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Extreme risk spillover between Chinese and global crude oil futures

Yuying Yang\textsuperscript{a}, Yan-Ran Ma\textsuperscript{b,c}, Min Hu\textsuperscript{d}, Dayong Zhang\textsuperscript{d}, Qiang Ji\textsuperscript{b,c,*}

\textsuperscript{a} Business School, University of Shanghai for Science and Technology, 200093, Shanghai, China
\textsuperscript{b} Institutes of Science and Development, Chinese Academy of Sciences, Beijing 100190, China
\textsuperscript{c} School of Public Policy and Management, University of Chinese Academy of Sciences, Beijing 100049, China
\textsuperscript{d} Research Institute of Economics and Management, Southwestern University of Finance and Economics, China

\begin{abstract}
This paper investigates the risk spillover between China’s crude oil futures and international crude oil futures by constructing upside and downside VaR connectedness networks. The findings show that China’s crude oil futures behave as a net risk receiver in the global crude oil system, in which Brent and WTI play the leading roles in risk transmission in the system. The dynamic results indicate that the risk spillover between Chinese and international crude oil futures presents obvious time-varying characteristics and has risen sharply since the beginning of 2020, induced by the COVID-19 pandemic.
\end{abstract}

\section{Introduction}

Since the global financial crisis in 2008, the international crude oil market has been in a fragile state, as there is high investor panic and the market price fluctuates violently. In particular, under the shocks of the global pandemic of COVID-19 in 2020, global oil demand was weak. In addition, with the breakdown of the OPEC + alliance negotiation, Saudi Arabia initiated an oil price war with Russia, which finally led to the price of WTI oil futures for May delivery falling into negative territory (-$37.63/bbl) for the first time in recorded history. The drastic volatility of international crude oil prices undoubtedly brings huge risks to market participants (Ji et al., 2020).

On March 26, 2018, China’s crude oil futures was officially launched and traded in Shanghai International Energy Exchange. After more than two years, it has become the third largest crude oil futures contract in the world, followed by WTI and Brent (Ji and Zhang, 2019). With China becoming the world’s largest crude oil importer, its influence in the global crude oil market has also been increasing. However, there is limited research on Chinese crude oil futures focusing on the evaluation of its market efficiency. Ji and Zhang (2019) first analysed China’s crude oil futures but only presented some stylized fact using three months of high-frequency data. Yang et al. (2019) and Li et al. (2020) discussed the market efficiency and hedging performance of China’s crude oil futures, confirming that China’s crude oil futures have preliminary futures market functions. Wang et al. (2019) compared the multifractal characteristics of Shanghai’s crude oil futures (INE) with those of WTI and Brent and found that the risk level of INE was lower than that of WTI and Brent.

In terms of the above research, there has been no quantitative analysis on the risk spillover relationship between China’s crude oil

\* Corresponding author at: Institutes of Science and Development, Chinese Academy of Sciences, China.
E-mail address: jqwxnjq@163.com (Q. Ji).

https://doi.org/10.1016/j.frl.2020.101743
Received 23 June 2020; Received in revised form 25 August 2020; Accepted 29 August 2020
Available online 30 August 2020
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futures and international benchmark crude oil futures. According to Ji and Zhang (2019), the night trading of China’s crude oil futures is more active, suggesting that traders in China’s crude oil market are more likely to follow international crude oil futures prices for pricing. Therefore, understanding the risk spillover relationship between China’s crude oil futures prices and international crude oil futures prices is of great importance for foreign investors to better capture the risk characteristics of China’s crude oil futures and for relevant decision-makers to formulate risk prevention and control measures.

The main contributions of this paper are two-fold. First, this paper is the first to quantitatively analyze the dynamic risk spillover relationship between Chinese and international crude oil futures (WTI, Brent and Oman), especially in terms of identifying the global crude oil market risk contagion since the new coronavirus outbreak in 2020. Secondly, this paper constructs a risk connectedness network of the global crude oil market based on the VaR measure. Specifically, we use various GARCH-class models to estimate the VaR of the return series of crude oil futures and use the connectedness network method proposed by Diebold and Yilmaz (2014) to explore the cross-market risk links between Chinese and international crude oil futures from the perspective of extreme risk, focusing on the international position of China’s crude oil futures in the global crude oil system. This paper provides the new evidence that China’s crude oil futures behave as a net risk receiver in the global crude oil risk system, in which Brent and WTI play the leading roles in risk transmission in the system.

The rest of this paper is structured as follows: Section 2 introduces VaR and the risk spillover network; Section 3 provides the data analysis and empirical results; and the last section concludes the main findings.

2. Methodology

In this section, four different GARCH models (GARCH, EGARCH, GJRGARCH and APARCH) are used to explore the optimal marginal distribution of each crude oil market return, and the corresponding market risk value (VaR) is calculated. Then, the network of the global crude oil futures system is constructed to identify the extreme risk spillover of crude oil futures.

2.1. VaR

The four selected GARCH-class models are introduced in Appendix A1. By estimating the optimal GARCH-class model, the marginal distribution of each crude oil futures return is obtained, then we can use VaR to quantify the extreme risk of crude oil futures returns. Following the definition of VaR, the upside risk and downside risk of crude oil futures returns can be given as follows:

\[
VaR^{U,t}_i = \mu_i + \tau^{-1}(1-\alpha)\sigma_i
\]

\[
VaR^{D,t}_i = \mu_i + \tau^{-1}(\alpha)\sigma_i
\]  

(1) (2)

2.2. Connectedness network modeling

Based on the connectedness network method proposed by Diebold and Yilmaz (2014), this paper constructs the risk spillover network of global crude oil futures VaRs. The connectedness network is a new method based on the vector autoregressive model and generalized variance decomposition to describe the explanatory power of the system. It has been widely used in the fields of risk contagion and systemic risk across markets. This method can more intuitively describe the direction and intensity of information spillover and has more advantages than traditional econometrical methods (e.g., cointegration, causal analysis, etc.) in the analysis of multivariate relations. The key point of this method is the H-step-ahead generalized forecast error variance obtained by using the generalized variance decomposition proposed by Pesaran and Shin (1998), $\theta^H_{ij} = \frac{\alpha^{-1}\sum_{h=0}^{H-1} A_h\Sigma_{ij}}{\sum_{h=0}^{H-1} A_h\Sigma_{ii} A_h\Sigma_{jj}}$. Then, a series of indexes are constructed to describe the network (for details, refer to Elie et al., 2018; Geng et al., 2021; Hu et al., 2020; Ji et al., 2019; Maghyereh et al., 2016; Song et al., 2019; Wu et al., 2020).

Table 1

| Summary statistics of crude oil futures returns. |
|------------------------------------------|
| **INE** | **WTI** | **Brent** | **Oman** |
| Observations | 537 | 537 | 537 | 537 |
| Mean | −0.08 | −0.18 | −0.13 | −0.14 |
| Max. | 8.18 | 24.67 | 21.02 | 20.79 |
| Min. | −9.02 | −24.59 | −24.10 | −26.91 |
| Std. Dev | 1.92 | 3.23 | 2.77 | 3.04 |
| Skewness | −0.36 | −0.15 | −0.26 | −0.81 |
| Kurtosis | 6.12 | 27.11 | 23.79 | 22.91 |
| Jarque-Bera | 229.38*** | 13,010.70*** | 9674.68*** | 8929.85*** |
| ADF | −19.15*** | −25.17*** | −21.03*** | −24.79*** |

Notes: *** denotes significance at the 1% level.
3. Data and empirical results

3.1. Sample analysis

This paper selects WTI, Brent, and Oman futures as the three benchmarks of international crude oil futures as well as the Shanghai crude oil futures (INE) as representative of China’s crude oil futures. The sample data ranges from March 26, 2018, which is the official launch date of China’s crude oil futures, to April 16, 2020, with 537 daily observations. All the data is from the wind financial database. Table 1 shows the summary statistics of the daily returns of crude oil futures. The means of the four crude oil futures are all negative but close to 0. China’s crude oil futures has the minimum standard deviation of 1.92, which indicates it has a weaker volatility than that of the international benchmark crude oil futures. In addition, the four crude oil futures present left-skewed and leptokurtosis characteristics and are not normally distributed, as verified by the Jarque-Bera test. All the return series are stationary verified by the ADF unit root test. The optimal model of the marginal distribution for each return series is confirmed according to the Loglikelihood and AIC criteria (The estimated coefficients are shown in Appendix A2). Among them, INE, WTI, Brent, and Oman correspond to the ARMA (1,2)-GARCH (1,1), ARMA (1,1)-EGARCH (2,2), ARMA (2,2)-EGARCH (2,1), ARMA (2,2)-EGARCH (1,1) models, respectively.

Fig. 1 presents the upside and downside VaRs for the four crude oil futures returns. It is found that the trends of the upside and downside VaRs are basically similar over time, and the fluctuation range of the downside VaR (absolute value) is slightly higher than that of the upside VaR. In addition, it also shows that, under the influence of the COVID-19 pandemic and the Saudi Arabia oil price war, the upside and downside VaRs of the four crude oil futures have fluctuated dramatically since 2020, and the risk values of the international markets are greater than that of China’s crude oil futures market.

3.2. Empirical results

3.2.1. Static analysis

In this section, we construct the connectedness network based on the estimated VaRs for VAR. All variance decomposition matrices are constructed by the VAR model with one lag and 10 steps ahead the generalized forecast variance decomposition results.

Table 2 presents the extreme risk spillover matrix between the Chinese and international benchmark crude oil futures. The table shows that the total connectedness spillover indices in the downside and upside risk network are 46.91% and 53.49%, respectively, which indicates that there is a high degree of risk integration in the international crude oil system. Specifically, the risk contribution of China’s crude oil market to the downside risk system is the smallest among the four crude oils, accounting for 8.73%, and its contribution to the upside risk system is also the smallest, only reaching 0.61%. In contrast, the contribution of the international benchmark crude oil to the system is far higher than that of China’s crude oil, with WTI having the largest downside risk contribution of 69.93% and Brent having the largest upside risk contribution of 81.87%.

From the perspective of net spillover level, the international benchmark crude oils behave as the net risk transmitter, in which Brent has the largest net risk contribution to the system for both the upside and downside risk system. China’s crude oil futures is the only net risk receiver in the system, and the net risk acceptance degree (absolute value) is higher than 30%. In other words, WTI and Brent play leading roles in the transmission of extreme risks in the crude oil system, while China’s crude oil has remained in a relatively passive position. The inflow and outflow of Oman’s risk spillover to the system are basically equal. According to the pairwise risk spillover of crude oils, the downward risk of China’s crude oil futures is mainly affected by the risk spillover from WTI and Oman, while its upward risk is mainly affected by WTI and Brent.

3.2.2. Dynamic analysis

In order to better understand the dynamic changes of the extreme risk between crude oil futures, we adopt the rolling window method to estimate the dynamic extreme risk spillover of the crude oil futures system. We choose 66 trading days (nearly three months) as the rolling window length.1

Fig. 2 shows the dynamic connectedness of the downside risk and upside risk of the crude oil futures system. As a whole, the overall change of the upside and downside risk connectedness in the crude oil futures system are similar, both showing a sharp fluctuation trend. Specifically, the trend can be divided into three periods. The first one covers the period from the beginning of the sample to April 2019, and the second covers the period from May 2019 to the end of 2019. During these periods, a series of emergencies, such as the US oil ban on Iran, the explosion of oil tankers in the Oman sea, and the rocket attack on Iraq’s oil production base, are the main reasons for the risk changes. The last stage has been appearing since the beginning of 2020, with the risk connectedness rising continuously, reaching a peak around the end of March 2020. This sharp change can be attributed to the COVID-19 pandemic, which has resulted in a global economic slowdown and a decline in crude oil demand.

In addition, Table 3 shows the basic statistics of the dynamic risk spillover of the international benchmark crude oils from and to China’s crude oil. It can be seen from the table that the mean of the net risk spillover of the three benchmark crude oils to China’s crude oil is positive, which is consistent with the static results. In addition, from the positive proportion of risk net spillover, although China’s crude oil market remains in a relatively passive position in general, there is still 20%–30% of time in the dynamic window period that

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1 We also estimate the dynamic results by selecting 66 and 132 trading days as window size for robustness check. The dynamic results for the crude oil system are similar based on the different window length indicating the stable connectedness between Chinese and the global crude oil markets. These robustness results can be requested from the authors for space saving.
China's crude oil can provide a net positive risk contribution to the international crude oil market. This also indicates that the fluctuation in China's crude oil futures will also have a certain impact on the international crude oil market in the short term, and the influence of China's market cannot be completely ignored.

4. Conclusions

This paper investigates the risk spillover effect between China's crude oil futures and international benchmark crude oil futures by constructing a network method based on extreme risk.

It was found that there is a high degree of integration in the extreme risk of the crude oil futures system. WTI and Brent play a leading role in the international crude oil market system. The spillover level of upside risk is higher than that of downside risk, and the Chinese crude oil market is more sensitive when the international crude oil market rises. The connectedness of extreme risk is easily affected by external events, showing obvious time-varying characteristics. Especially after the COVID-19 outbreak, the spillover level of the international benchmark crude oil to China's crude oil market rose sharply.

Generally speaking, China's crude oil futures is obviously exposed to risk spillover from the international crude oil market. Thus, all market participants should be cognizant of the bidirectional risk spillovers between Chinese and the global crude oil futures. The
For policy markers, they should remain vigilant of the effects of global crude oil market extreme movements on the Chinese markets. Specially, they should formulate effective regulatory policies to prevent the high risk induced by excessive speculation. In the future, the difficult task of improving the pricing influence of China’s crude oil market should receive greater focus.

Table 3
Pairwise risk connectedness between Chinese and international crude oils.

| Risk  | INE | Risk outflow | Risk inflow | Net risk spillover | Proportion |
|-------|-----|--------------|-------------|-------------------|------------|
|       | Mean | Std. Dev     | Mean        | Std. Dev          | Mean       | Std. Dev |
| Downside risk | WTI  | 13.56 | 10.98 | 4.27 | 3.91 | 9.29 | 10.78 | 79.19% |
|       | Brent | 9.18  | 8.27 | 4.21 | 4.09 | 4.97 | 7.24 | 83.65% |
|       | Oman  | 13.42 | 7.95 | 10.49 | 7.85 | 2.93 | 6.99 | 70.70% |
| Upside risk | WTI  | 19.44 | 8.56 | 6.72 | 6.24 | 12.72 | 13.10 | 84.71% |
|       | Brent | 14.32 | 9.44 | 4.75 | 4.38 | 9.58 | 11.48 | 77.71% |
|       | Oman  | 11.65 | 8.53 | 3.16 | 2.41 | 8.49 | 8.57 | 79.41% |

Note: Risk outflow means the risk spillover from the international crude oil to INE, while risk inflow means the risk spillover from INE to international crude oil. Net risk spillover is the difference between risk outflow and risk inflow. Proportion is the percentage of the positive values of the net risk spillover in all dynamic windows.

CRediT authorship contribution statement

**Yuying Yang:** Data curation, Methodology, Formal analysis, Writing - original draft. **Yan-Ran Ma:** Methodology, Writing - original draft, Writing - review & editing. **Min Hu:** Writing - original draft. **Dayong Zhang:** Supervision, Methodology, Writing - review & editing. **Qiang Ji:** Supervision, Writing - review & editing, Funding acquisition.

Acknowledgements

Supports from the National Natural Science Foundation of China under Grant No. 71974181, 71974159, 71774152, and Youth Innovation Promotion Association of Chinese Academy of Sciences (Grant: Y7×0231505) are acknowledged.

Appendix

A1. **GARCH-class models**

First, the mean equation is established using the ARMA (m, n) model as follows:
The crude oil futures return at time $t$, $\rho_t$, is the crude oil price at time $t$; and $\epsilon_t$ is the conditional variance. In addition, in order to capture the asymmetric and fat tail characteristics of the return series, the skew-t distribution is used instead of the normal distribution in this paper.

**A2. Coefficients estimation for marginal model of each crude oil returns**

|        | INE | WTI | Brent | Oman |
|--------|-----|-----|-------|-------|
| $\mu$  | 0.13*** | -0.35 *** | -0.13 *** | 0.13 *** |
|        | (6268.96) | (-14,225.4) | (-13,569.6) | (47,127.71) |
| AR(1)  | 0.99*** | 0.93 *** | 1.36 *** | 0.18 *** |
|        | (192.37) | (8545.4) | (18,370.2) | (5465.05) |
| AR(2)  | 0.99 *** | -0.82 *** | -14,837.7 | -1653.00 |
|        | (-11,740.38) | (-12,221.9) | (-3595.5) | (-5329.71) |
| MA(1)  | -0.92 *** | -0.90 *** | -1.38 *** | -0.17 *** |
|        | (1.01) | (12,988.01) | (19.06) | (19.06) |
| MA(2)  | 0.05 *** | 0.04 *** | 0.10 *** | 0.10 *** |
|        | (7,82) | (10,147.2) | (14,290.2) | (15.25) |
| $\omega$ | 0.37*** | 0.05 *** | 0.04 *** | 0.10 *** |
|        | (9181.6) | (12,988.01) | (19.06) | (19.06) |
| $\alpha_1$ | 0.14*** | -0.27 | -0.19 *** | -0.32 *** |
|        | (19.42) | (-13,396.6) | (-5375.4) | (-19.06) |
| $\alpha_2$ | -0.05 *** | -0.06 *** | -14,755.2 | -7283.5 |
|        | (96.35) | (17,342.3) | (16,300.3) | (2861.99) |

(continued on next page)
\[
\begin{array}{cccc}
\gamma_1 & 0.25^{***} & 0.23^{***} & 0.03^{***} & 0.24^{***} \\
       & (0.06)    & (0.03)    & (0.02)    & (0.03)    \\
\gamma_2 & 0.38^{***} & 0.18^{***} & 0.01^{***} & 0.30^{***} \\
       & (1495.71) & (12779.4) & (12787.4) & (1495.71) \\
Shape & 11.7^{***} & 2.6^{***} & 2.0^{***} & 1.9^{***} \\
       & (2.06)    & (1067.13) & (13075.1) & (15054.1) \\
LL & -1027.81 & -1142.09 & -1083.51 & -1118.73 \\
AIC & 3.87 & 4.29 & 4.08 & 4.21 \\
ARCH (20) & 179.08 & 233.74 & 196.48 & 186.15 \\
Q (20) & 30.53 & 71.00 & 45.58 & 53.31 \\
Q^2 (20) & 419.20 & 391.44 & 291.24 & 427.53 \\
K-S test & 0.00 & 0.00 & 0.00 & 0.00 \\
\end{array}
\]

Notes: This table reports the estimated coefficients for the optimal marginal distribution model verified by the Loglikelihood and AIC criteria. The lags p, q, m and n are selected using the AIC for different combinations of values ranging from 0 to 2. Standard deviations for each coefficient is shown in the parenthesis. Q (20) and Q^2 (20) are the Ljung-Box statistics for serial autocorrelation in the model residuals and squared residuals, respectively. ARCH is the Engle LM test for the ARCH effect in the residuals. K-S test denotes the Kolmogorov-Smirnov test (for which the p-values are reported). ***., ** and * significance at the 1%, 5% and 10% levels, respectively.

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