Energy Economics 114 (2022) 106243

Contents lists available at ScienceDirect

Energy Economics

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

The growth of oil futures in China: Evidence of market maturity through global crises

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ARTICLE INFO

JEL classification:
G00
G01
G10
G13
G14
G15

Keywords:
Oil
Futures markets
Spillovers
Volatility
Information asymmetry
China

ABSTRACT

Chinese oil futures products were created in 2018, and have since presented an alternative, regional exchange through which to invest. This research tests for evidence of developing market maturity during the time since the market was established, specifically focusing on static and time-varying spillovers of higher moments between Chinese oil futures prices and other international crude oil markets. Chinese oil markets are also valuable when considering contagion and informational effects within the COVID-19 outbreak. Results indicate significant evidence of market maturity, to the extent that Chinese oil futures play a dominant role in the risk transmission of volatility, information asymmetry and extreme values, to both the international oil market and China's domestic energy-related markets before the outbreak of the COVID-19. After the escalation of the COVID-19 pandemic, such maturity and informational effects deteriorate significantly. Such outcomes suggest that while Chinese oil futures markets were growing at pace to become a leading international oil product, the outbreak of COVID-19 has stalled such progress.

1. Introduction

International oil markets have grown substantially in recent decades, now incorporating crude oil futures in the Middle East and Asia, however, some issues persist. For example, Oman oil futures traded in the Dubai Mercantile Exchange (DME), have been failing to provide the competitively-driven functionalities of efficient pricing and information flows towards medium and heavy crudes in the Asian region, compared to the well-established West Texas Intermediate (WTI) and European Brent crude oil futures markets (Yang et al., 2020). The DME Oman futures market still represents the regional oil benchmark. Further competition was introduced in March 2018 when a new crude oil futures market was introduced in the Shanghai International Energy Exchange (INE) in China as a further development of a national financial infrastructure.[1] With ambitions to become a regional crude oil benchmark in Asia and even a global crude benchmark, the new Chinese crude oil futures market has started to attract interest from a variety of energy-related stakeholders, as reflected by substantial growth of both trading volume and liquidity (Ji and Zhang, 2019; Yang and Zhou, 2020). The fast-paced development of Chinese oil markets presents direct competition with the DME Oman futures in Asia. In this research, we set out to establish what role Chinese oil markets play in the transmission of volatility worldwide during the new exchanges' continued growth amongst a range of other key metrics such as return skewness and kurtosis.

The Chinese crude oil futures market shows some dependence on the international crude oil communities, as suggested by high correlations and comovement at short- and long-time horizons (Broadstock et al., 2012; Jia et al., 2015; Huang and Huang, 2020), bi-directional volatility spillovers (Kang and Yoon, 2019; Yang et al., 2020; Li and Li, 2021), the effects of external influence (Zhu et al., 2016; Xiao et al., 2018; Ji et al., 2019; Yun and Yoon, 2019; Wang and Wang, 2019; Tiwari et al., 2019; Ahmed and Huo, 2021; Guo et al., 2021), and connectedness of down-side risk (Yang et al., 2020). The functionalities that Chinese crude oil futures provide to spot assets, such as hedging, and diversification, are internationally comparable (Lv et al., 2020).

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[1] For a thorough review of the growth of Chinese financial infrastructure, please see Marinova and Raven (2006), Eckert (2013), Deng (2014), Claus and Oxley (2014), Megginson and Fotak (2015) and Natoli (2021).

[2] For those studies, an assumption of one-state return distribution is mostly imposed. As discussed in Chan et al. (2018), ignoring heterogeneity of the distributional properties under more than one regime might lead to inaccuracy and inefficiency in forecasting moments of the conditional distribution.

https://doi.org/10.1016/j.eneco.2022.106243
Received 27 July 2021; Received in revised form 4 May 2022; Accepted 9 August 2022
Available online 22 August 2022

The market has an inferior position in lead–lag relations with spot oil markets in the Asian region (Zhang et al., 2021). Some conflicting evidence revealed by Chen et al. (2017) indicates that the Chinese crude oil market possesses a dominant role in interactions with the Asian spot oils, despite being overshadowed by other international spot crude oils. A comparison of risk between the Chinese crude oil and international counterparts suggests that the Chinese oil futures are less risky than the WTI and Brent oil futures using multi-fractal analyses (Wang et al., 2019). Nonetheless, although some efforts have been made to explore the informational efficiency of the Chinese crude oil futures, prior studies mostly focus on the early stages of the futures market development. As the market has grown substantially, it is imperative to monitor changes closely. Moreover, the previous literature examined the spillovers and transmissions of the volatility, of return distributions between the Chinese crude oil futures and other regional and international crude oil futures counterparts. To date, no research has focused on the transmissions of the third and fourth moments, that is, skewness and kurtosis. Such evidence sheds light on the dependence of risks of asymmetry and extreme values, which provides more insights into the informational role of the Chinese crude oil futures market among a set of competitors. Furthermore, prior studies have not considered heterogeneous pricing dynamics under distinct regimes.[2] It is of more than academic interest, therefore, to explore evidence as to the pricing dynamics and information transmissions of the Chinese crude oil futures market in the context of multiple regimes and the switching among those.

The study is motivated by the following: First, previous literature has shown that volatility, skewness, and kurtosis carry information relevant to differential perceptions of risk, and in particular, volatility risk, asymmetric risk and risk of the occurrence of extreme volatility (Harvey and Siddique, 2000; Jurczenko and Maillet, 2006). These risks are important factors driving fundamental prices. Furthermore, the cross-market transmissions of those risks reveal evidence as to how efficiently that new information is incorporated into the pricing fundamentals of the markets under investigation, which further ranks informational efficiency. Of particular importance relates to the question, 'as to which market is an 'information transmitter' and as to which is an 'information receiver'?' (Del Brio et al., 2017; Gkillas et al., 2020). Testing for market spillovers in volatility, skewness and kurtosis provides further evidence based on risk transmission and is indicative of market informational efficiency, and market maturity. Furthermore, since skewness and kurtosis, the third and fourth moments of the return distribution, relate to risk perceptions relevant to asymmetry and extreme values that affect asset pricing, they also indicate levels of downside (upside) risk and the risk of an occurrence of extreme values, such as value at risk (VaR) and expected shortfall (ES). The size and the direction spillovers (transmission or receiver) provide critical evidence of the extent to which information is transmitted across borders. Therefore, both skewness and kurtosis spillovers are indicative of informational efficiency and market maturity in a set of closely related markets. Therefore, in this study, we examine the spillovers of volatility, skewness and kurtosis between the Chinese crude oil futures, and other crucial international and domestic energy markets to explore the growth and maturity of the newly established Chinese crude oil futures. Secondly, the COVID-19 pandemic has significantly affected global financial and commodity markets. There is clear evidence that the pricing dynamics of equities that have similar names to the coronavirus, have also been affected by the event. Furthermore, the effects of COVID-19 have created significant information flows and volatility spillovers between financial markets in China and international financial markets (Corbet et al., 2020a). The pandemic has changed the perceptions of investors in relation to, for example, safe-haven investment during the crisis including transactions in cryptocurrencies (Allen et al., 2021; Goodell et al., 2023; Urquhart and Wang, 2023; Corbet et al., 2023). Of particular significance to the work presented here, during the period April 2020, negative prices of WTI futures contracts were observed for the first time which resulted in instability of the global energy markets. The evidence on the effects of such an anomalous event on the information flows and volatility transmissions between crude oil and other related energy markets, stock markets, other commodities and exchange rates is presented in Corbet et al. (2021b,c). Focusing on China's financial markets, the COVID-19 pandemic affected the hedging functionality of the Chinese stock index futures and the financial connectedness of the COVID related stock indices (Corbet et al., 2022c,d) which extended to the volatility dynamics and liquidity in the cryptocurrency markets (Corbet et al., 2022b). In Europe, differentials in price discovery between government-supported and non-government-supported European banks were affected by the COVID-19 pandemic (Corbet et al., 2022a). However, despite the mounting evidence of COVID-19 effects on financial market stability and efficiency noted above, the effects, if any, on the pricing dynamics and information efficiency of the newly established Chinese crude oil futures, remains unclear. To fill this gap, this study is devoted to exploring the information transmission of multiple risks between the Chinese crude oil futures and other, more mature, international, and domestic counterpart markets. The results presented have clear and important economic implications for investment strategies associated with energy markets during the special COVID pandemic episode and potentially similar episodes in the further.

This study specifically investigates the static and time-varying spillovers of higher moments including volatility, skewness and kurtosis between the Chinese crude oil futures markets and international crude oil futures markets, including WTI, Brent, DME Oman oil futures and multiple domestic maturing energy-related futures, inclusive of fuel oil, coking coal, ethylene glycol (EG), iron ore, thermal coal, and methanol. A bivariate two-state regime-switching model developed by Chan et al. (2018) is employed for analysis[3] while an extended vector autoregressive (VAR) model is used to examine static spillovers, a rolling window procedure applied to the VAR model is used to gauge time-varying spillovers.[4] In this paper, several economic factors are considered, for example, risk exposures and portfolio diversification, and consideration of the effects of different stages of the COVID-19 pandemic on both the static and time-variant higher moments' spillovers.

The paper contributes to the literature in several ways. First, we investigate how volatility risks transmit among a set of crude oil-related markets. Such evidence provides important insights into the broad understanding of risks in crude oil markets arising from non-normality, and how these risks influence crude oil prices in an information-connected network, a result that is of interest to a variety of practitioners. Furthermore, we investigate both static and time-varying spillovers of skewness and kurtosis in addition to volatility spillovers, which sets Chinese crude oil at the centre of an Asian transmission network, where the transmission of information shocks is not limited to the international crude oil futures markets but extends to several maturing energy-related futures. To consider these and other issues, the paper develops a two-state regime-switching model which is subsequently used, for the first time in the literature, to consider information spillovers in energy markets. Not only does it consider the conditional distributions under two regimes, but it also allows the measurement of higher-order

[3] The model is used to estimate the time series of higher moments by considering conditional distributions under a bear regime (high-volatility-low-return) and a bull regime (low-volatility-high-return), as well as the time-varying transition probabilities between the two regimes.

[4] This paper considers a methodological context of conditional distributions under different regimes for the bivariate time series modelling, instead of that under only one regime. Chan et al. (2018) propose that considering the distributional moments under more than one regime leads to an improvement of the accuracy and robustness of model estimation. This is found to be methodologically progressive as one market exhibits heterogeneous pricing dynamics between a status where market volatility is low and a status where market volatility is high.

moments of a mixture of conditional distributions, under two regimes, from a non-parametric perspective.

The outbreak of the COVID-19 pandemic, occurring in late 2019, has affected financial markets both regionally and internationally (Goodell, 2020; Corbet et al., 2020c, 2021d). In particular, in late April 2020, the WTI May contract futures price turned negative. Corbet et al. (2020a) showed that there were substantive spillovers from crude oil markets to several key sectors in stock markets. Meanwhile, significant differences in Granger causality at differing time scales were also identified in Sharif et al. (2020), while overreactions in energy commodity markets, exposed to the dissemination of the COVID-19 pandemic, were confirmed by Borgards et al. (2021). To date, there have been very few studies investigating the impacts of the COVID-19 pandemic on the newly introduced Chinese crude oil futures market. Due to the market's rapid growth, it is important to understand how the COVID-19 pandemic may have changed information flows from China's crude oil futures through to international and regional energy counterparts. We produce evidence that sheds light on the efficiency of oil markets during an exogenous crisis to which this paper contributes to the literature in this regard.

Results suggest that the Chinese oil futures market plays a dominant role in the risk transmissions of volatility, asymmetry, and extreme values to the international and China's domestic energy-related markets before the outbreak of the COVID-19 pandemic. The evidence can be found in terms of both static and time-varying spillovers. The time-varying spillovers between the Chinese oil futures and the other international and regional counterparts exhibit varying patterns across multiple stages of the COVID-19 pandemic. Most evidence suggests that the information role of the Chinese oil futures is impaired by such an event in terms of the dependence of risks of multiple types, however, there was growing influence before the pandemic is identified.

The remainder of the paper is organised as follows. Section 2 summarises a review of related literature. Data are discussed and illustrated in Section 3 and the empirical methodology used in the paper are presented in Section 4. In Section 5, empirical results are presented and discussed while Section 6 concludes.

2. Previous literature

Renminbi-denoted oil futures only began trading in 2018 on the Shanghai International Energy Exchange (INE), while in 2019, the Chinese government relaxed restrictions on foreign investment in Chinese assets. With further growth came further international investment. Trading volumes on the exchange increased by over 20% in 2020, representing a fourfold increase in total oil futures contracts traded. Zhu et al. (2019) analysed and identified significant time-varying differentials based on the dependence of international crude oil and Chinese oil futures contracts with further evidence of strong asymmetry between Chinese and international oil futures was also identified by Zhang (2019). However, such research did not find evidence supporting oil market integration.

Considering research based on volatility spillovers, Kang and Yoon (2019) identified bi-directional flows when considering the behaviour of Chinese fuel oil futures, with substantially elevated correlations during the US and European financial crises. Jiang et al. (2015) compared the volatility forecasts from Chinese oil futures to find little improvements in informational advantage through out-of-sample forecast testing, while Lu et al. (2020) found that CBE OVX demonstrates significant price leadership on Chinese crude oil futures and presents predictive information for oil realised volatility. Furthermore, recent research has explored some stylised facts about the newly established Chinese crude oil futures market. The linkages between the Chinese crude oil futures and the international crude oil futures market such as WTI and European Brent are stronger than those between the former's major competitor in the Asian region, the Dubai Mercantile Exchange (DME)'s Oman futures, and the two international crude oil futures markets, in terms of return and volatility transmissions (Yang and Zhou, 2020). Furthermore, the linkages between China's crude oil futures and the international crude oil futures markets exhibit larger effects during the overnight trading session of INE. Much research has focused to date on market connectedness (Yang et al., 2020), where the outbreak of COVID-19 was found to have enhanced spillover effects. Chinese crude oil futures are found to be an effective tool for hedging against the spot oil assets including OPEC and Oman (Li and Li, 2021), and it can also provide sound hedging effectiveness for the petrochemical-related stocks in China (Lv et al., 2020).

When considering the use of Chinese crude oil futures for more effective hedging and diversification than that of WTI, Chinese crude oil futures have been found to be inferior in the lead–lag relation with multiple crude oil markets in the Asian region through the usage of VECM and DAG methodologies (Zhang et al., 2021). Other works investigated long-term dynamics (Chen and Lv, 2015), reversal of behaviour and liquidity dynamics (Wen et al., 2021), market co-movements (Wang et al., 2019; Huang and Huang, 2020), and realised volatility (Ji and Zhang, 2019). Zhu et al. (2016) identified that such shocks are heterogeneous across the conditional distribution of stock returns, while Li et al. (2012) identify that there is evidence of structural breaks in the relationship due to severe financial crises, with evidence of shifting Granger causality. Further evidence is presented based on the relationship between WTI and Chinese energy stocks by Li and Li (2021). Using a DCC-GARCH analysis, Hou et al. (2019) identify the existence of time-evolving patterns of bilateral volatility spillovers between Chinese oil and stock index futures, the latter which is found to primarily dominate the former. Ahmed and Huo (2021) identify uni-directional return spillovers from global oil markets upon Chinese stock markets, suggesting a strong dependence of the Chinese stock market on the oil market. Such research has developed based on the work of Broadstock et al. (2012) and Broadstock and Filis (2014), who found evidence that the US and Chinese oil markets exhibit systematically time-varying sectoral correlations, where Chinese markets appear to be more resilient to price shocks. Such shocks are also found to generate negative effects on output and investment (Tang et al., 2010).

The effects of COVID-19 on broad financial markets have been covered quite extensively (Goodell, 2020; Corbet et al., 2020d, 2021a), however, direct effects relating to oil markets have also been relevant when developing a robust methodological structure for the following research. Corbet et al. (2020a) identified that in the aftermath of the negative oil prices, generated by disruptive political and supply effects due to the pandemic, generating substantial spillovers from oil markets upon several key sectors. Sharif et al. (2020) identified substantial differentials using wavelet-based Granger causality tests, while Borgards et al. (2021) confirmed an overreaction hypothesis, with energy commodities being particularly exposed due to the onset of the COVID-19 pandemic. With regards to methodological selection, our work builds on the structures of Cioroianu et al. (2021), Corbet et al. (2020c), Corbet and O'Connor (2021), Hu et al. (2021), Akyildirim et al. (2020b), Corbet et al. (2020b) and Akyildirim et al. (2020a) that investigate differentials of information share and price discovery. Further interactions between the growth of renewable energy resources and Chinese oil markets were analysed in detail by Ma et al. (2010b) and Ma et al. (2010a) who provided a thorough analysis of the key literature along with surveys based on available literature. Developing their work further, the authors focused on the convergence and interactions between renewable energy sources in China, demonstrating the country's spatially partial, gradual, idiosyncratic energy reform process (Ma et al., 2008, 2009; Ma and Oxley, 2012).

3. Data

Daily settlement prices of the newly introduced crude oil futures contracts in China, which were launched at the Shanghai International Energy Exchange (INE) on March 26, 2018, were used for the study.

Additionally, energy-related futures contracts[5] in China includes futures contracts on fuel oil, coking coal, ethylene glycol (EG), iron ore, thermal coal, and methanol.[6] WTI, Brent and DME Oman futures contracts are U.S. dollar-denominated whereas INE crude oil futures contracts together with the other energy-related futures contracts in China are RMB yuan-denominated.[7] INE futures are comprised of a basket of medium and heavy crude oils produced in the Middle East and China and it has relatively high sulphur content, compared to the WTI and Brent spot crude oils that have light sulphur content. The spot crude oil of INE futures is very similar to that of DME Oman futures in terms of sulphur content, while the two futures form direct competition with each other since both reflect medium and heavy sour conditions in Asia (Yang et al., 2020).

To construct continuous time series of daily futures' prices, we choose recent contracts that are highly liquid and actively traded in the markets using the closest available contract at each point in time. The sample period runs from March 26, 2018, to October 1, 2020, where ten sample pairs, consisting of INE oil futures, are selected,[8] while the sample period covers the outbreak of the COVID-19 pandemic, we further split the entire sample into three sub-samples. That is, a sub-sample running from March 26, 2018, to November 16, 2019 (hereafter referred to as P1), a sub-sample running from November 17, 2019, to December 30, 2019 (hereafter referred to as the P2 period), and a sub-sample running from December 31, 2019, to October 1, 2020 (hereafter referred to as the P3 period). Variable selection explicitly surrounded Chinese crude oil markets, combined with a selection of the largest energy markets in the world, including West Texas Intermediate oil, Brent crude oil, DME Oman oil, and futures markets relating to fuel oil, coking coal, thermal coal, iron ore, ethylene glycol, and methanol, many of which have been analysed across several previous studies such as those presented by Kong et al. (2019), Mensi et al. (2021) and Dai and Zhu (2022). We split the data sample, in the same manner, following Corbet et al. (2020b). In particular, P1 is a period before the COVID-19 outbreak occurs in mainland China. Based on the fact that the South China Morning Post reported that the first case of the COVID-19 was identified in mainland China on November 17, 2019, the P2 period is regarded as a period where the COVID-19 infection rate increases domestically in China, without spreading its effects to other regions.[9] Due to the WHO announcement on December 31, 2019, we select this date as the beginning of the COVID-19 pandemic. We incorporate these periods into our model to examine pricing dynamics and spillovers across different stages of the development of the COVID-19 pandemic.

Daily price returns are calculated as the first differences in the natural logarithm of prices. Table 1 reports descriptive statistics of the return series for the selected ten futures contracts. The mean daily performance of the Chinese INE crude oil futures is larger in P2 than that in P1, where mean returns are positive in both periods. In P3, mean returns of INE futures turn negative, due to a substantial, sustained drop in oil prices during the international COVID-19 period. Turning to the international crude oil futures, a similar reverse U-shape pattern of mean returns is found for the WTI, Brent as well as the DME Oman futures across the three stages of the development of COVID-19. In terms of domestic energy-related futures in China, the futures of chemical products that are refined from crude oil such as fuel oil, EG and methanol, exhibit a reverse U-shape pattern in mean returns. Iron ore futures also show a similar changing pattern in means. Exceptions include coking coal and thermal coal futures that show varying patterns. For these two futures, there is a rise in mean returns moving from P2 to P3, while coal products are seen as alternatives to crude oil and its refined chemicals. Furthermore, as can be observed from Table 1, a U-shape pattern of standard deviation is observed for all the futures across the three phases. In P2, the standard deviation is the lowest for all the futures, while the standard deviation reaches a peak in P3, except for iron ore and coking coal. The extent to which prices of crude oil and other energy-related futures vary in P2 is relatively low; however, sharply appreciates, when COVID-19 becomes an international issue. It can be seen that all the futures product's returns exhibit asymmetry and have fat tails in their distributions, which show non-normality.

Fig. 1 depicts movements in the original futures prices. Focusing on the INE oil futures, the moving patterns of prices are similar in movement between P1 and P2, while we can see a sharp decrease as P3 begins. Price movements of the WTI, Brent and DME Oman futures have similar patterns to those of the INE futures when the global COVID-19 pandemic begins. The price movements of domestic energy-related futures have somewhat different patterns compared to international crude oil futures. The Chinese COVID-19 infections appear to be correlated with local energy markets, an observation that will be further examined via cointegration testing.

We test for the stationarity of the price series via the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests. All the price series are integrated at an order of one. The Johansen cointegration test is then used to test for pairwise cointegration of the price series. The test results suggest that pairwise cointegration respectively exists in the relationships between the INE oil futures and WTI, DME Oman and EG futures. For the other pairwise relations, there is no cointegration detected. The cointegrating relations will be considered further in our selected methodological structures.[10]

4. Methodology

4.1. A two-state regime-switching model

According to Chan et al. (2018), the two-state regime-switching model is the correct approach for modelling the multivariate distribution of return series. It considers two regimes of market conditions, that is, a bull state (high return-low volatility) and a bear state (low

[5] We also collect data of some other energy-related futures contracts on low sulphur fuel oil, liquefied petroleum gas (LPG), ethylbenzene and metallurgical coke. However, due to the low availability of data and small sample size, these futures are not suitable for the study.

[6] INE is a subsidiary of Shanghai Futures Exchange (SHFE) where its trading hours in Beijing time are from 9:00 a.m. to 11:30 a.m. for the morning session, from 1:00 p.m. to 3:00 p.m. for the afternoon session and from 9:00 p.m. to 2:00 a.m. the next day for the overnight session. In contrast, the trading hours of the WTI and Brent futures contracts are from 6 p.m. to 5 p.m. the next day (New York time) and from 1:00 a.m. to 11:00 p.m. (London time). In terms of the DME Oman crude oil futures, the trading session runs from 4:45 p.m. North American Central Standard Time/Central Daylight Time (CST/CDT) to 4:00 p.m. CST/CDT next day, Monday to Friday. On Sundays, the trading session starts at 4:00 p.m. CST/CDT. In comparison, concerning other domestic energy futures in China, the trading hours for fuel oil futures in SHFE in Beijing time are from 9:00 a.m. to 11:30 a.m. and from 1:30 p.m. to 3:00 p.m. The trading hours of coking coal, EG and iron ore futures traded in Dalian Commodity Exchange (DCE), as well as thermal coal and methanol futures traded in Zhengzhou Commodity Exchange (ZCE), are the same as for the fuel oil futures.

[7] All the futures contracts analysed are physically settled. All the data are collected from Thomson Reuters Eikon and DataStream.

[8] Note that regarding the sample of INE oil and EG futures, the starting date of the sample period is December 10, 2018, due to data availability of EG futures.

[9] On December 31, 2019, the World Health Organisation (WHO) formally recognised and confirmed the new novel coronavirus, according to a report by the Wuhan Municipal Health Commission in China concerning a cluster of cases of pneumonia in Wuhan, Hubei Province. After this date, COVID-19 was identified at a global level, and it subsequently started to spread widely across the world.

[10] Results of unit root tests and cointegration test are not reported for brevity of presentation, but available upon request.

Table 1
Descriptive statistics of return series.

	Chinese Crude			WTI			Brent		
	P1	P2	P3	P1	P2	P3	P1	P2	P3
Mean	0.0001	0.0023	−0.0030	−0.0003	0.0020	−0.0021	−0.0003	0.0021	−0.0023
Median	0.0000	0.0033	−0.0026	0.0010	0.0021	0.0000	0.0016	0.0028	0.0005
Maximum	0.0703	0.0191	0.1309	0.1342	0.0404	0.5812	0.1330	0.0342	0.1352
Minimum	−0.0549	−0.0252	−0.0987	−0.0821	−0.0514	−0.5686	−0.0893	−0.0449	−0.2600
Std. Dev.	0.0151	0.0085	0.0300	0.0210	0.0167	0.0785	0.0198	0.0145	0.0426
Skewness	−0.0487	−0.8882	0.2460	−0.0021	−0.7762	−0.1492	−0.0695	−0.8147	−1.7016
Kurtosis	4.8694	5.1054	6.3047	8.6588	5.6196	32.1333	9.6179	5.5803	14.2042
	DME Oman			Fuel oil			Coking coal		
	P1	P2	P3	P1	P2	P3	P1	P2	P3
Mean	−0.0001	0.0024	−0.0028	−0.0021	0.0064	−0.0010	−6.15E−05	−0.0021	0.0005
Median	0.0019	0.0015	0.0001	0.0000	0.0064	0.0000	0.0000	0.0000	0.0000
Maximum	0.1346	0.0322	0.1893	0.0619	0.0289	0.1386	0.1575	0.0144	0.0449
Minimum	−0.0860	−0.0327	−0.3135	−0.1299	−0.0209	−0.0997	−0.1149	−0.0503	−0.0605
Std. Dev.	0.0209	0.0142	0.0560	0.0177	0.0127	0.0296	0.0205	0.0119	0.0133
Skewness	−0.1202	−0.0941	−0.4840	−1.5377	−0.0595	0.1379	1.3333	−2.3581	−0.9003
Kurtosis	8.9844	3.4914	9.8214	12.6786	2.3457	8.7322	18.7674	10.0748	8.7919
	Ethylene glycol			Iron ore			Thermal coal		
	P1	P2	P3	P1	P2	P3	P1	P2	P3
Mean	−0.0007	−0.0001	−0.0015	0.0008	0.0025	0.0015	−0.0002	9.40E−05	0.0004
Median	0.0000	0.0000	0.0000	0.0012	0.0008	0.0006	0.0000	0.0007	0.0000
Maximum	0.0748	0.0408	0.0862	0.1055	0.0317	0.0969	0.0575	0.0138	0.0983
Minimum	−0.1228	−0.0520	−0.3117	−0.0943	−0.0161	−0.0828	−0.0621	−0.0240	−0.0459
Std. Dev.	0.0166	0.0157	0.0366	0.0207	0.0104	0.0181	0.0119	0.0070	0.0135
Skewness	−1.3211	−0.9708	−4.9377	−0.3363	0.8349	−0.1290	−0.5371	−1.7428	1.9553
Kurtosis	20.0600	7.6828	40.2091	7.7161	3.7331	8.5195	10.8853	7.8205	18.4252

Note: This table reports the descriptive statistics of return series of 10 crude oil and energy futures. Returns are calculated as the first differences of natural logarithms of price series. The results are shown for three sub-sample periods separately. P1 refers to the sample period from March 26, 2018 to November 16 2019. P2 refers to the sample period from November 17 2019 to December 30 2019. And P3 refers to the sample period from December 31 2019 to October 1, 2020. Note that the starting dates of P1 vary across the futures. Std. Dev. denotes the standard deviation.

Fig. 1. Movements of selected price series (2018–2020). Note: All the futures contracts under observation are physically settled. All the data is collected from Thomson Reuters Eikon and DataStream.

return-high volatility). Dynamic transition probabilities of the two time-varying regimes' switching, then contribute to a conditional two-state switching Markov chain. The higher-order moments of the joint multivariate return distribution are driven by the distribution moments under each regime and the conditional regime-switching Markov chain, regardless of whether the joint multivariate distribution is normal. The model provides ease of use and flexibility in forecasting higher-order moments especially when the return distribution is irregular. The conditional mean equation under a bivariate two-state regime-switching model is given by

$$r_t = u_{it} + \varepsilon_{it}, u_{it} = E\left(r_t | s_t = i, F_{t-1}\right), \quad \varepsilon_{it} | F_{t-1} \sim N(0, H_{it}) \tag{1}$$

where r_t is a 2 x 1 vector of returns given $R_t = (rt^c, rt^o)'$. rt^c denotes the returns of one international crude oil futures (WTI, Brent or DME Oman), and rt^o denotes the returns of the Chinese INE oil futures. s_t denotes the unobserved regime at time t. In this research, the model assumes two regimes, that is, regime 1 when $s_t = 1$, and regime 2 when $s_t = 2$. $u_{it} = (uit^c, uit^o)'$ is a 2 x 1 vector of conditional means of returns under regime i. F_{t-1} denotes the information set[11] at time t−1. Eq. (1) implies that the joint distribution of r_t is described by a combination of two bivariate normal distributions. Since we find cointegration exists between the INE futures and the WTI, DME Oman and EG futures, these samples' conditional mean equation under regime i in Eq. (1) is then shown as:

$$\begin{aligned} r_t^c &= \omega_{c,i} + ec_{c,i}ect_{t-1} + \alpha_{c,i}r_{t-1}^c + \beta_{c,i}r_{t-1}^o + \varepsilon_{i,t}^c, \\ r_t^o &= \omega_{o,i} + ec_{o,i}ect_{t-1} + \alpha_{o,i}r_{t-1}^c + \beta_{o,i}r_{t-1}^o + \varepsilon_{i,t}^o, \end{aligned} \tag{2}$$

where i = 1,2. $\omega_{c,i}$ and $\omega_{o,i}$ are the unconditional means of returns under regime i. ect_{t-1} is the lagged error correction term that points to a long-run equilibrium between two price series. $ec_{c,i}$ and $ec_{o,i}$ are therefore the error correction coefficients that capture the long-term responses of two markets to the pairwise disequilibrium. $\alpha_{c,i}$ and $\beta_{c,i}$ ($\alpha_{o,i}$ and $\beta_{o,i}$) examine the effects of the lagged returns on current ones under regime i. It should be noted that for the other samples where no cointegration exists between the INE futures and another one, ect_{t-1} and error correction coefficients are excluded in Eq. (2) and the equation reduces to a VAR(1) model. Further, H_{it} in Eq. (1) is assumed to be unconditional under regime i, that is, variances and covariances under regime i are static.[12] Nonetheless, under the two-state regime-switching model, time variations of higher-order moments can still be achieved via the first and second moments under each regime as well as a time-varying Markov chain. The specification for H_{it} is given by

$$H_{it} = D_i R_i D_i, \quad D_i = \begin{bmatrix} \sqrt{h_i^c} & 0 \\ 0 & \sqrt{h_i^o} \end{bmatrix}, \quad R_i = \begin{bmatrix} \rho_i & 1 \\ 1 & \rho_i \end{bmatrix}, \quad i = 1,2. \tag{3}$$

where h_i^c and h_i^o are the regime-dependant variances under regime i. ρ_i is the regime-dependant correlation under regime i. ρ_i is the correlation of return series under regime i. Moreover, we consider the effects of differing COVID-19 stages on variances under each regime, so that we have the following equations to specify h_i^c and h_i^o in Eq. (3).

$$\begin{aligned} h_{it}^c &= h_{c,i} + \delta_{c,i,1}d_{2t} + \delta_{c,i,2}d_{3t}, \\ h_{it}^o &= h_{o,i} + \delta_{o,i,1}d_{2t} + \delta_{o,i,2}d_{3t} \end{aligned} \tag{4}$$

where i = 1,2. d_{2t} is a dummy variable that takes a value of 1 between the COVID-19 growth period in China as identified by the first newspaper article based on an unknown virus[13] on November 17, 2019, through to the official WHO announcement on December 30, 2019, that is, P2, and zero otherwise. d_{3t} is a dummy variable that takes a value of 1 when time is from December 31, 2019, to October 1, 2020, that is, P3, and zero otherwise. $\delta_{c,i,1}$ and $\delta_{o,i,1}$, ($\delta_{c,i,2}$ *and* $\delta_{o,i,2}$) examine the effects of domestic (international) COVID-19 contagion on variances under regime i. Eq. (4) implies that variances under regime i may vary across different stages of the COVID-19 pandemic. Notes that h_{it}^c and h_{it}^o replace h_i^c and h_i^o in Eq. (4), respectively. Furthermore, the transition probabilities for regime-switching are specified to be time-variant. Time-varying transition probabilities are pronounced since substantial flexibility is obtained by allowing for time-varying transition probabilities compared to static ones (Gray, 1996; Chan et al., 2018). Following Chan et al. (2018), the transition probabilities are specified as:

$$P\left(s_t = j | s_{t-1} = i\right) = p_{i,j,t} \quad i,j \in 1,2, \text{ where } 0 \le p_i, j, t \le 1, \ \& \ \sum_{j=1}^{2} p_{i,j,t} = 1 \tag{5}$$

Further, $p_{ij,t}$ is specified to be a function of time trend. Then we have:

$$p_{ii,t} \equiv P\left(s_t = i | s_{t-1} = i\right) = \Upsilon\left(\theta_i + \lambda_i \text{trend}\right) \tag{6}$$

where i = 1,2. We also specify other factors to be drivers for the transition probabilities in Eq. (6). However, those specifications incur lower log-likelihood and higher penalised information criteria. The estimation on Eqs. (1)–(6) is conducted via the quasi-maximum likelihood estimation (QMLE). After the model estimates are obtained, we follow Chan et al. (2018) to calculate the time series of conditional variance, covariance, correlation, skewness, co-skewness, and kurtosis of the return series under question. Also, based on these series of higher-order moments, we compute the time series of the traditional systematic risk factor CAPM beta that is imposed on the INE oil futures by the international crude oil futures or imposed on China's domestic energy-related futures by the INE oil futures. At the same time, the time series of the standardised coskewness that pertains to the comovement in the long tail (volatility-return relationship) is obtained.[14] The derived series of variance, skewness and kurtosis are prepared for examining spillovers between the INE oil futures and a counterpart market.

4.2. Static and time-varying spillovers of higher moments

Next, we examine both the static and time-varying spillovers of volatility, skewness, and kurtosis in a pairwise relationship of the INE oil futures with one counterpart international oil/energy-related futures. First of all, the static spillovers are estimated via an extended VAR(1) model, which develops on generalised autoregressive conditional heteroscedasticity (GARCH) models. In particular,

$$\begin{aligned} HM_{c,t} &= a_0 + a_1\eta_{c,t-1} + a_2HM_{c,t-1} + a_3d_{1t}HM_{o,t-1} + a_4d_{2t}HM_{o,t-1} \\ &\quad + a_5d_{3t}HM_{o,t-1} + a_6d_{2t} + a_7d_{3t} + e_{c,t} \\ HM_{o,t} &= a_0 + b_1\eta_{o,t-1} + b_2HM_{o,t-1} + b_3d_{1t}HM_{c,t-1} + b_4d_{2t}HM_{c,t-1} \\ &\quad + b_5d_{3t}HM_{o,t-1} + b_6d_{2t} + b_7d_{3t} + e_{o,t} \end{aligned} \tag{7}$$

where $HM_{c,t}$ and $HM_{o,t}$ denote time series of higher order moments including variance, skewness and kurtosis that are obtained based upon estimates of the two-state regime-switching model. $HM_{c,t}$ refers to the series of WTI, Brent or DME Oman and $HM_{o,t}$ refers to the series of the INE oil futures, when the relevant samples are analysed. When the other samples are analysed, $HM_{c,t}$ refers to the series of the INE oil futures and $HM_{o,t}$ refers to the series of one domestic energy-related futures in China. $\eta_{k,t-1}$ $(k = c, o)$ denotes the standardised information shocks of higher moments at time t−1. For variance spillovers, $\eta_{k,t-1} =$

[11] Note that F_{t-1} excludes any information regarding s_t, lagged s_t or their probabilities. $\varepsilon_{it} = (\varepsilon_{it}^c, \varepsilon_{it}^o)'$ is a vector of innovations under regime i. H_{it} is a 2 × 2 conditional variance–covariance matrix of ε_{it} under regime i. ε_{it} is assumed to follow a bivariate normal distribution associated with regime i.

[12] We also consider specifying the variances and/or correlations to be time-varying following specifications of the bivariate constant conditional correlation (CCC) and dynamic conditional correlation (DCC) generalised autoregressive conditional heteroscedasticity (GARCH). However, similar to situations (Chan et al., 2018) face, these GARCH specifications yield nuisance parameters that do not improve the performance of the model given lower total log-likelihood and higher information criteria. Hence, we maintain our selected methodological specification of unconditional H_{it}.

[13] As per Corbet et al. (2021d) before the first identification of a 'mystery pneumonia' in Wuhan, there is much evidence to suggest that there were no previously identified mainstream media announcements before 17 November 2019. The is much evidence to suggest the existence of social media posts and online commentary before this date, but news based on what is now known to have been COVID-19 dissemination was not publicised on major international news outlets.

[14] For further details based on the calculation methods used for the estimation of higher-order moments' series, please see the Appendix provided by Chan et al. (2018).

$\left(\sum_{i=1}^{2} p_{it-1}\epsilon_{i,t-1}^{k}\right)^2$ $(k = c, o)$ and p_{it-1} is the probability of regime i (i=1,2) at time t−1. $\epsilon_{i,t-1}^{k} = \frac{\varepsilon_{i,t-1}^{k}}{\sqrt{_{i,t-1}^{k}}}$ $(k = c, o)$ where ε_{it-1}^{k} is the lagged residuals under regime i (i=1,2) from Eq. (2) and h_{it-1}^{k} is the lagged conditional variance under regime i relating to Eq. (4). For skewness and kurtosis spillovers, $\eta_{k,t-1} = \left(\sum_{i=1}^{2} p_{i,t-1}\epsilon_{i,t-1}^{k}\right)^3$ $(k = c, o)$ and $\eta_{k,t-1} = \left(\sum_{i=1}^{2} p_{i,t-1}\epsilon_{i,t-1}^{k}\right)^4$ $(k = c, o)$, respectively. d_{1t} is a dummy variable that takes a value of 1 when time period runs from March 26, 2018, to November 16, 2019, and zero otherwise. d_{1t} is the dummy for P1. As identified in Section 3, d_{2t} and d_{3t} are dummy variables for the P2 and P3 periods, respectively. Henceforth, in Eq. (7) we examine the spillovers of higher moments from $HM_{o,t}$ to $HM_{c,t}$ via coefficients a_3, a_4 and a_5 with respect to the P1, P2, and P3 periods, respectively. Meanwhile, we examine the spillovers of higher moments from $HM_{c,t}$ to $HM_{o,t}$ via coefficients b_3, b_4 and b_5 during the P1, P2, and P3 periods, respectively. In addition, the effects of the P2 and P3 periods on higher order moments are examined through the coefficients a_6, a_7, b_6 and b_7. The whole sample path will be employed for estimation.

Furthermore, we examine higher moments' spillovers from a time-varying perspective. In doing so, we apply a rolling window procedure to the VAR(1) model that is modified from Eq. (7) as below

$$
\begin{aligned}
HM_{c,t} &= c_0 + c_1\eta_{c,t-1} + c_2 HM_{c,t-1} + c_3 HM_{o,t-1} + e_{c,t} \\
HM_{o,t} &= d_0 + d_1\eta_{o,t-1} + d_2 HM_{o,t-1} + d_3 HM_{c,t-1} + e_{o,t}
\end{aligned} \tag{8}
$$

where $HM_{c,t}$ and $HM_{o,t}$ are time series of higher-order moments including variance, skewness, and kurtosis. $\eta_{k,t-1}$ $(k = c, o)$ denotes the standardised information shocks of higher moments at time t−1. Typically, within the rolling window procedure, the window size is 100 observations, and the step is one observation. The whole sample path is involved in the procedure. Our focus is on the derived time series of estimates of coefficients c_3 and d_3 that contain information on spillovers. We specify the net pairwise time-varying spillover from the INE crude oil futures to one counterpart futures as $|c_{3t}| - |d_{3t}|$, if relating to samples of WTI-INE, Brent-INE and DME Oman-INE. c_{3t} and d_{3t} are time series of estimates of c_3 and d_3, respectively. When the other sample is analysed, the net pairwise time-varying spillover from the INE crude oil futures to one counterpart futures as $|d3t| - |c3t|$. Note that the net time-varying spillovers focus on a difference in the strength of bilateral spillovers. We are interested in the movements of net time-varying spillovers of variance, skewness and kurtosis running from the INE oil futures to the other international crude oil and domestic energy-related futures across different stages of the COVID-19 pandemic.

5. Empirical results

5.1. The two-state regime-switching model

The estimation results of the two-state regime-switching model are presented in Table 2. The results of Hansen's standardised likelihood ratio test reject the null hypothesis that neither of the two states exists and the two-state regime-switching model is found to be invalid at the 1% level. Such evidence is identified for all of the analysed samples. Therefore, our selection of the two-state regime-switching model is not rejected.[15] In the analysed regimes, domestic contagion of the COVID-19 in China is found to significantly reduce the volatilities of the international crude oil futures including WTI and Brent, while the global pandemic significantly increases the volatilities of the two futures as investors attempt to seek safe havens during falling stock markets. In either analysed regime, the two stages of the COVID-19 are found to possess similar effects on the volatility of the DME Oman futures. During the Chinese COVID-19 contagion regime, evidence suggests a clear separation of behaviour, particularly when comparing INE futures with other international markets. Such evidence suggests that Chinese investors perceived the risks associated with COVID-19 and the severity of the challenge to which they face, well in advance of other international investors. While INE oil futures in China present evidence of domestic contagion significantly decreasing its volatility whereas the global pandemic significantly increases. Also, the transition probabilities are significantly driven by the time trend as presented by significant estimates of λ_1 and λ_2, which is evidenced across the three samples. Regarding the correlations between the INE futures and international crude oil futures, the correlations are high in the high-volatility regime and low in the low-volatility regime. This indicates that the links between Chinese crude oil and international oil are pronounced when the markets suffer high turmoil, that is, there is evidence of global oil market convergence.

Concerning INE futures and domestic energy-related futures in China, in either regime returns of the INE oil futures are significantly affected by their own lagged values. In either regime, the INE oil futures returns are also significantly influenced by lagged iron ore, thermal coal, and methanol futures returns.[16] Furthermore, Table 2 shows that the two regimes with low and high volatilities of the INE oil futures and domestic energy-related futures are significantly captured. The effects of COVID-19 on the volatilities of the INE futures returns vary under the two regimes, however, most results suggest that the domestic contagion in China reduces volatility, while the global pandemic led to an increase in volatility. Furthermore, the effects of the COVID-19 stages on the domestic energy-related futures also differ across the samples; however, it is pronounced and in both stages where there is a significant decrease in the volatilities of fuel oil, coking coal, EG and iron ore. Furthermore, the transition probabilities are significantly driven by the time trend. The correlations of the INE futures with fuel oil, iron ore, thermal coal and methanol are higher when the markets are more volatile. Higher correlations of the INE futures with coking coal and EG are found when the markets are relatively tranquil.

The movements of higher-order moments series that are obtained from the two-state regime-switching model are presented as Fig. 2, where the moving patterns of return volatilities vary across different futures markets. Differential behaviour is observed between the international crude oil and China's domestic energy-related futures markets. For instance, the volatilities of WTI, Brent and DME Oman futures decline during P2 and increase sharply as P3 begins, directly corresponding with the beginning of the pandemic. Their volatilities are maintained at the highest levels during the global COVID pandemic. In contrast, reduced volatility is observed during P2 for the futures of

[15] Concerning the estimation results of the samples of WTI-INE, Brent-INE and DME Oman-INE, it is found that the Brent and DME Oman futures returns are significantly affected by their own lagged returns only in the analysed regime. The INE oil futures returns are significantly affected by both their own lagged ones and the counterpart international oil futures returns in both regimes. Also, the error correction coefficients are not significant in either regime concerning the long-run equilibrium between the WTI and INE futures. However, in a regime with low volatilities of the DME Oman and INE futures returns, the INE futures significantly respond to the past deviation from the price equilibrium, suggesting that the former futures are led by the DME Oman futures market in the long run in such a regime.

[16] In a regime with low volatility, the fuel oil futures returns are significantly affected by both its own lagged values and the lagged INE futures returns. And in a regime with high volatility, the methanol futures returns can be significantly affected by its own lagged values only. Moreover, in a regime of high volatility, we find that the error correction coefficient for the EG futures is significant at the 1% level; however, under the same regime, it is not significant for the INE oil futures. This suggests that under such a regime, it is the INE oil futures market that initially identifies any disequilibrium, and it is the EG futures market that follows the pricing correction process. Under a regime of high volatility, the INE futures market leads the EG futures market in the long term.

Table 2
Two state regime-switching model.

Coefficient	Chinese Crude-WTI		Chinese Crude-Brent		Chinese Crud3-DME Oman	
	Estimate	P value	Estimate	P value	Estimate	P value
$\omega_{c,1}$	−0.0053	(0.2839)	0.0016**	(0.0319)	−0.0101	(0.1294)
$a_{c,1}$	−0.1750	(0.3324)	−0.1244***	(0.0001)	−0.1600	(0.2186)
$\beta_{c,1}$	0.2435	(0.3089)	0.0069	(0.8782)	0.3127	(0.2345)
$ec_{c,1}$	0.0438	(0.2648)			−0.0346	(0.1775)
$\omega_{o,1}$	−0.0006	(0.7216)	0.0005	(0.1647)	−0.0024	(0.4877)
$\alpha_{o,1}$	0.1708***	(0.0000)	0.5379***	(0.0000)	0.1575**	(0.0200)
$\beta_{o,1}$	0.3356***	(0.0002)	0.1389***	(0.0000)	0.2263*	(0.0523)
$ec_{o,1}$	−0.0057	(0.5891)			0.0051	(0.7590)
$\omega_{c,2}$	0.0019	(0.1208	−0.0062	(0.1474)	0.0026***	(0.0063)
$a_{c,2}$	−0.0575	(0.2072)	0.6737***	(0.0000)	−0.0600*	(0.0684)
$\beta_{c,2}$	0.0235	(0.6697)	0.2942	(0.1662)	−0.0150	(0.7130)
$ec_{c,2}$	0.0069	(0.4430)			−0.0087	(0.3961)
$\omega_{o,2}$	0.0003	(0.6072)	−0.0019	(0.1046)	−0.0009	(0.1099)
$\alpha_{o,2}$	0.5000***	(0.0000)	0.4124***	(0.0000)	0.4635***	(0.0000)
$\beta_{o,2}$	0.0714*	(0.0643)	−0.0154	(0.7413)	0.0547*	(0.0568)
$ec_{o,2}$	−0.0063	(0.1630)			0.0301***	(0.0000)
$h_{c,1}$	0.0017**	(0.0102)	0.0002***	(0.0000)	0.0015***	(0.0001)
$\delta_{c,1,1}$	−0.0009	(0.2240)	−0.0001***	(0.0000)	−0.0013**	(0.0279)
$\delta_{c,1,2}$	0.0165*	(0.0719)	0.0008***	(0.0000)	0.0053***	(0.0000)
$h_{0,1}$	0.0003*	(0.0647)	0.0001***	(0.0000)	0.0004***	(0.0000)
$\delta_{o,1,1}$	−0.0003*	(0.0983)	−0.0001***	(0.0000)	−0.0003	(0.1027)
$\delta_{o,1,2}$	0.0013***	(0.0002)	0.0012***	(0.0000)	0.0013***	(0.0000)
$h_{c,2}$	0.0002***	(0.0000)	0.0023***	(0.0001)	0.0002***	(0.0000)
$\delta_{c,2,1}$	−0.0002***	(0.0000)	−0.0017**	(0.0173)	−2.27E−05	(0.6781)
$\delta_{c,2,2}$	0.0002*	(0.0542)	−0.0008	(0.2440)	0.0002**	(0.0114)
$h_{o,2}$	9.36E−05***	(0.0000)	0.0004***	(0.0000)	9.17E−05***	(0.0000)
$\delta_{o,2,1}$	−8.79E−05***	(0.0000)	−0.0003***	(0.0063)	−6.37E−05***	(0.0000)
$\delta_{o,2,2}$	9.79E−06	(0.7275)	−0.0003***	(0.0005)	2.05E−05	(0.3673)
θ_1	0.2749	(0.7234)	1.2121***	(0.0093)	−1.3392	(0.4427)
λ_1	−0.0016**	(0.0152)	0.0024**	(0.0274)	0.0092***	(0.0014)
θ_2	1.9333***	(0.0000)	−1.2645	(0.1912)	0.5456	(0.3909)
λ_2	−0.0026**	(0.0148)	0.0071***	(0.0003)	0.0057***	(0.0005)
ρ_1	0.2315**	(0.0134)	0.0957*	(0.0777)	0.3289***	(0.0000)
ρ_2	0.0908*	(0.0605)	0.3729***	(0.0000)	0.0169	(0.7797)
Log-likelihood	3471.06		3531.35		3323.03	
AIC	−10.4789		−10.6749		−10.3755	
SIC	−10.2463		−10.4697		−10.1368	
Hansen's p value	0.0000		0.0000		0.0000	
	Chinese Crude-Fuel oil		Chinese Crude-Coking coal		Chinese Crude-Ethylene glycol	
$\omega_{c,1}$	−0.0008	(0.2947)	8.23E−05	(0.9242)	0.0011	(0.2613)
$a_{c,1}$	0.1108*	(0.0520)	0.2369***	(0.0000)	0.2140***	(0.0004)
$\beta_{c,1}$	0.0185	(0.7108)	−0.0281	(0.6047)	0.0855	(0.1410)
$ec_{c,1}$					−0.0035	(0.5830
$\omega_{o,1}$	0.0003	(0.6888)	2.20E−07	(0.9740)	1.72E−06	(0.5288)
$a_{o,1}$	−0.1298**	(0.0299)	−8.43E−06	(0.9707)	−7.60E−06	(0.9263)
$\beta_{o,1}$	0.2362***	(0.0000)	4.51E−05	(0.9276)	1.44E−05	(0.8142)
$ec_{o,1}$					8.42E−06	0.5288
$\omega_{c,2}$	−0.0002	(0.9344)	0.0011	(0.4891)	−0.0001	(0.9739)
$\alpha_{c,2}$	0.2348	(0.1173)	0.1314**	(0.0342)	0.2074**	(0.0212)
$\beta_{c,2}$	0.0058	(0.9691)	0.1318	(0.1057)	0.0980	(0.6559)
ecc,2					−0.0137	(0.6735)
$\omega_{o,2}$	−0.0011	(0.7497)	3.89E−05	(0.9830)	−0.0022	(0.6058)
$\alpha_{o,2}$	0.2610	(0.1838)	0.0668	(0.3523)	−0.1101	(0.4752)
$\beta_{o,2}$	−0.0373	(0.8506)	−0.0673	(0.5735)	0.0327	(0.8244)
$ec_{c,2}$					0.1491***	0.0000
$h_{c,1}$	0.0002***	(0.0000)	0.0002***	(0.0000)	0.0002***	(0.0000)
$\delta_{c,1,1}$	−9.46E−05***	(0.0072)	−0.0001***	(0.0000)	−0.0001***	(0.0000)
$\delta_{c,1,2}$	−7.17E−05***	(0.0014)	0.0006***	(0.0000)	0.0007***	(0.0000)
$h_{o,1}$	0.0001***	(0.0000)	0.0001***	(0.0000)	7.36E−05***	(0.0000)
$\delta_{o,1,1}$	9.88E−05	(0.4039)	−0.0001***	(0.0000)	−7.36E−05***	(0.0000)
$\delta_{o,1,2}$	−4.90E−05**	(0.0428)	−0.0001***	(0.0000)	−7.36E−05***	(0.0000)
$h_{c,2}$	0.0008***	(0.0000)	0.0005***	(0.0000)	0.0007***	(0.0004)
$\delta_{c,2,1}$	−0.0006***	(0.0003)	−0.0004***	(0.0000)	−0.0006***	(0.0029)
$\delta_{c,2,2}$	0.0005**	(0.0387)	0.0004***	(0.0015)	0.0002	(0.3269)
$h_{o,2}$	0.0017***	(0.0000)	0.0016***	(0.0000)	0.0011***	(0.0000)
$\delta_{o,2,1}$	−0.0015***	(0.0006)	−0.0014***	(0.0000)	9.58E−05	(0.9432)
$\delta_{o,2,2}$	−0.0004	(0.3227)	−0.0013***	(0.0000)	0.0007***	(0.0092)
θ_1	0.0374	(0.9673)	1.5414***	(0.0001)	1.5764**	(0.0166)

(*continued on next page*)

Table 2 (*continued*).

Coefficient	Chinese Crude-WTI		Chinese Crude-Brent		Chinese Crud3-DME Oman	
	Estimate	P value	Estimate	P value	Estimate	P value
λ_1	0.0109***	(0.0021)	0.0099***	(0.0012)	0.0091***	(0.0098)
θ_2	0.7065	(0.4840)	1.3533***	(0.0002)	0.7579	(0.3935)
λ_2	0.0059**	(0.0301)	0.0047***	(0.0002)	0.0088**	(0.0228)
ρ_1	0.7149***	(0.0000)	0.1850*	(0.0842)	0.2283**	(0.0334)
ρ_2	0.7523***	(0.0000)	0.0299	(0.7414)	0.0982	(0.3683)
Log-likelihood	2850.89		3886.15		3233.10	
AIC	−10.8915		−12.5608		−14.5745	
SIC	−10.6453		−12.3448		−14.2582	
Hansen's p value	0.0000		0.0000		0.0000	

Coefficient	Chinese Crude-Iron ore		Chinese Crude-Thermal coal		Chinese Crude-Methanol	
	Estimate	P value	Estimate	P value	Estimate	P value
$\omega_{c,1}$	−5.37E−05	(0.9353)	0.0012	(0.1448)	1.79E−05	(0.9842)
$\alpha_{c,1}$	0.1125***	(0.0035)	0.1075**	(0.0285)	0.1182**	(0.0248)
$\beta_{c,1}$	−0.0614*	(0.0830)	−0.0638	(0.3677)	0.0374	(0.4711)
$ec_{x,1}$						
$\omega_{o,1}$	0.0022***	(0.0015)	9.86E−05	(0.7063)	−9.29E−05	(0.8774)
$\alpha_{o,1}$	−0.0578	(0.1277)	−0.0242	(0.1081)	0.0044	(0.8904)
$\beta_{o,1}$	0.0376	(0.3053)	−0.0114	(0.6001)	0.0383	(0.3220)
$ec_{o,1}$						
$\omega_{c,2}$	9.30E−05	(0.9498)	−0.0016	(0.2578)	0.0004	(0.7402)
$\alpha_{c,2}$	0.2213***	(0.0028)	0.2836***	(0.0000)	0.1730***	(0.0042)
$\beta_{c,2}$	0.0113	(0.8917)	0.1945*	(0.0660)	0.1176*	(0.0759)
$ec_{o,2}$						
$\omega_{o,2}$	−6.31E−05	(0.9653)	0.0001	(0.9295)	−0.0006	(0.6855)
$\alpha_{o,2}$	0.0626	(0.3105)	−0.0238	(0.7205)	0.0408	(0.5566)
$\beta_{o,2}$	0.0127	(0.8418)	−0.0312	(0.7356)	0.1034*	(0.0861)
$ec_{o,2}$						
$h_{c,1}$	8.73E−05***	(0.0000)	0.0003***	(0.0000)	0.0001***	(0.0000)
$\delta_{c,1,1}$	−4.48E−05	(0.1793)	−0.0002***	(0.0000)	−9.05E−05***	(0.0009)
$\delta_{c,1,2}$	−1.52E−05	(0.4242)	−0.0002***	(0.0000)	−2.19E−05	(0.5036)
$h_{o,1}$	9.11E−05***	(0.0000)	1.74E−05***	(0.0000)	6.16E−05***	(0.0000)
$\delta_{o,1,1}$	7.44E−05	(0.3069)	−1.26E−05***	(0.0000)	2.49E−05	(0.7178)
$\delta_{o,1,2}$	8.69E−06	(0.7054)	2.21E−06	(0.6461)	−3.74E−05**	(0.0156)
$h_{c,2}$	0.0004***	(0.0000)	0.0002***	(0.0000)	0.0003***	(0.0000)
$\delta_{c,2,1}$	−0.0003***	(0.0000)	−2.48E−05	(0.7698)	−0.0002***	(0.0000)
$\delta_{c,2,2}$	0.0013***	(0.0000)	0.0013***	(0.0000)	0.0009***	(0.0000)
$h_{o,2}$	0.0009***	(0.0000)	0.0004***	(0.0000)	0.0006***	(0.0000)
$\delta_{o,2,2}$	−0.0008***	(0.0000)	−0.0002	(0.4334)	−0.0002	(0.3016)
$\delta_{o,2,2}$	−0.0003***	(0.0014)	−5.72E−05	(0.2096)	0.0000	(0.7452)
θ_1	1.0038***	(0.0000)	−3.0558***	(0.0000)	1.5899	(0.6467)
λ_1	0.0100***	(0.0000)	0.0115***	(0.0000)	−0.0055*	(0.0784)
θ_2	0.2899	(0.3425)	−13.0797***	(0.0001)	1.3594	(0.7193)
λ_2	0.0135***	(0.0000)	0.0333***	(0.0000)	−0.0028	(0.6427)
ρ_1	0.1655**	(0.0379)	0.2032***	(0.0022)	0.1035	(0.3332)
ρ_2	0.1662***	(0.0094)	0.0645	(0.3604)	0.2996***	(0.0000)
Log-likelihood	3502.15		3624.87		3235.79	
AIC	−10.5858		−11.7097		−10.4423	
SIC	−10.3807		−11.4937		−10.2264	
Hansen's p value	0.0000		0.0000		0.0000	

Note: This table reports the estimation result of the two state regime-switching model. Estimation is conducted for nine sample pairs each of which consists of the Chinese crude oil futures and an alternative international or Chinese energy futures. And results are separately shown. Hansen (1992)'s standardised likelihood ratio test is employed to test the existence of two regimes and associated *p*-value of test statistic is shown. P value, the p value for t test statistic on coefficient. AIC and SIC represent the Akaike Information Criterion and Schwarz Information Criterion respectively. ***, ** and * represent significance at the 1%, 5% and 10%, respectively.

fuel oil, coking coal, iron ore, thermal coal, and methanol, but their volatilities sharply increase during COVID-19 with differential effects observed in the markets for coal and EG. China's INE presents similar results to those observed for international oil markets where such observed patterns differ substantially from those of China's domestic energy-related futures markets.

Fig. 3 shows the movements of the skewness and kurtosis series of the analysed futures. In terms of the time-varying patterns of skewness, there are two different behavioural patterns across the affected periods of COVID-19. The first shows that, compared to the pre-COVID-19 period, the levels and extent of variations of asymmetry risk rise during P2 and continue to increase for WTI, DME, coal, oil, and methanol. The second pattern shows that the levels and extent of variations of skewness start to fall as P2 begins. Decreasing skewness persists over P3 in the market for Brent, fuel oil, EG and thermal coal. The moving pattern of skewness of the INE oil futures differs from both patterns above where it declines during P2 but becomes more volatile with the highest values occurring during P3.

Turning to the movements of the kurtosis series, we find that there are more varied patterns across the COVID-19 stages, for example, the kurtosis of the WTI and China's INE crude oil futures increases during the P2 and P3 periods. In contrast, the kurtosis of the Brent oil futures decreases from the P1 to P3 periods, reaching its lowest levels during the P3 period. The EG and iron ore futures' kurtosis series have similar patterns to those of Brent.[17]

[17] Moreover, a moving pattern with a drop in P2 followed by an increase in P3 is observed for coking coal, DME Oman and methanol. However, thermal

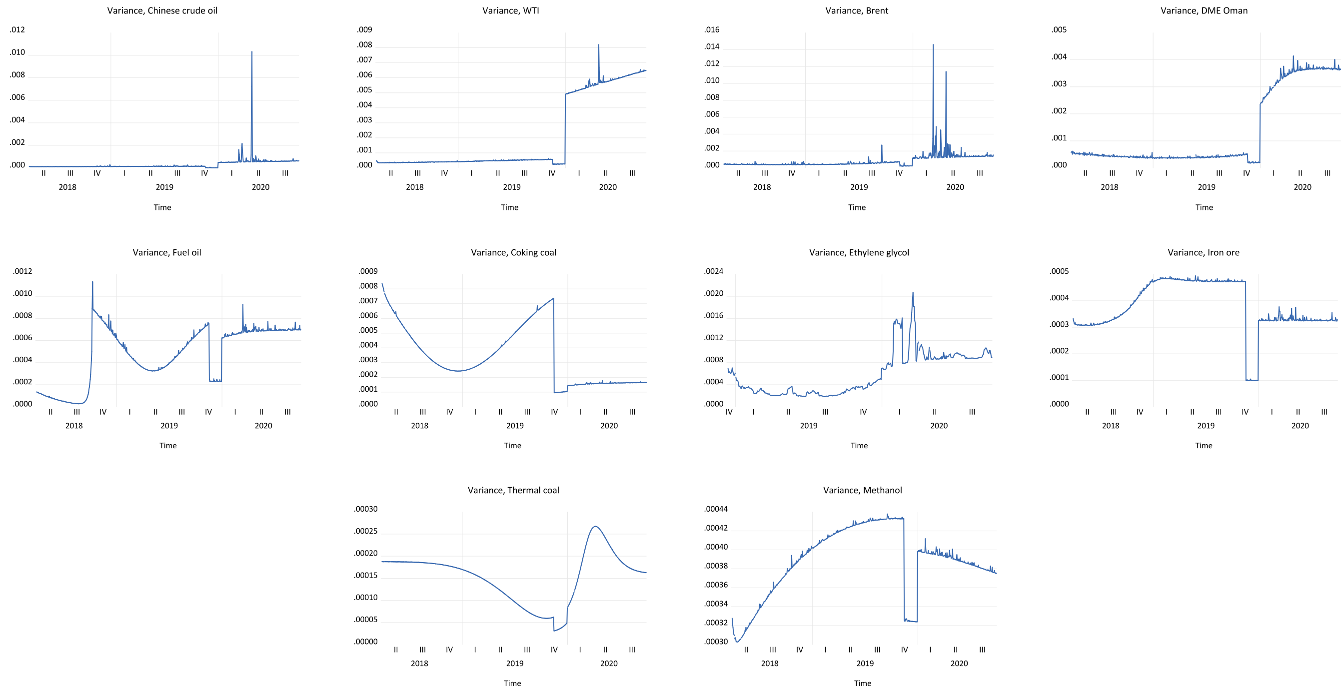

Fig. 2. Conditional variance, Movements of conditional higher order moments of selected price series (2018–2020). Note: Conditional series of variance, correlation, skewness, kurtosis, CAPM beta and standardised coskewness are derived based on estimates of the two state regime-switching model. I, II, III and IV in the above figures represent the first through fourth quarters respectively.

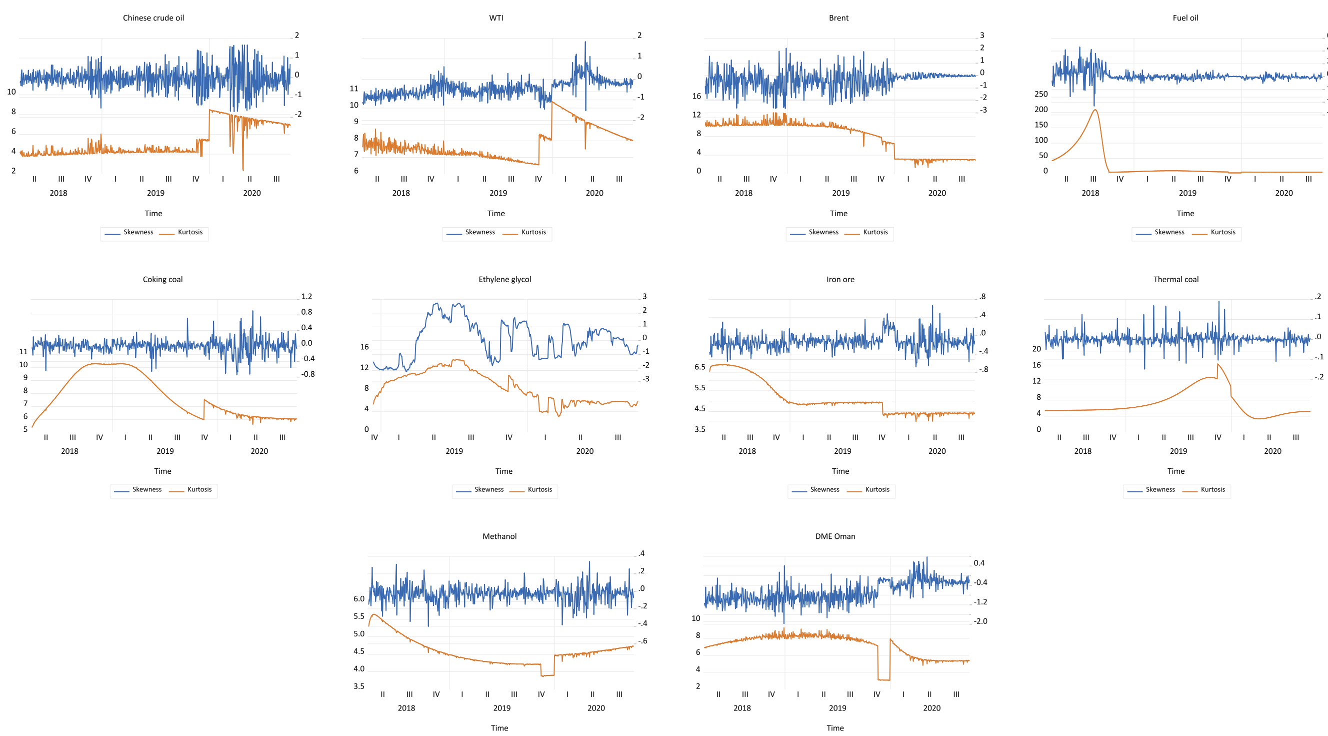

Fig. 3. Conditional skewness and kurtosis, Movements of conditional higher order moments of selected price series (2018–2020). Note: Conditional series of variance, correlation, skewness, kurtosis, CAPM beta and standardised coskewness are derived based on estimates of the two state regime-switching model. I, II, III and IV in the above figures represent the first through fourth quarters respectively.

coal has a kurtosis series that firstly rises when P2 begins but falls during the period thereafter. Overall, the dynamics of volatility, skewness and kurtosis exhibit inconsistent moving patterns across different futures markets. It is important, therefore, to consider how those markets interact with China's INE oil futures in terms of spillover effects.

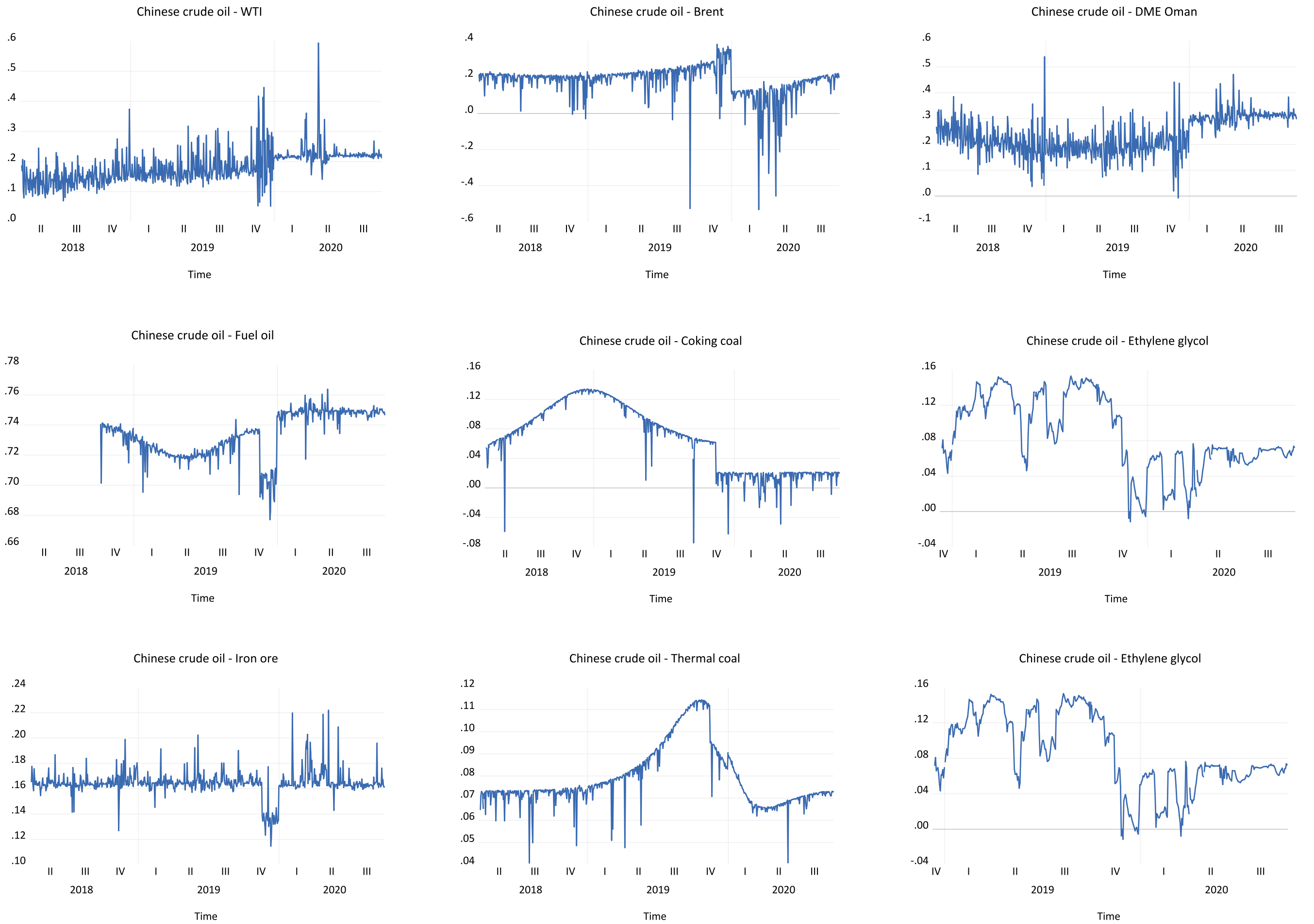

Fig. 4. Conditional correlations of selected price series (2018–2020). Note: Conditional series of variance, correlation, skewness, kurtosis, CAPM beta and standardised coskewness are derived based on estimates of the two state regime-switching model. I, II, III and IV in the above figures represent the first through fourth quarters respectively.

In Fig. 4, we present the correlation series of the INE oil futures with the other nine futures markets. Several relationships are revealed. The correlations between WTI, DME Oman and methanol steadily increase across the three stages of the COVID-19 pandemic, with some large oscillations in both P2 and P3. In contrast, the correlations with the Brent, coking coal, EG and thermal coal in P2, and continue to fall during P3.

5.2. Static and time-varying spillovers of higher moments

5.2.1. Static spillovers

The estimation results of the pairwise static spillovers of higher moments between the INE oil futures and the other analysed counterparts' futures are presented in Table 3. Panel A of the table shows the results for volatility spillovers. The results suggest that there is a unilateral spillover from INE to WTI during the relatively tranquil period before the COVID-19 pandemic occurs. There are bilateral spillovers between the two futures during the global pandemic period where the WTI has a higher spillover effect on the INE than the reverse. There are two-way spillovers between INE and Brent during P1 and the INE oil futures exert a larger effect. However, the result is reversed where it is the Brent futures that lead the INE futures during the P2 and P3 periods and spillovers exhibit one-way feedback. Our result is partially in line with Yang and Zhou (2020) who finds that two-way volatility transmissions between the INE crude oil futures and two international crude oil futures markets three months after the inception of the INE oil futures market. We develop such evidence in terms of the volatility spillovers under the impact of the COVID-19 pandemic. No spillovers exist between INE and DME Oman futures in P1. In contrast, the INE futures firstly leads the DME Oman futures during P2, then the result changes where the DME Oman futures lead the transmission in P3.

Turning now to the volatility spillovers between the INE oil futures and China's domestic energy-related futures, during P1, the INE oil futures lead the spillovers to the fuel oil and iron ore markets. However, the former is overshadowed by the other four futures markets during the same period. Once the domestic contagion of the COVID-19 begins in China, the INE oil futures take a leading role in the spillovers towards coking coal and iron ore. However, the market is led by three other futures markets including fuel oil, thermal coal, and methanol. During P3, the INE oil futures leads four domestic futures including coking coal, EG, iron ore and methanol. At the same time, it is led by fuel oil and thermal coal. As can be seen from Panel A, the international pandemic of COVID-19 impairs the information transmission of traditional risk from the INE futures to the international crude oil futures markets. The information content of the former markets regarding the second moment is weakened. In contrast, the information contents of the INE futures prices regarding volatility risk are somewhat enhanced by COVID-19's spread, as reflected in an increasing role in the domestic risk transmissions with major energy-related futures markets in China.

In Panel B of Table 3 presents the results for the skewness spillovers. For the transmission between the INE oil futures and WTI futures, the INE oil futures market dominates the process during P1. However, the result is reversed where the WTI futures lead the INE futures during the P2 and P3 periods. Looking at the interaction with the Brent futures, the INE oil futures are led by the Brent counterpart during the P1 and P3 periods and the spillover from Brent to INE is stronger in P3 than in P1.

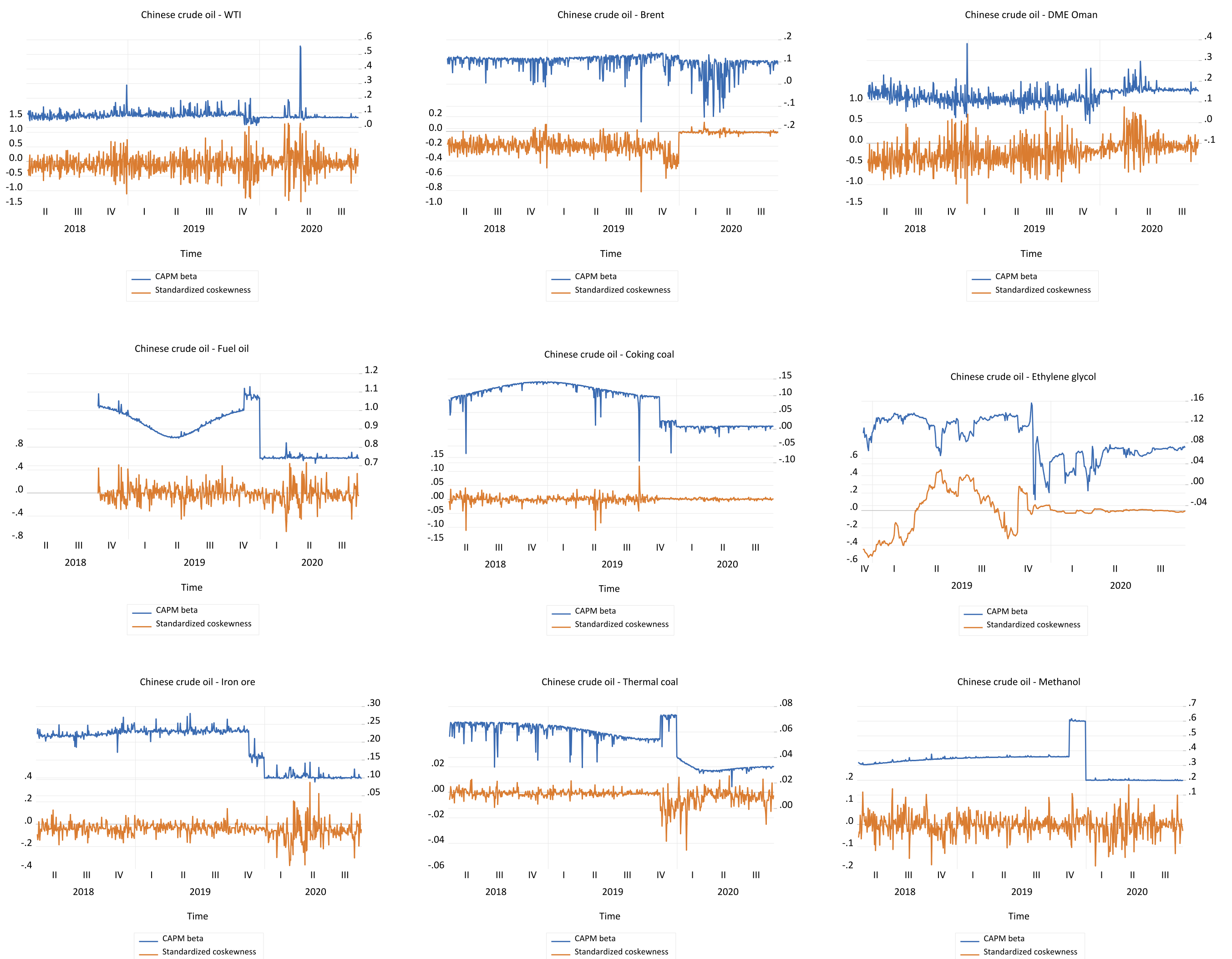

Fig. 5. CAPM beta and standardised co-skewness (2018–2020). Note: Conditional series of variance, correlation, skewness, kurtosis, CAPM beta and standardised coskewness are derived based on estimates of the two state regime-switching model. I, II, III and IV in the above figures represent the first through fourth quarters respectively.

The INE oil futures lead the DME Oman futures in both the P1 and P3 periods where the effect is higher in P1 than that in P3. The information transmission relating to the risk of asymmetry shows a reduced role for the INE oil futures with the international crude oil markets due to the occurrence of the COVID-19 pandemic.

In terms of the skewness spillovers between the INE oil futures and China's domestic energy-related futures, during P1, the INE futures lead three out of the six domestic markets including fuel oil, coking coal and EG. However, the result changes when moving to the P2 and P3 periods. INE futures effects are overshadowed by thermal coal and methanol futures in P2 only, but they cannot transmit information to the other domestic counterparts during the same period. Likewise, four of the six domestic futures markets dominate in the transmission processes towards the INE futures during P3. However, the latter market can rarely affect its counterparts at the same time. Hence, the information transmission of the INE futures, with the domestic energy-related futures, relating to the risk of asymmetry and INE's transmissions with the international oil markets, are reduced by the COVID-19 pandemic.

Further, in Panel C of Table 3 reports the kurtosis spillovers between the INE futures and the other counterpart futures. The WTI oil futures lead the INE futures during the three periods. The spillover effect from WTI to INE increases when moving from P1 to P2 but is slightly reduced from P2 to P3. The INE futures take a leading role in the spillovers with Brent during P1. However, the result is reversed during P2. Brent oil futures leads this process, with similar results identified in P3. Moreover, the DME Oman futures leads in the spillover process with the INE futures only during P3. Thus, the role of the INE oil futures market in the transmission of the risk of extreme values with the international crude oil markets is reduced by the spread of the COVID-19 pandemic. The evidence is consistent with the volatility and skewness of spillovers.

Moving to consider kurtosis spillovers of the INE oil futures with China's domestic energy-related futures, during P1, the INE oil futures lead the processes concerning five out of six domestic markets. These findings persist in P2 where the INE oil futures leads all the domestic counterparts. However, the resulting change during P3 where the INE oil futures lead only three out of six domestic markets. Therefore, the informational role of the INE oil futures is reduced by the global COVID-19 pandemic in terms of the interactions with the domestic energy futures. The evidence is consistent with the skewness spillovers but differentiated from the volatility spillovers. Hence, the impact of the COVID-19 on the information transmission of volatility risk associated with the INE oil futures behaves differently compared to those on the transmissions of the risks of asymmetry and extreme values.

5.3. Time varying spillovers

The time-varying net pairwise spillovers of higher moments reveal important evidence regarding the information transmission of risk.

Table 3
Static spillovers of variance, skewness and kurtosis, Panel A: Volatility spillovers.

Chinese Crude-WTI			Chinese Crude-Brent			Chinese Crude-DME Oman		
P1	0.7137*	(0.0533)	P1	4.8667**	(0.0120)	P1	0.0635	(0.8035)
P2	−1.1393	(0.3060)	P2	1.2549	(0.7591)	P2	−2.1810**	(0.0100)
P3	−0.1300***	(0.0000)	P3	0.2225	(0.2785)	P3	0.1162***	(0.0001)
Reverse Relationship								
WTI-Chinese Crude			Brent-Chinese Crude			DME Oman-Chinese Crude		
P1	0.1278	(0.6464)	P1	−0.0334***	(0.0075)	P1	0.1193	(0.2756)
P2	−0.0244	(0.9849)	P2	−0.1558**	(0.0176)	P2	−0.0732	(0.8484)
P3	0.1974***	(0.0001)	P3	−0.0251***	(0.0000)	P3	0.1537***	(0.0000)
Chinese Crude-Fuel oil			Chinese Crude-Coking coal			Chinese Crude-Ethylene glycol		
P1	−0.6649***	(0.0000)	P1	−0.1649***	(0.0000)	P1	0.0466	(0.7560)
P2	−0.0710*	(0.0769)	P2	−2.8243***	(0.0000)	P2	−0.2303	(0.2388)
P3	0.0003***	(0.0000)	P3	−0.0567***	(0.0000)	P3	−0.2179***	(0.0005)
Reverse Relationship								
Fuel oil-Chinese Crude			Coking coal-Chinese Crude			Ethylene glycol-Chinese Crude		
P1	0.2427***	(0.0000)	P1	0.1754***	(0.0000)	P1	0.1427***	(0.0000)
P2	−0.2320***	(0.0000)	P2	0.0001	(0.9970)	P2	0.0251	(0.4811)
P3	−0.0901***	(0.0020)	P3	−0.1085	(0.2982)	P3	−0.0012	(0.7278)
Chinese Crude-Iron ore			Chinese Crude-Thermal coal			Chinese Crude-Methanol		
P1	0.5586***	0.0000)	P1	−0.0008	0.9201)	P1	0.4778***	(0.0000)
P2	−1.7271***	0.0000)	P2	−0.1558***	0.0000)	P2	0.3885***	(0.0000)
P3	−0.2239***	0.0000)	P3	−0.0061***	0.0000)	P3	2.2718***	(0.0000)
Reverse Relationship								
Iron ore-Chinese Crude			Thermal coal-Chinese Crude			Methanol-Chinese Crude		
P1	0.3999***	0.0000)	P1	−0.3216***	0.0000)	P1	−0.4820***	(0.0000)
P2	−0.0006	0.9467)	P2	0.8850**	0.0380)	P2	−0.6741***	(0.0000)
P3	−0.0037	0.8989)	P3	5.4440***	0.0000)	P3	−0.1143***	(0.0000)
Chinese Crude-WTI			Chinese Crude-Brent			Chinese Crude-DME Oman		
P1	−0.5744***	(0.0000)	P1	0.1875	(0.5142)	P1	−0.5166***	(0.0000)
P2	−0.2558***	(0.0000)	P2	0.0773	(0.6992)	P2	−0.0592	(0.5110)
P3	−0.2843***	(0.0000)	P3	−0.0494	(0.7025)	P3	−0.2006***	(0.0000)
Reverse Relationship								
WTI-Chinese Crude			Brent-Chinese Crude			DME Oman-Chinese Crude		
P1	−0.1958*	(0.0539)	P1	−0.0456**	(0.0200)	P1	0.1438	(0.1211)
P2	−0.7009**	(0.0368)	P2	−0.1046	(0.1570)	P2	0.9100	(0.1756)
P3	−0.3174**	(0.0160)	P3	0.5113***	(0.0042)	P3	0.1491	(0.2914)
Chinese Crude-Fuel oil			Chinese Crude-Coking coal			Chinese Crude-Ethylene glycol		
P1	0.8555***	(0.0023)	P1	0.2979***	(0.0077)	P1	−2.0425***	(0.0004)
P2	0.0193	(0.9928)	P2	1.0018	(0.2821)	P2	−0.8543	(0.6850)
P3	0.0663	(0.8400)	P3	−8.9535	(0.5276)	P3	−4.7800	(0.1291)
Reverse Relationship								
Fuel oil-Chinese Crude			Coking coal-Chinese Crude			Ethylene glycol-Chinese Crude		
P1	−0.0186*	(0.0992)	P1	−0.0679	(0.4687)	P1	−0.0088***	(0.0000)
P2	0.2523	(0.6114)	P2	−0.0136	(0.8688)	P2	0.0006	(0.9022)
P3	−0.1172**	(0.0171)	P3	0.0123	(0.5872)	P3	−0.0005	(0.7851)
Chinese Crude-Iron ore			Chinese Crude-Thermal coal			Chinese Crude-Methanol		
P1	−0.0131	(0.7900)	P1	−0.0175	(0.2647)	P1	0.3948	(0.1467)
P2	−0.1113	(0.6901)	P2	−0.0239	(0.2039)	P2	0.2149	(0.1472)
P3	0.0079	(0.9226)	P3	0.0069	(0.4187)	P3	0.5123	(0.1001)
Reverse Relationship								
Iron ore-Chinese Crude			Thermal coal-Chinese Crude			Methanol-Chinese Crude		
P1	0.1398**	(0.0382)	P1	−0.3997**	(0.0411)	P1	−0.7707***	(0.0059)
P2	−0.0334	(0.8828)	P2	1.1156***	(0.0080)	P2	−1.5319**	(0.0242)
P3	0.1017	(0.1181)	P3	2.3372***	(0.0000)	P3	−0.6937***	(0.0055)
Chinese Crude-WTI			Chinese Crude-Brent			Chinese Crude-DME Oman		
P1	−0.1115***	(0.0063)	P1	−1.6496***	(0.0000)	P1	−0.0822	(0.1458)
P2	−0.2030**	(0.0197)	P2	0.0536	(0.7069)	P2	0.3641	(0.5473)
P3	−0.0430*	(0.0780)	P3	−0.0137	(0.5648)	P3	0.1782***	(0.0000)
Reverse Relationship								
WTI-Chinese Crude			Brent-Chinese Crude			DME Oman-Chinese Crude		
P1	−0.1713***	(0.0011)	P1	−0.0115	(0.3025)	P1	−0.0037	(0.9317)
P2	−0.6734***	(0.0065)	P2	0.7054***	(0.0000)	P2	0.0416	(0.6631)
P3	0.2606***	(0.0000)	P3	−0.6141***	(0.0000)	P3	0.4045***	(0.0000)

(*continued on next page*)

Table 3 (*continued*).

Chinese Crude-Fuel oil			Chinese Crude-Coking coal			Chinese Crude-Ethylene glycol		
P1	−0.0592	(0.1246)	P1	−0.1478***	(0.0023)	P1	−0.7785***	(0.0047)
P2	−2.5370*	(0.0787)	P2	3.0797***	(0.0000)	P2	2.4046***	(0.0000)
P3	−0.6600	(0.2634)	P3	−9.3499***	(0.0003)	P3	3.6344*	(0.0610)
Reverse Relationship								
Fuel oil-Chinese Crude			Coking coal-Chinese Crude			Ethylene glycol-Chinese Crude		
P1	0.0007***	(0.0058)	P1	−0.0189***	(0.0000)	P1	−0.0370***	(0.0000)
P2	−0.3866***	(0.0000)	P2	0.1480***	(0.0000)	P2	0.0029	(0.4657)
P3	−0.4779***	(0.0000)	P3	−0.0012	(0.9183)	P3	−0.0002	(0.9173)
Chinese Crude-Iron ore			Chinese Crude-Thermal coal			Chinese Crude-Methanol		
P1	0.4321***	(0.0000)	P1	−0.6082***	(0.0009)	P1	−0.2970***	(0.0031)
P2	−0.6531***	(0.0000)	P2	−1.8045***	(0.0000)	P2	0.4520***	(0.0000)
P3	−0.0768***	(0.0008)	P3	−0.0188**	(0.0453)	P3	−0.3973***	(0.0000)
Reverse Relationship								
Iron ore-Chinese Crude			Thermal coal-Chinese Crude			Methanol-Chinese Crude		
P1	0.3807***	(0.0000)	P1	−0.0109***	(0.0000)	P1	0.1551***	(0.0000)
P2	−0.0115	(0.8031)	P2	0.0013	(0.8787)	P2	0.3595***	(0.0000)
P3	0.0901***	(0.0017)	P3	0.6318***	(0.0000)	P3	0.2677***	(0.0000)

Note: This table reports model estimates of static spillovers of volatility, skewness and kurtosis between the Chinese crude oil futures and counterpart crude oil and energy futures. -> denotes the direction of spillovers. P1 refers to the sample period from March 26, 2018 to November 16 2019. P2 refers to the sample period from November 17 2019 to December 30 2019. And P3 refers to the sample period from December 31 2019 to October 1, 2020. Note that the starting dates of P1 vary across the futures. P value is the p value of t test statistic on coefficient. ***, ** and * represent significance at the 1%, 5% and 10% levels, respectively.

Table 4 reports the means of the time-varying net pairwise spillovers of volatility from the INE oil futures to the other counterpart oil futures. As can be seen from the table, all the means are statistically significant at the conventional levels across the three sub-sample periods. The mean of the net volatility spillover from the INE futures to the WTI is positive in P1, suggesting that INE leads WTI before the outbreak of the COVID-19, reversing when moving into the COVID affected periods where the mean net spillover is negative in both P2 and P3, with the size of the mean increasing from P2 to P3. However, WTI futures lead INE in terms of the volatility transmissions during the domestic and global contagion of the COVID-19. The leadership of the WTI futures is increased when COVID-19 becomes internationally widespread. The mean net spillover from the INE futures to Brent one is positive during P1, and it increases in size when moving to P2. However, the size of the positive mean net spillover falls during P3. This result suggests that COVID-19 has damaged the leading role of the INE oil futures in the volatility transmissions with Brent oil, a result that is potentially explained by the delayed realisation of the severity of the COVID-19 pandemic compared to that of the rest of the world. Concerning the volatility transmissions between the INE and the DME Oman futures, the positive mean net spillover declines as we move from P1 through to P3 which suggests that the dominance of the INE futures over the DME Oman futures, has also been influenced by COVID-19.[18]

Focusing on the volatility transmission of the INE futures towards China's domestic energy-related futures on average, first, the INE oil futures take a leading role in the transmissions with the domestic energy futures during either sub-period, except in the transmissions with the thermal coal futures. Secondly, we find evidence of several changing patterns of mean net spillovers moving from P1 through to P3. For instance, the mean net spillovers keep increasing in the transmissions of the INE futures with the fuel oil futures. The mean net spillovers firstly increase from P1 to P2 and then decrease when moving to P3. This is evident in the transmissions of the INE futures with the coking coal, iron ore and thermal coal futures. In terms of the transmission of the INE futures with the EG and methanol futures, the mean net spillovers decrease from P1 to P2 and increase when moving to P3. This evidence suggests that either domestic or international dissemination of COVID-19 contagion reduces the information content of the INE oil futures in terms of the transmission of volatility risk within the regional markets. This result is different from that based upon the assumption of static spillovers.

Table 5 presents the results for the means of the time-varying net skewness spillovers from the INE futures to the others across the three stages of the COVID-19 pandemic. All the means are significant at the 1% level, except one for the spillovers from INE oil to methanol futures during P1. In terms of the net spillovers between INE oil and international crude oil futures, spillovers from INE oil to WTI and Brent oil futures decline from P1 through to P3, however, during the P1 and P2 periods, the INE oil futures market leads the WTI and Brent oil in terms of the transmission of the risk of asymmetry given the positive mean net skewness spillovers. Considering the COVID-19 influenced period, WTI and Brent oil futures lead INE oil future's skewness transmissions. The mean net skewness spillovers from INE oil to the DME Oman oil futures are all positive in the three sub-periods, suggesting a leading role of the INE oil futures over the DME Oman counterpart in the skewness transmissions.[19] However, the time-varying spillovers exhibit more evidence in favour of the dominance of the INE oil futures over the international oil counterparts, especially during the relatively tranquil period.

Focusing on skewness transmissions from the INE oil to the domestic energy-related futures in China, results indicate a leading role for INE oil futures in the transmission processes in either sub-period, as represented by positive mean net spillovers. Moreover, there are several changing patterns of the mean net skewness spillovers across the three sub-periods.[20] We also find that the mean net spillovers from the INE

[18] The means of time-varying net volatility spillovers from the INE futures to the international crude oil suggest a different result compared to the static spillovers where the INE futures lead the Brent and DME Oman ones throughout. The former futures also lead the WTI during the relatively tranquil period. However, aligning with static spillovers, the mean time-varying net spillovers indicate reduced roles for the INE futures in the volatility transmissions due to the effects of the COVID-19 pandemic.

[19] We find that from the P1 to P2 periods the means of net spillovers increase but they substantially decrease from the P2 to P3 periods. Hence, the skewness transmissions show an impaired role for the INE oil futures created by the COVID-19 pandemic in terms of its transmission of the risk of asymmetry to the international crude oil futures markets. Such evidence aligns with the results presented in Table 3.

[20] For example, the mean net spillovers from the INE oil to the thermal coal futures decline from P1 through to P3. A substantial fall in the mean spillovers

Table 4
Time varying net volatility spillovers.

Chinese Crude -> WTI			Chinese Crude -> Brent			Chinese Crude -> DME		
	Mean	P value		Mean	P value		Mean	P value
P1	0.2326***	(0.0000)	P1	2.8541***	(0.0000)	P1	0.4394***	(0.0000)
P2	−0.1664***	(0.0000)	P2	3.9420***	(0.0000)	P2	0.1436***	(0.0000)
P3	−0.2382***	(0.0113)	P3	0.7209***	(0.0000)	P3	0.0645**	(0.0366)
Chinese Crude -> Fuel oil			Chinese Crude -> Coking			Chinese Crude -> Ethylene gl.		
	Mean	P value		Mean	P value		Mean	P value
P1	1.5732***	(0.0000)	P1	0.0127***	(0.0000)	P1	0.1420***	(0.0000)
P2	0.4933***	(0.0000)	P2	0.2349***	(0.0000)	P2	−0.0468***	(0.0000)
P3	0.2168***	(0.0000)	P3	−0.0751***	(0.0001)	P3	1.6413***	(0.0000)
Chinese Crude -> Iron ore			Chinese Crude -> Thermal			Chinese Crude -> Methanol		
	Mean	P value		Mean	P value		Mean	P value
P1	−0.1629***	(0.0000)	P1	−0.4286***	(0.0000)	P1	0.2807***	(0.0000)
P2	1.0831***	(0.0000)	P2	−0.1789***	(0.0000)	P2	−0.6945***	(0.0000)
P3	0.0311*	(0.0507)	P3	−2.9080***	(0.0000)	P3	−0.4738***	(0.0000)

Note: This table reports means of time varying pairwise net volatility spillovers from the Chinese crude oil futures to the other futures. Pairwise net spillovers are calculated as absolute values of spillovers from the Chinese crude oil futures to a counterpart futures less absolute values of spillovers of the other way around. Time varying spillovers are obtained from a rolling window estimation procedure. -> denotes the direction of spillovers. P1 refers to the sample period from March 26, 2018 to November 16 2019. P2 refers to the sample period from November 17 2019 to December 30 2019. And P3 refers to the sample period from December 31 2019 to October 1, 2020. Note that the starting dates of P1 vary across the futures. P value is the associated p value for t test statistic on the null hypothesis that mean equals zero. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 5
Time varying net skewness spillovers.

Chinese Crude -> WTI			Chinese Crude -> Brent			Chinese Crude -> DME		
	Mean	P value		Mean	P value		Mean	P value
P1	0.4669***	(0.0000)	P1	0.5464***	(0.0000)	P1	0.2578***	(0.0000)
P2	0.2462***	(0.0000)	P2	0.2926***	(0.0004)	P2	0.3188***	(0.0000)
P3	−0.0935***	(0.0000)	P3	−0.2925***	(0.0000)	P3	0.0597***	(0.0000)
Chinese Crude -> Fuel oil			Chinese Crude -> Coking			Chinese Crude -> Ethylene gl.		
	Mean	P value		Mean	P value		Mean	P value
P1	0.4519***	(0.0000)	P1	0.2949***	(0.0000)	P1	4.0593***	(0.0000)
P2	0.0989***	(0.0000)	P2	0.1202***	(0.0000)	P2	1.3286***	(0.0000)
P3	0.1857***	(0.0000)	P3	86.7840***	(0.0000)	P3	28.3370***	(0.0000)
Chinese Crude -> Iron ore			Chinese Crude -> Thermal			Chinese Crude -> Methanol		
	Mean	P value		Mean	P value		Mean	P value
P1	−0.2266***	(0.0000)	P1	−0.3170***	(0.0000)	P1	0.0140	(0.7131)
P2	0.0835***	(0.0000)	P2	−0.6374***	(0.0000)	P2	−0.2904***	(0.0000)
P3	0.0859***	(0.0000)	P3	−1.2123***	(0.0000)	P3	0.2788***	(0.0000)

Note: This table reports means of time varying pairwise net skewness spillovers from the Chinese crude oil futures to the other futures. Pairwise net spillovers are calculated as absolute values of spillovers from the Chinese crude oil futures to a counterpart futures less absolute values of spillovers of the other way around. Time varying spillovers are obtained from a rolling window estimation procedure. -> denotes the direction of spillovers. P1 refers to the sample period from March 26, 2018 to November 16 2019. P2 refers to the sample period from November 17 2019 to December 30 2019. And P3 refers to the sample period from December 31 2019 to October 1, 2020. Note that the starting dates of P1 vary across the futures. P value is the associated p value for t test statistic on the null hypothesis that mean equals zero. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

oil to the iron ore futures continue to rise from P1 to P3. Overall, the evidence suggests that either domestic or international contagion of COVID-19 leads to a more restrictive role for the information channels suggesting asymmetric risk transmitted from INE oil futures to the major domestic energy markets in China. This result is similar to that from the static spillover analysis; however, the time-varying spillover presents a clearer representation as to the extent to which INE oil futures transmits the risk of asymmetry to the regional energy markets.

Table 6 presents the results for the means of the time-varying net kurtosis spillovers from INE oil to the other counterparts during the three sub-periods. Similar to Tables 4 and 5, the majority of the calculated means are found to be significant at the conventional levels. In terms of the net pairwise spillovers from INE oil to the international crude oil futures markets, the WTI futures lead INE oil during all three sub-periods given the occurrence of negative means.[21] Furthermore, the mean net spillovers from INE oil to the Brent and DME Oman futures continue to decline from P1 through to P3 suggesting that the COVID-19 pandemic affects information transmission regarding the risk of extreme values from the INE oil to the international crude oil futures, by reducing the informational role of the INE oil futures associated with the transmissions of risk of that type. Such a result supports that of the static spillover analysis. Alternatively, the INE oil futures lead the domestic energy-related futures in China for most of the time in terms of the kurtosis transmission, as reflected by the positive means of the net pairwise kurtosis spillovers. It can be seen that the INE oil futures take a leading role in transmitting kurtosis risk when it interacts with fuel oil, coking coal and EG futures. There are several patterns of

is observed from P2 to P3. In terms of the net spillovers from the INE oil to the fuel oil, coking coal, EG and methanol futures, the means firstly suffer a large decline from P1 to P2 but then increase substantially from P2 to P3.

[21] The mean net spillovers firstly fall from P1 to P2 but then rise from P2 to P3. In contrast, during both the P1 and P2 periods, the INE oil futures lead both the Brent and DME Oman futures given the positive means. However, the former futures are minute when compared to the negative means of Brent and DME Oman futures.

Table 6
Time varying net kurtosis spillovers.

Chinese Crude -> WTI			Chinese Crude -> Brent			Chinese Crude -> DME		
	Mean	P value		Mean	P value		Mean	P value
P1	−0.2732***	(0.0000)	P1	0.5831***	(0.0000)	P1	0.0483***	(0.0000)
P2	−0.3036***	(0.0000)	P2	0.1562***	(0.0093)	P2	0.0477***	(0.0000)
P3	−0.2690***	(0.0000)	P3	−0.1444***	(0.0000)	P3	−0.2870***	(0.0000)
Chinese Crude -> Fuel oil			Chinese Crude -> Coking			Chinese Crude -> Ethylene gl.		
	Mean	P value		Mean	P value		Mean	P value
P1	0.5512***	(0.0000)	P1	0.0409***	(0.0000)	P1	0.5690***	(0.0000)
P2	0.2029***	(0.0000)	P2	0.1139**	(0.0290)	P2	0.1355	(0.1692)
P3	0.2996***	(0.0000)	P3	50.3162***	(0.0000)	P3	586.2717***	(0.0000)
Chinese Crude -> Iron ore			Chinese Crude -> Thermal			Chinese Crude -> Methanol		
	Mean	P value		Mean	P value		Mean	P value
P1	−0.0870***	(0.0000)	P1	0.0062*	(0.0579)	P1	0.5863***	(0.0000)
P2	0.1826***	(0.0000)	P2	0.1514***	(0.0000)	P2	−0.1325***	(0.0000)
P3	0.0409**	(0.0158)	P3	−0.3675***	(0.0000)	P3	0.2623***	(0.0000)

Note: This table reports means of time varying pairwise net kurtosis spillovers from the Chinese crude oil futures to the other futures. Pairwise net spillovers are calculated as absolute values of spillovers from the Chinese crude oil futures to a counterpart futures less absolute values of spillovers of the other way around. Time varying spillovers are obtained from a rolling window estimation procedure. -> denotes the direction of spillovers. P1 refers to the sample period from March 26, 2018 to November 16 2019. P2 refers to the sample period from November 17 2019 to December 30 2019. And P3 refers to the sample period from December 31 2019 to October 1, 2020. Note that the starting dates of P1 vary across the futures. P value is the associated p value for t test statistic on the null hypothesis that mean equals zero. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

changes in the mean of net spillovers across the three sub-periods for example, there is a changing pattern of decline followed by an increase, which is evidenced by the means of net spillovers from the INE oil futures to the fuel oil, EG and methanol. A pattern of increase to decline can be seen for the means of the net spillovers from INE oil futures to iron ore and thermal coal futures. We also find persistent increases in the mean of net spillovers from INE oil to coking coal futures over time. The result suggests that either domestic or international contagion of the COVID-19 impairs the transmission channels from INE oil to the domestic energy markets in China, in terms of the risk of extreme values. The effects are mostly adverse. Such evidence is clearer and more pronounced than that from the case of static spillovers, adding significant robustness to the results and the chosen methodological approaches taken.

Figs. 6 through 8 show the movements of time-varying net spillovers of higher moments across time. Fig. 6 shows the movement of time-varying net volatility spillovers from the INE oil futures to the other counterparts. In terms of the net spillovers from INE oil to the international oil futures, two typical patterns are observed. The net spillovers against the WTI and DME Oman oil futures move above zero during most of P1. When P3 begins, the net spillovers firstly rise substantially during the first quarter of 2020 and then fall sharply as the second quarter begins.[22] Concerning the net spillovers with Brent oil futures, the results are above zero for most time during P1 but drop sharply throughout P2 and P3, exhibiting a minimum during the latter period, again showing the influence of COVID-19. As can be seen from Fig. 6, the movements of the net volatility spillovers from INE oil futures to China's domestic energy-related futures exhibit differing patterns.[23] Although the effects of the domestic contagion stage of the COVID-19 in mainland China show mixed evidence in terms of the net volatility spillovers from INE oil to the domestic energy futures, there is a clearer picture in terms of the adverse impacts of the global pandemic on the information channels of volatility risk from the INE oil futures to the other counterparts.

The movements of the time-variant net skewness spillovers from the INE oil futures to the other counterparts are presented as Fig. 5. The net spillovers to WTI futures fall substantially at the start of P1 before increasing during the P2 period, before the second sharp fall takes place close to December 31, 2019. During the rest of P3, the net spillovers evidence more declines, and the values remain at very low levels. Both the markets for Brent and DME Oman future behave in a similar manner.[24] Overall, either the domestic contagion stage of the COVID-19 or the international pandemic produces adverse effects on the skewness of transmissions from the INE oil futures to the international crude oil futures. The effects of the latter stage are pronounced. Moreover, the net skewness spillovers from the INE oil futures to the domestic energy-related futures in China witnessed some adverse impacts of the COVID-19 pandemic, for example, we find the net spillovers to the fuel oil futures squeeze in magnitude when entering P2 and the values remain at very low levels, persisting over the P2 and P3 periods. The net spillovers to the methanol futures suffer several large oscillations moving into P2 where they stay at low levels for the rest of P2 and remain so across the start of P3. In contrast, one exception is that the net spillovers to the iron ore futures become positive as P2 begins. Such results reveal that the COVID-19 pandemic is not beneficial to the information role of the INE oil futures when it transmits the risk of asymmetry to the domestic energy futures markets in China.

Fig. 8 shows the movements of the net kurtosis spillovers from INE oil futures to the other counterparts.[25] The evidence concerning the time-varying kurtosis spillovers to the international crude oil futures

[22] For the rest of the period throughout 2020, the net spillovers remain negative, with large estimates observed.

[23] For instance, the net spillovers towards fuel oil, thermal coal and methanol futures show some downward trends across the P2 and P3 periods. In terms of the spillovers to the fuel oil futures, two substantial falls take place respectively following the starts of the P2 and P3 periods. One very large fall is observed on December 31, 2019, for the spillovers to the thermal coal and methanol futures. In addition, the net spillovers to the three futures remain at very low levels during P3. The net spillovers to the coking coal and iron ore futures behave somewhat differently where they firstly rise and stay at higher levels when moving to P2; however, they decline substantially adjacent to December 31, 2019, and remain at very low levels during the rest of P3.

[24] Likewise, the net spillovers to the Brent futures suffer a large decline after December 17, 2019, and they remain very low for the rest of P2. The net spillovers remain low entering P3, and they exhibit a huge trough in the late P3 period. In contrast, the net spillovers to the DME Oman futures rise after December 17, 2019, and then fall during the middle of P2. They continue to fall across the start of P3 and exhibit a downward trend during the rest of that period.

[25] The net spillovers to the WTI and Brent futures exhibit a substantial fall when P2 begins, while the net spillovers to the WTI futures continue to decline during the same period. During P3, the net spillovers to WTI experience two large troughs across the first and second quarters of 2020, however, in the late phase of the same period, there are some recoveries. The net spillovers towards

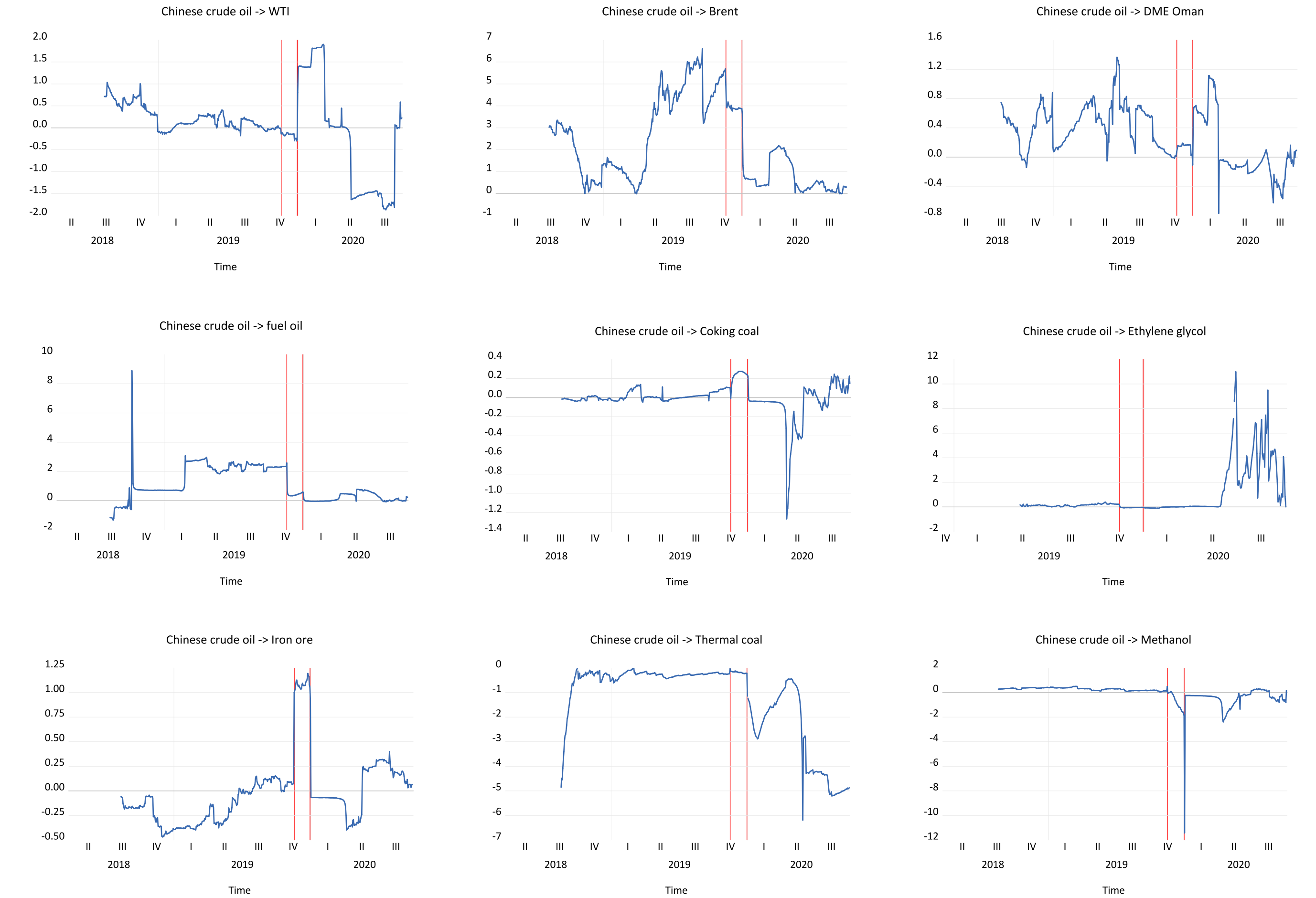

Fig. 6. Movements of time varying net volatility spillovers (2018–2020). Note: Pairwise net spillovers are calculated as absolute values of spillovers from the Chinese crude oil futures to a counterpart futures less absolute values of spillovers of the other way around. Time varying spillovers are obtained from a rolling window estimation procedure. -> denotes the direction of spillovers. The first red vertical line refers to the date November 16, 2019. The second red vertical line refers to the date December 30, 2019. I, II, III and IV in the above figures represent the first through fourth quarters respectively.

markets indicates the existence of some adverse impacts of the COVID-19 pandemic on the information contents of the INE oil futures prices in terms of the transmission of risk of extreme values. The impacts of the global pandemic seem even more severe. Alternatively, the time-varying net kurtosis spillovers from the INE oil futures to the fuel oil experience two spikes at the starting dates of the P2 and P3 periods. However, it is found that the magnitude of the net spillovers in P2 squeezes in contrast to that in P1. In the later phase of P3, the size of net spillovers recovers to some extent.[26] Overall, the information channels from the INE oil futures to China's domestic energy-related futures markets in terms of the risk of extreme values appear impaired by either the domestic or international contagion of COVID-19. Such evidence is consistent with that of the volatility and skewness spillovers presented in Figs. 3 and 4.

To sum up, Figs. 6 through 8 show that the INE oil futures market takes a superior role in transmitting risk of volatility, asymmetry, and extreme values to the international and domestic energy markets during the tranquil period before the outbreak of COVID-19. This result aligns with Tables 4 through 6. The dynamics of net spillovers in terms of volatility, skewness, and kurtosis from the INE oil futures to the other counterpart futures present different patterns across the affected periods of the COVID-19 pandemic. However, our evidence presents the view that the information content of the INE oil futures, in terms of the transmissions of risk, of multiple types, to closely related energy counterparts develop. The COVID-19 pandemic, however, reduces the information efficiency of the newly established crude oil futures market in China, where such evidence is particularly pronounced when focusing on the relationship between INE oil futures and the three international crude oil futures, as well as the three domestic energy futures including fuel oil, thermal coal, and methanol.

5.4. Economics implications

As presented in Fig. 2, we identify how the classical CAPM beta and standardised estimates of the co-skewness move across time, specifically presenting evidence that each of the WTI, Brent, and DME Oman crude oil markets are significant sources of influence upon INE futures markets. Specifically, we also identify that these risk channels present evidence of reduced interaction sourced from WTI and Brent markets

the Brent futures fall again after the start of P3. Following a small recovery, a downward trend persists during the late stage of that period. Moreover, the net spillovers to the DME Oman futures show a small trough when P2 begins. They also show some small oscillations around the beginning of P3. However, two large sharp declines appear in the later phase of that period.

[26] The net spillovers to the iron ore futures rise during P2. Nonetheless, they substantially fall at the beginning of P3, and the net spillovers indicate a large trough in the early stages of that period. Following the trough, the spillovers recover to higher levels for the rest of P3. The net spillovers to the thermal coal futures exhibit a high spike at the start of P2; however, they keep falling during P3. In contrast, some troughs are appearing during P2 for the net spillovers to the methanol futures. During the late phase of P3, the net spillovers attain higher levels with some oscillations.

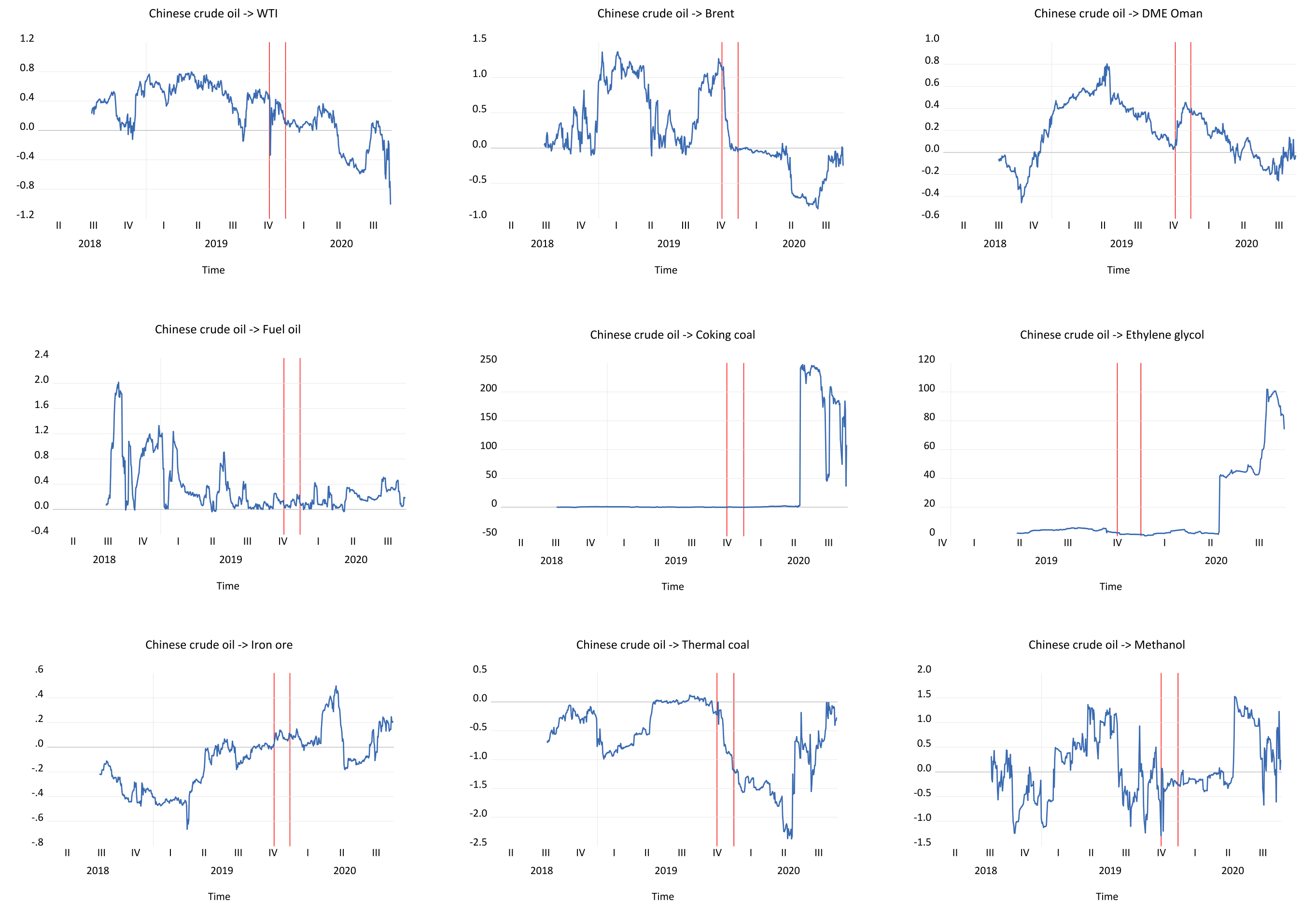

Fig. 7. Movements of time varying net skewness spillovers (2018–2020). Note: Pairwise net spillovers are calculated as absolute values of spillovers from the Chinese crude oil futures to a counterpart futures less absolute values of spillovers of the other way around. Time varying spillovers are obtained from a rolling window estimation procedure. -> denotes the direction of spillovers. The first red vertical line refers to the date November 16, 2019. The second red vertical line refers to the date December 30, 2019. I, II, III and IV in the above figures represent the first through fourth quarters respectively.

during the onset of the COVID-19 pandemic, albeit the presence of short windows of substantial disruption to these signals. However, estimated interactions between DME Oman crude oil and INE futures are found to elevate during the initial stages of COVID-19, while the estimated tail-risk stemming from the relationship of Chinese oil markets is found to elevate throughout the entirety of the estimated COVID-19 period analysed.

Further, the estimated CAPM betas stemming from the INE futures market on China's domestic energy-related futures markets are found to behave very differently. Two typical patterns are observed. The CAPM betas for coking coal, EG, and iron ore are estimated to fall significantly at the beginning of the COVID-19 period (P2 and P3 periods) and remain quite suppressed thereafter. However, the betas on fuel oil, thermal coal, and methanol, while showing similar patterns except for a brief, sustained, short-term elevations at the beginning of the pandemic. Regarding the co-movement in long tails between the INE futures market and the six analysed domestic energy-related futures markets, such identified risks are found to have elevated sharply during the pandemic for fuel oil, iron ore, thermal coal, and methanol, while no significant differentials are identified for markets relating to coking coal and EG. Specifically, we identify that when the true severity of the COVID-19 pandemic is realised as evidenced by the sharp shocks to international financial markets, the traditional beta risk in both crude oil and energy markets falls, however, risk related specifically to extreme movements becomes more substantive. Such results are found to align with those presented within the works of Umar et al. (2021), Si et al. (2021), Xie et al. (2021), Ouyang et al. (2022) and Tong et al. (2022).

To further consider the implications of such results, when we compute the optimal weights of the INE oil and one counterpart future to construct a minimum-variance portfolio consisting of the two securities, we follow Kroner and Ng (1998) to calculate the optimal weight of the INE oil futures as below:

$$w_t^{INE} = \frac{var_t^c - cov_t}{var_t^{INE} - 2cov_t + var_t^c}, \quad where \;\; w_t^{INE} = \begin{cases} 0, w_t^{INE} < 0 \\ w_t^{INE}, 0 < w_t^b < 1 \\ 1, w_t^{INE} > 1 \end{cases} \tag{9}$$

where w_t^{INE} denotes the optimal weight of the INE oil futures. var_t^c is the variance series of a counterpart futures. var_t^{INE} is the variance series of the INE oil futures. cov_t is the covariance series between the INE oil and one counterpart futures. Note that both variance and covariance series are calculated based on the estimates of the two-state regime-switching model. Also, w_t^{INE} is time-variant since its determinants are time-varying. The time-variant optimal weight of the other futures in the portfolio, w_t^c, should be $1 - w_t^{INE}$. The movements of w_t^{INE} and w_t^c are depicted in Fig. 9, observing the construction of the portfolio relating to the international crude oil futures of WTI, Brent and DME Oman is in favour of a large weight on INE oil futures where the weight on the INE oil futures is around 80% in P1. For the portfolios with the WTI and DME Oman futures, the weight on the INE oil futures is even higher during the periods affected by COVID-19. However, despite the higher weight of the INE oil futures against the Brent futures during P2, the weight falls substantially when P3 begins,

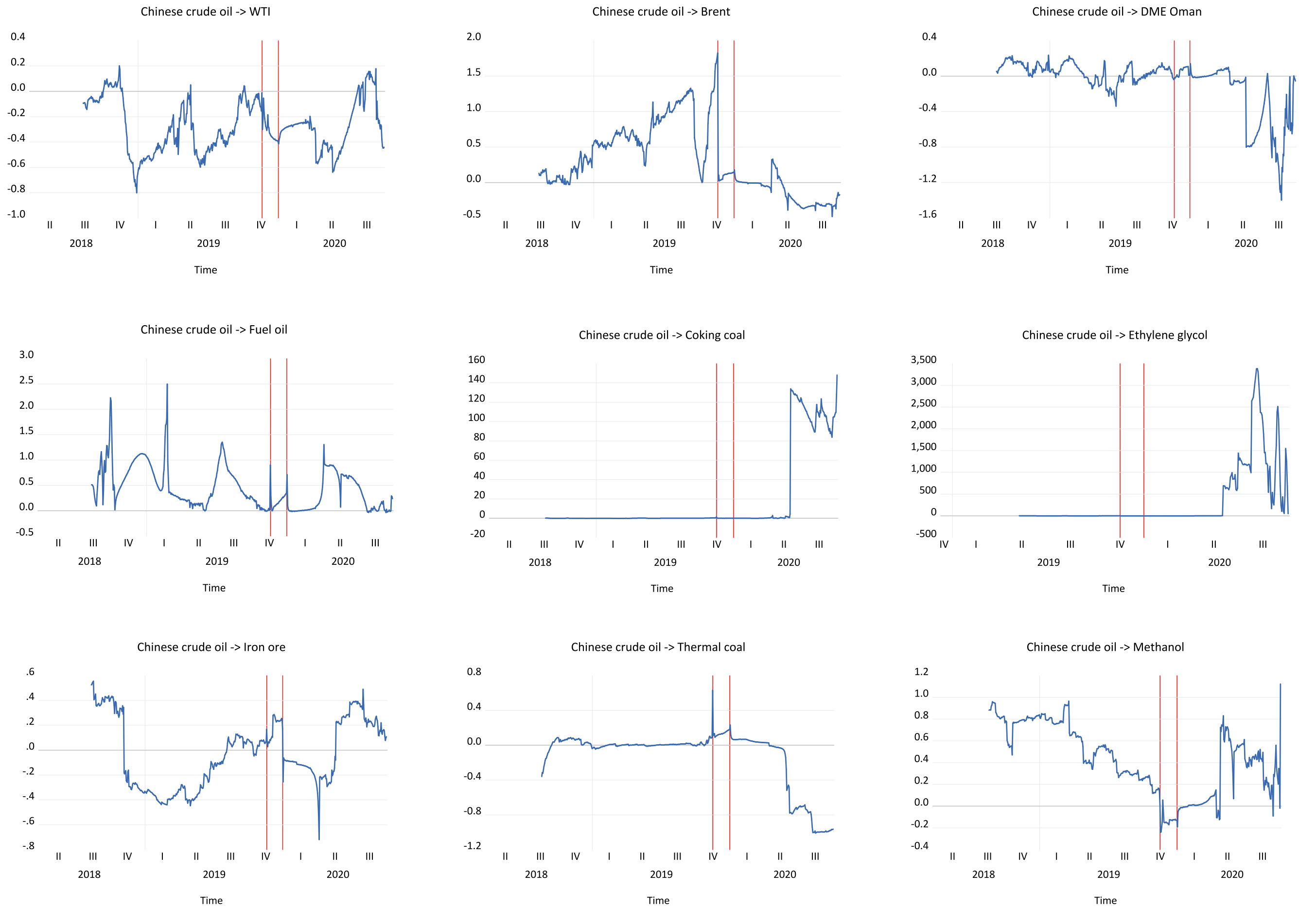

Fig. 8. Movements of time varying net kurtosis spillovers (2018–2020). Note: Pairwise net spillovers are calculated as absolute values of spillovers from the Chinese crude oil futures to a counterpart futures less absolute values of spillovers of the other way around. Time varying spillovers are obtained from a rolling window estimation procedure. -> denotes the direction of spillovers. The first red vertical line refers to the date November 16, 2019. The second red vertical line refers to the date December 30, 2019. I, II, III and IV in the above figures represent the first through fourth quarters respectively.

however, it remains at approximately 60%–80%. The evidence suggests that there is a diversification effect of the INE oil futures on the risk of international crude oil futures. Such effects remain substantial during the COVID-19 pandemic.

Moreover, we observe some interesting patterns of the optimal weight on the INE oil futures that are used to construct a portfolio with one of China's domestic energy-related futures. The weight of the INE oil futures is large during P1 when we construct portfolios with fuel oil, coking coal, iron ore and methanol futures. However, once P3 starts, the situation is reversed where larger weights are placed on the domestic energy futures. During P2 the INE oil futures always suggest a higher weight. However, the weight attached to INE oil futures remains low throughout when it is combined with thermal coal futures in a portfolio. This evidence suggests that there is a diversification effect of INE oil futures on most of the domestic energy futures in China. However, such an effect can only be found before the outbreak of COVID-19. The COVID-19 pandemic reduces the effectiveness of the INE oil futures to diversity the risks of the domestic energy futures in China.

Overall, when considering the above results in unison, it is important to note that investors now face significant differential behaviour when considering diversification avenues using Chinese oil futures as a result of the COVID-19 pandemic. This research specifically develops and supports evidence that underpins the continuing growth and maturity of Chinese crude oil futures markets. Using a two-state regime switching methodology, supported by static and time-varying spillover analyses, domestic contagion as a result of the outbreak of COVID-19 in China is found to significantly to have significantly increased the volatilities of international oil markets, with much concern surrounding the expected decline in Asian economic. During the Chinese contagion regime, evidence suggests a clear separation in behaviour when comparing INE futures with other international markets. Such evidence suggests that Chinese investors perceived the risks associated with COVID-19 and the severity of the challenge with which they were initially confronted, far in advance of other international investors. While focusing on differential results based on the analysed moments, China's INE futures present similar volatility estimates to those presented to international oil markets, but differential estimates to domestic energy-related futures, again as a result of suppressed economic expectations as a result of the COVID-19 pandemic. Further, when focusing on the third and fourth moments of analysis, evidence suggests significant differential behavioural effects when comparing Chinese and international oil markets, where Chinese oil futures share specific behaviour traits with DME Oman-traded crude oil, however, evidence of separation with both WTI and Brent crude oil is observed during the analysed phases of the COVID-19 pandemic. Such a result indicates that Chinese INE futures have grown to share broad behavioural traits with international oil markets, however, as a result of regional crises, or defined as the initial outbreak of COVID-19 in China, results indicate that sectoral diversification benefits exist. Further, international traders appear to have rationalised their expectations of regional economic implications due to the COVID-19 pandemic through Asian oil markets as opposed to world markets. Overall, while INE futures are found to have been developing a significant informational relationship with other international oil markets and domestic energy

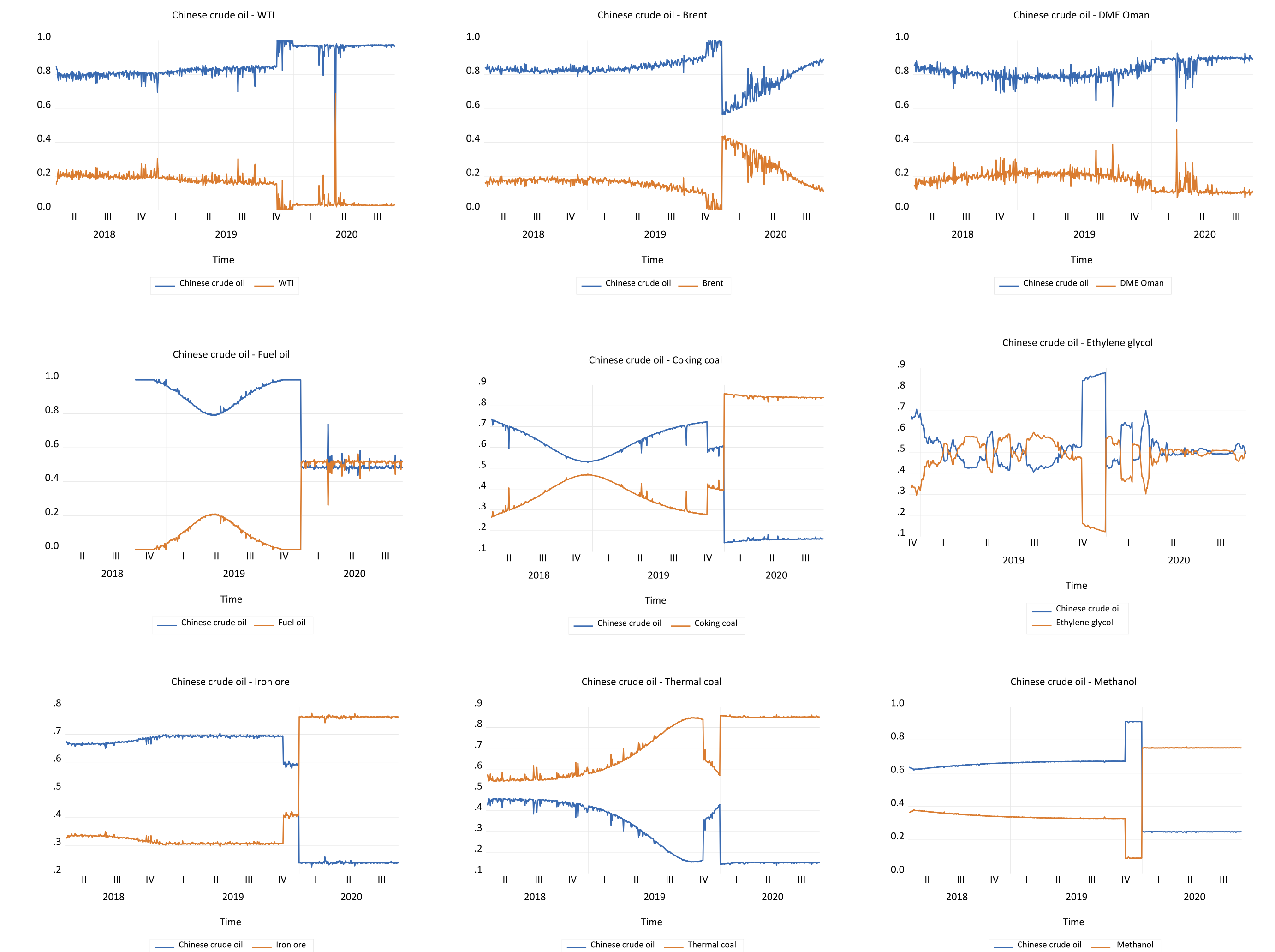

Fig. 9. Time varying optimal weights for minimum variance portfolio (2018–2020). Note: Time varying optimal weights are derived from conditional variances and covariance that are estimated from a two-state regime-switching model. I, II, III and IV in the above figures represent the first through fourth quarters respectively.

futures, the outbreak of the COVID-19 pandemic appears to have both significantly, and substantially disrupted this relationship. While informational efficiency reduced in the period after the international transmission of the COVID-19 pandemic, it is information flows relating to expected economic decline in China during the initial phases of the domestic spread of COVID-19, were appropriately accounted for in terms of suppressed regional expectations of economic performance. Such results are found to possess significant implications concerning investor portfolio diversification.

5.5. Robustness checks

To provide methodological robustness, we apply a wavelet analysis technique when examining whether the results obtained thus far, specifically relating to the time-varying net spillovers of multiple higher moments, are robust across differential time frequencies of analysis. In doing this, first, we employ multi-resolution analysis (MRA) based on a Maximum Overlap Discrete Wavelet Transform (MODWT), to specifically transform the time series of higher-order moments, including variance, skewness, and kurtosis, as well as the standardised information shocks of higher moments into wavelet-coefficient-governed time series at differing frequencies. Specifically, we focus on two specific timescales, that is, the eight-day time scale and the thirty-two-day time scale, which pertain to one week and one-month time intervals, respectively.[27] We must note that the MODWT has been widely employed in the literature to generate robust wavelet series at multiple time scales (Mishra et al., 2019; Jiang and Yoon, 2020). Secondly, we repeat the rolling window estimation procedure that was earlier conducted using Eq. (8) and re-estimate the time-varying net spillovers sourced from the Chinese crude oil futures upon counterpart futures using the estimates from the rolling window process. We plot each of the dynamic net spillovers of the three higher-order moments at both of the selected one-week and one-month intervals, which are presented through Figs. 10 through 15 respectively.

As observed in Figs. 10 and 11, presenting the dynamics of the estimated net volatility spillovers sourced from the INE futures, and presented to be directly influencing the other analysed futures at both one-week and one-month intervals, the presented evidence remains similar to that earlier provided in Fig. 6. Overall, robustness testing procedures continue to identify that there are significant adverse impacts sourced from the global pandemic that have directly influenced the information transmissions of volatility risks sourced from the INE oil futures. Regarding the presented results at larger time intervals regarding

[27] Further variations of analysis and time-frequency of the investigation were considered, however, for the brevity of analysis only those stated have been included. All other additional robustness testing procedures are available from the authors upon request.

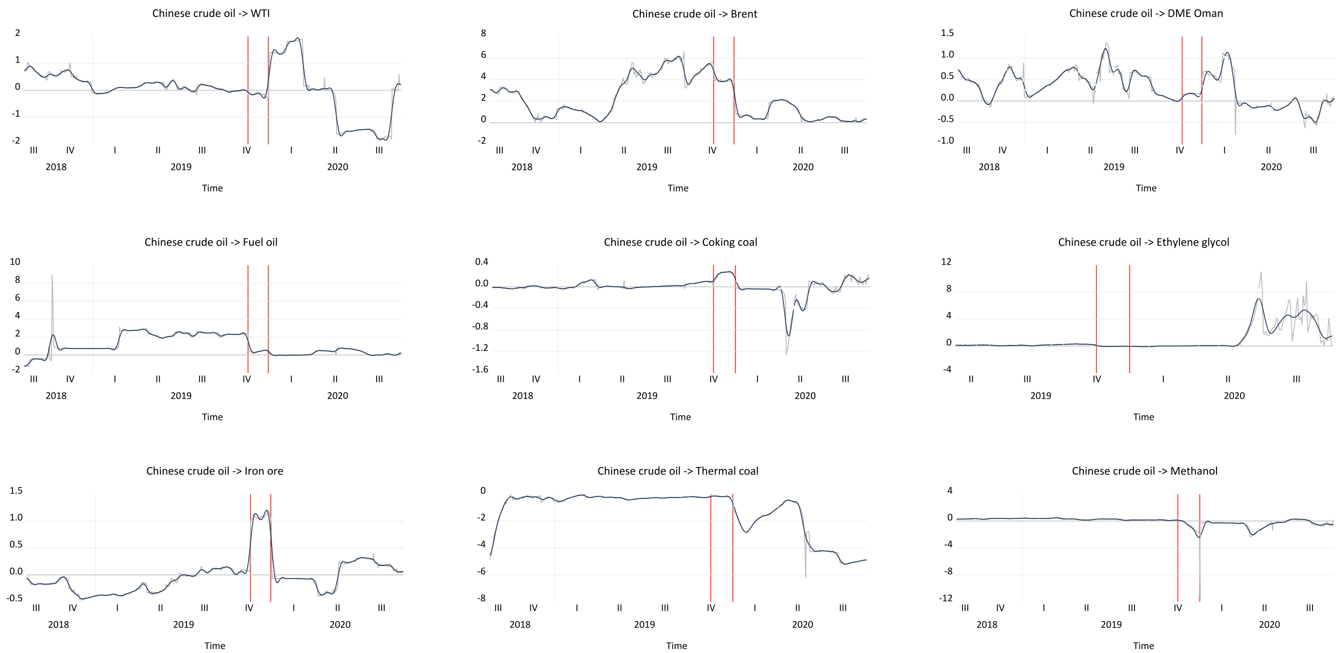

Fig. 10. Movements of time varying net volatility spillovers, one week time interval (2018–2020). Note: Pairwise net spillovers are calculated as absolute values of spillovers from the Chinese crude oil futures to a counterpart futures less absolute values of spillovers of the other way around. Time varying spillovers are obtained from a rolling window estimation procedure. Note that we employ the multi-resolution analysis (MRA) functions that use the Maximum Overlap Discrete Wavelet Transform (MODWT) to obtain the conditional variances series as well as volatility shocks at 8-day time scale that pertain to one week time interval. These wavelet transformed series are employed for the rolling window estimation procedure. -> denotes the direction of spillovers. The first red vertical line refers to the date November 16, 2019. The second red vertical line refers to the date December 30, 2019. I, II, III and IV in the above figures represent the first through fourth quarters respectively.

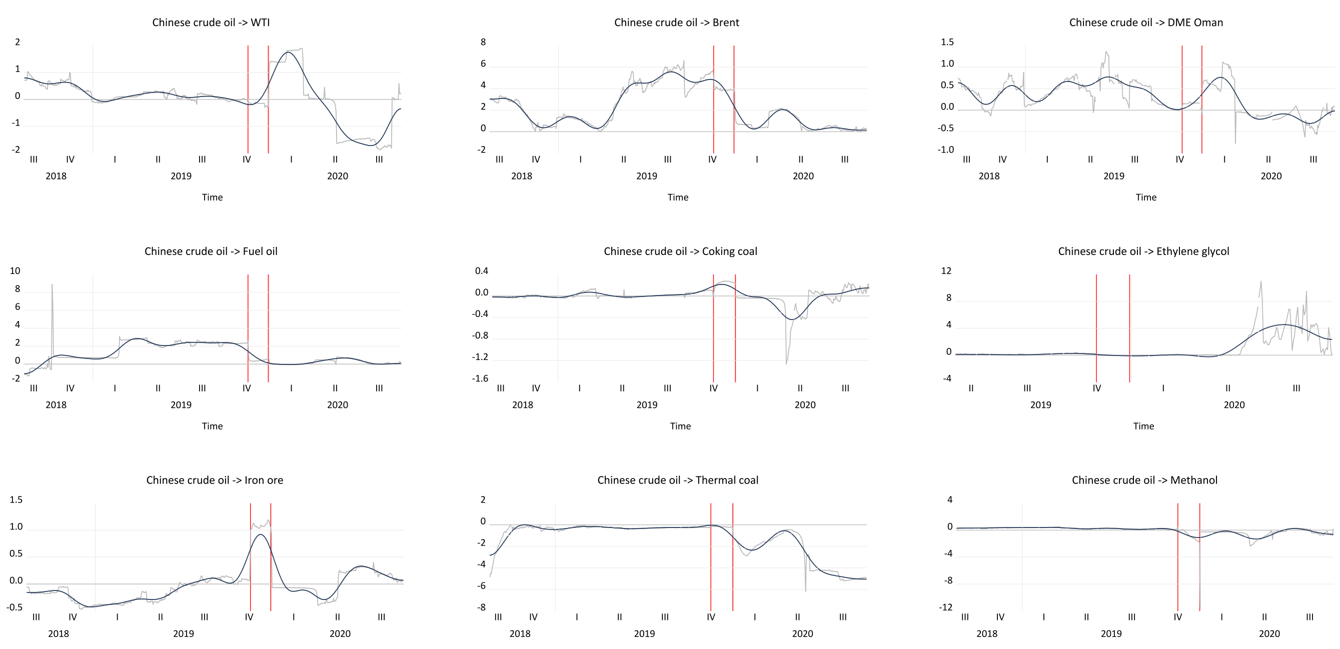

Fig. 11. Movements of time varying net volatility spillovers, one month time interval (2018–2020). Note: Pairwise net spillovers are calculated as absolute values of spillovers from the Chinese crude oil futures to a counterpart futures less absolute values of spillovers of the other way around. Time varying spillovers are obtained from a rolling window estimation procedure. Note that we employ the multi-resolution analysis (MRA) functions that use the Maximum Overlap Discrete Wavelet Transform (MODWT) to obtain the conditional variances series as well as volatility shocks at 32-day time scale that pertain to one month time interval. These wavelet transformed series are employed for the rolling window estimation procedure. -> denotes the direction of spillovers. The first red vertical line refers to the date November 16, 2019. The second red vertical line refers to the date December 30, 2019. I, II, III and IV in the above figures represent the first through fourth quarters respectively.

dynamic net skewness spillovers in Figs. 12 and 13, and the presented dynamic net kurtosis spillovers in Figs. 14 and 15 respectively, results remain similar to those presented analyses earlier presented in Figs. 7 and 8.

To summarise the results of the robustness testing procedures, the COVID-19 pandemic is found to directly influence the informational relationship sourced from INE oil futures, specifically when the market is found to transmit asymmetric risk and volatility sourced from extreme

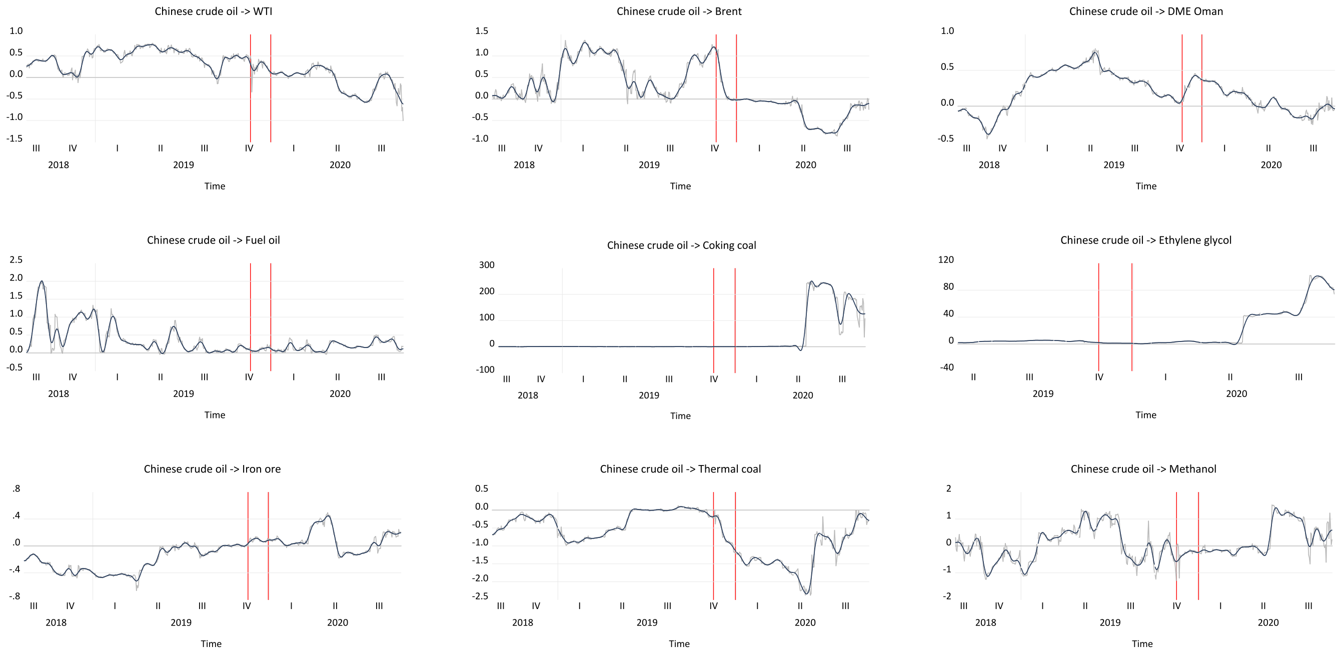

Fig. 12. Movements of time varying net skewness spillovers, one week time interval (2018–2020). Note: Pairwise net spillovers are calculated as absolute values of spillovers from the Chinese crude oil futures to a counterpart futures less absolute values of spillovers of the other way around. Time varying spillovers are obtained from a rolling window estimation procedure. Note that we employ the multi-resolution analysis (MRA) functions that use the Maximum Overlap Discrete Wavelet Transform (MODWT) to obtain the conditional skewness series as well as skewness shocks at 8-day time scale that pertain to one week time interval. These wavelet transformed series are employed for the rolling window estimation procedure. -> denotes the direction of spillovers. The first red vertical line refers to the date November 16, 2019. The second red vertical line refers to the date December 30, 2019. I, II, III and IV in the above figures represent the first through fourth quarters respectively.

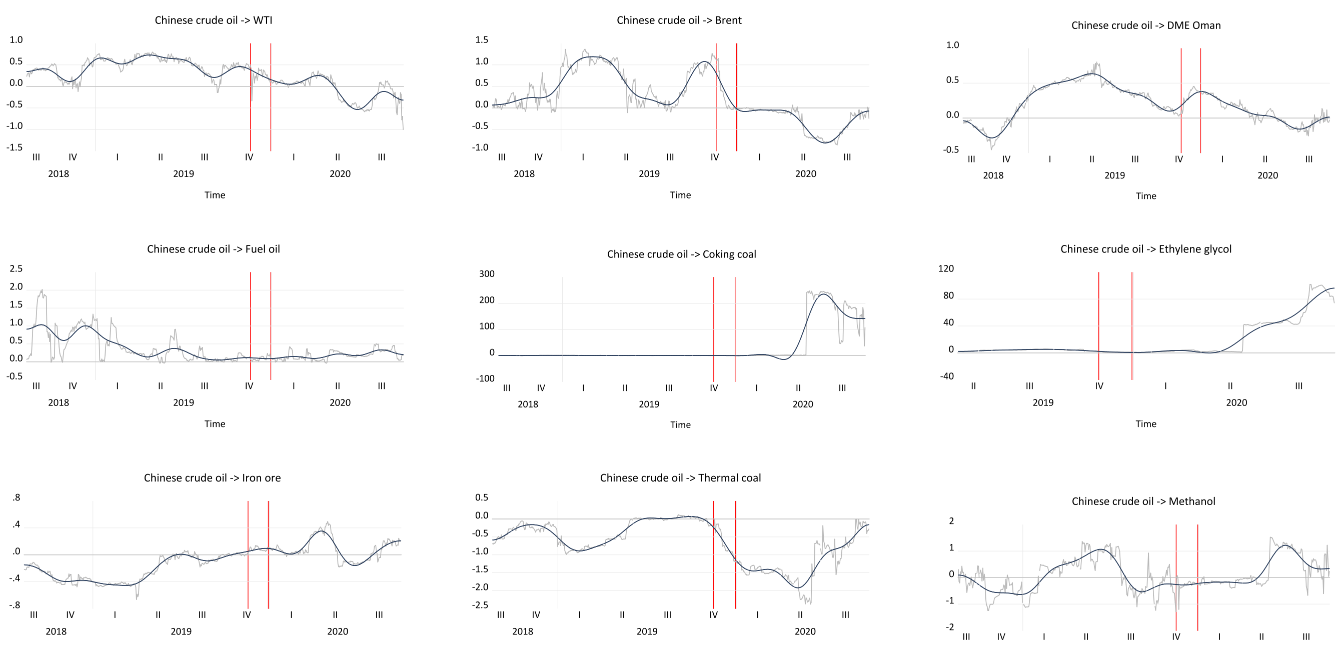

Fig. 13. Movements of time varying net skewness spillovers, one month time interval (2018–2020). Note: Pairwise net spillovers are calculated as absolute values of spillovers from the Chinese crude oil futures to a counterpart futures less absolute values of spillovers of the other way around. Time varying spillovers are obtained from a rolling window estimation procedure. Note that we employ the multi-resolution analysis (MRA) functions that use the Maximum Overlap Discrete Wavelet Transform (MODWT) to obtain the conditional skewness series as well as skewness shocks at 32-day time scale that pertain to one month time interval. These wavelet transformed series are employed for the rolling window estimation procedure. -> denotes the direction of spillovers. The first red vertical line refers to the date November 16, 2019. The second red vertical line refers to the date December 30, 2019. I, II, III and IV in the above figures represent the first through fourth quarters respectively.

volatility upon international oil futures and domestic energy-related futures in China. Also, results suggest that the information content of the INE oil futures, in terms of the transmissions of multiple risks to closely related energy counterparts, elevates substantially during the period surrounding the COVID-19 pandemic. The findings remain consistent, irrespective of to time period analysed. Moreover, we observe that as the time interval analysed increases, there is a smoothing transition of the pattern of net spillovers presented, with fewer peaks and troughs identified in the presented series.

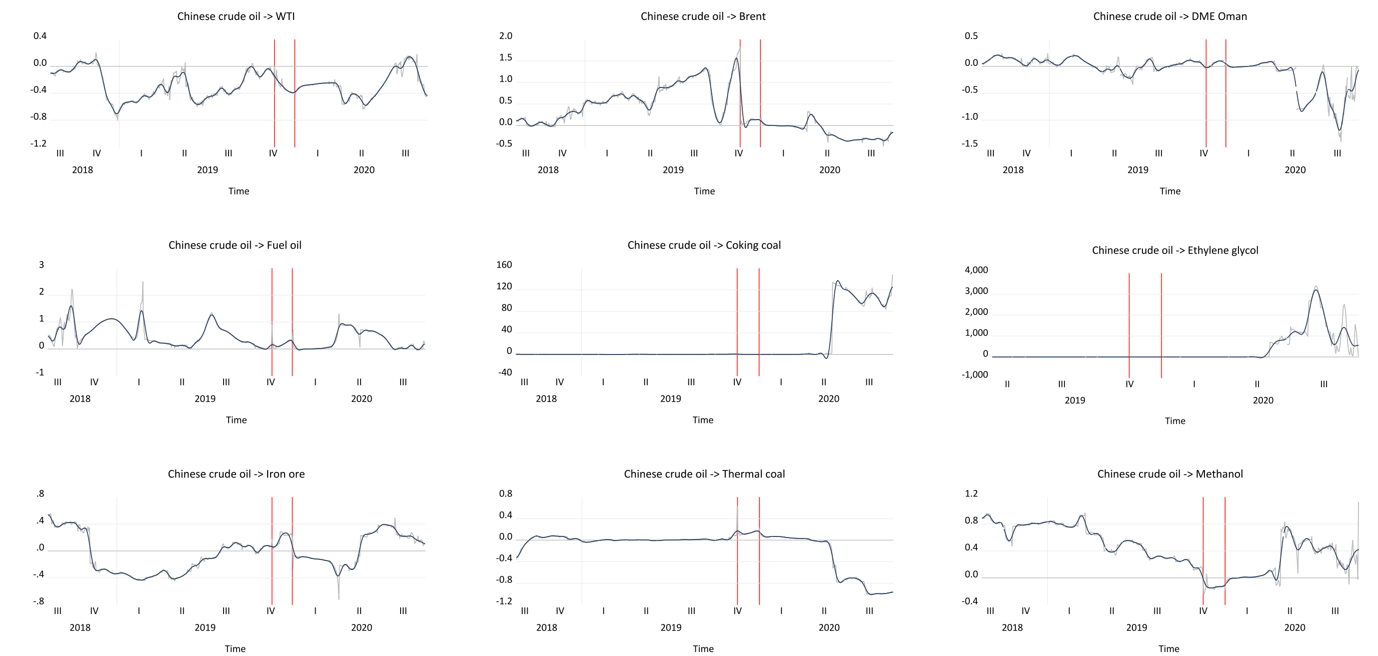

Fig. 14. Movements of time varying net kurtosis spillovers, one week time interval (2018–2020). Note: Pairwise net spillovers are calculated as absolute values of spillovers from the Chinese crude oil futures to a counterpart futures less absolute values of spillovers of the other way around. Time varying spillovers are obtained from a rolling window estimation procedure. Note that we employ the multi-resolution analysis (MRA) functions that use the Maximum Overlap Discrete Wavelet Transform (MODWT) to obtain the conditional kurtosis series as well as kurtosis shocks at 8-day time scale that pertain to one week time interval. These wavelet transformed series are employed for the rolling window estimation procedure. -> denotes the direction of spillovers. The first red vertical line refers to the date November 16, 2019. The second red vertical line refers to the date December 30, 2019. I, II, III and IV in the above figures represent the first through fourth quarters respectively.

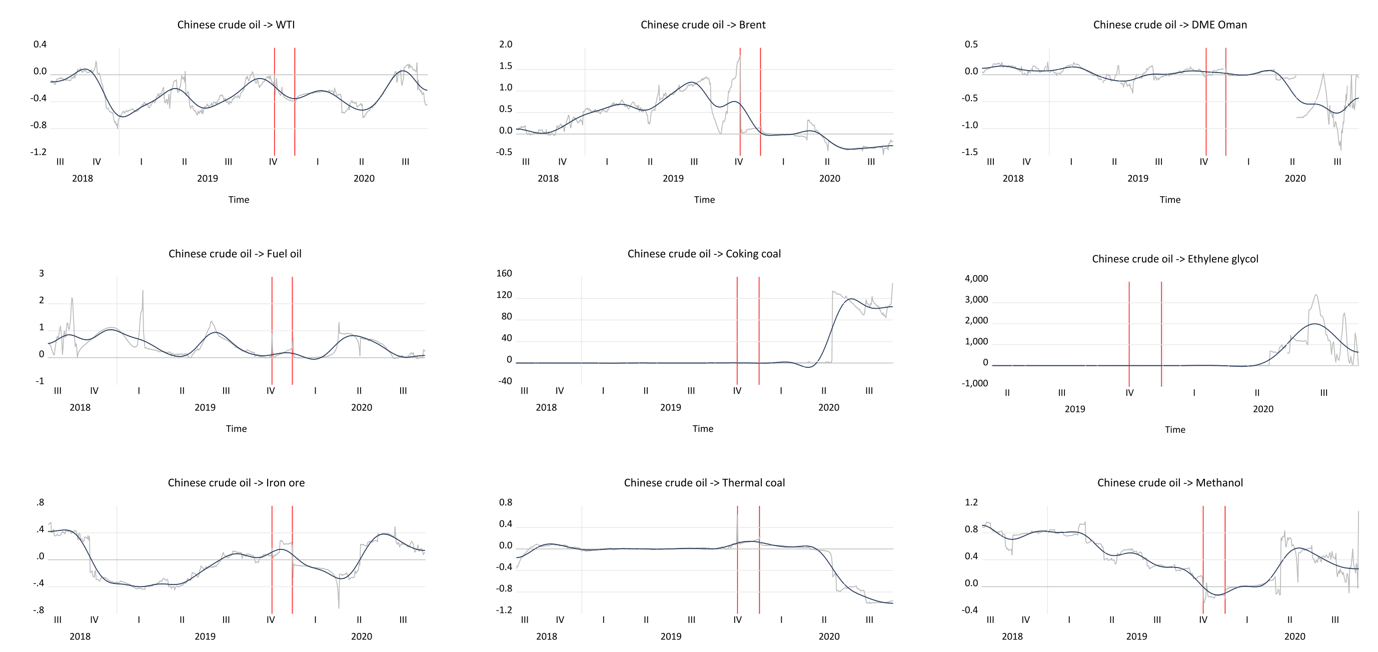

Fig. 15. Movements of time varying net kurtosis spillovers, one month time interval (2018–2020). Note: Pairwise net spillovers are calculated as absolute values of spillovers from the Chinese crude oil futures to a counterpart futures less absolute values of spillovers of the other way around. Time varying spillovers are obtained from a rolling window estimation procedure. Note that we employ the multi-resolution analysis (MRA) functions that use the Maximum Overlap Discrete Wavelet Transform (MODWT) to obtain the conditional kurtosis series as well as kurtosis shocks at 32-day time scale that pertain to one month time interval. These wavelet transformed series are employed for the rolling window estimation procedure. -> denotes the direction of spillovers. The first red vertical line refers to the date November 16, 2019. The second red vertical line refers to the date December 30, 2019. I, II, III and IV in the above figures represent the first through fourth quarters respectively.

6. Conclusions

The inception of the first crude oil futures market in China in March 2018 has attracted much attention and influence, therefore it is important to test its growing influence on world financial markets. One major goal when establishing a crude oil futures market in China is to fill the gap in the provision of an oil metric representative of China's economy while competing with other major crude oil markets both regionally and internationally, in an attempt to generate a superior role in the pricing mechanism of crude oil. It is important to improve our understanding of how the Chinese crude oil futures market interacts with both international counterparts and domestic energy markets in light of information transmissions of risk.

Results indicate that the volatility, skewness of returns, and kurtosis exhibit time-varying patterns among a set of futures markets. Typically, China's INE oil futures have a moving pattern of volatility that falls sharply during the domestic contagion period of the COVID-19 and returns to the highest levels as the international contagion of the COVID-19 pandemic begins. The skewness of the INE oil futures falls during the domestic contagion period of the pandemic but becomes more volatile during the growth of the international contagion period. Moreover, the kurtosis of China's INE crude oil futures continue to increase across the COVID-19 affected periods. Some patterns of correlations of China's INE oil futures with other oil and energy counterparts are revealed, for example, the correlations with the WTI, DME Oman and methanol steadily rise during the pandemic. In contrast, the correlations with Brent, coking coal, EG and thermal coal fall during the same period. The correlations with fuel oil and iron ore firstly decline when the domestic contagion period begins, but do not move substantially thereafter. Importantly, the INE oil futures market plays a leading role in the transmission of the risk of volatility, asymmetry, and extreme values to the international and domestic energy markets during the period before the outbreak of the COVID-19. The evidence is supported by both static and time-varying spillovers. The dynamics of net spillovers from the INE oil futures to the other counterpart futures show distinctive time-varying patterns across the affected periods of COVID-19. However, the information role of the INE oil futures in terms of the transmission of risks, of multiple types, to closely related energy counterparts is impaired by such an event. In other words, the COVID-19 pandemic is detrimental to the information efficiency of the newly established crude oil futures market in China, while some evidence suggests that contagion, sourced in Chinese oil, before the official WHO announcement based on COVID-19, indicating that the then identified 'mystery pneumonia' might have been generating significant effects due to local identification of transmission in advance of worldwide recognition of the scale of the forthcoming pandemic.

Regarding economic implications, the traditional beta risk imposed by WTI and Brent on the INE oil market declines during the COVID-19 affected periods. The CAPM beta of DME Oman on INE increases during the COVID-19 stages, while risk stemming from the volatility-return relationships between the INE futures and the international crude oil markets is increased during the COVID-19 periods. Moreover, when the COVID-19 pandemic becomes globally acknowledged, the traditional beta risk stemming from the INE oil futures on China's energy-related futures markets is weakened, while the risk relating to the relationship between the INE oil volatility and domestic energy futures returns, increases during the same period. Furthermore, a diversification effect of the INE oil futures on most of the domestic energy futures in China is identified, however, such an effect is temporary. The COVID-19 pandemic reduces the relevance of the INE oil futures to diversify the risks of the domestic energy-related futures markets in China.

While identifying significant evidence of market maturity, whereby Chinese oil futures are found to possess a dominant role in the risk transmission of volatility, information asymmetry and extreme values, to both the international oil market and China's domestic energy-related markets before the outbreak of the COVID-19, upon the onset and escalation of the COVID-19 pandemic, such maturity and informational effects are found to deteriorate significantly. Overall, evidence suggests that Chinese oil futures markets were growing at pace to become a leading international oil product, and while the outbreak of COVID-19 has temporarily disrupted such growth, it continues to be expected that Chinese oil futures will shortly become a major asset within international oil markets.

Declaration of competing interest

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

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