinese stock market is verified via the BEKK-GARCH model.
Step 2: Through AFD, the fast signal orthogonalization is performed on $S(t)$, which denotes the data series of the market that serves as a risk receiver. Then, the $S(t)$ is decomposed into $S_1(t)$, $S_2(t)$, ……, $S_n(t)$, representing different characteristics at different frequencies.
Step 3: Based on AFD, an instantaneous time-frequency distribution diagram is created, which is composed of a lot of colorful points and can characterize the frequency change characteristics of a time series on timescales. We can judge the structural breaks based on the change in the distance between the peaks of the composition of the colorful points and the density of the color points.

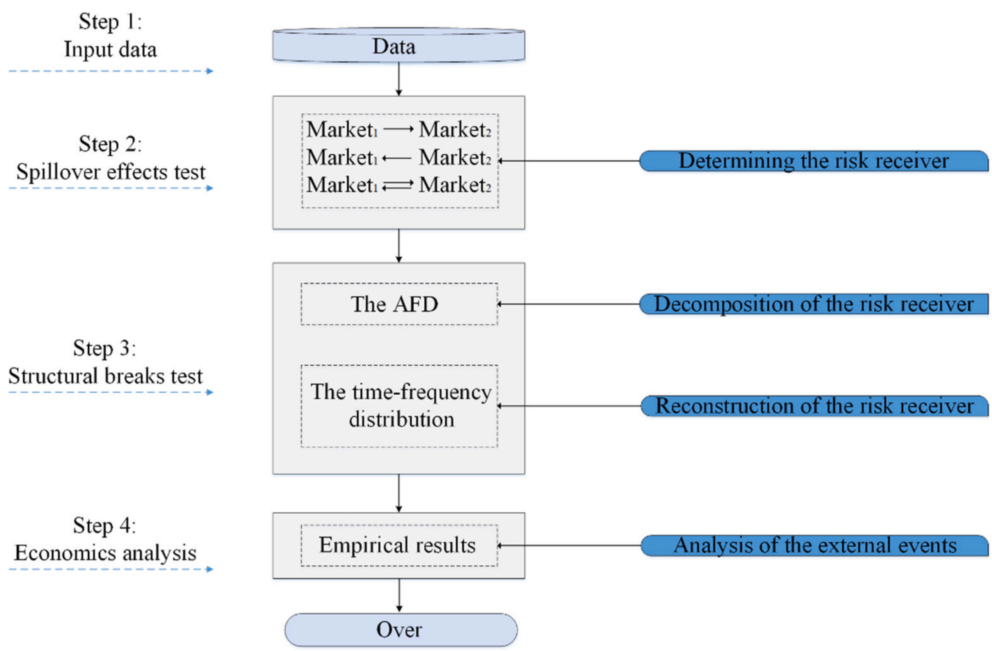

Fig. 1. Block diagram of BEKK-GARCH-AFD approach.

Step 4: This paper analyzes the extent to which external shocks in the market acting as a risk sender affect the market as a risk receiver.

2.2. Basic methods of BEKK-GARCH-AFD

The BEKK-GARCH-AFD algorithm mainly involves the methods for testing the spillover effect and structural breaks. Specifically, the BEKK-GARCH model is employed to test the spillover effect, and the AFD technique is used to achieve the fast orthogonalization of signals. Furthermore, the AFD-based instantaneous time-frequency distribution is exploited to perform the structural breaks test. The basic ideas of these methods will be described separately in the current section.

2.2.1. BEKK-GARCH model

The multivariate BEKK-GARCH (1,1) model is utilized to observe the time-varying volatility spillover effects between the international crude oil and the Chinese stock markets. The commonly used GARCH (1,1) form is:

$$R_t = X_t\theta + \varepsilon_t, \varepsilon_t|\Omega_{t-1} \sim N(0, h_t), \tag{1}$$

$$h_t = a_0 + a_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1}, \tag{2}$$

where X_t stands for the explanatory variable, θ denotes the coefficient vector, ε_t represents that the conditional residuals follow a normal distribution, and h_t denotes the conditional variance. The volatility spillovers between the two time series for the international crude oil and the Chinese stock markets are observed using the multivariate GARCH model, e.g., the vector GARCH model. At this point, the residual sequence of the mean equation follows a multivariate normal distribution. The conditional covariance matrix is denoted by H_t, and the variance equations are set up as follows:

$$H_t = W + A'\varepsilon_{t-1}\varepsilon_{t-1}'A + B'H_{t-1}B, \tag{3}$$

$$A = \begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix}, \quad W = \begin{pmatrix} \omega_1 & 0 \\ \omega_2 & \omega_3 \end{pmatrix}, \quad B = \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix}, \tag{4}$$

where W denotes the constant-coefficient matrix, A is the coefficient matrix of conditional residual matrix term, and B is the coefficient matrix of conditional covariance term. Specifically, the conditional covariance matrix of the BEKK-GARCH (1,1) model is written as:

$$\begin{aligned} h_t = \begin{pmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{pmatrix} &= \begin{pmatrix} \omega_1 & 0 \\ \omega_2 & \omega_3 \end{pmatrix}' \begin{pmatrix} \omega_1 & 0 \\ \omega_2 & \omega_3 \end{pmatrix} \\ &+ \begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix}' \begin{pmatrix} \varepsilon_{1,t-1} \\ \varepsilon_{2,t-1} \end{pmatrix} \begin{pmatrix} \varepsilon_{1,t-1} \\ \varepsilon_{2,t-1} \end{pmatrix}' \begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix} \\ &+ \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix}' \begin{pmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{pmatrix} \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix}. \end{aligned} \tag{5}$$

The above equation can be written separately as:.

$$\begin{aligned} h_{11,t} = \omega_1^2 + \alpha_{11}^2\varepsilon_{1,t-1}^2 + 2\alpha_{11}\alpha_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \alpha_{21}^2\varepsilon_{2,t-1}^2 \\ +\beta_{11}^2 h_{11,t-1} + 2\beta_{11}\beta_{21}h_{12,t-1} + \beta_{21}^2 h_{22,t-1} \end{aligned}, \tag{6}$$

$$\begin{aligned} h_{22,t} = (\omega_2^2 + \omega_3^2) + \alpha_{12}^2\varepsilon_{1,t-1}^2 + 2\alpha_{22}\alpha_{12}\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ +\alpha_{22}^2\varepsilon_{2,t-1}^2 + \beta_{12}^2 h_{11,t-1} + 2\beta_{12}\beta_{22}h_{12,t-1} + \beta_{22}^2 h_{22,t-1} \end{aligned}, \tag{7}$$

$$\begin{aligned} h_{12,t} = \omega_1\omega_2 + \alpha_{11}\alpha_{12}\varepsilon_{1,t-1}^2 + (\alpha_{11}\alpha_{22} + \alpha_{21}\alpha_{12})\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ +\alpha_{22}\alpha_{21}\varepsilon_{2,t-1}^2 + \beta_{11}\beta_{12}h_{11,t-1} + (\beta_{11}\beta_{22} + \beta_{21}\beta_{12})h_{12,t-1} \\ +\beta_{21}\beta_{22}h_{22,t-1} \end{aligned}, \tag{8}$$

where $h_{11,\ t}$ represents the conditional variance of the rate of return in the international crude oil market, $h_{22,\ t}$ denotes the conditional variance of the rate of return in the Chinese stock market, and $h_{12,\ t}$ signifies the conditional covariance of the rate of returns in both markets. It is particularly noteworthy that α_{11} and β_{11} describe the ARCH and GARCH volatility effects of the international crude oil market itself, α_{22} and β_{22}

denote the ARCH and GARCH volatility effects of the Chinese stock market itself, α_{12} and β_{12} describe the ARCH and GARCH volatility effects of the international crude oil market's return on the Chinese stock market's return (i.e. the changes in the conditional volatility of the Chinese stock market caused by past abnormal impacts of the international crude oil market, as well as the volatility spillover effects of the international crude oil market on the Chinese stock market), and α_{21}, β_{21} represent the ARCH and GARCH volatility effects of the Chinese stock market's return on the international crude oil market's return (i.e. the changes in the conditional volatility of international crude oil market caused by past abnormal impacts of the Chinese stock market, as well as the volatility spillover effects of the Chinese stock market on the international crude oil market).

The current work focuses on discussing the relationship between the secondary moments of the returns in the international crude oil market and the Chinese stock market since its primary tasks are characterization and examination of the volatility spillover effects between the two markets. To investigate the inter-market spillover effects, the Wald test is performed on matrix elements. There are a total of three hypotheses to be tested:

1. When the stock market has no direct spillover effect (unidirectional volatility spillover effect) on the oil market, the null hypothesis is $H_0 : \alpha_{21} = \beta_{21} = 0$.
2. When the oil market has no direct spillover effect (unidirectional volatility spillover effect) on the stock market, the null hypothesis is $H_0 : \alpha_{12} = \beta_{12} = 0$.
3. When there is no mutual spillover effect (bidirectional volatility spillover effect) between the two markets, the null hypothesis is $H_0 : \alpha_{12} = \beta_{12} = \alpha_{21} = \beta_{21} = 0$.

The direction of spillover effects between the international crude oil market and the Chinese stock market is determined based on the Wald test results, and thus the data under the structural change point test is decided. The following four results may occur:

1. If there is no volatility spillover effect between the oil market and the stock market, the experiment will end.
2. If there is a unidirectional volatility spillover effect from the oil market to the stock market, the stock market time series will be decided as the data under test.
3. If there is a unidirectional spillover effect from the stock market to the oil market, the oil market time series will be decided as the data under test.
4. If there is a bidirectional spillover effect between the oil market and the stock market, the time series of both markets will be decided as the data under test.

2.2.2. Adaptive Fourier decomposition (AFD)

Based on the Takenaka-Malmquist system, adaptive Fourier decomposition of the data under test is performed (Chen et al., 2016; Qian, 2009). The Takenaka-Maluquist system is defined as:

$$B_n(z) = B_{\{a_1,a_2,\cdots,a_n\}}(z) := \frac{1}{\sqrt{2\pi}}\frac{\sqrt{1-|a_n|^2}}{1-\overline{a_n}z}\prod_{k=1}^{n-1}\frac{z-a_k}{1-\overline{a_k}z}. \tag{9}$$

$a_n \in D$, $n = 1, 2, \ldots$, $D = \{z \in C : |z| < 1\}$, where C is the complex plane. For any sequence $\{a_n\}$ at D, the Takenaka-Malmquist system is orthonormal normal. Regarding all existing studies of the system, there is a premise condition:

$$\sum_{k=1}^{\infty}(1-|a_k|) = \infty, \tag{10}$$

which is sufficient and necessary for a TM system $\{B_n\}$ to be a complete basis in all the Hardy space $H^2(D)$ (Mo et al., 2015; Zhang et al., 2014).

For the standard case of $H^2(D)$, in AFD, we have a "dictionary" consisting of the elementary functions:

$$e_{\{a\}}(z) := B_{\{a\}}(z) = \frac{1}{\sqrt{2\pi}}\frac{\sqrt{1-|a|^2}}{1-\overline{a}z}, a \in D. \tag{11}$$

The function $e_{(a)}$ is called the evaluator at a (also reproducing kernel and shifted Cauchy kernel). Each evaluator gives rise to the evaluating functional essentially. In fact, for any $F \in H^2$, with the Cauchy Formula, we have:

$$\begin{aligned}\langle F, e_{\{a\}}\rangle &= \sqrt{2\pi}\sqrt{1-|a|^2}\,\frac{1}{2\pi i}\int_0^{2\pi}\frac{F(e^{it})}{e^{it}-a}de^{it}\\ &= \sqrt{2\pi}\sqrt{1-|a|^2}F(a)\end{aligned} \tag{12}$$

It is worth noting that the denotations of "e" in both sides of Eq. (12) remain the same. They both represent the natural logarithms (to the base e), valuing about 2.718. The reason why the forms of "e" are different on both the left and the right sides is that the "$e_{\{a\}}$" on the left is the unexpanded expression in the function, while the "e^{it}" on the right is the expanded expression.

Since for a real-valued signal $\widetilde{G}$, there holds the relation:

$$\widetilde{G} = 2ReG^{+} - c_0, \tag{13}$$

where c_0 stands for power series expansion coefficient of F. Here $G^{+} \in H^2$, $\widetilde{G}$ can be reconstructed through G^{+} and the specific algorithm steps are as follows:

(1) Maximize $|\langle G_1, e_{\{a\}}\rangle|^2$:

Let $G_1 = G = G^{+}$, among all possible selections of $a \in D$. Thus:

$$|\langle G_1, e_{\{a\}}\rangle|^2 = 2\pi\left(1-|a|^2\right)|G_1(a)|^2, \tag{14}$$

$$lim_{|a|\to 1-}\left\|G - \langle G, B_{\{a\}}\rangle B_{\{a\}}\right\| = \| G \|. \tag{15}$$

Let P_r denote the Poisson kernel for the unit circle, $r \in (0,1)$. For $\epsilon > 0$, let r sufficiently close to 1. Therefore, by the L^2-approximation property of the Poisson kernel, there holds:

$$\begin{aligned}&\| G \| \geq \left\|\langle G, B_{\{a\}}B_{\{a\}}\rangle\right\|\\ &\geq \left\|P_r*\left(G - \langle G, B_{\{a\}}\rangle B_{\{a\}}\right)\right\|\\ &\geq \|P_r*G\| - |\langle G, B_{\{a\}}\rangle| \, \| P_r*B_{\{a\}}| \\ &\geq (1-\varepsilon)\| G \| - \| G \| \left\|P_r*B_{\{a\}}\right\|\end{aligned}. \tag{16}$$

For a fixed r value, $B_{\{a\}} \in H^{\infty}(D)$, $z = re^{it}$,

$$P_r*B_{\{a\}}e^{it} = B_{\{a\}}e(z), \tag{17}$$

$$\begin{aligned}\left\|P_r*B_{\{a\}}\right\|^2 &= \frac{1}{2\pi}\int_0^{2\pi}\frac{1-|a|^2}{\left|1-\overline{a}re^{it}\right|^2}dt\\ &= \frac{1}{2\pi}\frac{1-|a|^2}{1-r^2|a|^2}\int_0^{2\pi}\frac{1-r^2|a|^2}{\left|1-|ra|e^{it}\right|^2}dt\\ &= \frac{1-|a|^2}{1-r^2|a|^2}\int_0^{2\pi}P_{r|a|}\left(e^{it}\right)dt\\ &= \frac{1-|a|^2}{1-r^2|a|^2}\end{aligned}. \tag{18}$$

When $|a|$ is close to 1, Equation (19) is given from Equation (16):

$$\|G\| \geq \left\|G - \langle G, B_{\{a\}}\rangle B_{\{a\}}\right\| \geq (1-2\epsilon)\|G\|. \tag{19}$$

Thus, we obtain the Maximal Projection Principle.

According to the Maximal Projection Principle, there is $a_1 \in D$. Thus:

$$\left|\langle G_1, e_{\{a_1\}} \rangle\right|^2 = max\left\{\langle |G_1, e_{\{a\}} \rangle\right|^2 : a \in D\right\}. \tag{20}$$

For the proof of the above fact, we can refer to (Qian, 2009; Qian et al., 2009).

(2) Give a decomposition function:

$$\begin{aligned} G_1(z) &= \langle G_1, e_{\{a_1\}} \rangle e_{\{a_1\}} + \left(G_1(z) - \langle G_1, e_{\{a_1\}} \rangle e_{\{a_1\}}\right) \\ &= \langle G_1, e_{\{a_1\}} \rangle e_{\{a_1\}} + R_1(z) \end{aligned}, \tag{21}$$

where $R_1(z)$ is recorded as the remaining standard.

(3) Perform maximum screening:

$$R_1(z) = G_2(z)\frac{z - a_1}{1 - \overline{a_1}z}, \tag{22}$$

where

$$G_2(z) = \left(G_1(z) - \langle G_1, e_{\{a_1\}} \rangle e_{\{a_1\}}(z)\right)\frac{1 - \overline{a_1}z}{z - a_1}. \tag{23}$$

Here $G_2(z)$ is in H^2 all along, when $z = a_1$,

$$G_1(z) - \langle G_1, e_{\{a_1\}} \rangle e_{\{a_1\}}(z) = 0. \tag{24}$$

By repeating the above process, we obtain AFD expansion of G^+. The algorithm is usually completed here. For more information on the AFD algorithm, we can refer to (Qian et al., 2011a, 2011b; Qian et al., 2009).

2.2.3. AFD-based instantaneous time-frequency distribution diagram

Data under test is regarded as signals *S(t)* (Chen et al., 2014b), where $s(t) = \rho(t)e^{i\phi(t)}$ and other definitions are presented as follows:

$$P(t,\xi) = \rho^2(t)\delta_M(\xi - \varphi'(t)), (t,\xi) \in R \times \left[-\frac{1}{2M}, +\infty\right), \tag{25}$$

where,

$$\delta_M(\xi - \varphi'(t)) = \begin{cases} M, & \xi \in \left[\varphi'(t) - \frac{1}{2M}, \varphi'(t) + \frac{1}{2M}\right] \\ 0, & \xi \notin \left[\varphi'(t) - \frac{1}{2M}, \varphi'(t) + \frac{1}{2M}\right] \end{cases}, \tag{26}$$

where M is a large enough positive constant. AFD is a basic method in time-frequency analysis. It produces intrinsic blocks of the signal under study (Dang et al., 2013). An induced time-frequency distribution of multi-components is based on the mono-component decomposition of the latter (Dang et al., 2013). If orthogonal decomposition could be used in a square-integrable analytic signal *S(t)* with mono-component decomposition, then the corresponding composing-transient-time-frequency distribution (CTTFD) is defined to be:

$$\begin{aligned} &P(t,\xi) = \sum_{k=1}^{\infty} P_k(t,\xi) = \sum_{k=1}^{\infty} \rho_k^2(t)\delta_M\left(\xi - \varphi_k'(t)\right) \\ &(t,\xi) \in R* \left[-\frac{1}{2M}, +\infty\right) \end{aligned}, \tag{27}$$

where $P_k(t,\xi)$ is the TTFD of the mono-component S_k. Through the application of AFD in the given signal, the series expansion for basic signals can be made, which is referred to as mono-components containing non-negative analytic phase derivatives (functions), or meaningful instantaneous frequencies (Qian et al., 2011a, 2011b). The presented new concept of instantaneous frequency puts forward a straightforward method with a simple formula and algorithm which can calculate the value. It may serve as the major supplement of the EMD algorithm and apply to the engineering application for high-frequency signal analysis. On the basis of the defined instantaneous frequency and signal decomposition, a stock index movement prediction method has been presented in Zhang et al. (2012). The experiment carried out using the stock market data of the Hong Kong Hang Seng Index well proves the validity of the presented method. According to former research, AFD definitely suits the research involving financial data.

3. Empirical analysis

3.1. Data description

For the oil market, the WTI futures is widely traded with its good liquidity and high price transparency, providing the reference of crude oil price. For the stock market, the Shanghai Stock Exchange (SSE) is the earliest stock exchange established in the mainland of China and has gradually formed a multilevel blue-chip stock market with large blue-chip enterprises as the center as well as the small and medium-sized ones surrounding it. The Shanghai Composite Index (SCI) is the earliest index released by the SSE, with its sample stocks being all listed stocks within it. It can reflect the fluctuations of the Chinese stock market comprehensively (Huang et al., 2018; Xu et al., 2019). Therefore, in the present study, we exploit the daily closing price of WTI futures and the SCI from the Wind database as the proxies to represent the international oil market and the Chinese stock market, respectively. To satisfy the data stability requirements for modeling, the original data is converted according to $R_{i,\,t} = 100 \times (P_{i,\,t}/P_{i,\,t-1})$, where $R_{i,\,t}$ expressed as a percentage denotes the rate of return series of a certain market on the t-th trading day; $P_{i,\,t}$ signifies the closing price of a certain market on the t-th trading day; and i=1, 2 represent the international crude oil market and the Chinese stock market, respectively. The sample period of returns covers January 4th, 2010, until February 10th, 2021, and contains a total of 2636 observations.

Fig. 2 displays the price and returns of the international oil market and the Chinese stock market. As revealed by the comparison of the closing prices between the two markets in (a) and (c) in Fig. 2, the international crude oil prices and China's stock prices fluctuated drastically almost in some same positions (e.g., June 2014, January 2016, April 2020). Besides, according to the comparison of the returns in (b) and (d) in Fig. 2, the two markets exhibited similar volatility clustering phenomena within certain periods (e.g., July 2014 to August 2016 and December 2019 to August 2020), indicating that there may exist a volatility shock transmission mechanism between them.

Table 1 presents the statistical summary of the returns of the WTI and the SCI. According to the results shown in Table 1, the standard deviation of the return series for the international crude oil market (2.978) is greater than that of the Chinese stock market (1.365), suggesting that the overall market fluctuation of the former is more intensive than that of the latter. For the two return series, the skewness coefficients with negative signs are different from the 0 value of the normal distribution, and the kurtosis coefficients (86.317 and 8.873, respectively) are all greater than 3, suggesting that all the return series show the high-peak and fat-tail phenomenon. Besides, the Jarque-Bera tests reject the null hypothesis of normality. Both the Augmented Dickey-Fuller (ADF) tests of the two markets reject the null hypothesis at the 1% significance level, indicating the stationarity of the return series, respectively.

Before applying the BEKK model, some preliminary tests are implemented to ensure that there exists an ARCH effect in the return series. The results of the autocorrelation and conditional heteroscedasticity tests for the return series of the two markets, the used ARMA and GJR-GARCH models, as well as the tests results after the estimations are presented in Panel B, C, and D in Table 1. From Panel B, it can be found that the statistics of the Ljung-Box (LB) test, the LB (2) test, and the LM test for the two markets are significant at 1% level, implying conditional heteroscedasticity characteristics in both returns of the international oil market and Chinese stock market. The suitable ARMA models for the two markets are displayed in Panel C. For the oil market and Chinese stock market, ARMA (4,1) and ARMA (3,3) are selected, respectively. Panel D provides the results of the ARCH effect after ARCH estimation and GJR-GARCH estimation. Obviously, the statistics for all the tests (the LB test, the LB (2) test, and the LM test) are not significant, reflecting the rationality of our estimations by using the ARMA-GJR-

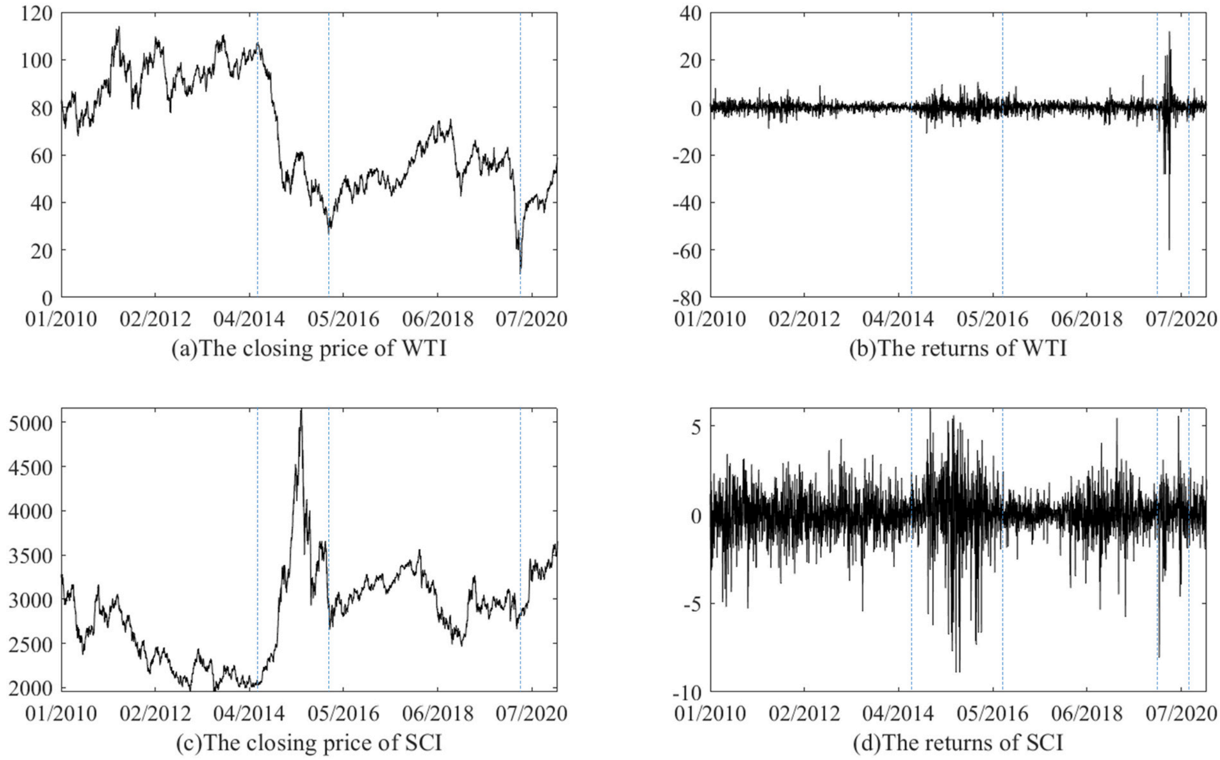

Fig. 2. The closing price and return series of WTI and SCI.

Table 1
Descriptive statistics and test results of market rates of return.

	WTI rate of return	SCI rate of return
Panel A: Descriptive statistical analysis		
Mean	−0.012	0.005
Maximum	31.963	6.040
Minimum	−60.168	−8.873
Standard deviation	2.978	1.365
Skewness	−2.892	−0.825
Kurtosis	86.317	8.873
J-B	765,823.000***	4086.600***
ADF	−13.979***	−13.578***
Panel B: Autocorrelation and ARCH effect tests (before)		
LB	86.084***	20.926**
LB(2)	834.960***	743.530***
LM	507.750***	309.290***
Panel C: The used models		
ARMA(p,q)	(4,1)	(3,3)
GJR-GARCH(p,q)	(1,1)	(1,1)
Panel D: Autocorrelation and ARCH effect tests (after)		
LB	6.128	15.281
LB(2)	6.373	4.578
LM	4.403	2.709

Note: (1) The J-B corresponds to the test statistic for the null hypothesis of normality in sample returns distribution. (2) The lags for LB, LB (2), and ARCH tests are set to 11. (3) ***, ** and * represent significance at the 1%, 5%, and 10% level respectively.

GARCH model.

3.2. Spillovers between international crude oil market and the Chinese stock market

In the current section, the spillovers between the two markets are investigated through bivariate BEKK-GARCH (1,1) modeling. Considering that the BEKK-GARCH model with the lag order of (1,1) has been proven to describe the characteristics of the risk spillovers between markets well (Efimova and Serletis, 2014; Okorie and Lin, 2020; Zolfaghari et al., 2020), this paper chooses the BEKK-GARCH (1,1) to capture the risk spillovers between the oil market and the stock market. Table 2 details the estimated results of the BEKK-GARCH (1,1).

At first, the diagonal elements α_{11} (0.330), α_{22} (0.218), β_{11} (0.937), and β_{22} (0.973) of the parameter matrices A and B are significant at the 1% confidence level, indicating that there exist obvious ARCH and GARCH effects in the two markets. That is to say, both the international oil market and Chinese stock market are affected by their own external shocks as well as intrinsic memories. Moreover, the reported ARCH coefficients α_{11} (0.330) and α_{22} (0.218) are smaller than the GARCH coefficients β_{11} (0.937) and β_{22} (0.973) obviously, implying that the conditional volatilities of the international oil market and the Chinese stock market do not change drastically with historical shocks, but with historical volatilities.

The results also contribute to understanding the risk transmission

Table 2
Parameter estimation for the multivariate BEKK-GARCH (1,1) model.

	Coeff	T-stat	Signifi
W(1,1)	0.304	255.249	0.000
W(2,1)	0.004	10.176	0.000
W(2,2)	0.100	629.535	0.000
A(1,1)	0.330	1197.118	0.000
A(1,2)	0.104	148.963	0.000
A(2,1)	−0.011	−346.151	0.000
A(2,2)	0.218	2885.585	0.000
B(1,1)	0.937	29,712.863	0.000
B(1,2)	−0.016	−263.967	0.000
B(2,1)	0.004	1184.091	0.000
B(2,2)	0.973	417,890.825	0.000

mechanism of the two markets. To be specific, the volatilities of the international oil market and the Chinese stock market may be stimulated by their own shocks and the historical volatilities, with the influence of the latter greater than that of the former. Our findings are consistent with Ahmed and Huo (2021) who have evidenced that there exist both ARCH and GARCH effects in global oil price and Chinese stock markets, and the GARCH effect is more obvious than the ARCH effect.

Then, the mean spillover effects are analyzed through the statistical significance of the off-diagonal coefficients in matrix A of the BEKK-GARCH model. As shown in Table 2, the non-diagonal element α_{12} (0.104) of matrix A rejects the null hypotheses at the 1% significant level, suggesting the presence of the mean spillover effects from the oil market to the stock market. That is to say, the past shocks in the international oil market have significant effects on the Chinese stock market's volatility over the sample period. Besides, there also exists an obvious influence of the past shocks in the Chinese stock market on the oil market as the parameter α_{21} (-0.011) of matrix A is significant at the 1% level as well.

Besides, the present study examines the volatility spillovers based on the statistical significance of the off-diagonal coefficients in matrix B of the BEKK-GARCH model. It can be found in Table 2 that the non-diagonal elements β_{12} (-0.016) and β_{21} (0.004) of matrix B are both significant at the 1% significant level, suggesting the presence of bidirectional volatility spillover effects between the oil and stock markets.

To further verify the direction of the volatility spillover effect between the two markets, we conduct a Wald test on the above parameters. Based on the Wald test results presented in Table 3, the null hypotheses that "there is no bidirectional volatility spillover effect between the two markets", "there is no unidirectional volatility spillover effect from the oil market to the stock market" are rejected, while the null hypothesis that "there is no unidirectional spillover effect from the stock market to the oil market" is accepted. These results can help us understand the roles played by the two markets in risk transmission. Obviously, the international oil market is the risk sender, while the Chinese stock market is the risk receiver. In other words, the risks in the oil market can be transmitted to the stock market. Besides, these results also support the view that China's stock market is integrating with other financial markets (the international crude oil futures market in this paper) in the world after the gradual financial liberalization reforms in 1998. As a result, with the surging oil imports, the Chinese stock market is more sensitive to oil price fluctuations (Xiao et al., 2018).

3.3. Impact of major events on the Chinese stock market

Based on the above research, we have confirmed that the international crude oil market generates a significant spillover effect on the Chinese stock market. However, the applied model has only determined the direction of the risk transmission, ignoring the specific time and the magnitude of the influence of the oil shock on the stock market. To fill this gap, the current work will detect structural breaks in the Chinese stock market to determine the specific time points of the oil shock on the stock market. Then, by combining the external events, this paper will analyze the extent to which the international crude oil impacts the Chinese stock market.

To achieve this, the AFD based on the Takenaka-Malmquist system is first applied to decompose the volatility of the Chinese stock market estimated by GARCH (1,1) (Charfeddine, 2014; Charles and Darné, 2014; Horpestad et al., 2019). Therefore, the instantaneous time-frequency distribution diagram of the estimated volatility is constructed to detect the structural breaks of the Chinese stock market. Then, after the breakpoints are determined, the present study will analyze the characteristics of China's stock market's volatility near the breakpoints to investigate the impacts of structural breaks due to the external oil shocks on the stock market.

Table 3
Spillover effect test based on the multivariate BEKK-GARCH (1,1) model.

Null hypothesis and results	
F(4,*)	*P* value
There is no unidirectional spillover effect from the stock market to the oil market	
H0: a21 = b21 = 0	
4.523	0.104
There is no unidirectional spillover effect from the oil market to the stock market	
H0: a12 = b12 = 0	
17.652	0.000
There is no bidirectional volatility spillover effect between the oil and the stock markets	
H0: a12 = b12 = a21 = b21 = 0	
21.804	0.000

3.3.1. Breakpoints test of the Chinese stock market

In this section, the volatility of the Chinese stock market is decomposed and reconstructed on the basis of the Takenaka-Malmquist system. Fig. 3 (a) presents the results of the decomposition and the reconstruction. The "decomposed no" represents the maximal steps of decomposition and the "energy difference" stands for the magnitude of the change of the decomposed signal compared to the original signal. The smaller the energy difference, the smaller the energy loss, which means the more original information about the real market is retained. The blue line represents the original volatility, while the red line represents the reconstructed volatility. As distinctly observed from Fig. 3 (a), the reconstructed signal is basically the same as the original signal with an extremely small energy difference (0.004), implying that almost all information is retained. These results prove the rationality of the decomposition and the reconstruction, meaning that we can further construct the instantaneous time-frequency distribution diagram of the Chinese stock market.

Fig. 3 (b) gives the instantaneous time-frequency distribution diagram constructed based on the AFD decomposition. The time-frequency distribution diagram is comprised of many colored dots, where the areas of the colored dots represent the magnitudes of frequencies. Higher frequencies indicate more drastic changes in volatility. Besides, the fluctuation of volatility will become severer as the peaks overlap each other or increase in value, indicating the existence of the structural breaks.

Based on (b), the peaks for instantaneous time-frequency distribution of volatilities appeared on November 19th, 2010, June 18th, 2013, June 8th, 2015, March 1st, 2019, and February 20th, 2020, respectively, indicating the presence of structural breaks of the volatility of the Chinese stock market, respectively.

3.3.2. The influence of the international oil market on the Chinese stock market

This paper will analyze the impact of the international oil market on the Chinese stock market considering the detected structural breaks due to the external events after 2010 (see Table 4). For a better analysis of the impact of the oil market on the Chinese stock market with the major events, the events corresponding to the time points of volatility structural breaks in the Chinese stock market are collated in Table 5. According to Table 5, the structural breaks of the Chinese stock market correspond well to the events listed in Table 4.

As shown in Table 5, the first structural breakpoint lies on November 19th, 2010 when the volatility of the Chinese stock market is relatively high, valuing at 1.894 (see Fig. 4). This can be attributed to the strikes in France and the implementation of a quantitative easing policy (see Table 5). In fact, from September to October 2010, a nationwide strike broke out in France, preventing 4000 gas stations (about 30% of the total) from supplying oil, and eventually resulting in the usage of the country's strategic oil. Therefore, the oil price has risen with the continuously increasing domestic tensions and national anxieties in France. Besides, the United States restarted the quantitative easing

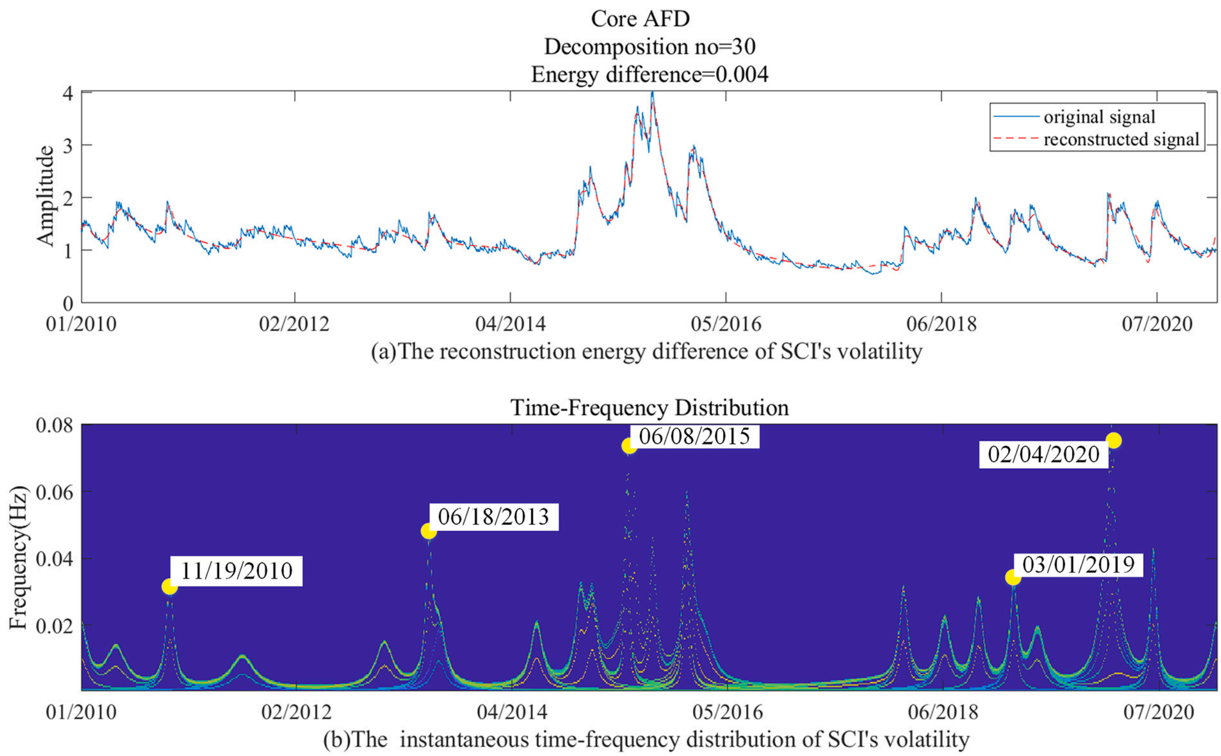

Fig. 3. The energy difference and the instantaneous time-frequency distribution of SCI's volatility.

Table 4
The list of major events affecting the Chinese stock market.

Event No.	Time	Major event
1	10/12/2010	The strikes in France
2	11/02/2010–11/03/2010	The Federal Open Market Committee was held
3	06/14/2013	The escalation of conflict in Syria
4	06/25/2013	The blockages of U.S. crude oil imports
5	05/29/2015	The Islamic State claimed responsibility for a suicide bomber struck in Saudi Arabia
6	06/12/2015	Saudi Arabia hinted at increasing oil production
7	01/01/2019	OPEC and its partners' agreement on the reduction of oil
8	01/28/2019	Sanctions on Venezuela's Petroleum Corporation by the U.S
9	01/20/2020	The outbreak of COVID-19
10	03/08/2020	The oil price war between the OPEC cartel and Russia
11	04/20/2020	The oil price goes below zero for the first time

Table 5
The time points of structural breaks and the corresponding events.

No.	The time point of volatility structural change	Corresponding event
1	11/19/2010	Events 1, 2
2	06/18/2013	Events 3, 4
3	06/08/2015	Events 5, 6
4	03/01/2019	Events 7, 8
5	02/04/2020	Events 9, 10, 11

policy after the Federal Open Market Committee (FOMC) that was held from November 2nd to 3rd, leading to the weak dollar undoubtedly, and influencing the bulk commodity market (the international oil market in this paper). These events inevitably aroused volatile changes in oil prices and further put great pressure on the Chinese stock market.

The second structural breakpoint is observed on June 18th, 2013 (see Table 5). At this point, although the volatility of the Chinese stock market is not at a high level (1.171), it immediately rose sharply and reached a peak on June 25th, 2013, valuing at 1.738 (see Fig. 4). This is undoubtedly caused by the fluctuating oil price due to the escalation of the conflict in Syria and the blockage of U.S. crude oil imports. On June 14th, 2013, the United States announced military support for Syrian rebels, which raised tensions in the Middle East and eventually aroused concerns about the Middle East crude oil supplies. As a result, oil prices rose. Besides, floods that occurred in Canada on June 25th, 2013 have led to the forced closure of three main pipelines, which are used to transport crude oil to the United States. As a result, the oil price fluctuated severely due to the shortage of supply of U.S. crude oil. These events generally aroused volatile changes in oil price and ultimately transmitted the risks to the Chinese stock market.

The third structural breakpoint can be noticed on June 8th, 2015 (see Table 5). It can be clearly observed from Fig. 4 that, the volatility of the Chinese stock market has reached a small peak near this point, valuing at 2.687. This can be attributed to the market concerns caused by the tense situation in the Middle East. Firstly, a bombing attack occurred in Saudi Arabia on May 29th, and the Islamic State claimed responsibility for this event, which stimulated oil prices to rise. Besides, after this time point, it can be distinctly found that the volatility of the Chinese stock market has further risen sharply (see Fig. 4). The market concerns caused by the increasing production of oil can be the reason. OPEC had been increasing production for several months. To be specific, Saudi Arabia boosted its oil production to a three-year high in March, adding over 650

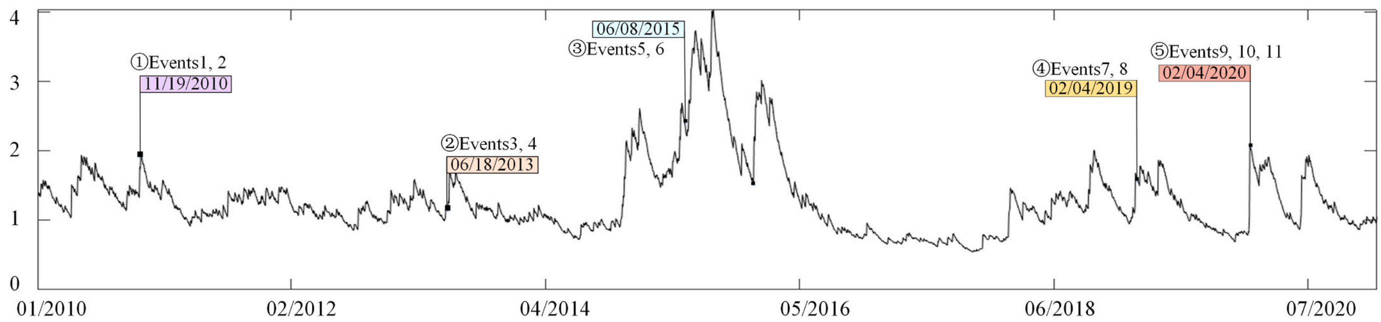

Fig. 4. The structural breaks of the Chinese stock market's volatility and the corresponding events.

thousand barrels a day. Moreover, on June 12th, it further announced that it would increase oil production in the future. As a result, this inevitably aroused market concerns about low oil prices in the future and stimulated the fluctuation of oil prices. In general, the market concerns in the oil market inevitably put pressure on the Chinese stock market, and finally resulted in volatile fluctuations in it.

The fourth structural breakpoint lies on March 1st, 2019 (see Table 5). It can be noticed that the volatility of the Chinese stock market has changed from a relatively low level to a relatively high level after February. Specifically, it reached a small peak around this time point, valuing at 1.681 (see Fig. 4). The low volatility of the Chinese stock market can be attributed to OPEC's production cuts at the beginning of 2019. To be specific, OPEC's crude oil production decreased by 797,000 barrels/day to 30.8 million barrels/day by January, offsetting the impact of the oversupply of crude oil caused by the shale-oil boom to some extent, which is beneficial for stabilizing the oil market. However, this kind of low fluctuation was broken by sanctions on Venezuela's Petroleum Corporation by the U.S. At the end of January, the United States announced sanctions against the Petroleo De Venezuela S.A (PDVSA), a Venezuelan state-owned energy company established in 1976. Venezuela is the world's largest crude oil producer and exporter, which is also the fourth-largest crude oil importer of the United States. Once sanctions are implemented, the U.S. refineries are forced to choose oil in other countries as an alternative. As a result, the balance of oil supply and demand will be disrupted, which will inevitably affect the crude oil market. In general, the disruption of the supply-demand balance undoubtedly aroused severe fluctuations in oil prices and further put great pressure on the Chinese stock market.

The fifth structural breakpoint is observed on February 4th, 2020 (see Table 5). It can be clearly seen from Fig. 4 that around this point, China's stock market fluctuates violently, with volatility valuing at 2.091. This is undoubtedly caused by the big drop in oil on the COVID-19 fears. At the beginning of 2020, a new coronavirus disease had been swiping the world, namely COVID-19. In order to prevent the spread of the pandemic, most countries and regions successively adopted strict contain measures that restricted economic activities such as travel (Jiang et al., 2021), thus stagnating economic development and hit global oil demand. Besides, what can be found in the following months is that the volatility of the Chinese stock market continued to retain at a relatively high level (around 1.755), and reached a small peak value (1.915) on March 26th, 2020. For one thing, the oil price war exploded on March 8th after the dramatic collapse of an alliance between the OPEC cartel and Russia is an important reason. In the days after that, the price of WTI futures had plunged more than 26%. For another, due to reasons like inventory pressure and transportation costs under the epidemic, the WTI futures price has closed 305% down to −37.63 dollars a barrel for the first time on April 20th. These things send shockwaves from the oil market to other markets, especially the stock market that has been reeling from the COVID-19 severely, through global finance.

4. Conclusions

To conclude, in this paper, a BEKK-GARCH-AFD approach is proposed to investigate the linkages between the international crude oil market and the Chinese stock market from the perspective of the time-frequency domain. Through the proposed approach, the present paper can not only determine the direction of the risk spillover between markets but also determine the specific time and extent of the impact of one market on another. Besides, the BEKK-GARCH-AFD approach considers both the time-domain and frequency-domain characteristics of the financial markets, and gives higher-resolution information concerning structural breaks in the frequency domain in contrast to the existing studies. Additionally, considering the influence of the COVID-19, evidence of risk transmission between the international oil market and the Chinese stock market is provided.

Our empirical analysis is based on the daily data of WTI crude oil prices and China's Shanghai composite index from January 1st, 2010 to February 10th, 2021. According to our empirical results, several following main findings are obtained in the current work. Firstly, due to the high sensitivity of the Chinese stock market to the volatile changes in the international oil price, the latter plays the role of risk sender, while the former is the receiver. Secondly, it is interesting to point out that, there are apparent structural breaks in the Chinese stock market. Oil supply and demand shocks caused by external events such as the strikes, the geopolitics, natural disasters, and some policies will make oil prices fluctuate dramatically, and inevitably put pressure on the Chinese stock market. In contrast, the influence of the bullish (bearish) events can be used to offset the bearish (bearish) events, thus balancing the oil market, which is beneficial for stabilizing the Chinese stock market.

The implications of our study are three-fold. Firstly, different from the literature which concentrates on the linkages between the international oil market and the Chinese stock market, the present paper further confirms when and to what extent the former affects the latter. It emphasizes the importance of paying attention to the influence of the structural breaks in the frequency domain on the markets due to external events. Secondly, this study is of great importance for understanding the interactive linkages between the international oil market and the Chinese stock market, which is beneficial for investors to manage portfolios risk by helping them decide whether to add an oil futures asset or a stock asset to their investment portfolio to hedge risks. Moreover, this study also provides significance for policymakers. Specifically, the results present that the fluctuation of the international oil market due to external events can stimulate the Chinese stock market. Therefore, policy-makers can quickly make countermeasures based on the historical experience once similar external events occur in the future.

Declaration of Competing Interest

The authors declare that they do not have any financial or nonfinancial conflicts of interest.

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Appendix A. Supplementary data

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