RESEARCH ARTICLE

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Toward energy finance market transition: Does China's oil futures shake up global spots market?

Abstract China is breaking through the petrodollar system, establishing RMB-dominating crude oil futures market. The country is achieving a milestone in its transition to energy finance market internationalization. This study explores the price leadership of China's crude oil futures and identifies its price co-movement to uncover whether it truly shakes up the global oil spots market. First, we find that for oil spots under different gravities, China's oil futures is only a net price information receiver from light-, medium-, and heavy-gravity oil spots, but it has a relatively stronger price co-movement with these three spots. Second, for oil spots under different sulfur contents, China's oil futures still has weak price leadership in sweet, neutral, and sour oil spots, but it has strong co-movement with them. Third, for oil spots under different geographical origins, China's oil futures shows price leadership in East Asian and Australian oil spots at the medium- and long-run time scales and strong price co-movement with East Asian, Middle Eastern, Latin American and Australian oil spots. China's oil futures may not have good price leadership in global spots market, but it features favorable price co-movement.

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1 Introduction

Having a solid position on crude oil pricing is a strategic aim that China has long pursued[1]. The establishment of a globally or regionally prominent energy finance market for oil futures transaction is an important means of achieving this goal (Gülen, 1998; Elder et al., 2014). On March 26, 2018, China launched its first-ever yuan-priced crude oil futures listed in the Shanghai International Energy Exchange (INE), and it is currently breaking through the decades-long petrodollar system toward its transition to energy finance market internationalization (Ji and Zhang, 2019; Zhang and Ma, 2021). This study reveals the influence of China's oil futures market from a global perspective.

The two most important functions of oil futures are price discovery and hedging (Garbade and Silber, 1983; Switzer and El-Khoury, 2007), whereby the two functions exactly meet the financialization needs of China's oil markets. On the one hand, China is importing medium-gravity crude oil for a long time, but the underlying spots of current benchmark futures variety (such as West Texas Intermediate (WTI) futures) are generally light-gravity crudes or sweet crudes with few sulfur content. China's oil futures is wished to act as price discoverer to pave the way for the oil pricing system reform in China or Asia. On the other hand, to realize China's vision of breaking the petrodollar system and improving RMB's internationalization, the transaction volume of China's oil futures matters. The hedging function of crude oil is a key point for attracting a wide range of investors[2].

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[1] China accounts for 16.1% of global crude oil consumption in 2020 and has held steady as the world's second-largest consumer in recent years (British Petroleum, 2021).

[2] According to the Commodity Futures Trading Commission (CFTC) position report, WTI crude oil futures has a large number of physical companies participating and conducting hedging operations.

Up to now, the open interest of China's oil futures volume was only surpassed by the world's two major crude oil futures trading varieties, WTI futures and Brent futures. Given the strong financial attributes of oil futures (Zhang and Wei, 2010; Sari et al., 2011), high trading volume, which is caused by massive speculation, does not necessarily mean that China's crude oil futures works well; it may be a bubble (Tsvetanov et al., 2016). The participation of a large number of potential individual speculators in China's crude oil futures market can hinder the perception of the market functioning (Buyuksahin and Harris, 2011). If China's oil futures really proves the transition to China's energy finance market internationalization and shakes up the global oil spots market, it should be able to serve as a price information transmitter that guides the oil spots market and maintain a good co-movement with the oil spots prices to be a useful hedge tool.

Mature international crude oil futures varieties, such as WTI futures, have demonstrated good features in futures–spots lead–lag relationship (Huang et al., 2009) and dependence structure (Pan et al., 2014; Basher and Sadorsky, 2016). Some studies also give a first look on the hedging ability and information spillover pattern of China's oil futures (Huang and Huang, 2020; Lu et al., 2020; Yang and Zhou, 2020; Li et al., 2021). As discussed before, the underlying of China's crude oil futures is mainly crude oil with neutral sulfur content, and the warehouse for delivery is concentrated in China. Especially, no satisfied benchmark exists for crude oil prices in the Asia–Pacific region before, which may not adequately reflect the fundamentals of crude oil supply and demand in East Asia. The novel design of China's crude oil futures in terms of gravity, sulfur content, and geographical origin makes it a potential force to drive the transition of China's energy finance market toward rapid internationalization.

In this backdrop, the aforementioned discussion motivates us to address and solve the following two key questions to reveal the international influence of China's oil futures: What is the price information transmitter pattern of China's oil futures to some kinds of oil spots markets worldwide classified by gravity, sulfur content and geographical origin? What is the co-movement patterns between China's crude oil futures and some kinds of oil spots markets worldwide classified by gravity, sulfur content, and geographical origin? Our conclusion shows that the interplay between China's oil futures and global spots markets depends on these three key attributes.

For comparison purpose, the US WTI crude oil futures is used to reveal the interplay relationship difference. We choose 34 kinds of oil spots markets from major producing regions of the world and classify them into different categories by gravity, sulfur content, and geographical origin. To reveal the information spillover pattern, we use a novel multi-time scale information spillover analysis method proposed by Baruník and Křehlík (2018) to describe whether China's oil futures is a net price information transmitter to different kinds of oil spots[1]. We also adopt the block dynamic conditional equicorrelation (BDECO) model of Engle and Kelly (2012) to determine the price co-movement between China's oil futures and a basket of a specific kind of oil spots compared with WTI futures.

To reveal the regional and international influence of China's oil futures and the operating functions of its markets, this study makes two contributions to existing research. First, building on the contributions of Ji and Zhang (2019), Huang and Huang (2020), and Yang and Zhou (2020), we reveal the information spillover pattern between China's oil futures and global oil spots to detect the price leadership of this novel oil futures variety. Rather than applying traditional pairwise analysis (Lee and Zeng, 2011; Chang, 2012; Chen et al., 2014; Chang and Lee, 2015), we reveal the "aggregate" magnitude of China's oil futures transmits to a kind of oil spots with specific gravity, sulfur content, and geographical origin.

Second, we systemically reveal the "aggregate" co-movement pattern between China's oil futures and a kind of oil spots market considering the spots' gravity, sulfur content, and geographical origin. As far as we know, this study is the first to reveal whether China's oil futures co-moves well with global oil spots in such a panoramic view. The conclusions reveal the successes and shortcomings of the momentous China's oil futures.

The rest of this paper is organized as follows. Section 2 introduces the econometrics approach. Section 3 illustrates the data selection of the 34 oil spots markets and two oil futures. Section 4 shows the empirical findings, and Section 5 concludes.

2   Econometrics approach

2.1   Modeling on information spillover index

Baruník and Křehlík (2018) construct a spillover index (BK spillover index for short) reflecting the information transformation between variates at different time scales (within different frequency bands). It can be viewed as an extension to the time-frequency analysis of the better-known spillover index approach of Diebold and Yilmaz (2012). We first construct a vector autoregressive (VAR) model and compute its generalized forecasting error variance decomposition (GFEVD) to measure the connectedness between n variables $\boldsymbol{x}_t = (x_{1,t}, x_{2,t}, ..., x_{n,t})'$. First, an

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[1] Spillovers between energy assets may vary over time scales — briefly, short-run spillovers differ from long-run spillovers (Miao et al., 2022; Tong et al., 2022).

n-variate VAR(p) takes the form of

$$B(L)x_t = \epsilon_t, \qquad (1)$$

where L is the lag operator, $B(L) = I_n - B_1L - ... - B_pL^p$ is the pth order $n \times n$ lag-polynomial, I_n is an identical matrix, and $\epsilon_t = (\epsilon_{1,t}, \epsilon_{2,t}, ..., \epsilon_{n,t})'$ is a white noise shock term and takes the form of $\epsilon_t \sim$ i.i.d.$(0, \Sigma)$ (Σ is the co-variance matrix of ϵ_t, and i.i.d. denotes independently identical distribution). Following Diebold and Yilmaz (2012), we build the following GFEVD between $x_t = (x_{1,t}, x_{2,t}, ..., x_{n,t})'$

$$\theta_{i,j}^{DY}(H) = \frac{\sigma_{jj}^{-1} \sum_{k=0}^{H-1} (e_i' C_k \Sigma e_j)^2}{\sum_{k=0}^{H-1} e_i' C_k \Sigma C_k' e_i} \times 100\%, \qquad (2)$$

where e_j is the selection vector for its jth element, and C_k is a kind of iteration matrix which could be referred to Diebold and Yilmaz (2012). Given that $\sum_{j=1}^{n} \theta_{i,j}^{DY}(H) \neq 1$, Diebold and Yilmaz (2012) normalize Eq. (2) and define the information spillover index from x_j to x_i as

$$\tilde{\theta}_{i,j}^{DY}(H) = \frac{\theta_{i,j}^{DY}(H)}{\sum_k \theta_{j,k}^{DY}(H)} \times 100\%. \qquad (3)$$

In this vein, by computing $\tilde{\theta}_{i,j}^{DY}(H)$, we can reveal the information spillover index between any two variables in x_t. However, the Diebold and Yilmaz spillover index only assesses spillover effect in the time domain. To describe the spillovers in frequency domain, the spectral representation of GFEVD must be considered. To solve this, Baruník and Křehlík (2018) give a Fourier transform of $\theta_{i,j}^{DY}(H)$, which can be seen as a function with respect to frequency ω, that is,

$$\theta_{i,j}(\omega, H) = \frac{\sigma_{jj}^{-1} \sum_{k=0}^{H-1} (\Sigma e_j)^2}{\sum_{k=0}^{H-1} e_i' C(e^{-ik\omega}) \Sigma C(e^{-ik\omega})' e_i} \times 100\%. \qquad (4)$$

Similarly, to normalize $\theta_{i,j}(\omega, H)$, Baruník and Křehlík (2018) give the spillover index x_j transmit to x_i at a given frequency value ω, which can be computed as

$$\tilde{\theta}_{i,j}(\omega, H) = \frac{\theta_{i,j}(\omega, H)}{\sum_k \theta_{j,k}(\omega, H)} \times 100\%. \qquad (5)$$

The frequency value ω is the inverse of period[1]. Generally, the comprehensive information spillover within a period band $b = [\omega_1, \omega_2]$ (frequency bands) is paid more attention than that in a single period (frequency) value ω (Wang et al., 2020; Dai et al., 2020; 2021) because

frequency band can better represent so called short-, medium-, or long-run time scales. Thus, the spillover pattern from x_j to x_i under some frequency band $b = [\omega_1, \omega_2]$ can be calculated as follows:

$$\tilde{\theta}_{i,j}(b, H) = \int_{\omega_1}^{\omega_2} \tilde{\theta}_{i,j}(\omega, H) d\omega. \qquad (6)$$

In this study, we employ $\tilde{\theta}_{i,j}(b, H)$ to uncover the information spillovers between a particular classification of crude oil spots market and oil futures. For example, let $\Lambda = \{j$ index set of all oil spots with heavy gravity$\}$ and i is the index for China's oil futures, then $\sum_{j \in \Lambda} \tilde{\theta}_{i,j}(b, H)$ is the "aggregate" information spillover from all oil spots with heavy gravity to China's oil futures at frequency band b, and $\sum_{j \in \Lambda} \tilde{\theta}_{j,i}(b, H)$ is the total information spillover from China's oil futures to oil spots with heavy gravity. Subsequently, the net spillover from heavy gravity oil spots to China's oil futures at frequency band b can be computed as

$$S_{net}^b = \sum_{j \in \Lambda} \tilde{\theta}_{i,j}(b, H) \times 100\% - \sum_{j \in \Lambda} \tilde{\theta}_{j,i}(b, H) \times 100\%. \qquad (7)$$

If $S_{net}^b > 0$ ($S_{net}^b < 0$), following the previous example, there is a net information spillover from (to) all heavy gravity oil spots to (from) China's oil futures. In Section 4.1, we use the arrow from the one node to another to represent the direction of net information spillover, and the thickness of arrow represents $|S_{net}^b|$. Generally, if

$$N_{i,net}^b = \sum_{i=1,i \neq j}^{n} \tilde{\theta}_{i,j}(b, H) \times 100\% - \sum_{j=1,j \neq i}^{n} \tilde{\theta}_{i,j}(b, H) \times 100\% < 0, \qquad (8)$$

then asset i is the net information receiver from all other assets; otherwise ($N_{i,net}^b > 0$), asset i is the net information transmitter to all other assets. $|N_{i,net}^b|$ reflects the net spillover intensity asset i receives or transmits.

Following Baruník and Křehlík (2018) and Dai et al. (2021), we set H to 100 for a stable result of GFEVD and BK spillover index and determine p in Eq. (1) by minimizing Akaike information criterion (AIC) value. The choice of frequency bound varies between studies and generally focuses on the two watersheds of 5 and 22 days (Ferrer et al., 2018; Kang et al., 2019; Wang and Wang, 2019; Ouyang et al., 2021). This is because 5 days is the length of a trading week, whereas 22 days is the length of a trading month. Some multi-scale studies that only considered the short- and long-run time scales as these two time scales are widely discussed (Mohammadi, 2009; Charfeddine and Barkat, 2020). Nevertheless, the pattern of medium-run interplay among oil assets is important (Dai et al., 2020; Peng et al., 2021). In this vein, we analyze information spillovers from three time scales: Short-run (1–5 days), medium-run (5–22 days)

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[1] In economics, we often use the terms "time scales" or "economic cycle" to represent term "period".

and long-run (> 22 days) time scales.

2.2   Modeling on dynamic co-movement

To model on dynamic co-movement, we first use the ARMA-GARCH-T model to construct a time-varying marginal distribution of each asset returns, that is,

$$r_t = \mu + \sum_i^m \psi_i r_{t-i} + \varepsilon_t + \sum_j^n \varphi_j \varepsilon_{t-j}, \tag{9}$$

$$\varepsilon_t = \sigma_t \xi_t, \quad \xi_t \sim T(0, 1), \tag{10}$$

$$\sigma_t^2 = \omega + \sum_k^p \alpha_k \varepsilon_{t-k}^2 + \sum_l^q \beta_l \sigma_{t-l}^2, \tag{11}$$

where r_t is the returns of assets, σ_t is the volatility of the asset returns, and μ, ψ_i, φ_j, ω, α_k, and β_l are scalar coefficients of the ARMA-GARCH-T model. To describe the higher peak and fat tail phenomenon in oil futures and spots returns, a T-distribution specification is applied in innovation ξ_t.

We use the linear correlation to be the measure of co-movement pattern. A correct dynamic conditional correlation (cDCC) model derived from the DCC model of Engle (2002) can depict the time-varying correlation between n assets, that is,

$$\xi_t = (\xi_{1,t}, \xi_{2,t}, ..., \xi_{n,t})', \tag{12}$$

$$Q_t = \overline{Q} + \alpha \cdot \tilde{Q}_{t-1}^{1/2} \xi_t \xi_t' \tilde{Q}_{t-1}^{1/2} + \beta \cdot Q_{t-1}, \tag{13}$$

$$R_t^{cDCC} = \text{diag}\{Q_t\}^{-1/2} Q_t \text{diag}\{Q_t\}^{-1/2}, \tag{14}$$

where $\xi_{i,t}$ ($i = 1, 2, ..., n$) is the innovation in Eq. (10), and $\tilde{Q}_t$ is the matrix replacing the off-diagonal elements of Q_t with zeros. The element $R_t^{cDCC}(i, j)$ in R_t^{cDCC} represents dynamic linear correlation $\rho_{i,j,t}$ between individual assets i and j at given time t.

To reveal the "aggregate" dynamic correlation between China's crude oil futures and all oil spots under a specific classification, a BDECO model of Engle and Kelly (2012) developed from cDCC model can explore the inter-section block correlation of one set of assets with another set (Pan et al., 2016; Mensi et al., 2017; Zhang and Yan, 2020) rather than the correlation between two individuals like cDCC model.

For example, if we want to uncover the co-movement among China's oil futures (indexed as a), WTI futures (indexed as b), all m sweet oil spots (indexed as c), all k medium oil spots (marked as d), and all l sour oil spots (marked as e) under sulfur content classification, we can apply the following BDECO model.

First, the innovation ξ_t of Eq. (12) can be divided into five blocks marked as $\Lambda = \{a, b, c, d, e\}$, that is,

$$\xi_t = (\xi_{a,t}, \xi_{b,t}, \xi_{c,t}, \xi_{d,t}, \xi_{e,t})', \tag{15}$$

where $\xi_{a,t}$ is the innovation of China's oil futures, $\xi_{b,t}$ is the innovation of WTI futures, $\xi_{c,t} = (\xi_{c_1,t}, \xi_{c_2,t}, ..., \xi_{c_m,t})$ is the innovations of sweet oil spots, $\xi_{d,t} = (\xi_{d_1,t}, \xi_{d_2,t}, ..., \xi_{d_k,t})$ is the innovations of medium oil spots, and then $\xi_{e,t} = (\xi_{e_1,t}, \xi_{e_2,t}, ..., \xi_{e_l,t})$ is the innovations of sour oil spots.

Second, the block correlation R_t^{BDECO} of the upper five sets of assets can take the following form by Engle and Kelly (2012),

$$R_t^{BDECO} = \begin{bmatrix} \rho_{a,a,t} J_{1\times1} & \rho_{a,b,t} J_{1\times1} & \rho_{a,c,t} J_{1\times m} & \rho_{a,d,t} J_{1\times k} & \rho_{a,e,t} J_{1\times l} \\ \rho_{b,a,t} J_{1\times1} & \rho_{b,b,t} J_{1\times1} & \rho_{b,c,t} J_{1\times m} & \rho_{b,d,t} J_{1\times k} & \rho_{b,e,t} J_{1\times l} \\ \rho_{c,a,t} J_{m\times1} & \rho_{c,b,t} J_{m\times1} & \rho_{c,c,t} J_{m\times m} & \rho_{c,d,t} J_{m\times k} & \rho_{c,e,t} J_{m\times l} \\ \rho_{d,a,t} J_{k\times1} & \rho_{d,b,t} J_{k\times1} & \rho_{d,c,t} J_{k\times m} & \rho_{d,d,t} J_{k\times k} & \rho_{d,e,t} J_{k\times l} \\ \rho_{e,a,t} J_{l\times1} & \rho_{e,b,t} J_{l\times1} & \rho_{e,c,t} J_{l\times m} & \rho_{e,d,t} J_{l\times k} & \rho_{e,e,t} J_{l\times l} \end{bmatrix}$$

$$+ \begin{bmatrix} -\rho_{a,a,t} I_{1\times1} & 0 & 0 & 0 & 0 \\ 0 & -\rho_{b,b,t} I_{1\times1} & 0 & 0 & 0 \\ 0 & 0 & -\rho_{c,c,t} I_{m\times m} & 0 & 0 \\ 0 & 0 & 0 & -\rho_{d,d,t} I_{k\times k} & 0 \\ 0 & 0 & 0 & 0 & -\rho_{e,e,t} I_{l\times l} \end{bmatrix} + I_{n\times n}, \tag{16}$$

where J denotes the matrix with all elements one, and $\rho_{\Lambda_i,\Lambda_j,t} \in [-1, 1]$ represents the dynamic linear correlation (i.e., co-movement) between different oil assets set under particular classification. According to

Engle and Kelly (2012), $\rho_{\Lambda_i, \Lambda_j, t}$ could take the following forms as

$$\rho_{\Lambda_i, \Lambda_j, t} = \frac{1}{\text{num}(\Lambda_i) \times \text{num}(\Lambda_j)} \sum_{d \in \Lambda_i, f \in \Lambda_j} \frac{q_{d,f,t}}{\sqrt{q_{d,d,t} q_{f,f,t}}},$$
$$i \neq j, \qquad (17)$$

$$\rho_{\Lambda_i, \Lambda_j, t} = \frac{1}{\text{num}(\Lambda_i) \times (\text{num}(\Lambda_j) - 1)} \sum_{d \in \Lambda_i, f \in \Lambda_j, d \neq f} \frac{q_{d,f,t}}{\sqrt{q_{d,d,t} q_{f,f,t}}},$$
$$i = j, \qquad (18)$$

where $\Lambda = \{a, b, c, d, e\}$, and $q_{d,f,t}$ is the d row and f column of $\boldsymbol{Q}_t$ in Eq. (13), which can be rewritten as

$$\boldsymbol{Q}_t = \overline{\boldsymbol{Q}} + \alpha \cdot \tilde{\boldsymbol{Q}}_{t-1}^{1/2} (\xi_{a,t}, \xi_{b,t}, \xi_{c,t}, \xi_{d,t}, \xi_{e,t}) (\xi_{a,t}, \xi_{b,t}, \xi_{c,t}, \xi_{d,t}, \xi_{e,t})' \tilde{\boldsymbol{Q}}_{t-1}^{1/2} + \beta \cdot \boldsymbol{Q}_{t-1}. \qquad (19)$$

Thus, combining Eq. (9) with Eqs. (14) and (16), we can build a BDECO model to reveal the dynamic correlation between different oil assets set.

As mentioned above, for instance, $\rho_{a,c,t}$ represents the co-movement between China's oil futures and all sweet oil spots. In the same way, we can classify all oil spots markets by gravity and geographical origin, which allows us to illustrate the dynamic co-movement patterns between multiple asset groups.

3 Data

The data set for this study consists of 34 kinds of oil spots markets and two kinds of oil futures. We classify crude oil spots markets by gravity, sulfur content, and geographical origin. Gravity represents the density of crude oil and is measured in American Petroleum Institute (API) degree[1], which classifies crude oil into three categories: Light, medium, and heavy. Sulfur content is also an important indicator. High-sulfur crude oil (defined as sour oil) and low-sulfur crude oil (defined as sweet oil) have crucial industrial usage and are purchased by different manufacturers. These two indicators are valuable references for manufacturers to purchase crude oil. Therefore, studying the information spillover and linkage between crude oil futures and spots oil under these two classification systems is meaningful so as to construct a portfolio. Our grouping is based on definitions from Wikipedia:

● An API gravity of 34° or higher is "light oil"; between 31° and 34°, "medium oil"; 31° or below, "heavy oil".

● Oil is considered "sweet oil" if it is low in sulfur content (< 0.5%/weight), "sour oil" if high (> 1.0%/weight), and "neutral oil" if between the two thresholds.

We also split oil spots based on geographical origin and OPEC (Organization of Petroleum Exporting Countries) membership to reveal the leadership power of China's crude oil futures on crude oil prices in different regions and its radiation range compared with other oil futures.

● The regions include East Asia, North America, Middle East, Latin America, Europe, Africa, Central Asia, and Australia.

According to the oil spots selection in Chen et al. (2009), Ji and Fan (2016), Kaufmann (2016), Zhang et al. (2019), and Ouyang et al. (2021), we choose the following 34 kinds of oil spots as shown in Table 1. The reasons supporting our sample choice are two-fold. First, they are representative spots crude oil. WTI, Brent, and Dubai are the benchmarks for world oil prices. Bonny (Nigeria) is the benchmark for pricing in Africa (Ji and Fan, 2015). Tapis and Minas are also important references for the Far East market (Zhang et al., 2019). Many other benchmarks exist (see Weiner, 1991; Gülen, 1999; Motomura, 2014). Second, the number of each species is relatively balanced. The number of each block contributes to the stable results of the BK model and more stable results of the BDECO model.

We do not use an oil price index such as OPEC basket price or Japan crude cocktail price so as to analyze the impact of oil spots on futures under another classification perspective. The blend price index can represent the comprehensive price of spots crude oil from one classification perspective, but it cannot be decomposed. We abandon this kind of data here. The choice of oil futures is China's crude oil futures and WTI crude oil futures (WTI futures for short) traded in NYMEX (New York Mercantile Exchange). For WTI futures and China's crude oil futures, we select the one front month futures whose delivery time is the closest delivery month.

Our analysis is based on the daily closing prices (P_t) spanning from March 27, 2018 (the issue date of China's crude oil futures) to August 19, 2019. A total of 236 days of prices are obtained from the DataStream and the US Energy Information Agency (EIA). All prices, except for China's crude oil futures, are in USD per barrel, and their log-returns are defined as $R_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$. To eliminate the influence of exchange rate factors and for the convenience of hedging calculation, we use the intermediate RMB/USD exchange rate (FX_t) to convert the charge unit of China's crude oil futures into USD. The corrected log-returns are $R_t^c = \ln\left(\frac{P_t}{FX_t}\right) - \ln\left(\frac{P_{t-1}}{FX_{t-1}}\right) = \ln\left(\frac{P_t}{P_{t-1}}\right) - \ln\left(\frac{FX_t}{FX_{t-1}}\right)$.

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[1] It is defined as the ratio of relative density to pure water. Crude oil is considered "heavy" if it has long hydrocarbon chains or "light" if it has short hydrocarbon chains. Generally, the higher the API gravity (the "lighter" it is), the more valuable the crude.

Table 1 Information of chosen crude oil spots

Name	API	Category	Sulfur content	Type	Country	Region	OPEC membership
Brent	37.9°	Light	0.45%	Sweet	UK	Europe	N
WTI	42.0°	Light	0.45%	Sweet	US	North America	N
Shengli	24.0°	Heavy	0.90%	Neutral	China	East Asia	N
Daqing	32.7°	Medium	0.10%	Neural	China	East Asia	N
Nanhai	39.5°	Light	0.05%	Sweet	China	East Asia	N
ESPO	36.0°	Light	0.50%	Neutral	Russia	Europe	N
Oman	33.3°	Medium	1.06%	Sour	Oman	Middle East	N
Dubai	31.0°	Medium	2.04%	Sour	UAE	Middle East	Y
Tapis	46.0°	Light	0.02%	Sweet	Malaysia	East Asia	N
Minas	35.0°	Light	0.08%	Sweet	Indonesia	East Asia	N
Cinta	32.7°	Medium	0.12%	Sweet	Indonesia	East Asia	N
Duri	21.5°	Heavy	0.20%	Sweet	Indonesia	East Asia	N
Kuwait	31.0°	Medium	2.52%	Sour	Kuwait	Middle East	Y
Sokol	35.6°	Light	0.27%	Sweet	Russia	Europe	N
Isthmus	33.6°	Medium	1.30%	Sour	Mexico	Latin America	N
Olmeca	39.3°	Light	0.80%	Neutral	Mexico	Latin America	N
Iran	33.7°	Medium	1.50%	Sour	Iran	Middle East	Y
Iran Heavy	30.7°	Heavy	1.80%	Sour	Iran	Middle East	Y
Cossack	48.0°	Light	0.04%	Sweet	Australia	Australia	N
Murban	40.4°	Light	0.79%	Neutral	UAE	Middle East	Y
Bonny Light	34.5°	Light	0.14%	Sweet	Nigeria	Africa	Y
Bonny Medium	/	Medium	/	Neutral	Nigeria	Africa	Y
Girassol	31.0°	Medium	0.33%	Sweet	Angola	Africa	Y
Zafiro	29.5°	Heavy	0.26%	Sweet	Equatorial Guinea	Africa	Y
Oseberg	39.6°	Light	0.20%	Sweet	Norway	Europe	N
Gippsland	48.0°	Light	0.10%	Sweet	Australia	Australia	N
Arab Heavy	28.0°	Heavy	2.80%	Sour	Saudi Arabia	Middle East	Y
ANS	31.4°	Medium	0.96%	Sweet	US	North America	N
Arab Medium	31.0°	Medium	2.55%	Sour	Saudi Arabia	Middle East	Y
Mars	28.0°	Heavy	1.93%	Sour	US	North America	N
CPC	46.6°	Light	0.55%	Neutral	Kazakhstan	Central Asia	N
Azeri Light	34.9°	Light	0.55%	Neutral	Azerbaijan	Central Asia	N
Bonito	33.5°	Medium	1.32%	Sour	US	North America	N
Poseidon	30.5°	Heavy	1.70%	Sour	US	North America	N

Note: Data source: Energy insights by McKinsey.

4 Empirical findings

4.1 Information spillovers between oil futures and spots

In this subsection, we reveal the information spillover pattern between China's oil futures and some kinds of oil spots with specific gravity, sulfur content, and geographical origin. By calculating the net spillover index with Eq. (7), we obtain the direction and magnitude of price information spillover channel, which are vividly shown in Figs. 1 to 3.

We first look into the price information spillover patterns when considering gravity. As shown in Fig. 1, the price information spillovers patterns are significantly time scale-varying, which echoes the findings of Huang and Huang (2020). At the short-run time scales, that is, within the frequency bands of 1–5 days, both China's oil futures and WTI futures are net information spillover receivers from light-, medium-, and heavy-gravity oil spots markets. The numbers on each edge show the magnitude of net spillover index. Light- and
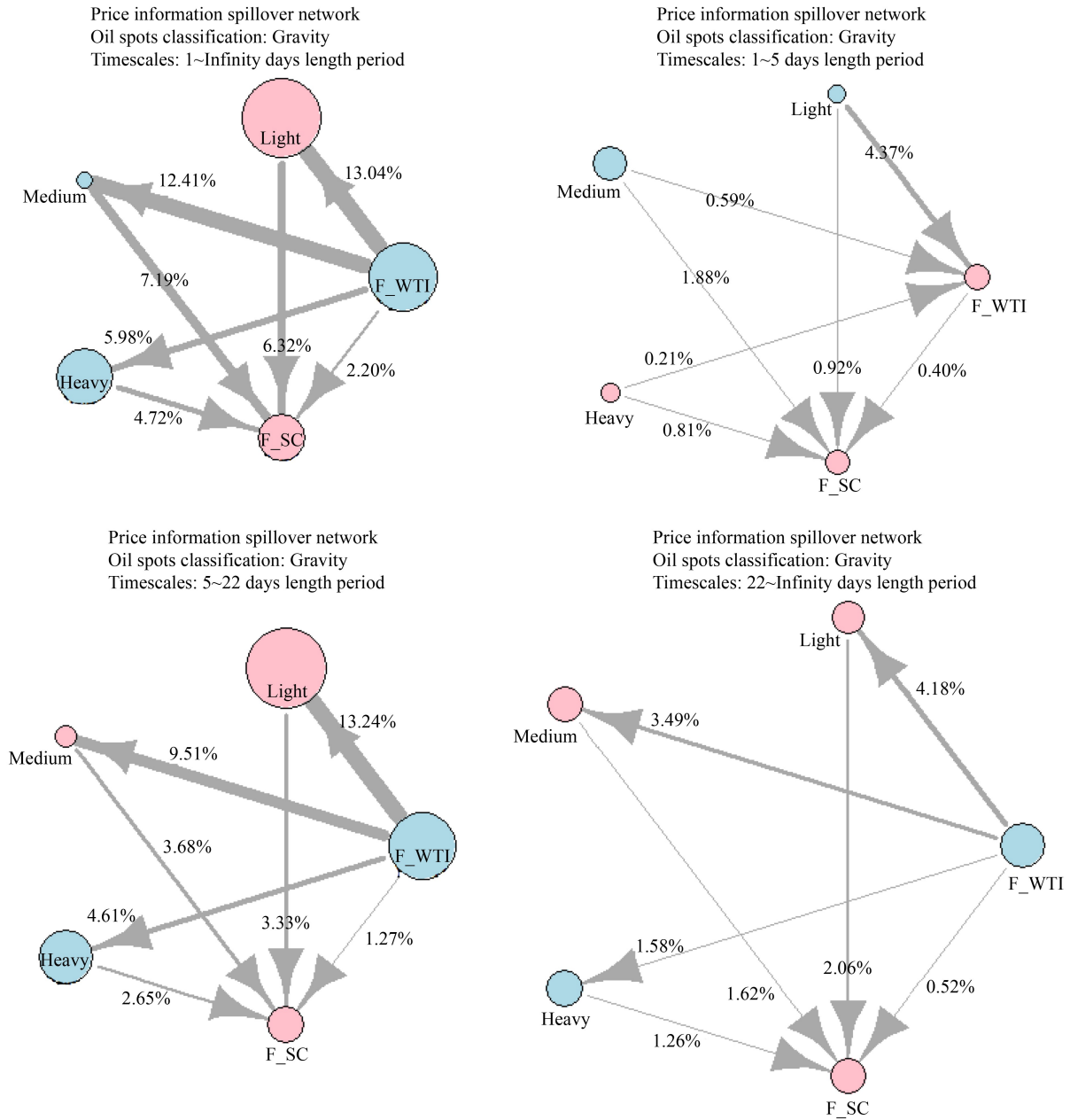
Fig. 1 Net price information spillover network in oils spots under different gravities.

Notes: F_SC denotes China's oil futures and F_WTI denotes WTI futures. We classify the 34 kinds of oil spots into three categories: Light-gravity oil (labeled as "Light"), medium-gravity oil (labeled as "Medium"), and heavy-gravity oil (labeled as "Heavy"). The color of the node represents that it is a net returns spillover transmitter $N_{i,\text{net}}^{b} > 0$ (blue) or net receiver $N_{i,\text{net}}^{b} < 0$ (pink). The size of the node also reflects its net spillover intensity $\left|N_{i,\text{net}}^{b}\right|$ it transmits (receives) as a net transmitter (receiver). The definition of $N_{i,\text{net}}^{b}$ can refer to Eq. (8). The thickness of the edge reflects the size of each net pairwise spillover $\left|S_{\text{net}}^{b}\right|$. In addition, we mark the value of $\left|S_{\text{net}}^{b}\right|$ (%) on (near) each edge. Moreover, the direction of arrow means the start node transmit $\left|S_{\text{net}}^{b}\right|$ magnitude spillover to the end node. The definition of S_{net}^{b} can refer to Eq. (7).

medium-gravity oil transmit more information spillover to WTI futures and China's oil futures, respectively, at the short-run time scales.

When the time scale lengthens, the spillover pattern under the classification of gravity changes substantially. At the medium-run time scales, that is, 5–22 days, WTI futures shows intensive net information spillovers to all three kinds of oils, whereas China's oil futures remains a

net information spillover receiver. Such a transmission channel is shown in the left bottom of Fig. 1; especially, WTI futures gives 13.24% net spillover to global light oil spots market. We can witness the poor ability of China's crude oil futures' price leadership to different oil spots classified by different gravity levels compared with WTI futures at the medium-run time scales.

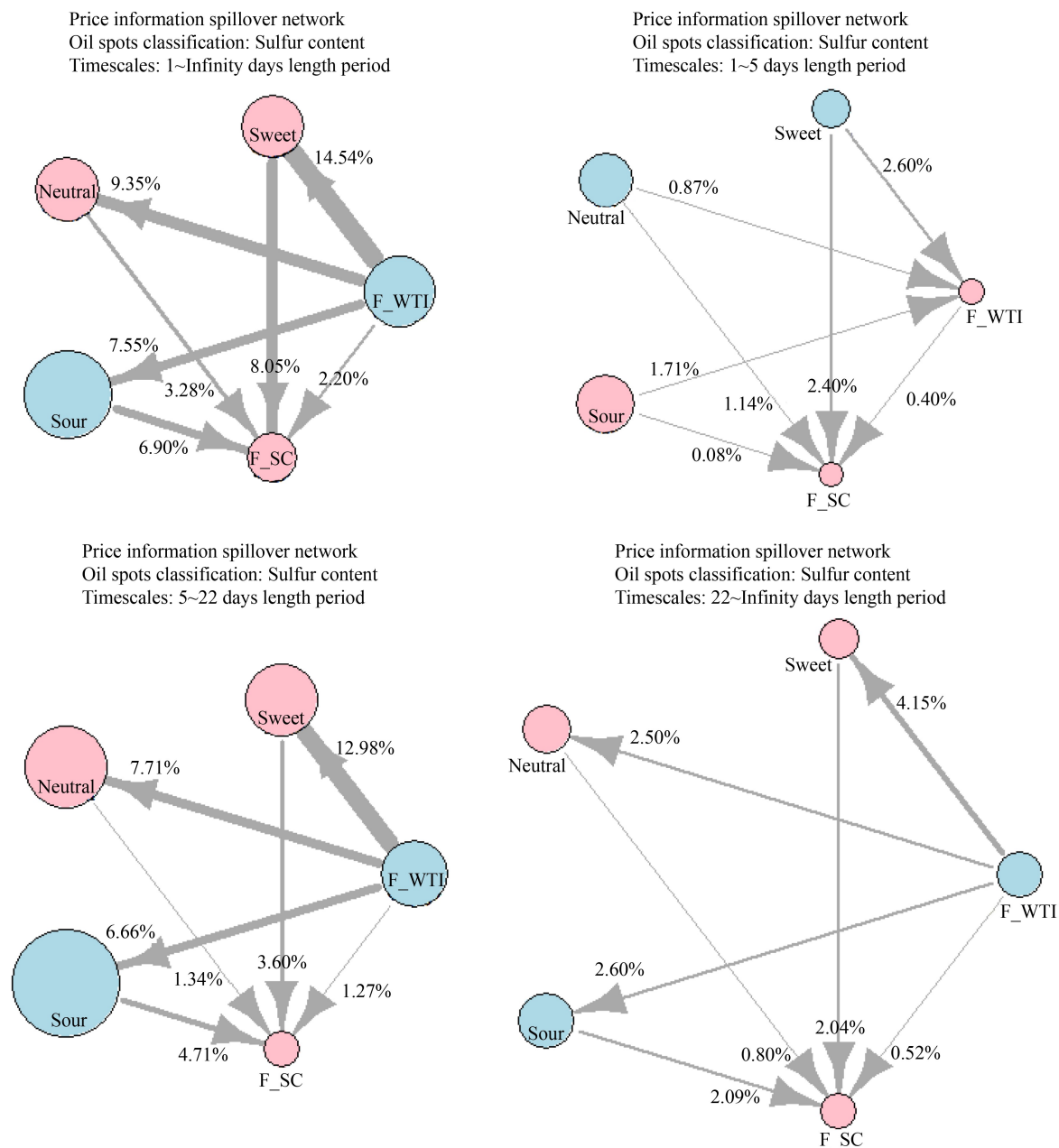At the long-run time scales (within 22 to infinity days),

Fig. 2 Net price information spillover network in oil spots under different sulfur contents.

Notes: F_SC denotes China's oil futures and F_WTI denotes WTI futures. We classify the 34 kinds of oil spots into three categories: Sweet oil (marked as "Sweet"), neutral oil (marked as "Neutral"), and sour oil (marked as "Sour") by sulfur content. The detailed explanation of each node and edge can refer to the notes of Fig. 1.

China's oil futures still shows "aggregate" weak price leadership to light-, medium-, and heavy-gravity oil spots compared with WTI futures' performance. In the right bottom of Fig. 1, all arrows from spots markets point to China's oil futures. Although the magnitude of net information spillover China's oil futures received is not that as strong as the magnitude at the medium-run time scales, it does not show obvious evidence that China's oil futures is a net information transmitter to light-, medium-, and heavy-gravity oil spots.

As previously discussed, the underlying spots for China's crude oil futures should be medium-gravity oil spots. However, the empirical results show that regardless of time scales, China's oil futures, compared with WTI futures, has no price leadership over medium-gravity oil spots. China's crude oil futures also has no leadership over light- and heavy-gravity oil spots. The difference in leadership between China's crude oil futures and WTI futures is greatest at the medium time scales. This finding suggests that although Li et al. (2021) uncover the good hedging effectiveness of China's oil futures, its price leadership may not be that good.
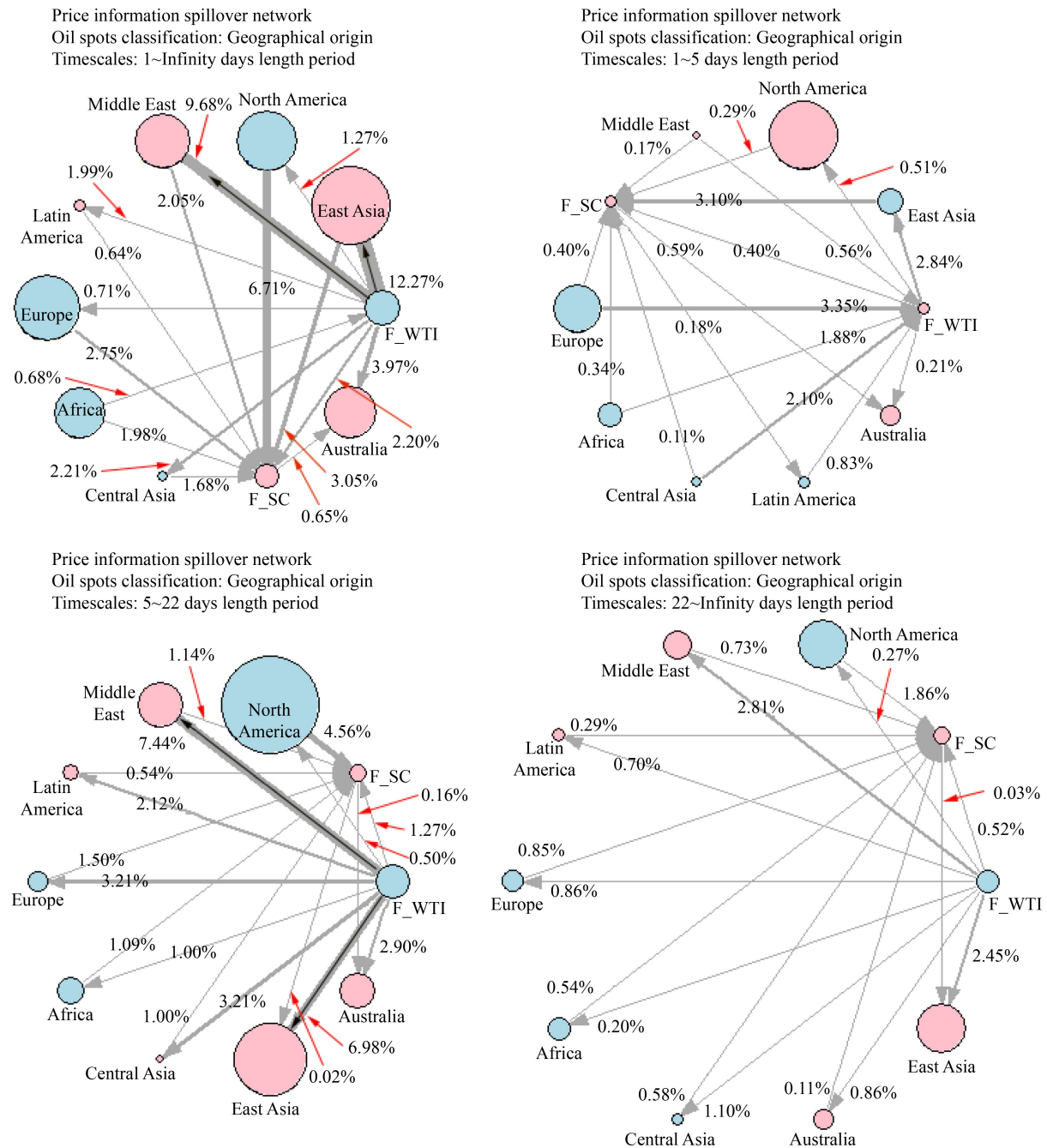
Fig. 3 Net price information spillover network in oil spots under different geographical origins.

Notes: F_SC denotes China's oil futures and F_WTI denotes WTI futures. We classify the 34 kinds of oil spots into eight categories: Spots in Middle East, Latin America, Europe, Africa, Central Asia, East Asia, Australia, and North America, respectively. The detailed explanation of each node and edge can refer to the notes of Fig. 1.

When we classify the oil spots markets by sulfur content, we find that the spillover network pattern is similar to that in the case of classifying by gravity. This outcome is mainly due to the close relationship between oil gravity and sulfur content (Awadh and Al-Mimar, 2015). The left top subfigure of Fig. 2 shows that within 1−∞ days, WTI futures transmits very strong information spillovers to all sour, neutral, and sweet oil spots, especially to sweet oil spots (14.54%). By contrast, China's oil

futures is only net information spillover receiver from all sour, neutral, and sweet oil spots.

When considering the time scales, at the short-run time scales, China's oil futures and WTI futures are net information receiver to sour, neutral, and sweet oil spots. At the medium- and long-run time scales, WTI futures is net price information transmitter to all three kinds of oil spots, which is shown in the bottom of Fig. 2. Futures prices are generally referenced when pricing crude oil

spots. However, from Fig. 2, we find that China's oil futures is inherently information spillover receiver from WTI futures. WTI futures is in a very high information leadership position.

Based on the close relationship between oil gravity and sulfur content (Awadh and Al-Mimar, 2015), we conclude that at the medium- and long-run time scales, China's oil futures shows much weaker price information leadership than WTI futures to oil spots classified under gravity and sulfur content. The short-run drivers of spots markets are diverse, including short-run OPEC cut plan, so the futures leadership is not shown at the short-run time scales.

Regarding to the classification of geographical origin, important information can be extracted from Fig. 3. From the left top subfigure of Fig. 3, we find that China's oil futures is net price information spillover receiver from many regions but is net spillover transmitter to oil spots in Australia within 1–∞ days. The patterns vary under different time scales.

At the short-run time scales, the China's oil futures leads the oil spots in Latin America and Australia well. WTI futures only leads the Australian, East Asian, and North American oil spots. Under short-run time scales, both futures do not show strong price leadership, which is similar to the analysis results when we classify oil spots by gravity and sulfur content.

An interesting observation is that at the short-run time scales, there is also information spillover from China's crude oil futures to Latin American crude oil futures. The oil trade between China and Brazil is close, with imports from Brazil accounting for 7.94% of China's total imports[1]. At the short-run time scales, the price of China's crude oil futures reflects short-term balance of supply and demand, which inevitably affects the price of Latin American oil, which is exported to China in large quantities. However, as long-run agreements on crude oil trade have long been signed between China and Latin American countries and the pricing drivers for oil prices in the agreements do not include China's crude oil futures, China's oil futures does not have an impact on Latin American crude oil spots at the medium- and long-run time scales.

At the short- and medium-run time scales, WTI futures receives stronger spillovers of crude oil from Europe and Africa, which also reflects that China's crude oil futures may not be affected by too much crude oil price information from Europe and Africa. This can be explained by the difference in the crude oil trading system. However, in the long-run, that is not the case, and China's oil futures remains weak.

Figure 3 depicts that net spillover pattern between oil futures and spots markets under different geographical origins varies within different frequency bands. Although

oil spots in East Asia is a net contributor for China's crude oil futures, it receives net spillovers from China's oil futures at medium- and long-run time scales. In the long-run, China's crude oil futures plays a price guiding role in East Asia's spots crude oil. China's crude oil futures also offers price guidance for Australia's crude oil in the short and medium terms and even net spillovers for Latin American crude oil in the short term. These findings may because China imports a considerable amount of crude oil from those places.

At the medium- and long-run time scales, as shown in the bottom two subfigures of Fig. 3, WTI futures shows price leadership to oil spots in all regions. This strong leadership in price information comes from the fact that the very sophisticated US energy finance market has become the global benchmark for price information. After the shale gas revolution, the US leads the world in energy, politics, and military. Any change in the US energy policy or energy markets will move the global political and economic landscape. China's oil futures only transmits 0.02% net spillover to oil spots in East Asia and 0.16% net spillover to spots in Australia at the medium-run time scales. At the long-run time scales, China's oil futures only transmits 0.03% net spillover to spots in East Asia. Although Central Asia, Middle East, and China are geographically very close, China's crude oil futures is still net information receiver to oil spots in these places. These findings reflect the influence of China's crude oil futures is not strong enough and only has price leadership for the Asia–Pacific region.

4.2 Price co-movement between oil futures and oil spots markets

In this subsection, using the BDECO model of Engle and Kelly (2012), we reveal the co-movement pattern between China's oil futures and global oil spots under the classification of gravity, sulfur content, and geographical origin.

Figure 4 depicts the calculation result of dynamic equicorrelation of Eq. (16), which reflects the "aggregate" co-movement pattern among all 34 kinds of crude oil spots and two kinds of oil futures. China's oil futures has a higher correlation level with all 34 kinds of spots compared with WTI futures. As the WTI futures market pays more attention to the pricing of North American crude oil, the relative decoupling from the world crude oil price causes this phenomenon.

The two curves had a sudden drop in the second half of 2018 as the crude oil market experienced a big bear market at the time. After October 2018, world crude oil prices plunged because of the increase in US crude oil production. Over this period, a certain degree of linkage decoupling is evident between futures and spots.

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[1] China's crude oil imports from Latin America have increased from 0% to 13% since 2000.
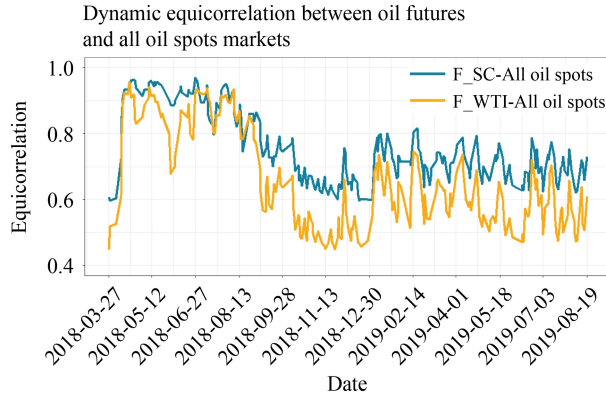
Fig. 4 Price co-movement between oil futures and all oil spots markets.

Notes: F_SC denotes China's oil futures and F_WTI denotes WTI futures. To calculate the yellow and blue trajectories in Fig. 4, we first classify all 36 assets into three categories: China's oil futures, WTI futures, and 34 oil spots. The innovation of Eq. (12) can be divided into three blocks marked as $\boldsymbol{\xi}_t = (\xi_{a,t}, \xi_{b,t}, \boldsymbol{\xi}_{c,t})_{36\times1}$, where $\xi_{a,t}$ is the innovation of China's oil futures, $\xi_{b,t}$ is the innovation of WTI futures, and $\boldsymbol{\xi}_{c,t}$ is the innovation vectors of sets of 34 oil spots. Second, similar to the BDECO calculation process from Eqs. (15)–(19), we can calculate $\rho_{a,c,t}$, which describes the dynamic "aggregate" co-movement pattern between China's oil futures and sets of 34 oil spots, and $\rho_{b,c,t}$, which describes the dynamic "aggregate" co-movement pattern between WTI futures and sets of 34 oil spots. The blue line in Fig. 4 is $\rho_{a,c,t}$, and the yellow line is $\rho_{b,c,t}$.

The above findings imply that China's oil futures and all 34 oil spots markets over the world have a better "aggregate" linkage. As can be seen in Fig. 5, regardless of which kind of gravity the oil spots market is, the co-movement pattern between spots and China's oil futures is stronger than that between spots and WTI futures. We find that the difference between the yellow and blue curves is the highest in the middle subfigure of Fig. 5. This outcome is unsurprising because the underlying spots of China's oil futures is medium oil. The co-movement performance of China's oil futures is quite different from its information spillover performance. It shows the good price linkage of China's oil futures.

Figure 6 plots the co-movement for oil futures and spots classified by sulfur content. All trajectories are similar to those in Fig. 5, given that sulfur content has close relation to crudes gravity. The correlation coefficient between China's crude oil futures and oil spots with any sulfur content is higher. Although the underlying spots of WTI futures are sweet and light oil, from the evidence of Figs. 5 and 6, we find China's oil futures has better co-movement with global light oil spots and sweet oil spots.

We reveal the co-movement pattern between China's oil futures and oil spots classified by geographical origin. As shown in Fig. 7, the co-movement level between China's oil futures and oil spots in East Asia is significantly higher than that between WTI futures and oil spots in East Asia, especially after August 2018 by when China's
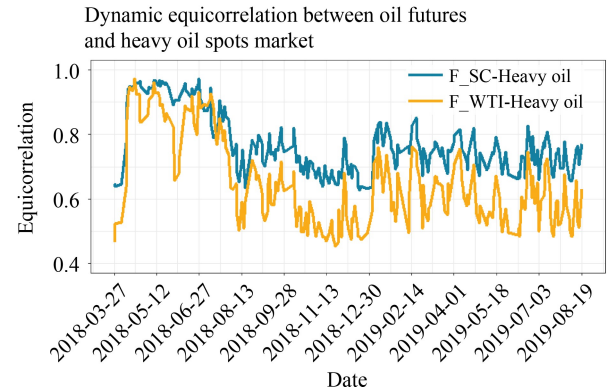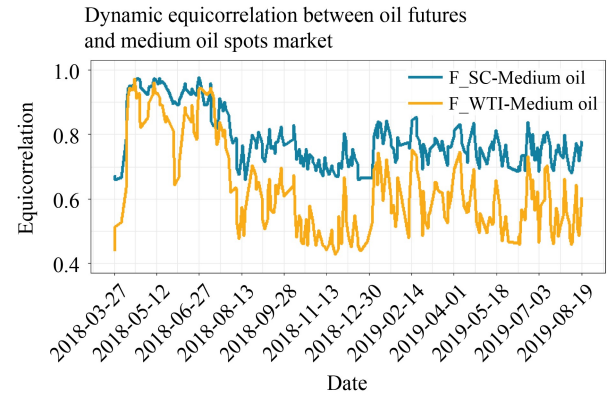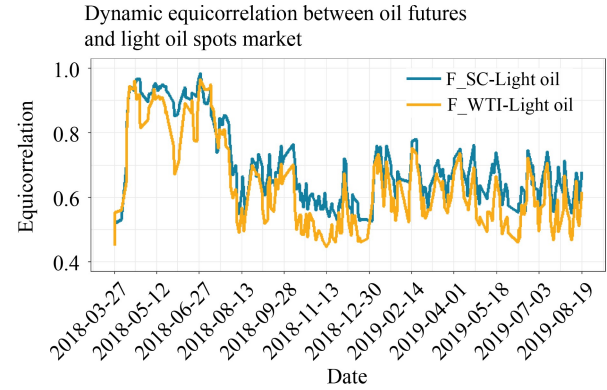

Fig. 5 Price co-movement between oil futures and oil spots markets under different gravities.

Notes: F_SC denotes China's oil futures and F_WTI denotes WTI futures. To calculate the yellow and blue trajectories in Fig. 5, we classify all 36 assets into five categories: China's oil futures, WTI futures, oil spots with light gravity, oil spots with medium gravity, and oil spots with heavy gravity. The innovation of Eq. (12) can be divided into five blocks marked as $\boldsymbol{\xi}_t = (\xi_{a,t}, \xi_{b,t}, \boldsymbol{\xi}_{c,t}, \boldsymbol{\xi}_{d,t}, \boldsymbol{\xi}_{e,t})_{36\times1}$, where $\xi_{a,t}$ is the innovation of China's oil futures, $\xi_{b,t}$ is the innovation of WTI futures, $\boldsymbol{\xi}_{c,t}$ is the innovation vectors of set of oil spots with light gravity, $\boldsymbol{\xi}_{d,t}$ is that of oil spots with medium gravity, and $\boldsymbol{\xi}_{e,t}$ is that of oil spots with heavy gravity. Similar to the BDECO calculation process from Eqs. (15)–(19), we can calculate $\rho_{a,c,t}$, which describes the dynamic "aggregate" co-movement pattern between China's oil futures and all light oil spots, and $\rho_{b,c,t}$, which describes the dynamic "aggregate" co-movement pattern between WTI futures and all light oil spots. We then place the trajectories of $\rho_{a,c,t}$ (blue line) and $\rho_{b,c,t}$ (yellow line) in the upper subfigure of Fig. 5. In this way, we finally calculate the $\rho_{a,d,t}$ and $\rho_{b,d,t}$ in the medium subfigure and calculate the $\rho_{a,e,t}$ and $\rho_{b,e,t}$ in the lower subfigure of Fig. 5.
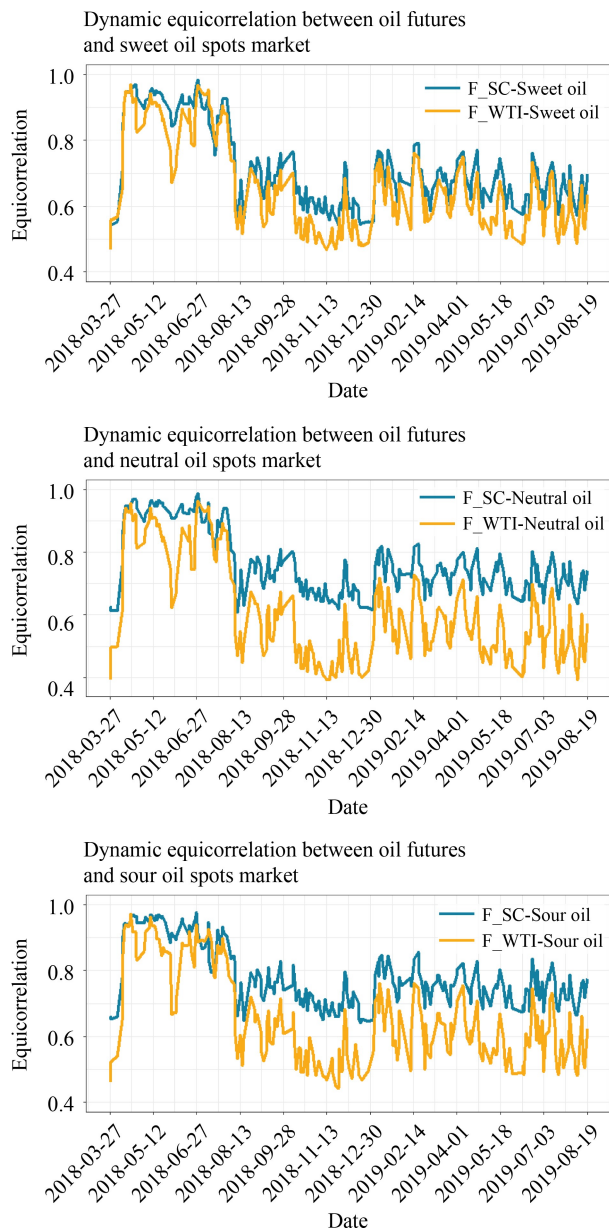
Dynamic equicorrelation between oil futures and sweet oil spots market

Dynamic equicorrelation between oil futures and neutral oil spots market

Dynamic equicorrelation between oil futures and sour oil spots market

Fig. 6 Price co-movement between oil futures and oil spots markets under different sulfur contents.

Notes: F_SC denotes China's oil futures and F_WTI denotes WTI futures. To calculate the yellow and blue trajectories in Fig. 6, we classify all 36 assets into five categories: China's oil futures, WTI futures, sweet oil spots, neutral oil spots, and sour oil spots. For the calculation process, refer to the notes of Fig. 5 or Section 2.2.

oil futures had been issued for five months. Similarly, China's oil futures has higher co-movement level to oil spots in Middle East compared with WTI futures. The underlying spots markets of China's oil futures are mainly in Middle East and China[1]. Investors participating in China's crude oil futures will give quotes based on the supply and demand of crude oil in Middle East and China with spot arbitrage opportunities, so China's

crude oil futures co-moves well with the aforementioned regions compared with WTI futures. From the evidence of Fig. 7, we find that the dynamic equicorrelations of China's oil futures and spots in East Asia and Middle East are greater than 0.8 for a long period, which implies highly "aggregate" linear correlation.

Besides, the co-movement pattern between oil spots in Latin America and China's oil futures is significant, which can be explained by the close crude trades between China and Latin America. Geographical distance is not a decisive factor in co-movement pattern, with trade exchanges becoming one of the key influencing factors. The co-movement level between China's oil futures and spots in Australia is relatively higher than that between WTI futures and spots in Australia, although the BDECO of both two trajectories is less than 0.8 for most time.

From the evidence of Fig. 7, there is relatively no difference between co-movement level of China's oil futures and European oil spots and that of WTI futures and European oil spots. The BDECO of these two pairs is very high before August 2018 and drops into a low level afterward. Similarly, there is relatively no difference between the co-movement level of China's oil futures and African oil spots and that of WTI futures and African oil spots. At present, the crude oil pricing system in Africa and Europe mainly refers to Brent crude oil futures, and China's crude oil imports from Africa are benchmarked against Brent crude oil futures prices with a premium and discount. Under this pricing system, neither China's crude oil futures nor WTI futures has a strong co-movement linkage to crude oil spots in African and European regions. There will be a spread between China's crude oil futures and European (African) crude oil spots. When the spread is too wide or too small, there will be scope for arbitrage. At the same time, this scope for arbitrage allows the spread to change dynamically, making the co-movement between China's crude oil futures and European crude oil spots be at a relatively low level.

Undoubtedly, WTI futures is the benchmark for spots pricing in North America. The availability of arbitrage opportunities makes the linkage between WTI futures and North American crude oil spots very strong. As China's crude oil futures cannot ultimately use North American oil spots for delivery, the linkage between them is necessarily weak. Figure 7 reflects these outcomes. The co-movement between China's oil futures and Central Asian oil spots is also relatively at a weak level.

5 Discussion

Compared with WTI futures, China's crude oil futures does not seem to have strong price leadership in the spots markets, despite having a relatively better co-movement

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[1] The underlying spots markets of China's oil futures are in UAE, Oman, Qatar, Yemen, Iraq, and China.
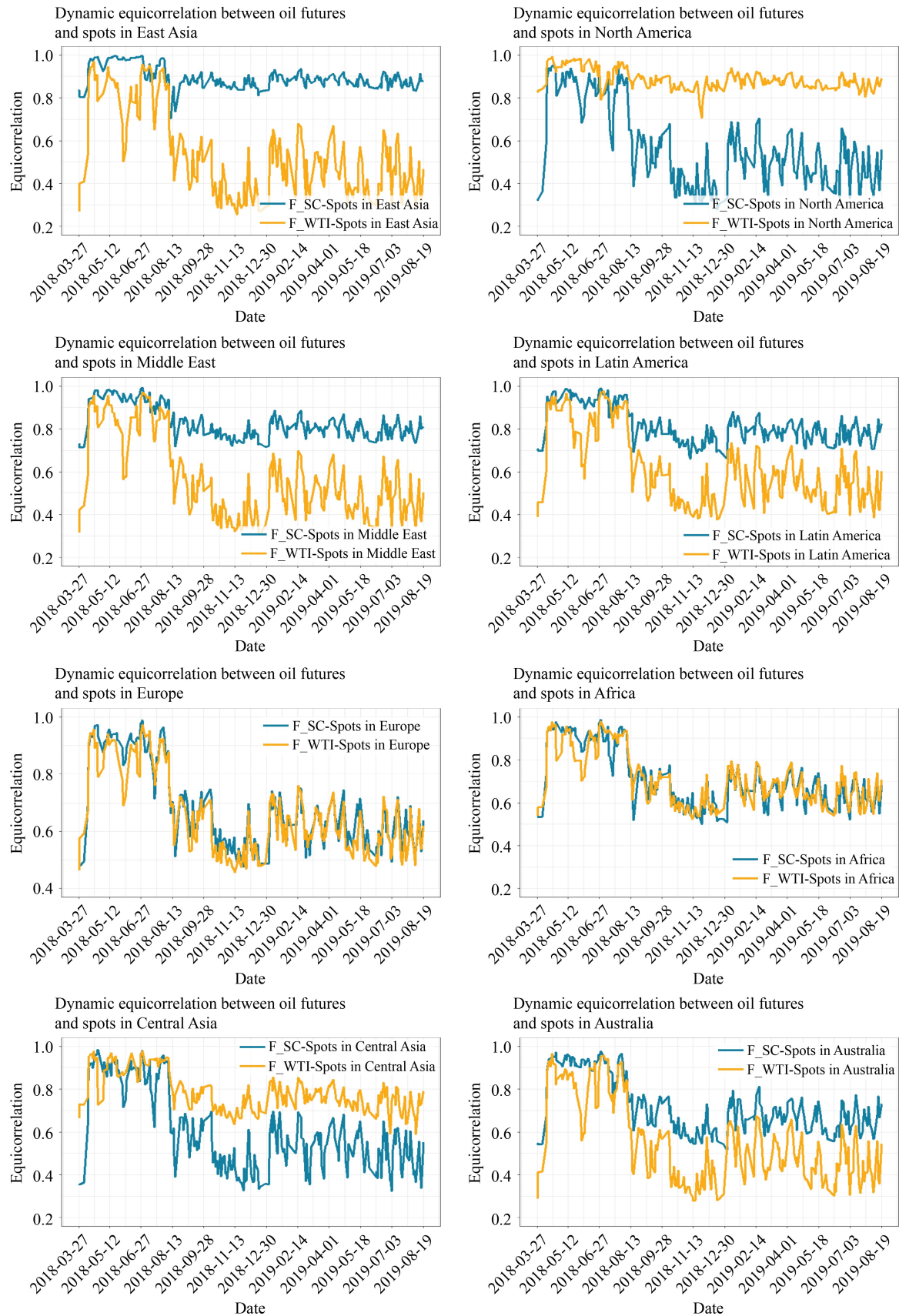
Fig. 7 Price co-movement between oil futures and oil spots markets under different geographical origins.

Notes: F_SC denotes China's oil futures and F_WTI denotes WTI futures. To calculate the yellow and blue trajectories in Fig. 7, we classify all 36 assets into 10 categories: China's oil futures, WTI futures, and oil spots in East Asia, North America, Middle East, Latin America, Europe, Africa, Central Asia, and Australia, respectively. The innovation of Eq. (12) can be divided into 10 blocks marked as $\xi_t = \left(\xi_{a,t}, \xi_{b,t}, \xi_{c,t}, \xi_{d,t}, \xi_{e,t}, \xi_{f,t}, \xi_{g,t}, \xi_{h,t}, \xi_{i,t}, \xi_{j,t} \right)_{36 \times 1}$. For the calculation details, refer to the notes of Fig. 5 or Section 2.2.

with the crude oil spots markets. China's crude oil futures has yet to rock the global crude oil spots market.

We provide at least two potential reasons for this situation. The first reason is that the volume and turnover of China's crude oil futures are far inferior to those of WTI futures. When a crude oil futures market attracts a large number of energy investors around the world, its price movements are a direct reflection of the sentiment of global energy investors. According to the CFTC report, WTI futures contains a large number of hedgers and spot vendors expecting physical delivery. By contrast, China's crude oil futures market contains mainly individual investors who prefer to speculate. The participants in the WTI futures market are the influencers of the price of WTI futures and the crude oil industry around the world. China's crude oil futures market may only be able to further enhance its global pricing influence by expanding the size of the market and adjusting the structure of market participants.

The second reason is that the US is uniquely positioned as a global political and economic leader, making it always more attractive to global investors. At present, the petrodollar system is still firmly in place, and the level of internationalization of RMB is far from that of the USD. The further development of China's crude oil futures market continues to depend on the further enhancement of the country's economic and political status. It is also highly relevant to the level of internationalization of the RMB. Achieving this will require not only continued GDP growth but also adjustments to regulatory policies related to restrictions on capital flows in China.

In terms of geopolitical strategy and China's oil import strategy, the country's crude oil futures does not provide price leadership in global medium-gravity oil spots. Nevertheless, it provides price leadership over the medium to long terms in the East Asian crude oil market. China's crude oil futures already meets strategic needs. This is due to China's enormous political and economic influence in East Asia. As the world's second largest economy, China's huge energy financial market potential is demonstrated by the construction and rapid development of a crude oil futures market. The development of financial markets is inextricably linked to the level of economic infrastructure. Russia has also sought to gain pricing power in the Far East and has built the Eastern Siberian Pacific Ocean (ESPO) pipeline. However, for a number of reasons, including the decline of its state power and

Western sanctions, ESPO prices have not reached the level of influence that Russia hopes for. In this light, China's crude oil futures is likely to further expand its price leadership in East Asia in the future as long as China's economy and industrial system continue to develop resiliently[1].

China's crude oil market receives wide attentions from investors (Zhang and Li, 2021; Zhang and Pan, 2021). The high co-movement level between China's crude oil futures and oil spots is likely to make the former an important tool for hedging. However, as mentioned earlier, how this feature is applied to attract investors depends in part on the attractiveness of the RMB versus the USD.

6 Conclusions

China's crude oil futures has received much attention since its issuance and is seen as a key step in China's efforts to break the petrodollar system and transition toward energy finance market internationalization. Applying the spillover index model of Baruník and Křehlík (2018) and BDECO model of Engle and Kelly (2012), we explore the price information spillover ability of China's crude oil futures and its price co-movement with oil spots markets. We reveal the international influence of China's oil futures by comparing it with WTI futures. We select 34 kinds of global oil spots classified by gravity, sulfur content, and geographical origin to carry out the empirical study. We come across the following three findings.

First, when we classify the oil spots markets by gravity into light-, medium-, and heavy-gravity oil spots, China's oil futures is pure net price information spillover receiver from all three kinds of oil spots markets at all the short-, medium- and long-run time scales. By contrast, WTI futures is net price information transmitter at the medium- and long-run time scales. Nevertheless, China's oil futures shows better co-movement patterns and higher level linkage with light-, medium-, and heavy-gravity oil spots than WTI futures.

Second, when we classify the oil spots markets by sulfur content into sweet, neutral, and sour oil spots, we find that China's oil futures is still pure net price information spillover receiver from all three kinds of oil spots markets at any time scales, implying very weak price

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[1] Despite China's efforts to develop green energy and green industries (Zhai and An, 2020; 2021; An et al., 2021; Zhang et al., 2022a; 2022b), crude oil remains an irreplaceable chemical raw material.

information leadership. Nonetheless, compared with WTI futures, China's oil futures shows good co-movement relationship with sweet, neutral, and sour oil spots.

Third, for oil spots markets under different geographical origins, China's crude oil futures only has net price information spillover to oil spots markets in Australia and Latin America at the short-run time scale, only to oil spots markets in East Asia and Australia at the medium-run time scale, and only to oil spots market in East Asia at the long-run time scale. Regarding price co-movement, China's oil futures shows stronger linear linkage with oil spots markets in East Asia, Middle East, Latin America, and Australia than WTI futures.

China's oil futures may not lead oil spots price well, but it co-moves well with oil spots. In sum, China's crude oil futures has yet to rock the global crude oil spots market. China's crude oil futures still needs to increase its trading activity and international influence to enhance its pricing voice.

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