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Evolution of the information transmission between Chinese and international oil markets: A quantile-based framework

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ABSTRACT

This paper investigates the evolution of the information transmission between Chinese and international crude oil markets from the perspective of return and volatility spillovers through a quantile-based framework. Using a causality-in-quantiles test, we find the asymmetric and nonlinear transmission featured by uni-directional spillovers from international WTI to China's Shanghai oil markets in different conditions of the two markets, but not the other way around. Moreover, the degree of the information transmission is estimated using a Quantile-on-Quantile approach. Through this, marginal impacts of return and volatility of the WTI oil benchmark on that of the Shanghai oil market in a full-distributional environment are respectively gauged. We find that both return and volatility spillovers demonstrate an overall positive and heightening intensity with increases in the corresponding quantiles of the Shanghai oil market. The spillovers would be weakened by extreme events in the China domestic market, suggesting an important role of internal innovations in governing the Chinese and international oil market relationship. Overall, our results do not support the 'one great pool' hypothesis in the global oil market, and possess important implications. A battery of robustness checks reassures our findings.

1. Introduction

As a strategic resource driving the modern economy, crude oil plays an integral role by far in the economic development and national security worldwide.[1] In the face of rising global uncertainty, the fluctuation in crude oil prices would result in a rising difficulty for various stakeholders (e.g. policymakers and oil market participants) in optimization of their decision-making (Jie et al., 2020). Importantly, it would also impact the production cost of carbon-regulated sectors and their willingness of moving towards cleaner energy or less carbon-intensive production (Duan et al., 2021). Price dynamics of crude oil and its role in the economy have long attracted great attention to academicians and market practitioners (Shah et al., 2021; Balcilar et al., 2021; Lyu et al., 2021; Khan et al., 2021; Ren et al., 2023b). This therefore leads to a heated research topic in the information transmission among global crude oil markets, in particular, the integration between Chinese and international oil markets.

China has become the world largest oil importer and the world second largest oil consumer after the United States (Zhang, 2019). It is widely embraced that the global oil-spike during 2003–2008 was largely caused by the strong demand from emerging markets

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[1] Nowadays, while being in the transition process of the energy structure towards clean-energy, by far, crude oil still remains a crucial role in driving the world economy. According to International Energy Agency (2021), in 2021, the oil demand is expected to rebound by 6% in the post era of the COVID-19 pandemic, which is the most rapid increase since 1976.

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notably including China due to its prosperous economic growth (Kilian, 2009; Hamilton, 2009; Ren et al., 2022). Moreover, since 26 March 2018 when China officially launched the trade of crude oil futures contracts in Shanghai International Energy Exchange, it has already exceeded Dubai and become the world third-largest crude oil market following by the West Texas Intermediate (WTI) and Brent (Niu et al., 2021). The Chinese renminbi-denominated trading therefore possesses an increasingly-important role in influencing the global crude oil market dynamics and challenging the dominance of conventional oil benchmarks (Zhang, 2019).

Investigation on whether China's oil market co-moves with the global benchmark market possesses significant implications, especially in an environment with rising uncertainty, due to the following reasons. First, if the two markets are integrated, China's energy policy-making process and its conditions of the oil demand and supply will likely reverberate across the world market, and vice versa (Li and Leung, 2011). This therefore suggests high effectiveness of energy policy transmissions worldwide. In contrast, if the markets are regionalized, the opportunity of cross-market arbitrage would emerge, indicating inefficiency of crude oil markets (Liu et al., 2013). Second, high integration among oil markets weakens the effectiveness of the diversification strategy, indicating that inclusion of oil-related assets from different markets in the same portfolio would be unable to mitigate the investment risk and uncertainty. Third, studying the information transmission between Chinese and international oil markets can examine if the recent viewpoint (see, e.g. Kilian, 2009; Hamilton, 2009) that rising global oil price is driven by the aggregate demand shock in China is tenable. If the two markets are not integrated, the argument will not hold, and vice versa. However, while China's oil market serves as a critical test-bed for investigating the global oil market integration, the existing effort in this regard is nevertheless sparse.

This paper fills the gap by studying the potentially asymmetric and nonlinear evolutionary pattern of information transmission between Chinese and international oil markets in an environment with full-distributional characterization. The transmission is captured by both price changes (returns) and volatility spillovers. Specifically, we first test the direction of the information transmission at different quantiles of the return/volatility distribution of the two markets using a non-parametric quantile causality method, i.e. the causality-in-quantiles (CIQ) test, proposed by Balcilar et al. (2017). Then we gauge varying degrees of the information transmission in different market conditions. To do this, we estimate marginal impacts from the identified 'information giver' to the 'information receiver' over different quantiles of their return/volatility distributions through a Quantile-on-Quantile (QQ) approach by Sim and Zhou (2015). The level of economic policy uncertainty is controlled when interpreting the information transmission.

Our main contributions are summarized in the following aspects. First, we employ a causality-in-quantiles (CIQ) test, through which the direction of the information transmission between the two target markets at various locations of the data distribution is examined. We further measure the asymmetric and non-linear transmission from the 'information giver' to the 'information receiver' under the full-distributional characterization through a Quantile-on-Quantile (QQ) method. Through this, the impact magnitude of the 'giver' on the 'receiver' over different quantiles in their joint distributions is quantified. Second, the transmission mechanism is investigated by accounting for the information spillover respectively on the perspective of return and volatility. Accordingly, a comprehensive interpretation of the information spillover between Chinese and international oil markets can be then made.

Third, as a non-parametric local linear regression approach, our employed QQ method can endogenize underlying structural changes in the real data, rather than assuming that the structural break timing is unknown (Sim and Zhou, 2015). Fourth, the price series of crude oil futures contracts are exploited to stand for the price level in both international benchmark (i.e. WTI) and Chinese markets (i.e. Shanghai International Energy Exchange). It reconciles the long-standing mismatch of futures and spot prices when studying the relationship between these two markets. In addition, our employed quantile research framework including CIQ test and QQ method is able to relax the conventional assumption of linearity by capturing potentially non-linear information spillovers across markets (Duan et al., 2021).

Employing the CIQ test, we find empirical evidence of a uni-directional information transmission of return and volatility spillovers from international WTI oil benchmark to China's Shanghai oil market. The transmission is found to be asymmetric and non-linear in different market conditions in a full-distributional environment. Moreover, our QQ estimation indicates that the asymmetric return and volatility spillovers from WTI to Shanghai oil markets are overall positive. The spillovers further depict a broadly heightening intensity with increases in quantile levels of Shanghai oil return and volatility, respectively. We also find that the information spillovers would be weakened due to extreme events in domestic markets, denoting the importance of local innovations on driving the relationship between Chinese and international oil markets. Overall, our results do not support the hypothesis of 'one great pool' in international oil markets. A series of robustness checks reassures our main findings.

The remainder of the paper proceeds as follows. Section 2 reviews the extant related literature. Section 3 describes employed estimation techniques and our empirical dataset. Section 4 reports our estimation results with discussions of the related literature. Section 5 concludes the paper with a discussion of underlying policy implications.

2. Literature review

Our research is generally related to strands of literature in the field of global oil market integration, and the relationship between Chinese and international oil markets. Although whether global oil markets are integrated is a long-standing and hot issue that has raised extensive attention in academia, no consensus has been reached. The earliest research regarding the world oil market integration can be traced back to Adelman (1984) who points out that the world oil market is 'one great pool'. This hypothesis implies that the oil market is integrated, i.e. unified worldwide, and has been supported by many existing studies. Gulen (1997) finds that the world oil market was unified during the period of 1980–1995 through a cointegration analysis using both spot and futures oil prices in 15 oil markets. The above research is further extended and confirmed by Gulen (1999) who applies a higher frequency data and indicates co-movement among international crude oil markets. Kleit (2001) employs the arbitrage theory and investigates convergence of world oil markets driven by the reduction in transaction costs between markets over time.

Recently, instead of using the correlation-related method that may provide weak explanation, Pukthuanthong and Roll (2009) propose a multi-factor model and empirically find a marked increase in integration of the global oil market co-movement. Li and Leung (2011) adopts an appropriate time-series modeling technique and finds that Chinese and world oil market is co-integrated evinced by a bi-directional causation between the two markets. Reboredo (2011) suggests an evident world oil market integration by showing a highly dependent structure between several benchmark markets. By building a minimal spanning tree for the world crude oil market through graph theory, Ji and Fan (2016) provide evidence of the market integration by depicting the bi-directional linkage among the markets, and find that the oil market integration tends to be increasingly reinforced. Employing a wavelet-based complex network model, Jia et al. (2017) investigates the evolutionary pattern of world crude oil market integration, and two large stable homogeneous groups of regional oil markets are identified. Empirical findings that support the globalization of the (crude) oil market is also reported in recent literature (See, e.g., Kuck and Schweikert, 2017; Galay, 2019; Ren et al., 2022a).

Nevertheless, empirical evidence of the hypothesis of the world oil market integration has been devoid of consistency. Since the hypothesis is proposed by Adelman (1984), it is questioned by Weiner (1991) who employs correlation and regression analyses and reports a rejection of the hypothesis, suggesting that dynamics of world oil markets behave as a pattern of regionalization instead of co-movement. There exists a number of studies that confirm such the regionalization pattern. Fattouh (2010) studies the linkage between oil markets through a threshold unit root approach and finds that oil markets are not inter-linked in every time period, suggesting inconstant dynamics of oil price differentials. Hammoudeh et al. (2008) employ a threshold cointegration technique and investigate dynamic pair-linkages of the four benchmark oil prices. While they find the long-run equilibrium relationship between the four oil price series, the error adjustment process is shown to be asymmetric. Liu et al. (2013) examine the hypothesis of world oil market integration through investigation of price and volatility transmission, and provide empirical evidence of rejection of the hypothesis. Khalifa et al. (2014) point out presence of differential information transmission patterns between the Gulf Cooperation Council (GCC) and the global markets, showing a strong linkage of the former with the global equity markets instead of the oil markets. Through a VAR approach, Zhang et al. (2019) investigate dynamic information transmission mechanism in global crude oil markets, and report that Asian oil markets are net information receivers of the world oil markets in both networks built by return and volatility.

Moreover, while interpretation of information transmission between Chinese and global oil markets is important, scant research investigates the interconnection between the two markets. As an exception, Li and Leung (2011) demonstrate an integral role of the Chinese oil market in governing dynamics of the wold oil market indicated by a cointegration and bi-directional causal relationships between the two markets. However, empirical evidence regarding the comovement between international and Chinese oil markets is not consistent. Liu et al. (2013) report a uni-directional volatility transmission from the global oil benchmarks to the Chinese oil market through both in-sample and out-of-sample analyses, questioning the validity of the hypothesis of the global oil market integration. Employing the test proposed by Diebold and Yilmaz (2012), Zhang (2019) builds a spillover index and finds an evident asymmetry in the relationship of Chinese and world oil markets. The spillover from the global benchmark market to the Chinese oil market is much greater than the reverse. Empirical evidence in favor of a net information receiver of Chinese oil market from the global market has also been confirmed in extant related literature (See, e.g., Yang et al., 2020b; Zhang et al., 2019; Ji and Zhang, 2019; Ren et al., 2022b).

Needless to say, interpreting the potential co-movement pattern between global oil markets, the information transmission between Chinese and international oil markets, in particular, is of great importance and has raised enormous attention. However, the existing relevant studies are limited in the following ways. First, extant literature related to the cross-market correlation is based on only the linear method through the OLS estimation (He et al., 2020). Surprisingly little accounts for the potential asymmetry of the information transmission between target markets over the data distribution, although the asymmetric and non-linear property is known to characterize the cross-market interconnection in the field of natural resources. Second, when studying the market interconnection, majorities of the existing research focus on the return linkage, while little considers the cross-market volatility spillovers although the latter possesses different and important implications.[2]

Third, existing related studies either ignore the potential structural changes in the data generating process of the crude oil prices, or simply assume that the timing of the structural breaks is known (Lutz et al., 2013). Since extreme events, such as the recent financial crisis, can alter the information transmission pattern between global oil markets (Zhang, 2019), scant literature has endogeneized the role of the potential break in this regard. In addition, earlier research employs the spot price series to represent Chinese oil market dynamics due to data limitation, although futures contracts could better capture the recent financialization trend of the oil market than spot contracts (Zhang et al., 2019). Futures contracts are known to alleviate potential data breaks and abnormal price jumps as being characterized by the spot contracts (Mansanet-Bataller et al., 2007; Wang et al., 2022; Ren et al., 2023a).

To this end, in the light of the existing research and the corresponding limitations encountered so far, our paper employs a recently-developed quantile-related method to uncover the dynamic information transmission between the Chinese oil market and international benchmarks in an environment with full-distributional characterization.

[2] According to Zhang et al. (2019), interpreting the transmission mechanism of the price return is helpful to predict the oil price dynamics, while volatility spillovers are important on risk management.

3. Methodology and data

3.1. Methodology

3.1.1. The quantile-on-quantile approach

In this section, we will introduce the quantile-on-quantile (QQ) approach (Sim and Zhou, 2015) that is employed to investigate the linkage between Shanghai crude oil futures prices and WTI crude oil futures prices. The QQ method uses the nonparametric estimation to empirically investigate how the quantiles of the independent variables affect the conditional quantiles of the dependent variable, and it is known to feature the following strengths compared to the traditional quantile regression. First, QQ methods provide a powerful tool for estimating heterogeneity in price distributions of both explanatory and dependent variables, compared with conventional mean-based and quantile methods. Second, it also can provide a more comprehensive and precise understanding of the relationship between the variables under different market conditions. Third, by using the QQ method, we relax the conventionally assumed linear model setting, and can well capture the potentially-existing non-linearity between explanatory and dependent variables. Fourth, the QQ method ameliorates endogeneity problems such as the simultaneity given its model specification, and contributes to accurate model estimates. Fifth, by using a *cross-validation method*, we further improve the original version of the QQ approach proposed by Sim and Zhou (2015) to find a more suitable bandwidth, which can provide a more sensible balance between the bias and the variance during the estimation. Thus, the QQ method enables us to uncover the real linkages between different quantiles of Shanghai and WTI crude oil futures prices, and can provide more meaningful information in contrast to both OLS and traditional quantile regression.

Noteworthy, in addition to the quantile-on-quantile (QQ) approach and the causality-in-quantiles test, there exists several other quantile-based techniques notably including the quantilogram and cross-quantilogram proposed by Linton and Whang (2007), Han et al. (2016), as well as the extremogram developed by Davis and Mikosch (2009), Davis et al. (2012, 2013). These alternative quantile approaches have also widely applied in empirical finance research particularly when studying the cross-market spillover. Among others, Naeem et al. (2022) employ the cross-quantilogram technique to study the extreme quantile dependence between decomposed oil shocks and stock market dynamics in BRIC countries, and report an evident asymmetry of the linkage over the data distribution. By using the cross-quantilogram approach, Bouri et al. (2020) study the quantile relationship between crude oil and CDS markets, and find that the cross-market linkage features time-varying and asymmetry across quantiles. Li et al. (2016) use the extremogram technique and find the evident tail dependence between individual stocks and the aggregate market in China. In sum, the quantilogram is used to test the directional predictability of a given time series and performs well for heavy tailed series. The cross-quantilogram is a multivariate version of the quantilogram, which could provide a complete picture of the predictability structure. Differently, the QQ method is not only a powerful tool for estimating heterogeneity in the data distribution of both explanatory and dependent variables, but also provides a more comprehensive and precise understanding of the impact of the explanatory variable on the dependent variable under different market conditions.

To introduce our employed QQ method, we first consider the following nonparametric quantile regression equation for the θ-quantile of the Shanghai crude oil futures price return (S_t) as a function of WTI crude oil futures return (N_{t-1}) as:

$$S_t = \beta^{\theta}(N_{t-1}) + \epsilon_t^{\theta} \tag{3.1}$$

where N_{t-1} represents WTI crude oil futures return in following empirical research at time $t-1$, the residual term ϵ_t^{θ} has a zero θ-quantile. Due to the lack of prior information on the relationship, $\beta^{\theta}(\cdot)$ is assumed to be an unknown function.

To examine the impact of the τ-quantile of WTI crude oil futures price shocks on θ-quantile of the Shanghai crude oil futures price return, we expand the unknown function $\beta^{\theta}(\cdot)$ by taking a first order Taylor expansion around N^{τ}:

$$\beta^{\theta}(N_{t-1}) \approx \beta^{\theta}(N^{\tau}) + \dot{\beta}^{\theta}(N^{\tau})(N_{t-1} - E^{\tau}) \equiv b_0(\theta,\tau) + b_1'(\theta,\tau)(N_{t-1} - N^{\tau}). \tag{3.2}$$

By substituting Eq. (3.2) into Eq. (3.1), we can obtain

$$S_t = \beta^{\theta}(N^{\tau}) + \dot{\beta}^{\theta}(N^{\tau})(N_{t-1} - N^{\tau}) + \alpha^{\theta} S_{t-1} + \epsilon_t^{\theta}. \tag{3.3}$$

Then, we solve Eq. (3.3) by considering

$$\begin{pmatrix} \hat{b}_0(\theta,\tau) \\ \hat{b}_1(\theta,\tau) \end{pmatrix} = \arg\min_{b_0,b_1} \sum_{t=1}^{T} \rho_{\theta}\left[S_t - b_0 - b_1\left(N_{t-1} - N^{\tau}\right)\right] K\left(\frac{F\left(N_{t-1}\right) - \tau}{h}\right), \tag{3.4}$$

where $\rho_{\theta}(y) = y(\theta - I_{\{y<0\}})$ and I_A is the indicator function of set A. K is a Gaussian kernel function on $\mathbb{R}$, and $h > 0$ is the bandwidth. The empirical distribution function is defined as $F\left(N_{t-1}\right) = \frac{1}{T}\sum_{k=1}^{T} I\left(N_k < N_{t-1}\right)$.

The choice of bandwidth is important for a nonparametric estimation, which is because the bandwidth decides the size of variance and bias in the estimation. Therefore, a suitable bandwidth can provide a balance between the bias and the variance. Sim and Zhou (2015) and other empirical literature uses constant bandwidth, $h = 0.05$, which may not be suitable for different real data and cause biased estimation results. Unlike these studies, we will use the cross-validation method (Stone, 1984; Li and Racine, 2004) to choose the optimal bandwidth in this study, which can derive a more accurate estimate of the model. The leave-one-out cross-validation estimator of Eq. (3.3) is

$$M(h) = \sum_{k=1}^{T} \rho_{\theta}\left(S_k - \hat{b}_{0,-k} - \hat{b}_{1,-k} N_{k-1}\right), \tag{3.5}$$

where $\hat{b}_{0,-k}$ and $\hat{b}_{1,-k}$ are the local linear estimators obtained from Eq. (3.4) after removing kth observation. Then the optimal bandwidth parameter is:

$$h_{CV} = \arg\min_{h} M(h). \tag{3.6}$$

3.1.2. The causality-in-quantiles approach

We further use a non-parametric quantile causality method from Jeong et al. (2012) and Balcilar et al. (2017) to shed light on the nature of causality between Shanghai and WTI crude oil futures prices. Jeong et al. (2012) detect the nonlinear causality in the first moment between any given two variables, recovering thus a possible nonlinearity in the causal relationship. In other words, possible non-linear causality is not seen as an outcome of an apriori defined theoretical construct, rather it is a broad representation of multitudinous factors, which a researcher can ostensibly model to lend credence to a confounded theory. Balcilar et al. (2017) extend the Jeong et al. (2012) framework to the causality based on the 2nd moment, which can test the nonlinear causality running from WTI crude oil futures price returns to the volatility of Shanghai crude oil futures price returns.

Denote Shanghai crude oil futures price return as y_t and WTI crude oil futures price return as x_t. Following Jeong et al. (2012), the quantile causality is defined as follows: x_t does not cause y_t in the θ-th quantile with regard to the lag vector of $\{y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{t-p}\}$ if:

$$Q_\theta\left(y_t | y_{t-1}, \ldots, y_{t-p}, x_{t-1}^n, \ldots, x_{t-p}^n\right) = Q_\theta\left(y_t | y_{t-1}, \ldots, y_{t-p}\right), \tag{3.7}$$

where $Q_\theta\left(y_t|\right)$ is the θth quantile of y_t depending on t and $0 < \theta < 1$. Let $Y_{t-1} \equiv \left(y_{t-1}, \ldots, y_{t-p}\right)$, $X_{t-1}^n \equiv \left(x_{t-1}, \ldots, x_{t-p}\right)$, $Z_t = \left(X_t^n, Y_t\right)$, and $F_{y_t|Z_{t-1}}\left(y_t|Z_{t-1}\right)$ denote the conditional distribution functions of y_t given Z_{t-1}. The hypotheses are:

$$H_0 = P\left\{F_{y_t|Z_{t-1}}\left\{Q_\theta\left(Y_{t-1}\right)|Z_{t-1}\right\} = \theta\right\} = 1 \tag{3.8}$$

$$H_1 = P\left\{F_{y_t|Z_{t-1}}\left\{Q_\theta\left(Y_{t-1}\right)|Z_{t-1}\right\} = \theta\right\} < 1. \tag{3.9}$$

Then (Jeong et al., 2012) consider the following distance measure:

$$J = E\left[\left\{F_{y_t}|Z_{t-1}\left\{Q_\theta\left(Y_{t-1}\right)|Z_{t-1}\right\} - \theta\right\}^2 f_Z\left(Z_{t-1}\right)\right], \tag{3.10}$$

where $f_Z\left(Z_{t-1}\right)$ is the marginal density function of Z_{t-1}. Note that $J \geq 0$, if and only if, H_0 is true. Therefore, we can use J to test H_0 consistently. The kernel-based test statistic for J is:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s\neq t}^{T} K_{ts}\hat{\varepsilon}_t\hat{\varepsilon}_s, \tag{3.11}$$

$$= \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s\neq t}^{T} K_{ts}\left[1\left\{y_t \leq \hat{Q}_\theta\left(x_t\right)\right\} - \theta\right]\left[1\left\{y_s \leq \hat{Q}_\theta\left(x_s\right)\right\} - \theta\right], \tag{3.12}$$

where $K_{ts} = K\left(\frac{Z_{t-1}-Z_{s-1}}{h}\right)$ is the kernel function, h is a bandwidth, T is the sample size, p is the lag order, and $\hat{\varepsilon}_t$ is the estimate of the regression error.

As an extension of the (Jeong et al., 2012) approach, Balcilar et al. (2017) consider a null and alternative hypothesis for causality in variance as follows:

$$H_0 = P\left\{F_{y_t^2|Z_{t-1}}\left\{Q_\theta\left(Y_{t-1}\right)|Z_{t-1}\right\} = \theta\right\} = 1 \tag{3.13}$$

$$H_1 = P\left\{F_{y_t^2|Z_{t-1}}\left\{Q_\theta\left(Y_{t-1}\right)|Z_{t-1}\right\} = \theta\right\} < 1. \tag{3.14}$$

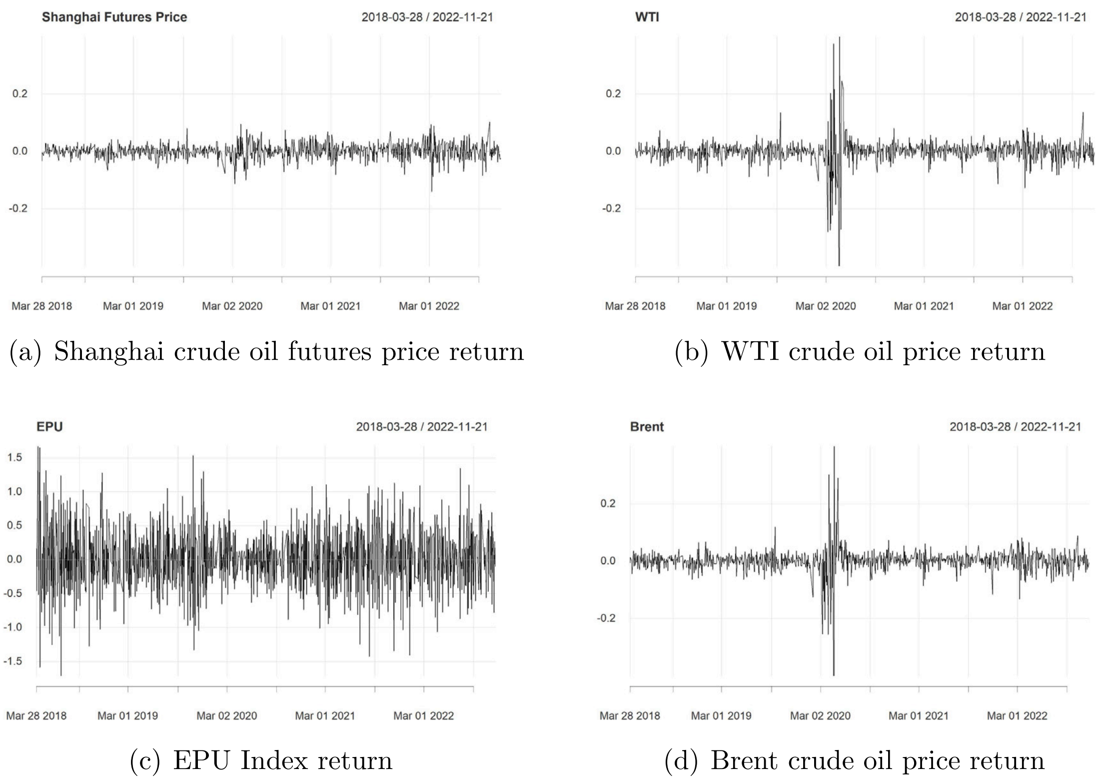
This method can test that x_t Granger causes y_t in quantile θ based on the second moment, using Eq. (3.13) to formulate the feasible kernel-based test statistic following (Jeong et al., 2012).

3.2. Data

To analyze the dynamic interdependence between Chinese and global crude oil market, the empirical data are collected in the following sources. Regarding the global crude oil benchmark, we follow literature by using the West Texas Intermediate (WTI) crude oil futures contracts. WTI is one of the world's most significant oil benchmarks, and its price fluctuations clearly reflect dynamics of the global oil market. The WTI oil futures contracts trade on NYMEX (New York Mercantile Exchange) and then deliver in Cushing, Oklahoma. As for the Chinese crude oil futures market, it is organized at the Shanghai International Energy Exchange (INE), which develops fast and has recently become the world's third largest oil trading platform. Thus, our data contains daily futures prices of Shanghai crude oil futures.[3] and WTI crude oil futures[4] Our daily data start since the establishment of the INE, i.e. a period from 27 Mar 2018 to 21 Nov 2022.

[3] Raw data from Bloomberg.

[4] Cushing, OK Crude Oil Future Contract 1 (Dollars per Barrel). Raw data from Energy Information Administration.



(a) Shanghai crude oil futures price return

(b) WTI crude oil price return

(c) EPU Index return

(d) Brent crude oil price return

Fig. 1. Time series plots of the daily return of Shanghai crude oil futures price, WTI crude oil futures price, Economic policy uncertainty (EPU) index and Brent crude oil futures price, from 27 Mar 2018 to 21 Nov 2022.

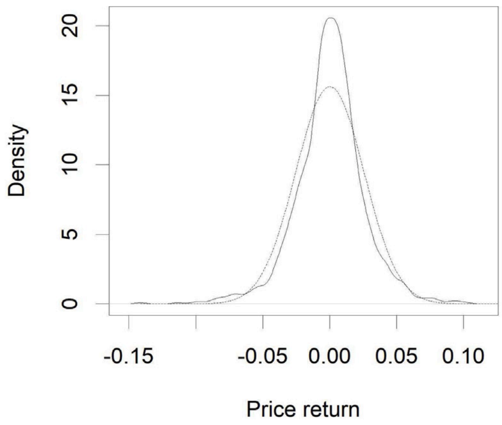
Table 1
Descriptive statistics.

	Shanghai crude oil	WTI crude oil	EPU	Brent crude oil
Minimum	−0.1412	−0.7203	−1.7103	−0.7727
Maximum	0.1024	0.4258	1.6672	0.4120
1. Quartile	−0.0121	−0.0123	−0.2960	−0.0117
3. Quartile	0.0137	0.0150	0.2835	0.0151
Mean	0.0002	0.0002	0.0015	0.0002
Stdev	0.0255	0.0462	0.4521	0.0434
Skewness	−0.3075	−2.7635	0.0502	−4.5359
Kurtosis	2.6691	71.3610	0.6633	107.2068
JB test	337.686***	229715***	337.6863***	229715***
ADF test	−9.8657***	−11.7337***	−9.8657***	−11.7337***

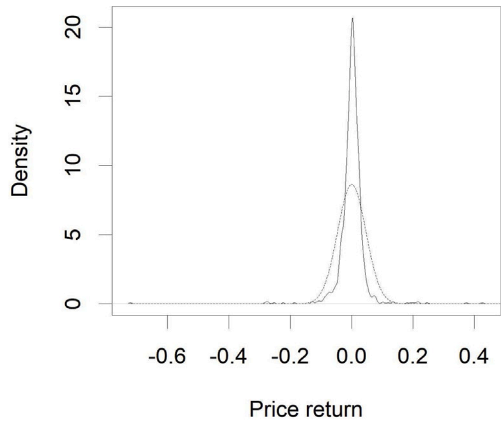
Note: (i) This table summarizes descriptive statistics of the returns of Shanghai crude oil futures, WTI crude oil futures, Brent crude oil futures, and EPU index. (ii) The sample period is from 27 Mar 2018 to 21 Nov 2022. (iii) The Jarque–Bera (JB) statistics test for the null hypothesis of normality of target series. The Augmented Dickey–Fuller (ADF) test reports unit root test results with the null hypothesis of non-stationarity. (iv) * denotes the 10% significance level; ** denotes the 5% significance level; *** denotes the 1% significance level.

Fig. 1 plots the growth pattern of target series over time, including Chinese (Shanghai) oil futures prices, international crude oil benchmarks (WTI in the main results; Brent in the robustness), and economic policy uncertainty (EPU, i.e. controlled variable). The corresponding summary statistics of target series in the return format are presented in Table 1. Specifically, the positive kurtosis values indicate the asymmetric data feature with heavier tails other than the normal distribution, while significant rejection of the null of the Jarque–Bera test further demonstrates the asymmetry feature, implying the appropriateness of the quantile research framework applied in the data distribution of both dependent and independent variables.

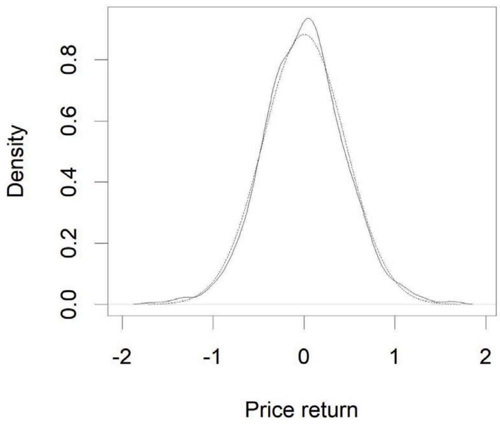
As a further illustration of the non-normal distribution of our incorporate variables, the density plot as shown in Fig. 2 again confirms the asymmetry data property. In addition, it is necessary to test whether the series are non-stationary as non-treatment of the latter might bias our inference of causal relationship — dynamically or otherwise. As depicted in Table 1, the null hypothesis of the ADF test favoring the presence of a unit root is rejected at the 1% statistical significance level, indicating stationarity of our target variables in the return format.



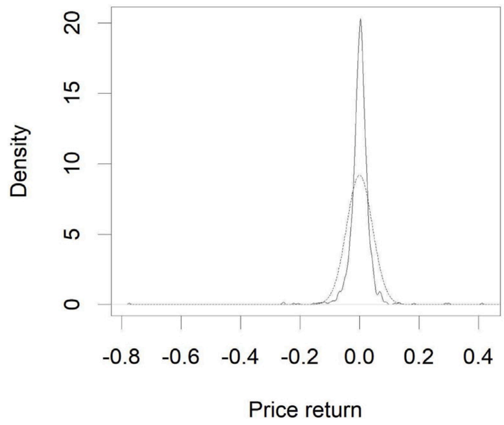
(a) Shanghai crude oil futures price return



(b) WTI crude oil price return



(c) EPU Index return



(d) Brent crude oil price return

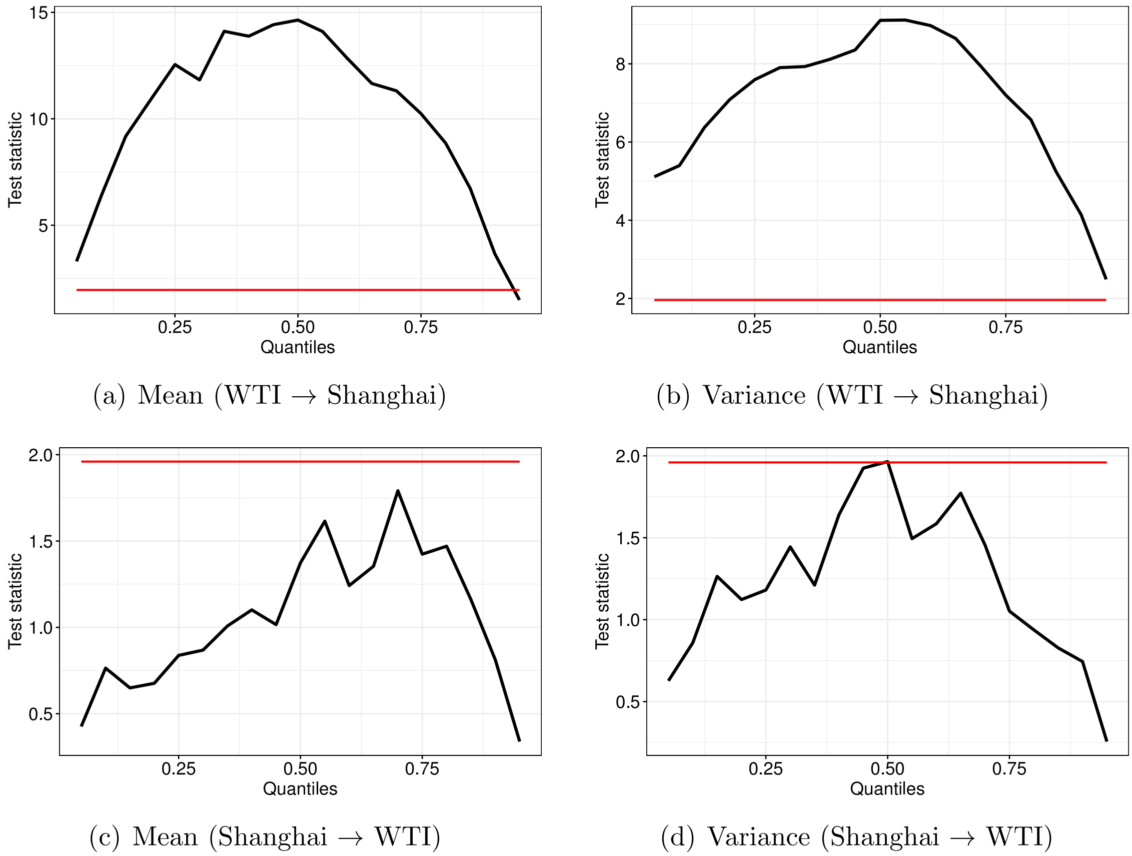
Fig. 2. Density plots of the daily return of the Shanghai crude oil futures price, WTI crude oil futures price, EPU Index and Brent crude oil futures price, from 27 Mar 2018 to 21 Nov 2022.

4. Empirical results

To consider the non-linearity and asymmetry characterized in our data, we employ a quantile research framework, through which information transmission between Chinese and international oil markets is uncovered. In this section, we first examine the transmission direction by quantifying the causality relation between Shanghai and WTI crude oil markets in a quantile context though the causality-in-quantiles (CIQ) test. The degrees of the transmission from 'information giver' to 'receiver' through channels of return and volatility are respectively quantified using the Quantile-on-Quantile method. Through this, characteristics of the transmission pattern in a full distributional context involving the two oil market dynamics are unveiled. Explanations of our results are provided, indicating the consistency with extant related literature and our expectations.

4.1. Causality-in-quantiles test

We now present results of the causality-in-quantiles (CIQ) test, through which the direction of cross-market information transmission in different market conditions through return and volatility can be respectively gauged with the results shown in Fig. 3. Regarding the transmission from WTI to Shanghai oil markets, as depicted in Panels (a) and (b) of Fig. 3, the corresponding null hypothesis of no Granger causality in return and volatility is rejected at the most quantiles of shanghai oil futures mean and



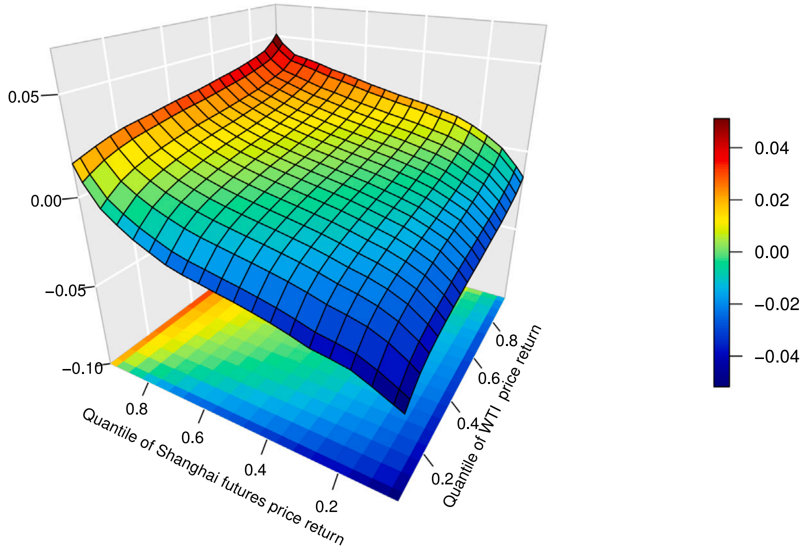
(a) Mean (WTI → Shanghai)
(b) Variance (WTI → Shanghai)
(c) Mean (Shanghai → WTI)
(d) Variance (Shanghai → WTI)

Fig. 3. Causality-in-quantiles test results.
Note: (i) The figure plots results of the non-parametric causality-in-mean and causality-in-variance tests between WTI crude oil futures and Shanghai crude oil futures. Through this, the return spillovers (Figs. 3(a) and 3(c)) and volatility spillovers (Figs. 3(b) and 3(d)) between the two markets are illustrated, respectively. The corresponding estimate of the 5% critical value (CV) represented as the horizontal red solid line. (ii) The vertical axis reports test statistics of the null hypothesis of the test, and the horizontal axis indicates different quantile levels (from $q = 0.05$ to q=0.95).

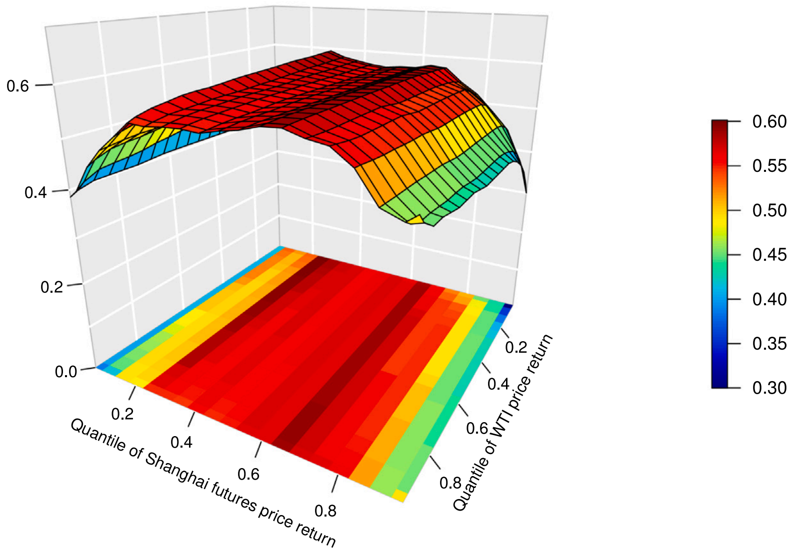
variance, respectively, except at extreme quantiles. The inverted U-shaped causality-in-mean curve shows that the transmission from WTI to Shanghai oil futures price returns is non-linear and asymmetric (Fig. 3(a)). It indicates a stronger predictive power of WTI oil return around the middle quantiles (normal market conditions); the power gradually decreases at upper and lower quantiles, eventually turning insignificant at the extreme high quantiles (as correspond to the bull market).

Similarly, the Granger causality-in-variance presents a inverted U-shaped pattern across quantiles of Shanghai oil futures volatility and is shown to be statistically significant at all quantile levels (Fig. 3(b)). It is worth noting that results of both causality-in-mean is statistically insignificant when the level of return of Shanghai oil futures is high, indicating that the predictive power of dynamics of WTI oil futures to that of Shanghai oil futures is weak under extreme bullish situations. The non-linear and asymmetric causal relationship between Shanghai and WTI oil markets under differential market conditions demonstrates the importance of a full-distributional characterization when quantifying the degree of information transmission between the two markets. Conversely, as shown in Figs. 3(c) and 3(d), the null hypothesis favoring Granger causality of both return and volatility from Shanghai to WTI oil futures cannot be rejected at various return and volatility quantiles of WTI oil futures, respectively. The results confirm no predictive power of Shanghai oil futures to the WTI benchmark.

Thus, it can be concluded that China's crude oil futures behave as a net information receiver in the global crude oil system, while the latter is recognized as a net information giver. The obtained results corroborate the recently growing evidence regarding the uni-directional information transmission mechanism from international to Chinese oil markets, i.e. the rejection of the 'one great pool' hypothesis (See, e.g., Liu et al., 2013; Zhang, 2019; Yang et al., 2020b; Zhang et al., 2019). Our findings are also consistent with Yang et al. (2020a), which find the uni-directional Granger causal relation from WTI and Brent to Shanghai oil prices, indicating limited influence of China's oil market in crude oil pricing worldwide. Wu and Zhang (2014) also point out that China factor plays less important role on the price discovery of the international oil benchmark such as Brent. In the next section, we will further investigate how the degree of the transmission evolves across differential locations of data distribution of the two oil markets. Ji and Zhang (2019) suggest that traders in China's oil market tend to be the price followers of the international oil benchmark.



(a) $b_0(\theta, \tau)$



(b) $b_1(\theta, \tau)$

Fig. 4. Q–Q estimates for the impacts of WTI crude oil futures returns on Shanghai crude oil futures returns.

4.2. Quantile-on-quantile estimates

In this section, we present and discuss QQ estimation results regarding the impact of the WTI oil benchmark on the Chinese oil market through the information spillover channels of return and volatility, respectively. Regarding the return spillover, Fig. 4 displays estimates of the two coefficients in Eq. (3.2), i.e. $b_0(\theta, \tau)$ (that represents a constant model intercept) and $b_1(\theta, \tau)$ (that represents the impact of the τth quantile of WTI crude oil futures price return on the θth quantile of Shanghai crude oil futures price return). Likewise, Fig. 6 presents the estimation results for the impacts of the τth quantile of WTI benchmark price volatility

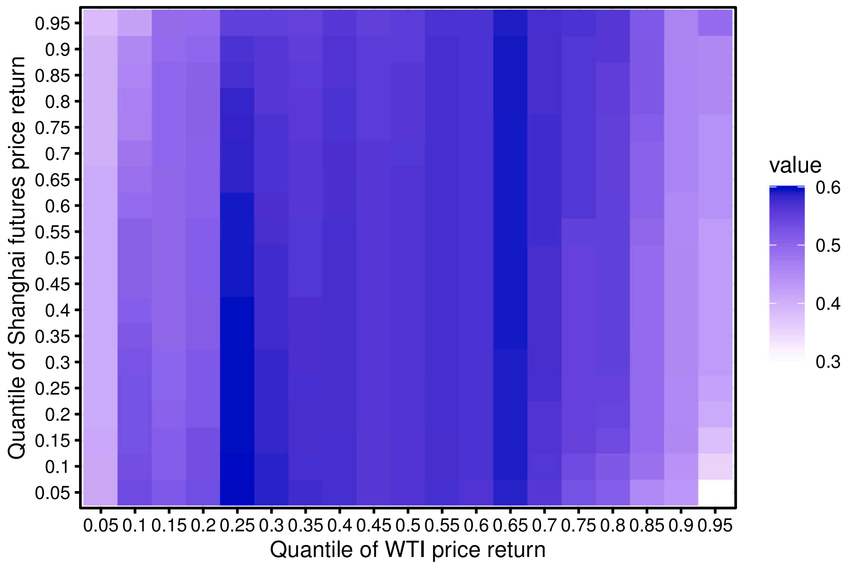


Fig. 5. The heat map of estimated coefficients of WTI crude oil futures returns on Shanghai crude oil futures returns by the QQ method.
Note: (i) This figure is the 2-D reproduction of the same results reported in Figs. 4 in the 3-D format. (ii) The legend describes the extent of impacts of WTI crude oil futures returns on Shanghai crude oil futures returns. (iii) The vertical axis indicates different quantile levels (from $q = 0.05$ to q=0.95) of Shanghai futures return. The horizontal axis denotes different quantile levels (from $q = 0.05$ to q=0.95) of WTI futures return.

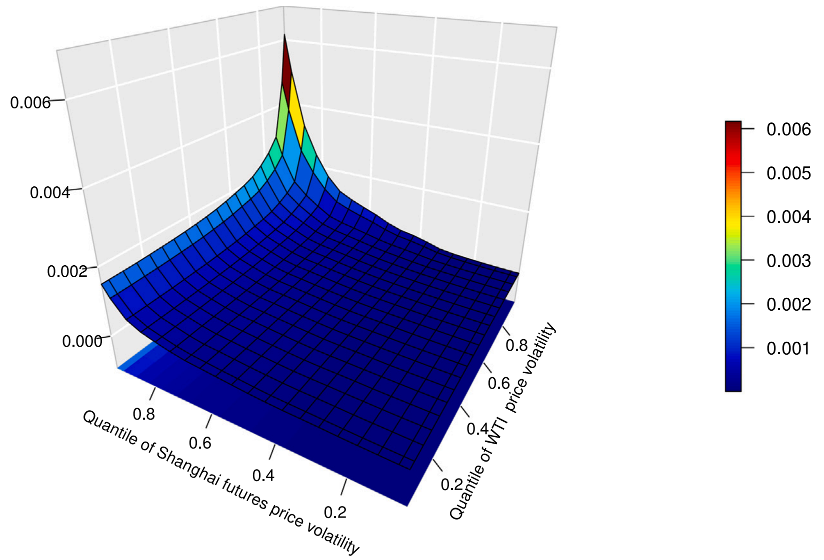
on the θth quantile of Shanghai oil price volatility. Figs. 5 and 7 are 2-D reproduction of the same results of the estimated $b_1(\theta, \tau)$ reported in Figs. 4 and 6 in the 3-D format, respectively.

The QQ estimation results are summarized as follows. As for the return spillover shown in Figs. 4 and 5, the impact of price returns of WTI benchmark oil futures on that of Shanghai oil futures is overall positive but depicts an obvious asymmetric tendency. It generally depicts an increasing impact pattern with increases in quantiles of Shanghai futures returns, while it experiences a decline at the extreme high quantiles, showing as an inverted U-shaped pattern across the joint distribution of Shanghai and WTI oil futures price returns. That is, the impact first increases from 0.3857 to 0.60 and then decreases to 0.2998 with increases in quantile levels of Shanghai oil returns, indicating that the degree of return spillovers is the strongest at median quantiles and is relatively weakened at lower and higher quantiles. In contrast, regarding the volatility spillover shown in Figs. 6 and 7, the impact of price volatility from WTI to Shanghai oil futures broadly witnesses a consistent increasing pattern with increases in quantiles of Shanghai price volatility.

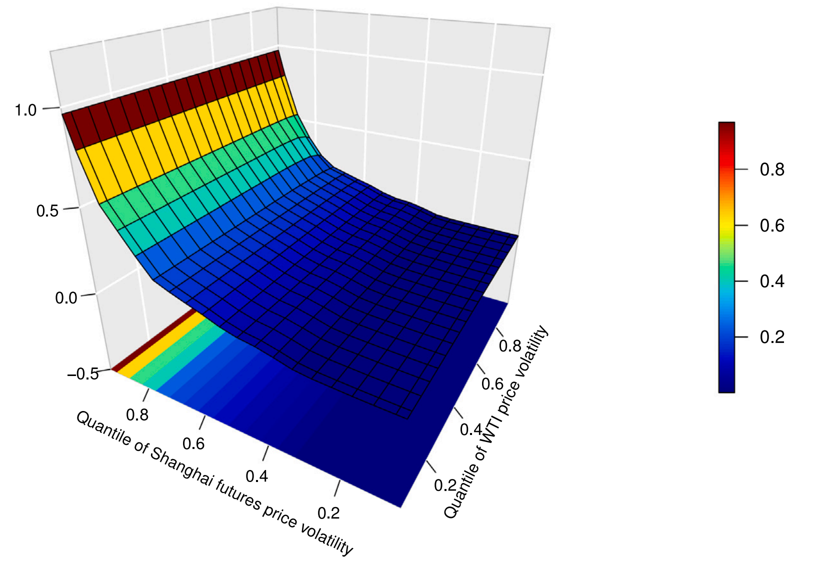
Thus, it is clear that information transmission from the WTI benchmark to the Shanghai oil futures in the form of both return and volatility depicts an non-linear and asymmetric pattern, indicating that the international to China's oil market are not integrated; this conforms to the existing literature as previously discussed (See, e.g., Yang et al., 2020b). Among others, Du et al. (2010) find that economic activities in China play only a negligible role in affecting dynamics of world oil prices; such the exogenous role indicates limited pricing power of China's oil market in the international oil price discovery. Zhang and Wang (2014) analyze that while return and volatility spillovers between China's and international oil markets are bi-directional, the direction of the spillovers is governed from international benchmark to the china market; the converse spillover tend to only have a lesser extent. Li et al. (2017) point out that the contribution of China's oil stock returns to international oil price shocks is rising while the current role of the former is still limited.

While existing research related to the relationship between Chinese and international oil markets is scant, our findings are consistent with limited research showing that the information spillover is prone to jumps in the face of extreme events as represented by extreme quantiles of the data distribution (He et al., 2020). More specifically, the spillover tends to become weaker at extreme quantiles of China's oil market dynamics, while depicting a symmetric pattern over various conditions of the international oil benchmark. This indicates that changes in the extent of the international-Chinese oil market linkage are driven by domestic forces rather than the world's common fundamentals. The reason might be that China's oil market dynamics are largely affected by domestic regulation and rules; such an important and even dominant role of the government tends to prevent the influence of intentional extreme events on the domestic oil market (Zhang, 2019). This is also supported by the ongoing COVID-19 epidemic. When the world's first infected case of the epidemic being reported in China on 31 December 2019, China has made a prompter action of lockdown relative to other countries that largely limits the information flow between China and the globe for prevention of the epidemic spread.[5] The adverse COVID-19 shock has therefore led to a plunge in the oil price due to the following economic

[5] COVID-19 was officially announced as a pandemic by the WHO on 11 March 2020, i.e., two months later after the first infected case being reported. This indicates that China's lockdown action is two months earlier than other countries on average.



(a) $b_0(\theta, \tau)$



(b) $b_1(\theta, \tau)$

Fig. 6. Q–Q estimates for the impacts of WTI crude oil futures volatility on Shanghai crude oil futures volatility.

depression, which associated lockdown policy has in turn induced a weakened linkage between global and China's oil markets. This finding is further supported by the dynamic rolling-window analysis to be discussed in the next.

Do our findings drawn by the quantile research framework also hold in conventional techniques? To further examine the validity of our results, we employ the OLS method and the traditional quantile regression to estimate the return and volatility spillover from the WTI oil benchmark to the Shanghai oil market with the results shown in Tables 2 and 3, respectively. The temporal lagged terms of the economic policy uncertainty (L.EPU) and Shanghai futures return (L.Shanghai) are controlled in the estimation. Intuitively, the

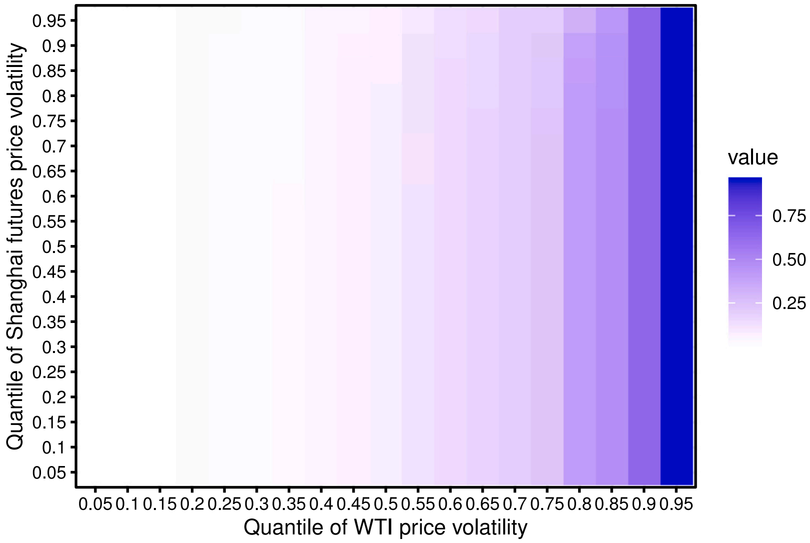


Fig. 7. The heat map of estimated coefficients of WTI crude oil futures volatility on Shanghai crude oil futures volatility by the QQ method.
Note: (i) This figure is the 2-D reproduction of the same results reported in Figs. 6 in the 3-D format. (ii) The legend describes the extent of impacts of WTI crude oil futures volatility on Shanghai crude oil futures volatility. (iii) The vertical axis indicates different quantile levels (from $q = 0.05$ to q=0.95) of Shanghai futures volatility. The horizontal axis denotes different quantile levels (from $q = 0.05$ to q=0.95) of WTI futures volatility.

Table 2
OLS and quantile regression results for the return spillover.

Variable	OLS	Quantile		
		0.1	0.5	0.9
Constant	0.0002	−0.0232***	0.0002	0.0250***
	(0.7655)	(0.0000)	(0.7853)	(0.0000)
WTI	0.2545***	0.3193***	0.4251***	0.1956**
	(0.0000)	(0.0000)	(0.0000)	(0.0270)
EPU	0.2545	0.0003	0.0002	0.0044*
	(0.4460)	(0.8995)	(0.8339)	(0.0862)
y.log	−0.0917***	−0.0716	−0.1514***	−0.0886
	(0.0012)	(0.2081)	(0.0001)	(0.2045)

Note: (i) This table reports the estimation of OLS and traditional quantile regression for the impacts of Shanghai crude oil futures returns on WTI crude oil future returns, respectively. (ii) $\alpha = 0.1$, $\alpha = 0.5$ and $\alpha = 0.9$ denote different quantile levels of Shanghai crude oil futures returns. The temporal lagged terms of the economic policy uncertainty (L.EPU) and Shanghai futures return (L.Shanghai) are controlled in the estimation. (iii) P values are in parentheses. (iv) * denotes the 10% significance level; ** denotes the 5% significance level; *** denotes the 1% significance level.

information spillovers in both return and volatility are overall positive and significant, while depicting an non-linear and asymmetric impact pattern across different quantiles of Shanghai oil market, indicating consistency with our main findings.

In addition, the traditional quantile estimation confirms the consensus that the mean-based technique such as the OLS method overlooks the asymmetry and non-linearity over the real data distribution and only paint an incomplete picture about the true impact of WTI crude oil futures return on Shanghai crude oil futures return. Moreover, the traditional quantile regression still could not fully capture the potentially different impact at various quantiles of the independent variable, i.e. returns and volatility of the WTI benchmark market, respectively, indicating the importance of using the QQ method in our analysis.

4.3. Robustness checks

4.3.1. Alternative estimation strategy: The τ-averaged QQ estimation

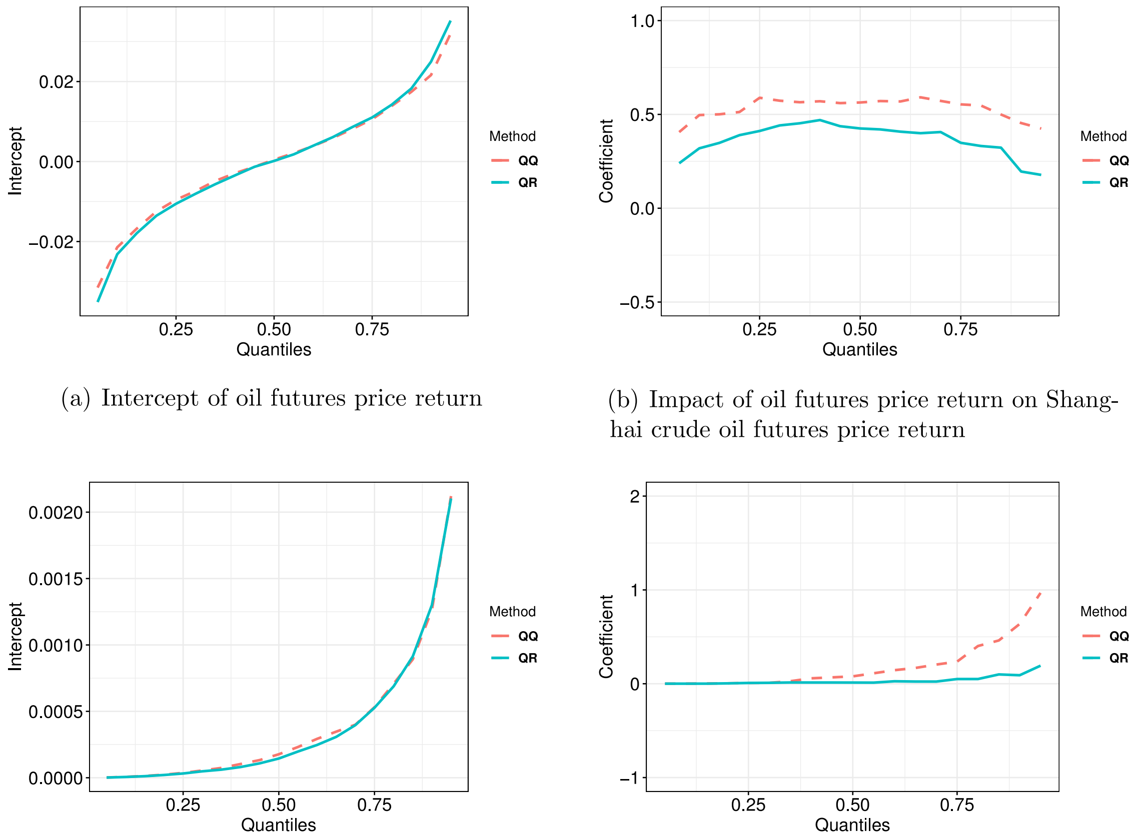
How sensitive are our results to the method specification? The QQ method can capture specific impacts of the explanatory variable at different quantile levels, which can be viewed as a decomposition of tradition quantile regression (Sim and Zhou, 2015). In this context, a simple way to check the validity of the QQ approach is to compare the estimated quantile regression parameters with the τ-averaged QQ parameters.

$$\gamma_0(\theta) \equiv \overline{\hat{b}_0}(\theta) = \frac{1}{S} \sum_{\tau} \hat{b}_0(\theta, \tau), \tag{4.1}$$

Table 3
OLS and quantile regression results for the volatility spillover.

Variable	OLS	Quantile		
		0.1	0.5	0.9
Constant	0.0006***	0.0000***	0.0001***	0.0013***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
WTI	0.0138***	0.0006	0.0124	0.0906
	(0.0000)	(0.7575)	(0.3525)	(0.4732)
EPU	0.0138*	0.0000	0.0000	−0.0004***
	(0.0731)	(0.3867)	(0.2120)	(0.0015)
y.log	0.1411***	−0.0002	0.0516	0.3724
	(0.0000)	(0.8774)	(0.2085)	(0.1534)

Note: (i) This table reports the estimation of OLS and traditional quantile regression for the impacts of Shanghai crude oil futures volatility on WTI crude oil future volatility, respectively. (ii) $\alpha = 0.1$, $\alpha = 0.5$ and $\alpha = 0.9$ denote different quantile levels of Shanghai crude oil futures volatility. The temporal lagged terms of the economic policy uncertainty volatility (L.EPU) and Shanghai futures volatility (L.Shanghai) are controlled in the estimation. (iii) P values are in parentheses. (iv) * denotes the 10% significance level; ** denotes the 5% significance level; *** denotes the 1% significance level.



(a) Intercept of oil futures price return

(b) Impact of oil futures price return on Shanghai crude oil futures price return

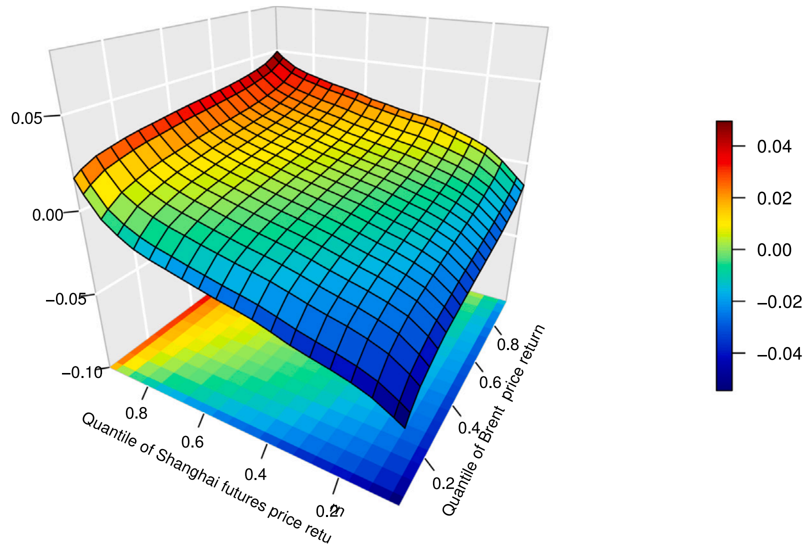
(c) Intercept of oil futures price volatility

(d) Impact of oil futures price volatility on Shanghai crude oil futures price volatility

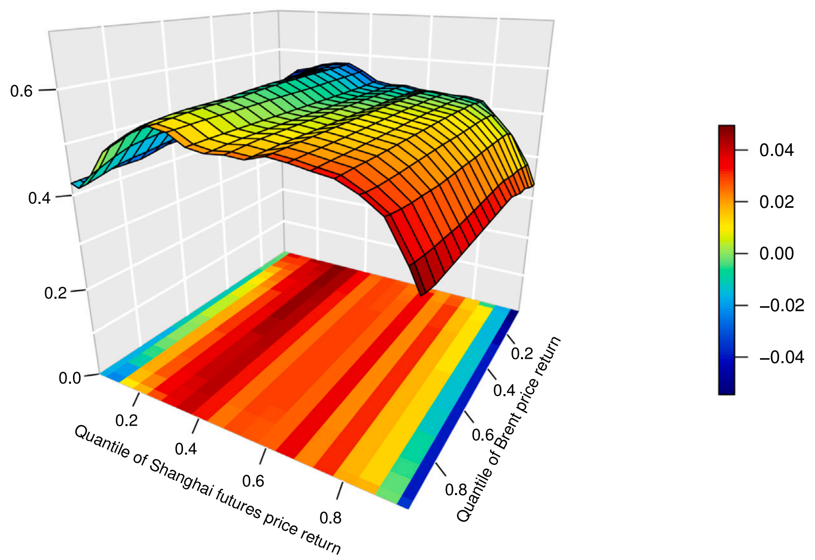
Fig. 8. The robustness check: Comparisons of the results from the quantile regression and the QQ estimate.
Note: The graph plots and compares the estimates of the traditional quantile regression parameters, denoted by QR (blue dash line), and the averaged Q–Q parameters (red dotted line) regarding averaged impacts of the WTI crude oil futures returns (volatility) on Shanghai crude oil futures returns (volatility).

$$\gamma_1(\theta) \equiv \overline{\hat{b}_1}(\theta) = \frac{1}{S}\sum_{\tau} \hat{b}_1(\theta, \tau), \tag{4.2}$$

where S is the number of points of the grid of τ. Panels (a) and (b) of Fig. 8 present comparisons between estimations of quantile regression and the averaged QQ method regarding the return spillovers from WTI to Shanghai crude oil markets. Moreover, Panels



(a) $b_0(\theta, \tau)$

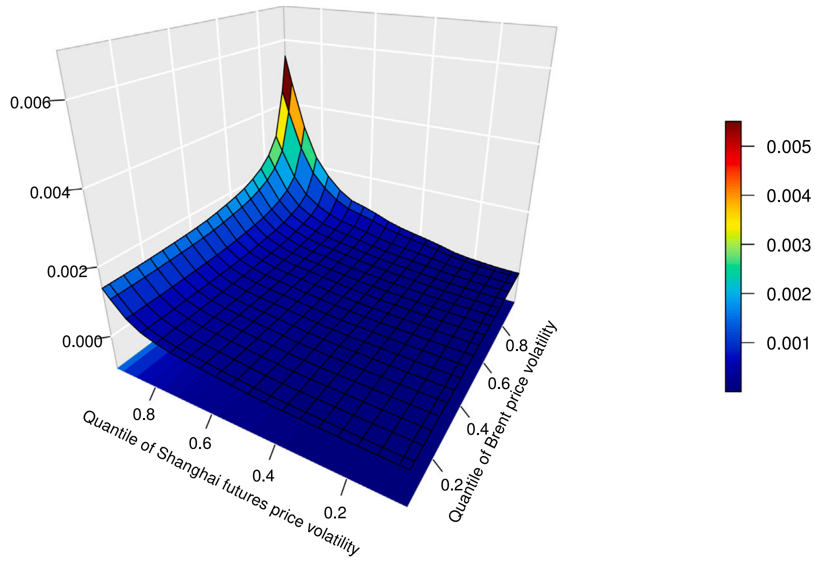


(b) $b_1(\theta, \tau)$

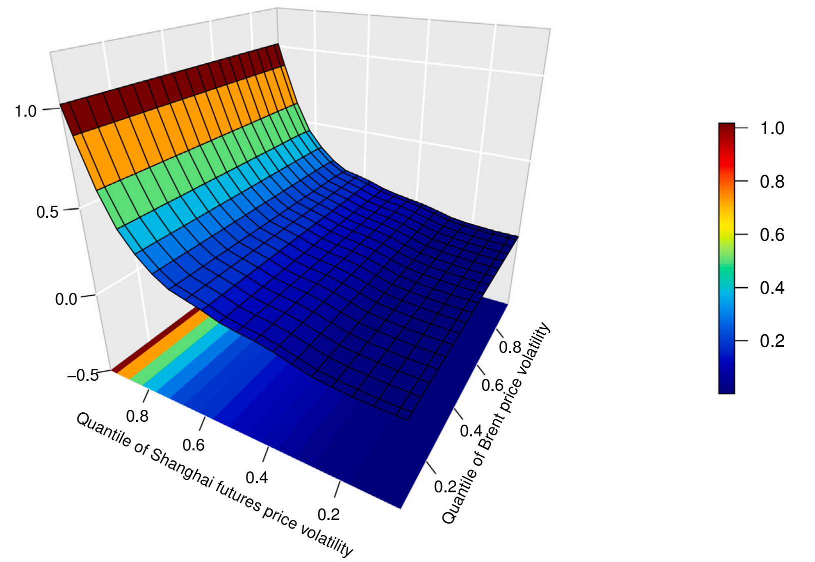
Fig. 9. Q–Q estimates for the impacts of Brent crude oil futures returns on Shanghai crude oil futures returns.

(c) and (d) of Fig. 8 present the corresponding result comparisons regarding the volatility spillovers. The results show that the averaged QQ parameters are similar to the quantile regression estimators.

These plots provide a simple validation of the QQ method employed in the preceding section by showing that the main features of the traditional quantile regression model can be recovered by summarizing the more disaggregated information contained in the QQ estimation. Thus, it demonstrates that changing estimation strategy does not alter our main findings obtained using the QQ estimation.



(a) $b_0(\theta, \tau)$

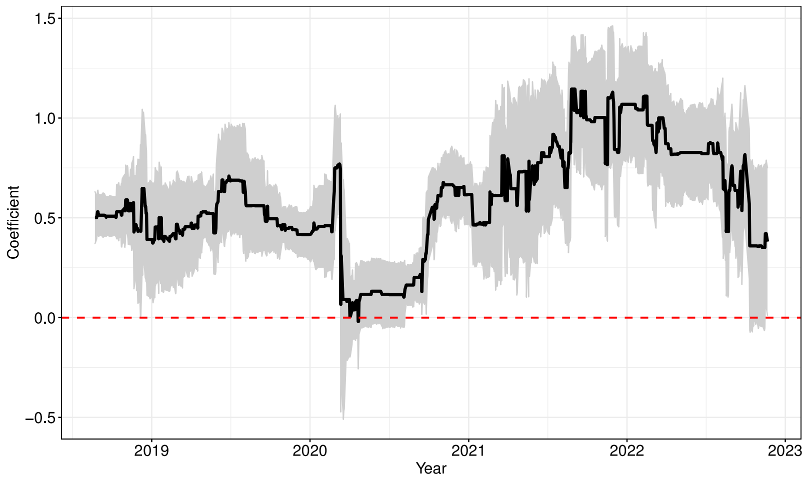


(b) $b_1(\theta, \tau)$

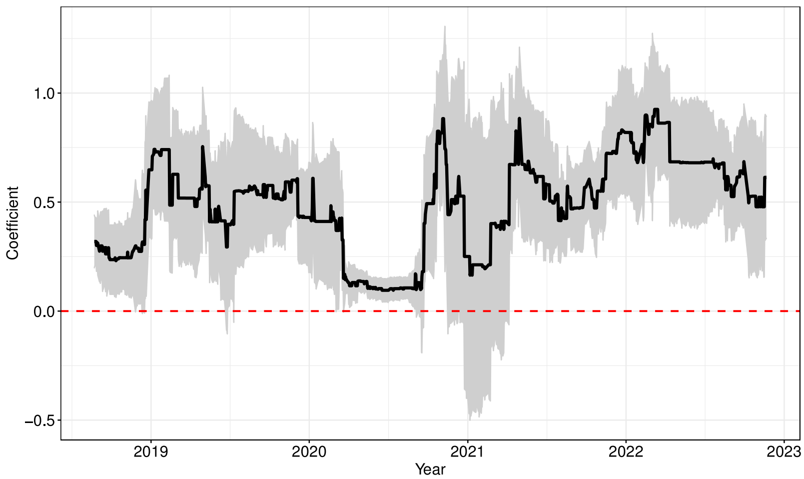
Fig. 10. Q–Q estimates for the impacts of Brent crude oil futures volatility on Shanghai crude oil futures volatility.

4.3.2. Alternative international oil benchmark: Brent crude oil futures

To further examine the robustness of our main findings, we replace our selected WTI crude oil market by another recognized international oil benchmark, i.e. Brent crude oil market, and re-estimate the QQ model regarding the return and volatility spillovers from international to Chinese oil markets as shown in Figs. 9 and 10, respectively. Consistent to our main results drawn by the WTI benchmark (presented in Figs. 4(b) and 6(b)), return and volatility spillovers from the Brent benchmark to the Shanghai oil market respectively exert an overall positive and declining impact intensity with increases in the corresponding quantiles of the Shanghai oil market (shown in Figs. 9(b) and 10(b)). Hence, the robustness of our main findings is further confirmed.



(a) $\tau = 0.05$



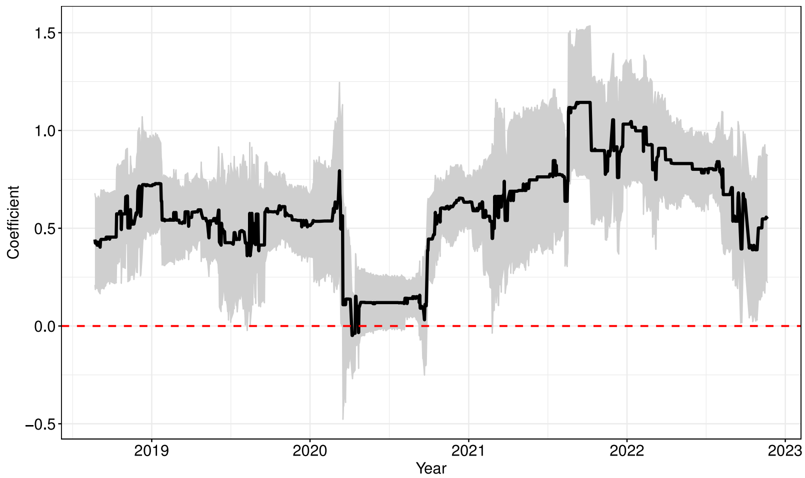
(b) $\tau = 0.95$

Fig. 11. Rolling-window quantile regression estimates of the impact of WTI oil returns on Shanghai crude oil futures returns with windows=95. Note: The solid black line is the 5% (95%) quantile. Shaded areas correspond to 95% confidence intervals of quantile estimation.

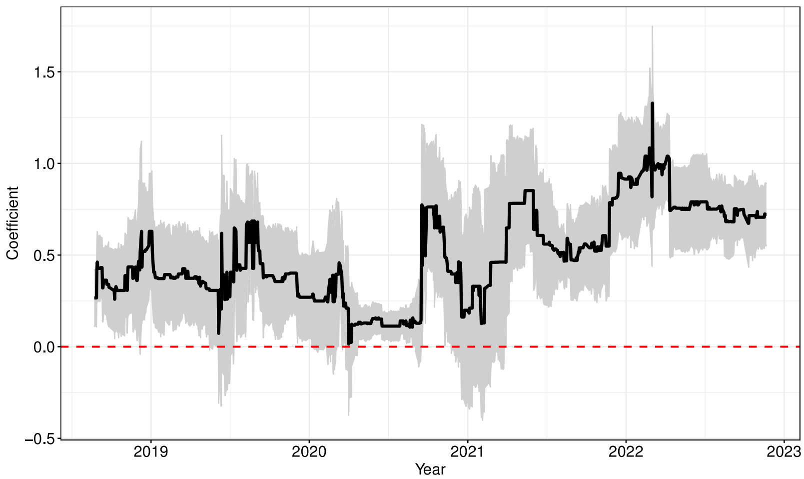
4.4. *Dynamic analysis: Rolling window investigation*

Given the time-varying nature of spillover effects from domestic and international crude oil markets and the importance of cross-market impacts under extreme conditions, we further employ rolling window quantile regression with windows #95 (Wu, 2021) and explore the influence of WTI crude oil and Brent crude oil on Shanghai crude oil futures over time under extreme upper (95th quantile level) and lower quartile (5th quantile level) scenarios. From Fig. 11, WTI crude oil returns consistently have a significant positive impact on Shanghai crude oil returns under the two-tail estimation, and to a slightly greater extent at the 5% quantile than at the 95% quantile, indicating a stronger downside return spillover effect between crude oil markets. In addition, we can visualize a clear "dip" in the time-varying impact coefficient in 2020, which means that some sudden external events such as the COVID-19 pneumonia pandemic could lead to strong fluctuations and structural changes in variation.

The results in Fig. 12 also show that in addition to the extremely short-term negative impact at the beginning of 2020, the return of Brent crude oil has always shown a positive spillover effect on Shanghai crude oil. Similar to the case of WTI, the contraction in oil demand exacerbated by the spread of the epidemic following the declaration of COVID-19 as a global pandemic by the World Health Organization in March 2020 has similarly led to a weakening of this effect. Furthermore, we also observed that the impact coefficients of the left and right tails both rose significantly and reached the maximum value from the end of 2021 to the beginning of 2022, which was attributed to the superposition effect of the epidemic rebound and the Russian–Ukrainian conflict amplifying the extreme tail contagion between crude oil markets. In general, our analysis emphasizes the applicability and importance of dynamic models for information transmission and risk assessment under extreme market conditions.



(a) $\tau = 0.05$



(b) $\tau = 0.95$

Fig. 12. Rolling-window quantile regression estimates of the impact of Brent oil returns on Shanghai crude oil futures returns with windows=95. Note: The solid black line is the est 5% (95%) quantile. Shaded areas correspond to 95% confidence intervals of quantile estimation.

5. Conclusion

In this paper, we investigate potentially asymmetric evolution of the information transmission in forms of return and volatility spillovers between Chinese Shanghai and international WTI oil markets in different market conditions. Instead of conventional approaches that fail to account for the asymmetry and non-linearity in the transmission, we employ recently-developed quantile techniques, i.e. causality-in-quantiles (CIQ) test and Quantile-on-Quantile (QQ) method to construct an environment with full distributional characterization. Using the CIQ test, we find that China's (Shanghai) oil market is a net information receiver; and WTI oil benchmark is a net information giver over different locations of the data distribution. In parallel, the impact magnitude of return and volatility spillovers from the WTI oil benchmark to Shanghai oil market is estimated by the QQ method. It depicts an overall positive and increasing pattern of the impact magnitude with increases in quantiles of Shanghai oil price returns and volatility, respectively.

Overall, our results suggest a significant predictive power of the dynamics of WTI to that of Shanghai oil futures markets via return and volatility spillovers, not vice versa. The uni-directional spillover from the international oil benchmark to China's oil markets provides empirical evidence that the 'one great pool' hypothesis in the global oil market does not hold. Since China is the second-largest oil consumer after the United States and the largest oil importer worldwide, international oil price shocks undoubtedly exert important impacts on the Chinese economy (See, e.g., Wang et al., 2013; Zhang, 2019). However, our main findings reveal a weak oil pricing power of China, leading to exposure of the Chinese economy to shocks and uncertainty from the international oil benchmark, but not the other way around.

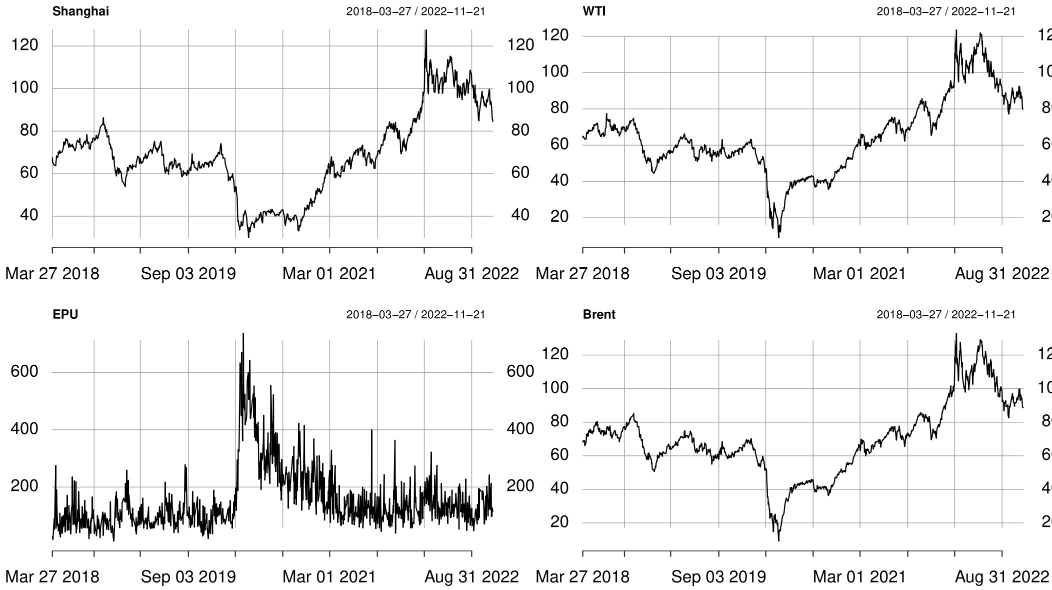


Fig. 13. Time series plots of the daily price of Shanghai crude oil futures price, WTI crude oil futures price, Economic policy uncertainty (EPU) index and Brent crude oil futures price, from 27 Mar 2018 to 21 Nov 2022.

Thus, a clear policy implication is the importance and necessity of enhancing the Shanghai oil futures market. Through this, the Renminbi-denominated oil futures trading would offer an effective instrument to both domestic traders for risk mitigation from the global oil market and policymakers for improvement of China's oil pricing power. At the same time, information spillovers from international to China's oil markets become weaker when extreme events occur in domestic markets. This indicates that some important driving powers of the information transmission stem from domestic economic innovations instead of common shocks from the global oil market. This further implies that the China oil market tends to only partially co-move with global oil benchmarks.

CRediT authorship contribution statement

Kun Duan: Conceptualization, Validation, Writing, Formal analysis. **Xiaohang Ren:** Conceptualization, Methodology, Software, Writing, Formal analysis. **Fenghua Wen:** Supervision, Writing – review & editing. **Jinyu Chen:** Writing – review & editing.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Acknowledgments

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Appendix A

See Fig. 13.

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