Modeling Extreme Risk Spillovers between Crude Oil and Chinese Energy Futures Markets

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Abstract

This paper aims to model the extreme risk spillovers between crude oil and Chinese energy futures markets to assess the effect of excessive oil price volatility on Chinese

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energy sectors. To this end, we set up a Generalized Autoregressive Conditional Heteroskedasticity - Extreme Value Theory Value-at-Risk specification (or GARCH-EVT-VaR hereafter) to flexibly model extreme risks. Moreover, we focus on two international crude oil futures markets and ten Chinese energy futures markets to measure the extreme risk spillovers. Our findings point to two main results. First, we find significant evidence of extreme risk spillovers from the two international crude oil markets to Chinese energy futures markets, which are asymmetric. More specifically, the spillover effects across extreme risks are more significant than those measured with the return series. Second, some Chinese energy future markets also exhibit internal extreme risk spillovers from the petrochemical sector to the coal sector. These findings reveal the potential vulnerability of Chinese energy sectors and call for active risk management policies to better hedge Chinese energy futures markets against extreme events.

Keywords: Connectedness; Network analysis; Energy futures markets; Extreme risk spillovers

1 Introduction

The focus on extreme risk spillovers of crude oil market for China is important for at least two reasons. On the one hand, while crude oil market is a global market, it has shown over the two last decades an excessive volatility and extreme risk caused by different shocks: a demand shock (2008-2009 global financial crisis, COVID-19, etc.), a supply shock (shale revolution in 2014, failure of Russia-Saudi Arabia meeting in March 2020, etc.) and a (geo)-political shock (geopolitical tensions in Gulf countries, COVID-19 lockdown related measures, the war in Ukraine in 2022, etc.). These different events have disturbed the pricing of oil on the global market and caused a significant volatility, which has also disturbed regional or local oil markets. For example, the price of the WTI turned negative for the first time in the history in April 2020.

On the other hand, in addition to being an important trade partner, China has become the biggest oil consumer country in the world. Oil price has become increasingly dependent on Chinese oil demand. In fact, the decline of Chinese economy in 2020 and therefore the decline of Chinese oil consumption of 30% has caused a serious oil price correction during the coronavirus pandemic. At the same time, more evidence shows the dependence of Chinese energy sectors on oil price. At the beginning of 2023, the China Petroleum and Chemical Industry Association announced that China's external dependence on crude oil imports in 2022 was more than 70%. China imported 508.28 million tons of crude oil, which decreased by 0.9% year-on-year, but the cost increased by 41.4% year-on-year. This indicates that the import burden increased sharply.

For this reason, it is important to assess further interactions and risk spillovers between the global oil market and Chinese Energy Futures markets (Pan et al., 2021, Si et al., 2021, Wen et al., 2021, Duan et al., 2023a). This is particularly interesting, considering the fact that the excessive oil price volatility and the relative short establishment of Chinese futures markets are always used for hedging strategies and their small-scale market size (Chun et al., 2014, Ji et al., 2018, Shen et al., 2018, Yang et al., 2021, Duan et al., 2023b). While still in their infancy, China's energy futures markets are crucial for China to strengthen its internal energy supply and demand structure, hedge risks, enrich financial investment products, and expand its global impact. It is crucial to investigate the network architecture of the Chinese energy futures market, the interaction between network nodes, and their sensitivity to changes in the price of crude oil (Chen et al., 2021, Niu & Hu, 2021).

In the literature, previous studies showed further evidence of spillover effects between the global crude oil market and Chinese energy markets (Yang & Zhou, 2020, Yang et al., 2021, Gong et al., 2021, Li et al., 2022, Ouyang et al., 2022, Ren et al., 2022), suggesting that the Chinese domestic market is closely linked to the international crude oil market. However, the investigation of these spillover effects is still challenging and inconclusive. Furthermore, the channels behind these spillover effects are not investigated.

Unlike previous related papers that have always limited their analyses of extreme risk spillovers to a few energy markets (Zhang & Sun, 2016, Geng et al., 2021b, Ahmad & Rais, 2018, Gong et al., 2021, Ouyang et al., 2022, Ren et al., 2023, Wang et al., 2023), this study extends this literature by considering a large class of key Chinese energy commodities and a more flexible econometrics framework. To achieve this, we construct a multi-energy market analysis framework and we provide a large matrix analysis for potential losses in the Chinese energy futures market. In particular, we focus on 10 different Chinese energy commodities that include almost all the major energy futures markets in China. Additionally, we analyze their further spillover effects with regard to two international major crude oil markets: the WTI and the Brent, as well as across Chinese energy futures markets.

Methodologically, we proceed in different steps. On the one hand, we propose to compute the extreme risk or the highest loss for each energy market using the Value at Risk (VaR) based on the Extreme Value Theory (EVT) and the Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH) model. On the other hand, we test and estimate the extreme risk spillover effects among the energy markets under consideration using the methodology proposed by Diebold & Yilmaz (2009, 2012).The approach they created fits the peculiarities of financial data and depicts the situation at the extreme tail better, and increases accuracy by basing it on the concepts of variance decomposition and time-varying likelihood. The performance of extreme spillover among energy futures markets matches properly with this proven method for measuring spillover effect.

Overall, our results point to two interesting findings. First, we find that the global oil market constitutes a net transmitter of risk to Chinese energy futures markets, suggesting further vulnerability/dependence of the Chinese energy sectors to the international oil market. Second, there is no denying the existence of cross-market risk spillover among these energy futures markets, but it does always depend on the couple of domestic energy sectors under consideration. More specifically, the petrochemical sector has the leading role in risk transmission to the coal sector but not for all other sectors. A significant extreme risk spillover effect across domestic sectors is a sign of close integration between the Chinese energy futures markets. The performance of extreme risk spillover can be exploited to assess diversification investment.

The contribution of our current study is twofold. On the one hand, unlike the related previous literature that focuses on risk transmission across return or volatility spillover, we propose to investigate risk spillover effects via an extreme risk way, which is particularly relevant to reproduce risk transmission induced by extreme events. On the other hand, by focusing on a large class of key Chinese Energy futures markets, we provide a more complete analysis of the Chinese network structure of energy markets, while identifying leading sectors and vulnerable sectors to risk spillovers. This categorization is particularly useful to set up an efficient risk management strategy.

The rest of the paper is organized as follows. Section 2 briefly presents the related literature on extreme risk estimation methods. Section 3 discusses the methodology related to the value at risk (VaR) and the connectedness measurement methods. The data and preliminary analysis are presented in Section 4. Section 5 discusses the main empirical results related to extreme risk spillovers among the energy futures. The last section concludes.

2 Literature

While the investigation of spillover's effects between energy markets is not a new question (Lin & Tamvakis, 2001, Haigh & Holt, 2002), previous studies have basically conducted this question either for developed economies or for oil countries producers to test their dependence to the oil sector. Further, several previous studies considered often a couple of two markets (i.e. dynamic volatility spillovers across oil and natural gas futures markets, carbon and fossil energy markets (Gong et al., 2021), and spillover's effect between oil and stock market (Jawadi & Arouri, 2011), etc.

The analysis of spillover's effects for energy sectors for China and through a multi-analysis is still scarce and inconclusive in particular about the drivers of these spillover's effects. But the energy futures market is playing a bigger and bigger part in China's economic system lately as a sector that has received considerable support from the Chinese government (Lv et al., 2020). The copula-based model developed by Wen & Nguyen (2017) validates the potential for risk diversification that comes with China's energy futures, which may be used in conjunction with gold and other commodity markets to reduce investor risk. Through the use of the VAR(1)-DCC-GARCH(1,1) model, Lin & Chen (2019) and Cao et al. (2022) proved the long-term persistence and significant spillover effects among the financial markets, carbon trading market, and coal futures market. Li et al. (2022) recently investigated the volatility spillovers of international crude oil markets on seven major Chinese energy markets, and the authors associated these spillovers to the COVID-19 pandemic. Further, most previous studies examine the spillover's effect assumption using first and second moments, which are not suitable enough to capture inter-market spillovers caused by extreme events and extreme risks, source of systemic risk by excellence (Wu et al., 2021).

Even, for the energy futures market, given the important and frequent shifts in energy prices, the focus on spillover's effect around the extreme values is relevant and it enables us to capture further extreme risk co-movement. To this end, the Extreme Value Theory (EVT), always used to investigate extreme events, is a relevant framework (McNeil & Frey, 2000). In such context, Marimoutou et al. (2009) calculated the VaR of the oil market and found that conditional extreme theory performs better than traditional methods. Feng et al. (2012) also used GARCH-EVT-VaR model to study the risk spillover of carbon futures and spot markets in extreme risk conditions. They found that a dynamic VaR calculated with GARCH fully estimates the risk of carbon return fluctuation, and that a dynamic VaR based on GARCH-EVT is more accurate than a dynamic VaR based on GARCH. Youssef et al. (2015) confirmed that considering asymmetry and fat tails in the behavior of energy commodity price returns combined with filtering processes, such as EVT, improves risk management assessments and hedging strategies in the highly volatile energy market.

That is, it is however worth to recall that the VaR approach measures only the maximum of potential losses and one needs to adopt other methods to estimate spillover effects among markets. Obviously, there are a variety of ways to analyze risk transmission. Tiwari et al. (2020) used the delta conditional value at risk (ΔCoVaR) to capture the risk spillovers across the oil and stock markets. Diebold & Yilmaz (2009) applied a measure of volatility connectedness based on variance decomposition, which includes the generalized vector auto-regressive framework in the spillover measurement so that the variable ordering remains unchanged. Their method has been extended and improved several times later by the same authors (Diebold & Yilmaz, 2012, 2014). Since then, this method of risk spillover measurement has been widely used. Xiao et al. (2020) used it to estimate the connectedness of 18 commodities in China. Naeem et al. (2020) applied this approach and its extension in the frequency domain to investigate the temporal and frequency links between the electricity, carbon, and clean energy markets, as well as oil price demand and supply shocks. Geng et al. (2021a) applied a connectedness network analysis to explore the dynamic information connectedness effect of the natural gas market, uncertainty, and the stock market in North America and Europe.

In this study, given the suitability and enough flexibility of the Diebold & Yilmaz (2009, 2012, 2014) method in measuring the spillover effects among markets, we apply this approach hereafter to examine risk transmission across energy futures markets. In particular, in line with Ouyang et al. (2022), we propose to investigate linkages between oil market and energy futures in China as well as spillovers across Chinese domestic energy sectors. To this end, we propose a GARCH-EVT-VaR measure for extreme risk and we build a framework similar to Diebold & Yilmaz (2012)'s work to measure extreme risk spillovers.

3 Econometric Methodology

Our methodology refers to two types of financial econometrics framework. First, we estimate the VaR of each energy futures sequence while relying on GARCH-EVT models, which can provide a more accurate estimation of extreme tails. Second, we provide a connectedness matrix of pairwise VaRs using Diebold & Yilmaz (2009, 2012, 2014)'s approach.

3.1 The VaR estimation

We propose to model the daily return of the energy futures price by the following GARCH(p,q) model to capture the further clustering and heteroskedasticity effects in the data:

$$\begin{aligned} R_{t+1} &= \mu_{t+1} + \varepsilon_{t+1} \\ \varepsilon_{t+1} &= z_{t+1}\sigma_{t+1} \\ \sigma^2_{t+1} &= \omega + \sum_{i=1}^{p} \alpha_i \varepsilon^2_{t+1-i} + \sum_{i=1}^{q} \beta_i \sigma^2_{t+1-i}, \end{aligned} \tag{1}$$

where μ_{t+1}, σ_{t+1} denote the conditional mean and volatility of the energy future return given all the information up to time t, respectively. ε_t is an independent and identically distributed error term and $z_t \sim N(0,1)$.

The simplest form of this equation, corresponds to a GARCH (1,1) model, which is the most commonly used specification in practice. This specification has only one lagged squared term of unexpected returns and one autoregressive term, i.e.,

$$\sigma^2_{t+1} = \omega + \alpha_1 \varepsilon^2_t + \beta_1 \sigma^2_t\,, \quad \text{with } \alpha_1 + \beta_1 < 1. \tag{2}$$

In practice, this specification is useful to produce a standard residual sequence that satisfies the approximate independent homo-distribution, and the elimination of variance dynamic assumptions required by the EVT framework. Regarding the EVT framework, it is important to recall that, basically elaborated by Emil Julius Gumbel who proposed the Gumbel distribution, the EVT is often used to analyze probabilistic rare situations. In this paper, we propose to apply the Peaks Over Threshold (POT) modeling of EVT, which models extreme events while focusing not only on the largest (maximum) events but also on all events greater than some large preset threshold. Accordingly, the EVT holds that tails follow the following Generalized Pareto distribution (GPD):

$$GPD(y;\xi,\beta) = \begin{cases} 1-\left(1+\frac{\xi y}{\beta}\right)^{-\frac{1}{\xi}} & \text{if } \xi > 0 \\ 1-e^{\left(-\frac{y}{\beta}\right)} & \text{if } \xi = 0 \end{cases}, \tag{3}$$

where the so-called tail-index parameter ξ controls the shape of the tail of the distribution and in particular how quickly the tail goes to zero when the extreme, y, goes to infinity. It can be estimated with the Maximum Likelihood Estimate (MLE). In practice, before we estimate it, the tail should be defined, and a threshold u should be set. If the value exceeds the threshold, it is in the tail. The value of the parameters in the estimation of the GPD distribution is taken only from the tail—that is, from the value that is not smaller than the threshold u. If u is too large, the tail value will be very small and this estimate will not be stationary. However, if u is too small, the tail value will be too large to conform to the hypothesis of the EVT model, leading to biased results. That is, using the empirical estimation method proposed by Christoffersen (2012), we select the threshold u which could guarantee that the number of tail values is about 50.

The tail-index parameter ξ of the GPD distribution can be estimated with the Hill estimator. The key idea behind the Hill estimator is to approximate the GPD distribution (3) by

$$F(y) = 1 - cy^{-1/\xi} \approx 1 - (1+\xi y/\beta)^{-1} = GPD(y;\xi,\beta)\ ,$$

for $y > u$ and $\xi > 0$. Then, we can use the maximum likelihood estimation methods(MLE) to get the Hill estimator as follows,

$$\xi = \frac{1}{T_u}\sum_{i=1}^{T_u} \ln\left(\frac{y_i}{u}\right)\ , \quad \text{for } y_i > u\,, \tag{4}$$

where T_u is the number of observations y larger than u. The parameter c is estimated by

$$c = \frac{T_u}{T} u^{1/\xi}\,, \tag{5}$$

where T is the total number of observations. The cumulative density function for observations beyond u is accordingly approximated by

$$F(y) = 1 - cy^{\frac{1}{\xi}} = 1 - \frac{T_u}{T}\left(\frac{y}{u}\right)^{\frac{1}{\xi}}\,. \tag{6}$$

Dynamic VaR is commonly used to measure the risk of returns in practice, since it will change drastically in according to a drastic change in returns. The dynamic VaR from the EVT combined with the variance model can be calculated as:

$$\mathrm{VaR}^{p}_{t+1} = \mu_{t+1} + \sigma_{PF,t+1} F^{-1}_{1-p} \tag{7}$$

where the loss quantile F^{-1}_{1-p} is given by

$$F^{-1}_{1-p} = u\left[\frac{p}{\left(\frac{T_u}{T}\right)}\right]^{-\xi} \tag{8}$$

and $\sigma_{PF,t+1}$ is estimated by using the GARCH model.

3.2 Connectedness

Based on a vector auto-regression (VAR) model, the decomposition of the generalized forecasting error variance is an essential part of the framework of Diebold & Yilmaz (2012). First, we set up the following Generalized VAR (GVAR) model:

$$X_t = \sum_{i=1}^{P} \Phi_i X_{t-i} + \varepsilon_t \tag{9}$$

where: X_t stands for an $N \times 1$ vector of the possible endogenous variables. Φ_i stands for the $N \times N$ auto-regressive coefficient matrices, while $\varepsilon \sim (0, \Sigma)$ is a vector of independent and identically distributed disturbances with 0 mean and Σ covariance matrix. We can represent the VaR process explained above as:

$$X_t = \sum_{i=1}^{\infty} B_i \varepsilon_{t-i} \tag{10}$$

where: B_i denotes an $N \times N$ coefficient matrix, which satisfies a recursion of the form $B_i = \Phi_1 B_{i-1} + \Phi_2 B_{i-2} + \cdots + \Phi_p B_{i-p}$. B_0 among them is the $N \times N$ identity matrix, while $B_i = 0$ when $i < 0$. Then, based on the H-step ahead Forecasting Error Variance Decomposition (FEVD) method, we define our own variance components and cross-variance components for the energy markets in our work. The spillover index $\theta_{ij}(H)$ is the cross-variance components defined as:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' B_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' B_h \Sigma B_h' e_i\right)} \tag{11}$$

where: Σ denotes the covariance matrix of the vector of errors ε, and σ_{jj} represents the standard deviation of the error term of the j^{th} equation and e_i is a selection vector with the i^{th} element as 1 and the remaining elements as 0. Then, we standardize the spillover index in Eq.(11) as follows:

$$\tilde{\theta}_{ij}(\mathrm{H}) = \theta_{ij}(H) / \sum_{j=1}^{N} \theta_{ij}(H) \tag{12}$$

with $\sum_{j=1}^{N} \tilde{\theta}_{ij}(\mathrm{H}) = 1$ and $\sum_{ij=1}^{N} \tilde{\theta}_{ij}(\mathrm{H}) = N$ by construction. Among them, the $\tilde{\theta}_{ij}(\mathrm{H})$ is the pairwise directional connectedness which is from j to i at the level H. And then total spillover index can be calculated as:

$$C(H) = \frac{\sum_{ij=1, j\neq i}^{N} \widetilde{\theta}_{ij}(H)}{\sum_{ij=1}^{N} \widetilde{\theta}_{ij}(H)} \times 100 = \frac{\sum_{ij=1, j\neq 1}^{N} \widetilde{\theta}_{ij}(H)}{N} \times 100 \tag{13}$$

Next, we further measure the total direct connectedness of individual markets to analyze the specific market's contribution to the process of risk spillovers. We concentrate on each single market and assess the total risk it receives or transfers. The from connectedness that measures the shocks from all other sectors to sector i is calculated as:

$$C_{i \leftarrow *}(H) = \frac{\sum_{j=1, j\neq i}^{N} \widetilde{\theta}_{ij}(H)}{\sum_{ij=1}^{N} \widetilde{\theta}_{ij}(H)} \times 100 = \frac{\sum_{j=1, j\neq 1}^{N} \widetilde{\theta}_{ij}(H)}{N} \times 100. \tag{14}$$

The connectedness, which represents the total risk that released by market i to the other 11 markets in the network in the framework is computed as:

$$C_{* \leftarrow i}(H) = \frac{\sum_{j=1, j\neq i}^{N} \widetilde{\theta}_{ji}(H)}{\sum_{ij=1}^{N} \widetilde{\theta}_{ji}(H)} \times 100 = \frac{\sum_{j=1, j\neq 1}^{N} \widetilde{\theta}_{ji}(H)}{N} \times 100. \tag{15}$$

Finally, we specify the net directional connectedness of market i to all other markets as:

$$C_i(H) = C_{*\leftarrow i}(H) - C_{i\leftarrow *}(H) \tag{16}$$

Hereafter, We will construct a connectedness table to visualize the connectedness network. The elements in this table will show the pairwise directional connectedness between each two markets.

4 Data and Preliminary Analysis

4.1 The Data

Figure 1 shows the energy markets selected for this study and the criteria used to classify them. The Chinese energy markets include coal, fuel oil, etc, while the international crude oil markets are the Brent and WTI crude oil markets. We divide the 10 energy markets in China and the two dominant international crude oil markets into upstream and downstream players based on the industry characteristics. Also, based on the industry chains, they are divided into the petrochemical industrial chain and the coal industrial chain. Table 1 shows the symbols of all of the energy futures markets. We obtained daily price data for energy futures from the Wind database. Considering the time of the establishment of Chinese energy futures markets and the data availability and representativity, we select the daily price series of the main futures contracts of the 12 energy commodities from June 17, 2014, to March 22, 2022. The data include all the main energy futures listed and traded on Chinese futures exchanges (see Table 1).

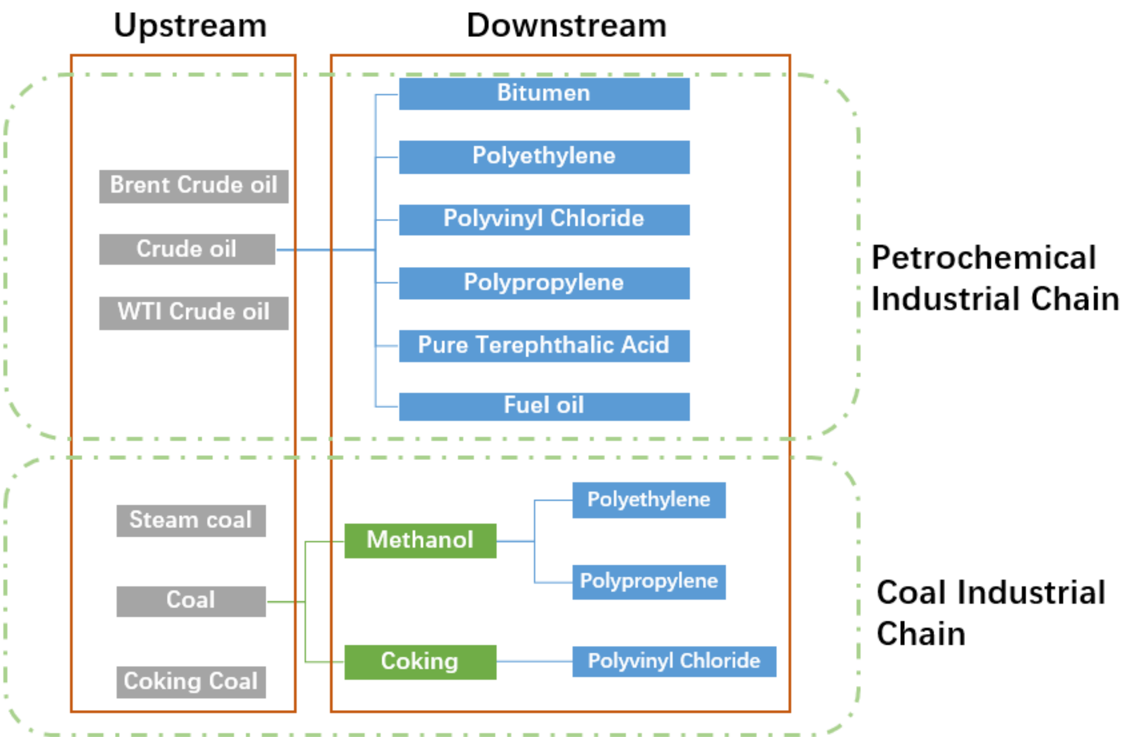


Figure 1: Energy industrial chains.

Table 1: Symbol of commodities

Commodity	Symbol	Exchange	Commodity	Symbol	Exchange
Bitumen	BU	SHFE	Polypropylene	PP	DCE
Fuel oil	FU	SHFE	Methanol	MA	ZCE
Coke	J	DCE	Pure Terephthalic Acid	TA	ZCE
Coking Coal	JM	DCE	Steam Coal	ZC	ZCE
Polyethylene	L	DCE	Brent Crude Oil	Brent	ICE
Polyvinyl Chloride	V	DCE	WTI Crude Oil	WTI	NYMEX

Note: This table lists the abbreviations for the energy futures markets in this paper. In addition, SHFE, DCE, ZCE, ICE and NYMEX correspond to the Shanghai Futures Exchange, Dalian Commodity Exchange, Zhengzhou Commodity Exchange, Intercontinental Exchange and New York Mercantile Exchange, respectively.

4.2 Preliminary Analysis

We transform daily prices into logarithm and we compute the return series as a first different of prices in logarithm. Table 2 shows the main descriptive statistics of these series and we note different remarks. First, the coke (noted J) and coking coal (noted JM) futures price log returns show highest average values (0.062 and 0.071, much larger than the others), while polyethylene (noted L) has the lowest returns (–0.015). Four of the 12 commodities show negative average returns (i.e., the futures markets for bitumen (noted BU), Polyethylene (noted L), Polypropylene (noted PP), and Pure Terephthalic Acid (noted TA), indicating that the average return on futures trading in these markets is not satisfactory. Second, the WTI crude oil (WTI) shows the biggest standard deviation value, followed by fuel oil (FU) and Brent crude oil (Brent), which is inline with the volatility excess that has characterized the oil sector over the last period. Third, except for methanol (MA), the returns of all commodities are apparently left biased. The WTI crude oil series has the highest left skew, suggesting that there are numerous small gains and sudden extreme losses in the WTI market. Fourth, the kurtosis of steam coal (ZC), Brent crude oil (Brent), and WTI crude oil is much larger than 3, showing that their tail of the distribution of returns is fatter and has an obviously higher peak shape. Therefore, most of the data are clustered in a similar manner, making the application of Extreme Value Theory to these data a prior appropriate method. Finally, the results of Augmented Dickey-Fuller (ADF) tests show that all return series under consideration are stationary at the 99% confidence level.

Next, We present the performance of the VaR and return series for each energy futures market in Figure 2. The red colour in the figure represent the VaR performance, and the blue colour represents the energy returns. Overall, we note a high volatility. Every energy futures market experiences frequent and erratic oscillations, but when measured along the vertical axis, China's energy futures market primarily varies between [-10, 10], with a few exceptions. Only the swings in the global crude oil market can reach -30 or -50, however. This demonstrates that the change in the crude oil market is more difficult to foresee and may has a greater damaging impact, while the change in the China energy futures market is rather steady. We also point to further evidence of significant clustering effects regardless of the energy futures market.

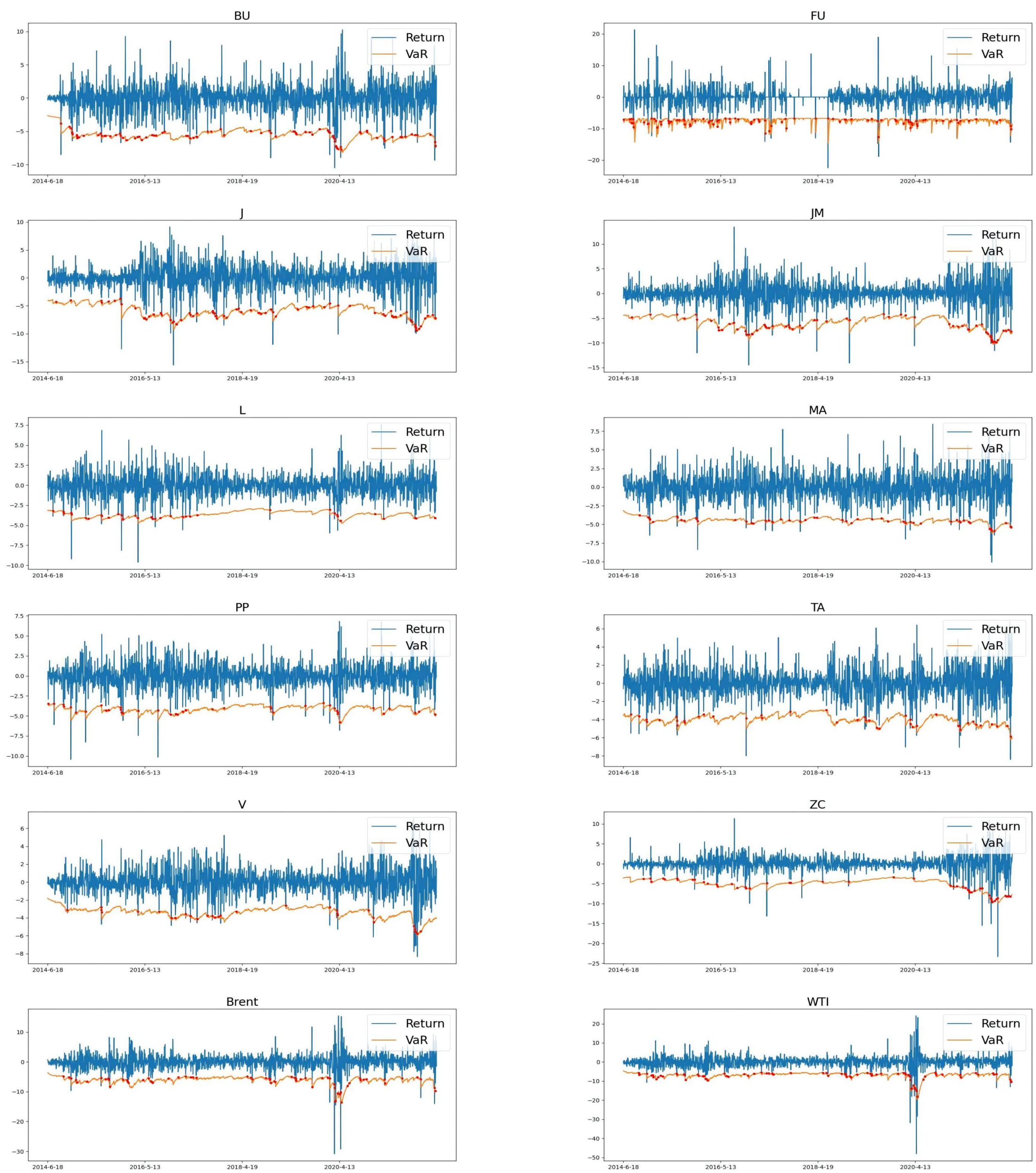


Figure 2: Returns and VaRs.

Note: Figure 2 shows the price returns series and Value-at-Risk measured of twelve energy futures markets from June 17, 2014 to March 22, 2022: BU, Bitumen; FU, Fuel oil; J, Coke; JM, Coking coal; L, Polyethylene; MA, Methanol; PP, Polypropylene; TA, Pure Terephthalic Acid; V, Polyvinyl Chloride; ZC, Steam Coal, as well as as those of the WTI and Brent crude oil futures markets.

Table 2: Descriptive statistics of commodity returns.

Commodity	Mean(%)	Std	Min	Max	Skewness	Kurtosis	ADF
BU	-0.007	2.077	-10.502	10.263	-0.099	6.288	-40.519***
FU	0.005	2.849	-22.461	21.311	-0.088	13.189	-45.076***
J	0.062	2.265	-15.621	9.112	-0.648	7.144	-42.005***
JM	0.071	2.355	-14.509	13.467	-0.361	8.372	-44.167***
L	-0.015	1.417	-9.621	7.622	-0.228	7.682	-42.771***
MA	0.004	1.804	-10.093	8.434	-0.01	5.637	-41.903***
PP	-0.013	1.522	-10.431	6.807	-0.422	7.655	-42.052***
TA	-0.008	1.57	-8.402	6.782	-0.135	5.702	-42.350***
V	0.002	1.419	-8.349	7.091	-0.23	6.904	-41.399***
ZC	0.029	2.033	-23.327	11.303	-1.525	20.915	-41.090***
Brent	0.000	2.623	-30.856	15.449	-1.504	26.023	-43.974***
WTI	0.001	3.262	-48.081	24.131	-2.049	43.803	-11.409***
No. of Obersevations	1812						

Note: ADF denotes the statistic of ADF test for the return series. (***) denotes the rejection of unit root at the 1% significance level. BU, Bitumen; FU, Fuel oil; J, Coke; JM, Coking coal; L, Polyethylene; MA, Methanol; PP, Polypropylene; TA, Pure Terephthalic Acid; V, Polyvinyl Chloride; ZC, Steam Coal, WTI and Brent, are the symbols for Energy Futures markets and the two international crude oil futures markets respectively.

5 Empirical results

5.1 Results of Estimate of the Value at Risk

First, we need to test for presence of an Auto-regressive Conditional Heteroscedasticity (ARCH) effect in the data before performing a GARCH model. The results of the Lagrange Multiplier test (LM test) that we reported in Table 3, do not reject the alternative hypothesis of an ARCH effect in the data. Second, with reference to the Akaike information criterion (AIC) rule, the GARCH (1,1) model seems as the most suitable specification to represent the returns of the energy futures markets under consideration

Furthermore, for a matter of robustness, we measure the efficiency of the VaR model used in this work, following the backtesting methods of Kupiec (1995) and Christoffersen (1998). Briefly, assuming that the predicted VaR on day t is VaR_{t+1}, when the actual loss on day $t+1$ exceeds this VaR, it is said that the model fails to measure the VaR of day $t+1$. If the violation rate of the model is statistically consistent with the assumed violation rate, then it can be considered that the model can accurately and effectively measure the risk at a given significance level.

Thus, we applied the Christoffersen (1998) independence test to assess the predictive performance of the VaR model. Measured volatilities may be interdependent or interfere with each others, and the occurrence of one violation may not be independent of the occurrence of a previous violation. However, a successful VaR model should try to satisfy the independence. Then, we construct the independence statistic LR_{IND} and if the chi-square test of this statistic is significant at a certain significance level, the model can be seen as invalid.In addition, we carried out the Christoffersen conditional coverage test to compute the LR_{cc} statistic and the Kupiec unconditional coverage test to estimate LR_{uc}. If the p-values of these testing statistics are large enough, the model is considered as effective.

Table 3: Results of Lagrange Multiplier test

Commodity	P-value	Commodity	P-Value
BU	0.0006	PP	0.0068
FU	0.0005	TA	0.0000
J	0.0003	V	0.0000
JM	0	ZC	0.0000
L	0.0268	Brent	0.0000
MA	0.4918	WTI	0.0000

Note: a LM statistic with a p-value less than 10% denotes the presence of an ARCH effect at the significance level of 10%.

Table 4: Backtesting Results

Commodity	Violation Rate(%)	LR_{uc}		LR_{IND}		LR_{cc}	
		T-Statistic	p-value	T-Statistic	p-value	T-Statistic	p-value
BU	1.159	0.434	0.507	1.368	0.242	2.255	0.324
FU	0.938	0.071	0.789	2.075	0.150	2.216	0.330
J	0.938	0.071	0.789	2.075	0.149	2.216	0.330
JM	0.993	0.001	0.977	0.361	0.548	0.363	0.834
L	0.938	0.071	0.789	0.322	0.570	0.463	0.794
MA	0.938	0.071	0.789	0.322	0.570	0.463	0.794
PP	0.938	0.071	0.789	0.322	0.570	0.463	0.794
TA	0.938	0.074	0.789	0.323	0.571	0.463	0.794
V	1.159	0.434	0.507	10.325	0.001	11.212	0.004
ZC	1.049	0.043	0.837	5.981	0.015	6.068	0.048
Brent	0.828	0.576	0.448	2.525	0.112	3.671	0.160
WTI	0.938	0.071	0.790	6.852	0.009	6.993	0.030

Note: We construct independence statistic LR_{IND}, if the chi-square test of it is significant at a certain significance level, the model is invalid. In addition, we also carry out Christoffersen conditional coverage test to compute the statistic LR_{cc} and Kupiec unconditional coverage test to compute the statistic LR_{uc}. The significance level is set as 5%. When p-value of the test is greater than 5%, it is considered to have passed the test.

Overall, as shown in Table 4, the violation rates of the VaR performance for all energy futures markets are stable and nearly at the risk level $\alpha = 0.01$. According to the results of the unconditional coverage test, independence test, and conditional coverage test, the GARCH-EVT-VaR model can accurately forecast the VaR, and the proposed model is thus effective.

5.2 Static connectedness: Full sample

After confirming the accuracy of the VaR model, we propose to continue with the test of inter-market risk spillover's effects. To this end, we first show the main descriptive statistics of the VaR series for all energy futures markets in Table 5.

From Table 5, we can see that the average VaR of fuel oil (FU) is the largest (7.592), indicating that the average maximum possible loss of fuel oil futures market is the largest among these markets. Both international oil markets also point a high level of losses on average. In contrast, the Polyvinyl Chloride Futures market (V) shows the smallest average maximum possible loss, showing that its extreme risk may be smaller than the others. Further, for several Chinese energy future markets (J, JM, ZC) as well as the two oil international markets, the variance of the VaR is significantly high suggesting further evidence of volatility excess of their losses. Also, We note that the Kurtosis of the VaR for fuel oil, Brent, and WTI crude oil futures is so high, indicating that their VaR have a more dispersed distribution and a leptokurtic excess. Overall, this finding might point to further interconnectedness between international oil markets and the Chinese energy future markets.

Next, we apply the spillover tests of Diebold & Yilmaz (2012) to better characterize the spillover's effects among these 12 energy futures markets as well their interactions with the international oil market. The static, full sample extreme risk spillovers in the network are summarized in Table 6. The total extreme risk spillover index is 41.65 for the full sample, meaning that the spillover effect between energy future markets explains 41.65% of the total net extreme risks of the energy futures markets network. This value is close to 50%, indicating that nearly half of the extreme risk spillovers in the market network are due to risk contagion or exacerbation caused by inter-market links. This result is relevant and it indicates that even an unusual extreme risk in just one market can affect the prices and performance of other energy futures markets. The conclusion is established when China's energy futures markets are confronted with the impact of the international crude oil market, showing that once China's energy futures market network is brought into the impact of the international crude oil market, there is a noticeable inter-market risk spillover effect. More information on the crude oil market's specific influence on the Chinese energy futures markets is now available in Table 6.

Table 5: Main Descriptive Statistics of Commodity VaRs

Commodity	Mean	Std	Skewness	Kurtosis
BU	5.521	0.8	-0.606	6.54
FU	7.592	0.977	2.733	13.563
J	5.941	1.174	0.311	3.076
JM	5.979	1.297	0.652	3.288
L	3.684	0.416	0.107	2.201
MA	4.498	0.392	0.591	5.9
PP	4.171	0.453	0.807	3.716
TA	4.024	0.543	0.388	3.254
V	3.418	0.628	0.928	5.184
ZC	5.012	1.32	1.472	5.088
Brent	6.147	1.333	2.521	12.569
WTI	7.009	1.682	3.72	21.497
No. of Obersevations	1812			

Note: This tables reports the main statistics for the VaR for ten Chinese energy futures markets (BU, Bitumen, FU, Fuel oil, J, Coke, JM, Coking coal, L, Polyethylene, MA, Methanol, PP, Polypropylene, TA, Pure Terephthalic Acid, V, Polyvinyl Chloride, ZC, Steam Coal) and the WTI and Brent crude oil futures markets.

Table 6: VaR Connectedness Matrix of Commodity (Full sample)

	BU	FU	J	JM	L	MA	PP	TA	V	ZC	Brent	WTI	From
BU	51.1	2.84	0.89	0.11	3.42	3.29	5.34	8.45	2.1	0.05	12.09	10.32	48.9
FU	1.62	75.42	0.17	0.17	2.13	0.71	1.81	2.45	0.33	0.1	8.03	7.06	24.58
J	2.17	0.05	62.75	13.47	2.32	3.15	7.01	1.71	2.47	4.64	0.18	0.07	37.25
JM	0.79	0.02	16.67	58.27	1.44	2.94	8.64	0.76	4.82	5.33	0.22	0.1	41.73
L	3.07	1.59	1.84	0.46	47.11	5.02	18.43	4.96	9.62	0.39	4.18	3.33	52.89
MA	3.49	1.43	2.29	0.25	5.5	58.49	10.01	6.04	7.04	1.2	2.45	1.81	41.51
PP	2.28	1.41	3.48	0.59	16.86	5.54	51.23	4.22	6.93	0.4	3.72	3.34	48.77
TA	5.82	2.23	0.53	0.14	4.11	3.24	7.06	56.89	2.23	0.92	8.97	7.85	43.11
V	3.8	1.04	1.92	0.48	9.23	7.21	8.64	2.56	60.52	1.88	1.52	1.2	39.48
ZC	0.23	0.39	2.23	4.93	0.53	2.43	1.72	1.22	3.69	82.48	0.12	0.02	17.52
Brent	2.05	1.23	0.32	0.01	1.97	1.43	3.21	2.79	0.29	0.04	45.75	40.9	54.25
WTI	1.51	0.64	0.16	0.01	1.23	1.1	3	1.75	0.2	0.02	40.17	50.2	49.8
To	26.82	12.88	30.5	20.64	48.74	36.07	74.87	36.91	39.73	14.98	81.65	76	
Net	-22.07	-11.7	-6.75	-21.09	-4.15	-5.43	26.1	-6.2	0.25	-2.55	27.4	26.21	41.65

Note: This table reports the connectedness of a market i to another market j. The results are based on the 10-day forecast error variance and the underlying VAR is estimated with 2 lags for the Ten Chinese energy futures marketsand the WTI and Brent international crude oil futures markets.

Table 7: Net VaR connectedness matrix of commodity: Full sample.

	BU	FU	J	JM	L	MA	PP	TA	V	ZC	Brent	WTI
BU	0	1.22	-1.28	-0.69	0.35	-0.2	3.06	2.62	-1.69	-0.18	10.04	8.81
FU	-1.22	0	0.11	0.15	0.54	-0.72	0.39	0.22	-0.72	-0.29	6.8	6.42
J	1.28	-0.11	0	-3.2	0.48	0.87	3.54	1.18	0.55	2.41	-0.14	-0.09
JM	0.69	-0.15	3.2	0	0.98	2.69	8.04	0.62	4.34	0.4	0.21	0.09
L	-0.35	-0.54	-0.48	-0.98	0	-0.48	1.58	0.85	0.39	-0.14	2.21	2.09
MA	0.2	0.72	-0.87	-2.69	0.48	0	4.47	2.8	-0.17	-1.23	1.02	0.71
PP	-3.06	-0.39	-3.54	-8.04	-1.58	-4.47	0	-2.84	-1.71	-1.32	0.51	0.34
TA	-2.62	-0.22	-1.18	-0.62	-0.85	-2.8	2.84	0	-0.32	-0.3	6.18	6.1
V	1.69	0.72	-0.55	-4.34	-0.39	0.17	1.71	0.32	0	-1.81	1.22	1
ZC	0.18	0.29	-2.41	-0.4	0.14	1.23	1.32	0.3	1.81	0	0.07	0.01
Brent	-10.04	-6.8	0.14	-0.21	-2.21	-1.02	-0.51	-6.18	-1.22	-0.07	0	0.73
WTI	-8.81	-6.42	0.09	-0.09	-2.09	-0.71	-0.34	-6.1	-1	-0.01	-0.73	0

Note: This table shows the net connectedness between each two energy markets.

Table 8: Return connectedness matrix of commodity: Full sample.

	BU	FU	J	JM	L	MA	PP	TA	V	ZC	Brent	WTI	From
BU	43.36	2.88	2.59	2.6	5.31	6.2	5.61	8.52	4.19	0.79	9.16	8.78	56.64
FU	4.57	68.97	0.42	0.33	1.43	2.2	1.59	4.59	0.5	0.11	8.03	7.26	31.03
J	2.77	0.29	46.43	23.91	2.64	4.47	3.9	2.22	5.26	7.5	0.36	0.23	53.57
JM	2.78	0.21	23.59	46.01	2.39	4.42	2.99	1.68	5.13	10.5	0.15	0.14	54
L	4.47	0.77	2.06	1.9	36.64	9.62	22.3	5.82	10.94	1.02	2.35	2.1	63.36
MA	5.9	1.37	3.93	3.75	10.86	40.74	11.79	7.43	7.12	2.36	2.63	2.12	59.26
PP	4.62	0.81	2.99	2.3	21.68	10.02	35.58	5.95	10.07	1.22	2.54	2.22	64.42
TA	8.5	2.81	2.31	1.65	6.86	7.78	7.38	42.96	3.76	0.76	8	7.24	57.04
V	4.11	0.3	4.86	5	12.86	7.54	12.29	3.81	42.97	3.51	1.46	1.28	57.03
ZC	1.1	0.15	9.99	13.83	1.63	3.62	2.03	1.05	4.87	60.34	0.72	0.67	39.66
Brent	2.69	1.02	0.37	0.17	1.74	1.14	1.51	1.65	0.84	0.19	49.22	39.46	50.78
WTI	2.67	0.86	0.25	0.16	1.38	0.86	1.38	1.68	0.74	0.14	39.76	50.12	49.88
To	44.18	11.48	53.35	55.61	68.79	57.88	72.77	44.41	53.42	28.1	75.16	71.51	
Net	-12.46	-19.55	-0.21	1.62	5.43	-1.38	8.35	-12.63	-3.61	-11.56	24.38	21.63	53.05

Note: This table reports the return connectedness of a market i to another market j. The results are based on the 10-day forecast error variance and the underlying VAR is estimated with two lags.

Table 9: Net return connectedness matrix of commodity (Full sample)

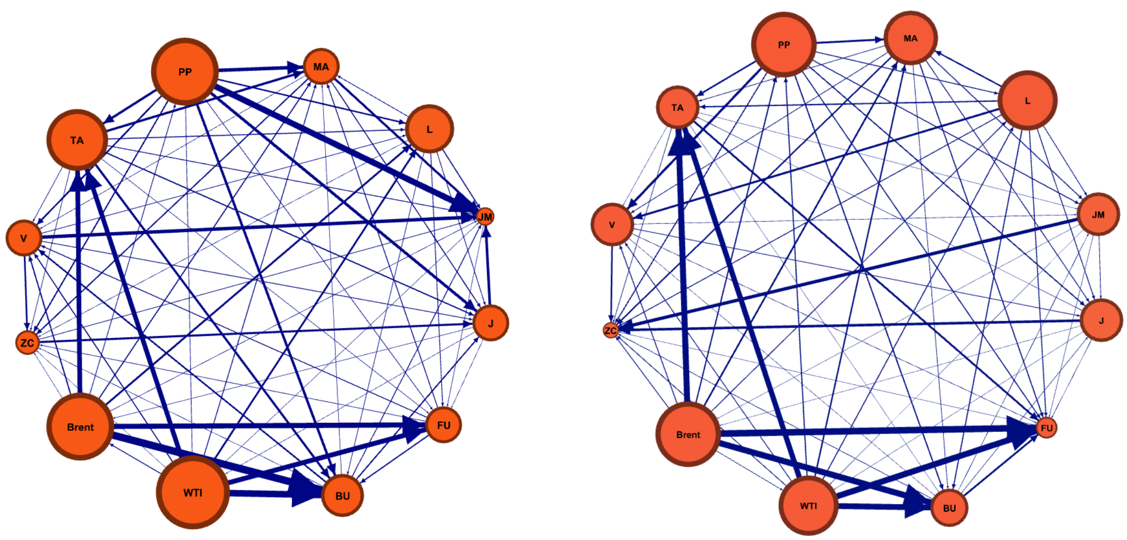
	BU	FU	J	JM	L	MA	PP	TA	V	ZC	Brent	WTI
BU	0	-1.68	-0.19	-0.18	0.84	0.3	1	0.02	0.07	-0.31	6.48	6.11
FU	1.68	0	0.13	0.11	0.66	0.83	0.79	1.78	0.19	-0.04	7.01	6.4
J	0.19	-0.13	0	0.32	0.58	0.55	0.91	-0.09	0.4	-2.49	-0.01	-0.02
JM	0.18	-0.11	-0.32	0	0.49	0.67	0.69	0.04	0.13	-3.33	-0.02	-0.03
L	-0.84	-0.66	-0.58	-0.49	0	-1.24	0.62	-1.04	-1.92	-0.61	0.61	0.72
MA	-0.3	-0.83	-0.55	-0.67	1.24	0	1.77	-0.35	-0.42	-1.26	1.5	1.26
PP	-1	-0.79	-0.91	-0.69	-0.62	-1.77	0	-1.43	-2.22	-0.82	1.03	0.85
TA	-0.02	-1.78	0.09	-0.04	1.04	0.35	1.43	0	-0.05	-0.29	6.35	5.56
V	-0.07	-0.19	-0.4	-0.13	1.92	0.42	2.22	0.05	0	-1.37	0.62	0.54
ZC	0.31	0.04	2.49	3.33	0.61	1.26	0.82	0.29	1.37	0	0.53	0.53
Brent	-6.48	-7.01	0.01	0.02	-0.61	-1.5	-1.03	-6.35	-0.62	-0.53	0	-0.29
WTI	-6.11	-6.4	0.02	0.03	-0.72	-1.26	-0.85	-5.56	-0.54	-0.53	0.29	0

Note: This table shows the net return connectedness matrix between each two energy markets.

Overall, The performance of the VaR connectedness between the individual markets is confirmed. For example, the WTI crude oil futures market has a maximum pairwise connectedness of 40.17 with the Brent oil futures market, showing that the Brent market receives 40.17% of its shocks from the WTI. This connection is no a surprise as volatilities of the two major international crude oil markets are often influenced by the same factors (demand shock, supply shock, geopolitical tensions, etc), which might explain their spillover effects (Klein, 2018). From Table 6, we can also see that the top five pairwise connectedness pairs are WTI-Brent, PP-L, J-JM, Brent-BU, and WTI-BU. The smallest pairwise connectedness was found in the pairs JM-WTI, ZC-Brent, JM-TA, FU-J, and FU-JM. The energy futures market in China, particularly the market for bitumen, is obviously more significantly impacted by crude oil (WTI or Brent). Surprisingly, however, the risk spillover effect of coke futures on coking coal futures and polypropylene futures on polyethylene futures exceeds that of crude oil. This demonstrates that it is important to consider the potential of spillover between futures markets that deal with related subject matters. These results confirm that there is more connectedness between commodities from the same sector and less connectedness between two sectors. Indeed, as revealed in Table 7, we find evidence of not only of an extreme risk flowing from the upstream to the downstream severe, but there are also some mutual impacts.

Furthermore, to better clarify the superiority of the extreme risk framework, we also measure inter-market risk spillovers for the price return series itself and we report the main results in Table 8. Accordingly, we find that the total net return spillover is about 53.05, which is higher than the total net extreme risk spillover. In addition, to represent the net connectedness effect between different energy markets more clearly, we report the net connectedness between two markets directlyi in Table 9 and we visualize the static network performance in Figure 3(a) and Figure 3(b). Accordingly, we find that the risk spillover effects are more intuitive. The negative values represent the role of net risk spillover receivers. In Figure 3, the red circles in Figures 3(a) and 3(b) represent each energy market, and the size represents the relative position in the spillover effect. The line between the different circles represents the risk spillover relationship, while the direction of the arrows represents the transmitter to the recipient. The thickness of the line also indicates the strength of the spillover relationship. The analysis of this finding points to the relevance and dynamics of spillover's effects between the Chinese energy future markets and the international oil market. We note for example that the international oil market plays an important role that is more pronounced for the WTI than for the brent. Furthermore, it appears that the polypropylene market shows the highest and more strongest actors in terms of spillover's transmission. Finally, when comparing 3(a) and 3(b), we note that the use of ETV is helpful to capture more significant interconnection and spillover's effects across Chinese energy future markets.

Overall, from Figure 3, we can note that the most influential markets of the VaR connectedness network are the Brent and WTI crude oil markets, as well as the polypropylene market. These markets are equally dominant in the net connectedness network, but the role



(a) VaR Connectedness Network

(b) Return Connectedness Network

Figure 3: connectedness network: Full sample.

Note: This figure reproduces the connectedness across ten Chinese energy futures markets (BU, Bitumen, FU, Fuel oil, J, Coke, JM, Coking coal, L, Polyethylene, MA, Methanol, PP, Polypropylene, TA, Pure Terephthalic Acid, V, Polyvinyl Chloride, ZC, Steam Coal) and the WTI and Brent nternational crude oil futures markets.

Table 10: Net receivers and net transmitters of petrochemical sector and coal sector

	Net Receivers	Net Transmitters
Return		
Petrochemical Sector	BU, FU, TA	Brent, WTI
Coal Sector	J, V, MA, ZC	JM, L, PP
VaR		
Petrochemical Sector	BU, FU, TA	Brent, WTI
Coal Sector	J, JM, L, MA, ZC	V, PP

Note: Ten Chinese energy futures markets: BU, Bitumen; FU, Fuel oil, J, Coke, JM, Coking coal, L, Polyethylene, MA, Methanol, PP, Polypropylene, TA, Pure Terephthalic Acid, V, Polyvinyl Chloride, ZC, Steam Coal. WTI and Brent are two international crude oil futures markets.

of the other markets in both networks has changed. For example, the JM market is an obvious risk receiver in the VaR connectedness network, and the PP market has a very strong influence on it. Otherwise, when considering the return connectedness network, the JM market becomes a transmitter of spillover effects, while the PP market does not have a prominent impact on it. To sum up, We summarize the main performance of each energy futures market in the spillover process more clearly in Table 10.

From an extreme risk perspective (Table 10), the coal industry is almost always a net receiver of spillovers, but its role as a net receiver is not as pronounced in the return-based spillover outcomes. We can see that the markets of the net transmitters and receivers in the petrochemical industry do not change in any way across the different network structures, but the sub-markets in the coal industry have a more differentiated function. The significant disruption outside the international crude oil market makes it necessary for the Chinese government to manage the risk diffusion from the international energy market, and we can see that the TA, BU, and FU markets are some of the most vulnerable domestic energy markets. At the same time, the extreme risk spillover effects of the PP and V markets on the JM market cannot be ignored. Based on the network structure, managers can very clearly know which market pairs should be focused on for management.

5.3 Total dynamic extreme risk spillovers

The analysis static spillover across energy future markets in a static framework is however restrictive as it neglects the fluctuations in the target markets' conditions over time, in particular when considering commodities. Indeed, the links between the commodities prices are likely to be time-varying especially throughout periods of turmoil. The static spillover analysis may therefore be biased and misleading. To deal with this problem and double check the robustness of our conclusions, we set up a rolling window–based analysis model about the spillovers among these markets. In particular, with reference to Naeem et al. (2020) and Mensi et al. (2021), we set the rolling window length to 200 days, which is the approximate number of trading days in a year. The dynamic extreme risk spillovers are shown in Figure 4 and show different interesting results. Indeed, we can see that on July 7, 2015, and on March 22, 2022, the total spillovers fluctuate around 40% and 70.00%, with the lowest value occurring in September 2016 and the highest occurring in July 2020. Interestingly, it appears that the influence of risk spillover is small before a crisis and during recovery periods after economic crises, while it is significantly higher during periods of market turbulence and instability. That is, our analysis captures the most spillovers effects caused by endogenous (i.e. oil supply shock) or exogenous (i.e. monetary policy shift, COVID-19 shock, trade war between China and the USA, etc) factors.

That is, we note that for some major events, the total extreme risk spillovers increased significantly. For example, The first one was around the Chinese stock market crash in June 2015 and that of crude oil in late 2015 (shale revolution), during which the prices of commodities fell sharply and caused a panic in the market. In the following months, the risk transmission among the international crude oil market has increased, and the systemic risk in the domestic markets was serious as well. Second, in the following year, the commodity futures price index in the oil industry continued to decline, the energy futures markets suffered from serious losses, and the total spillovers remained high. The third was the outbreak

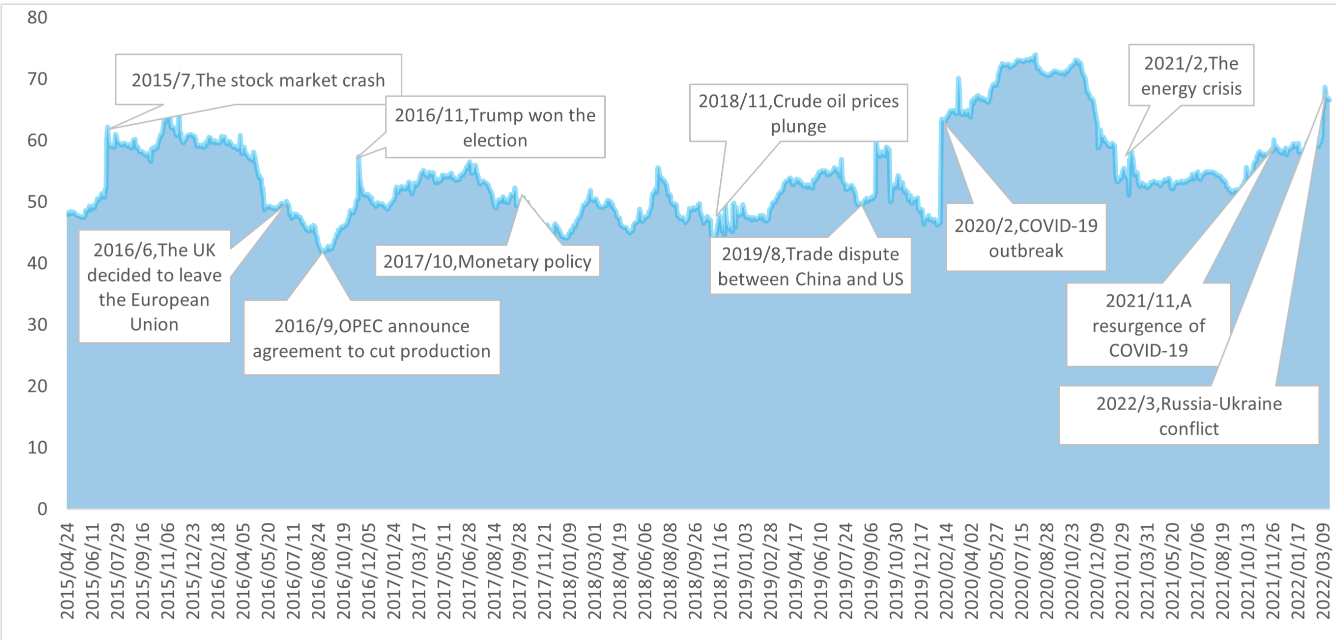


Figure 4: Total Extreme Risk Spillover Dynamic: The rolling window in this study is set as 200 days, while the predictive window for variance decomposition is set as 10 days.

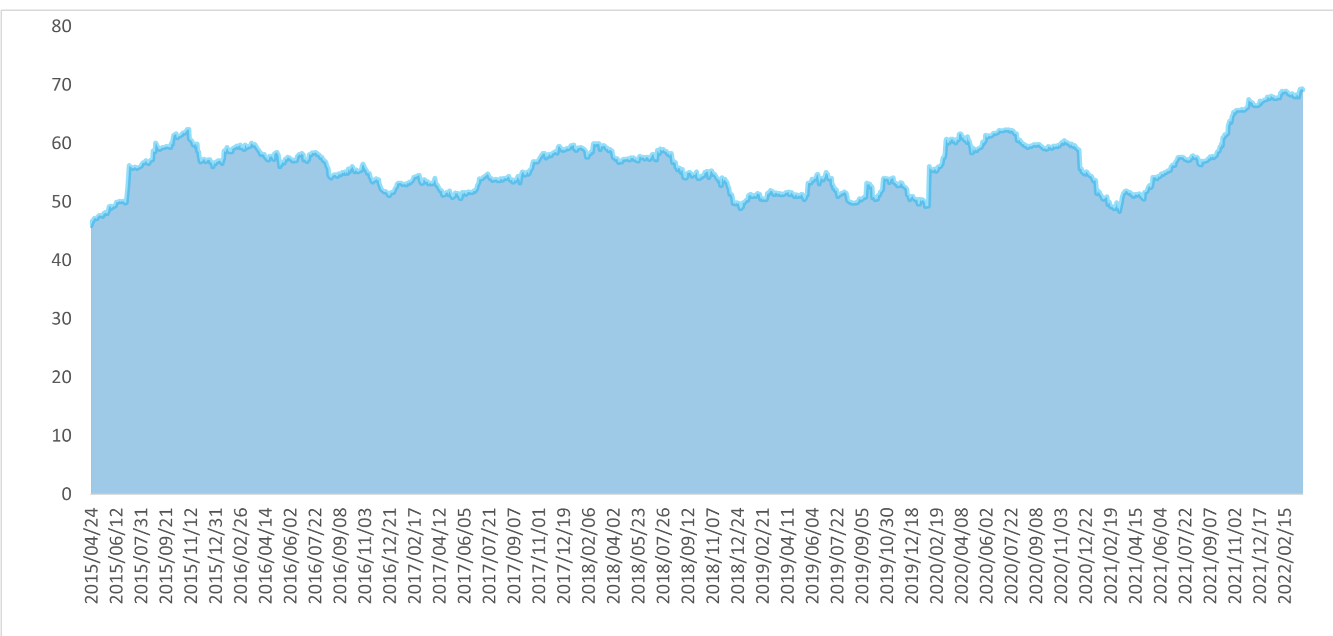


Figure 5: Total return spillover dynamic.

of COVID-19 at the beginning of 2020, during which the increase in total spillovers was close to 20%. The COVID-19 outbreak resulted in a significant decrease in the demand for energy products (i.e. Oil consumption in China decreased of 30 % and further disturbed the stabilization of the energy system. In addition, the export of energy derivatives in global trade plummeted, especially China's coal exports. Specifically, they fell of 46.67 %, hitting a 7-year low. Moreover, there was the global energy crisis in 2021 and the Russia–Ukraine conflict in early 2022. Another noteworthy phenomenon is the aggregate dynamic extreme risk spillover, which represents the risk transfer between the international crude oil market and the Chinese futures market. We can see that this spillover of extreme risk is consistently prominent at the 200-day window. This also suggests that the link between the international crude oil market and the Chinese energy market has always been close and that the impact of risk contagion may be long-lasting and serious, which is an issue that all stakeholders need to be aware of.

As a matter of robustness to highlight the usefulness of our EVT analysis, we also carry out and report the dynamic return spillover (Figure 5). Accordingly, we observe more peaks and troughs in the dynamic extreme risk spillover (Figure 4) than in the dynamic return spillover (Figure 5), giving more credit to the EVT framework. Indeed, from Figure 5, the fluctuations are much smoother, and there are no obvious steep changes. In other words, the total extreme risk spillover is more sensitive when compared with the return spillover in responding to events. This suggests that return-based spillover risk does not accurately reflect shocks from extreme events and may overlook potential risks that are well hidden. This is consistent with our findings when using static spillover analysis, which demonstrates the robustness of our EVT analysis. Therefore, the EVT approach is more suitable to assess spillover's effects from the perspective of extreme risk.

5.4 Net Dynamic Extreme Risk Spillovers

For instance, we describe the net extreme risk spillover of each energy futures market for further understanding of the risk transmission channels. The dynamic performance of the markets' net extreme risk spillover is plotted in Figure 6. The part above the horizontal scale of 0 represents the net spillover effect transmission, while the part below it represents the net spillover effect receiving.

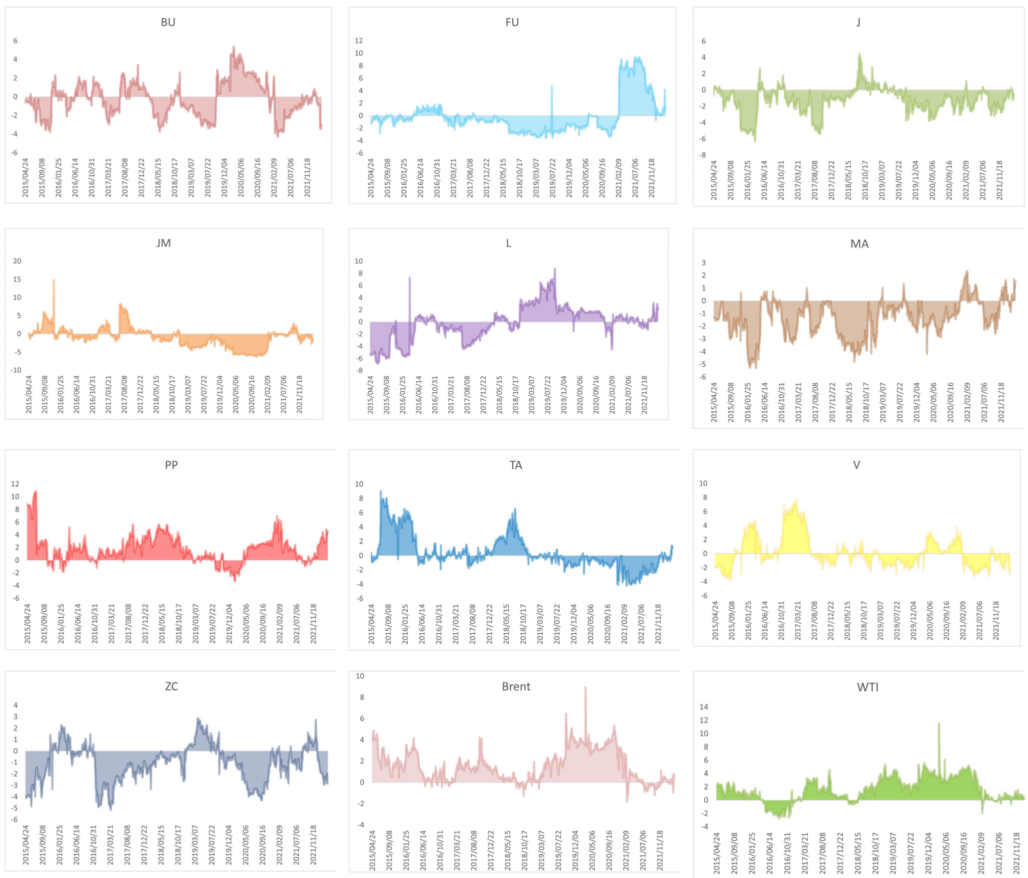


Figure 6: Net Extreme Risk Spillover of each Energy Market

Note: This figure plots net extreme risk spillover for Ten Chinese energy futures markets (BU, Bitumen, FU, Fuel oil, J, Coke, JM, Coking coal, L, Polyethylene, MA, Methanol, PP, Polypropylene, TA, Pure Terephthalic Acid, V, Polyvinyl Chloride, ZC, and Steam Coal), and the two international crude oil futures markets (WTI and Brent).

From Figure 6, we note that the occurrence of extreme events exacerbates risk spillover effects and may shift the direction of the spillover transmission. For example, the JM market is a clear net receiver (the colored portion is largely below the horizontal line), and the PP market is a prominent net passer in these domestic energy markets (the colored portion is

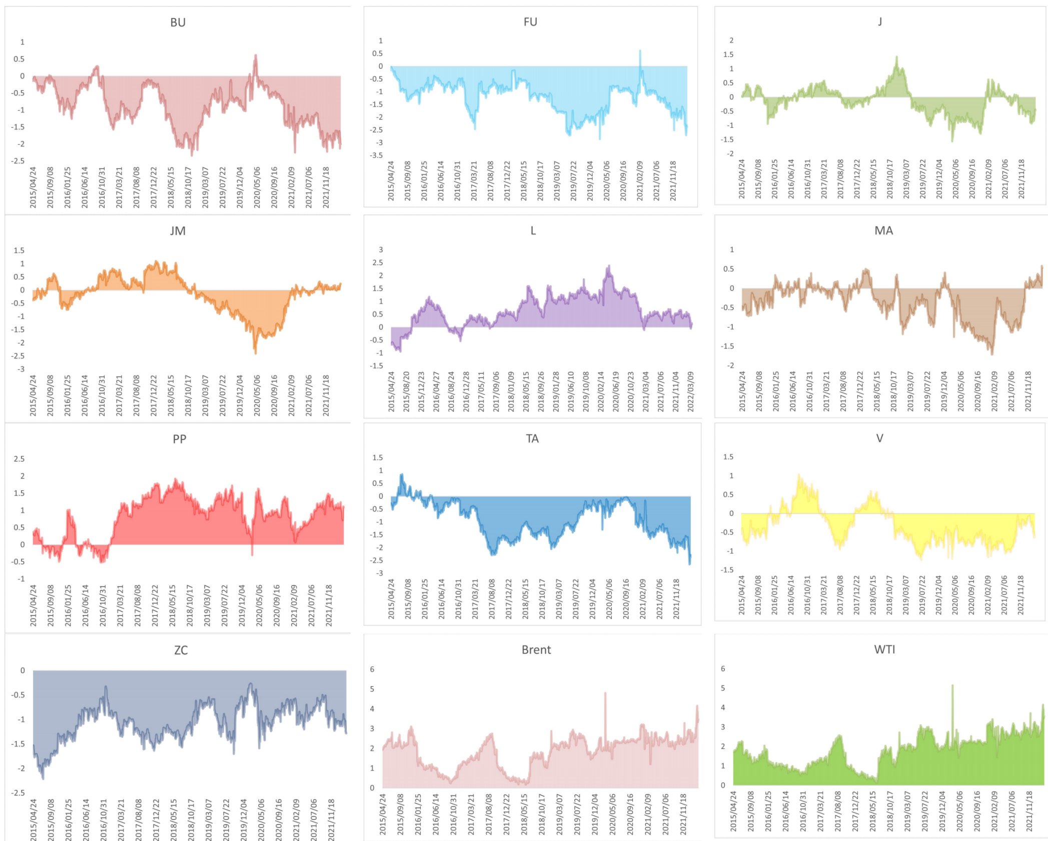


Figure 7: Net return spillover of each energy market.

Note: This figure plots net return spillover for Ten Chinese energy futures markets (BU, Bitumen, FU, Fuel oil, J, Coke, JM, Coking coal, L, Polyethylene, MA, Methanol, PP, Polypropylene, TA, Pure Terephthalic Acid, V, Polyvinyl Chloride, ZC, and Steam Coal), and the two international crude oil futures markets (WTI and Brent).

largely above the horizontal line). Further, the stability of the Chinese energy futures market is significantly weaker than that of the global crude oil futures market when extreme events occur. For instance, from the surge of COVID-19 in early 2020 to the energy crisis in 2021, the roles of most Chinese energy futures markets have changed at least twice, while the WTI and Brent futures are always the net spillover transmitters. Therefore, it is important to adjust the viewpoints of extreme risk transmission over time to implement appropriate risk management strategies.

We also compute and report the dynamic net return spillover in Figure 7. Accordingly, we note that for individual markets, the return spillover effects also behave more smoothly and with much less volatility. In fact, the focus on return series interaction generally underestimate the extreme risk for China's domestic market. When comparing these two figures, we note that the risk spillover is more serious from an extreme risk perspective. The risk based on return measurement may "absorb" certain swings, but the sharp variations it overlooked are one of the most probable causes of risk for these energy futures markets, which may be the possible explanation for the outcomes of these two figures. Therefore, the extreme risk spillovers framework can provide a more accurate and cautious estimation of risk spillovers among China's energy futures markets, especially in periods of high uncertainty. This is particularly relevant to assess an appropriate risk management framework.

6 Conclusion

This study explores the issue of risk spillover between the global crude oil market and the Chinese energy futures markets, as well as the risk spillover effects among local Chinese futures markets. To this end, we set up a methodological framework that we define while considering the industrial chain and market network elements. Econometrically, we measure the Value-at-Risk of each market as well as inter-market connectedness based on the GARCH-EVT model. Through analysing the spillover's effect assumption from the perspective of energy futures returns and extreme risk perspective, we find a significant evidence of of risk transmission between these markets from the perspective of spillover effects of extreme risks. Indeed, we provide new insights into which perspective is better for examining inter-market risk spillovers through a comparison of extreme risk spillovers and return series, comparing the results of extreme risk spillover effects with the return series' spillovers for the energy markets network. Thus, we validate the strength and direction of risk spillovers among 12 markets and demonstrate the accuracy of our model formulation. This study reveals that extreme risk analysis, as opposed to typical return series analysis, is more effective in capturing changes in risk spillovers. According to empirical findings in this paper, the Chinese energy futures market is dependent on the global oil market. We also discover that there are considerable risk spillovers across the Chinese domestic energy futures market.

Specifically, based on a static connectedness network analysis of the full sample, we identify the net receivers in the petrochemical and coal industries, as well as the net transmitters comparatively. We observe that in most instances, the coal sector is exposed to high risks that are transmitted from the petrochemical sector. Additionally, the analysis from the VaR and return viewpoint demonstrates that the two energy futures markets with the highest pairwise connectedness always originate from the same industrial chain and that excessive risk spillovers can alter the degree of pairwise connectedness between certain commodities. We also analyze dynamic spillovers with the rolling window and find that the occurrence of extreme events increased the overall risk spillover in the markets. In addition, the spillover based on extreme risk is more sensitive to the crisis than the spillover based on the return series. Chinese energy futures reverse the roles of transmitters or receivers quite frequently over time, while international crude oil futures are always net transmitters. Finally, for Chinese domestic energy futures markets, return spillovers obviously underestimate the spillover effect, implying that return spillovers cannot represent extreme risk spillovers. Therefore, there is a need to develop more scientific econometric models to predict and address extreme risk spillovers in China's energy futures markets.

For regulators and market participants, these findings have a variety of implications. First, regulators should put more emphasis on how each of the two highly interconnected markets performs when establishing policies for the purpose to reduce extreme risk and provide risk spillover alerts. Second, our findings may be useful in illuminating for stakeholders the true function of each market in the risk spillover process. Third, we warn about the possibility of extreme occurrences and their consequences through our research of potential risk spillovers between markets. The results demonstrate that when a crisis arises, investors should pay attention to more than just the markets' capacity to confront risks; as well, they need to consider how these markets tie into the overall network of the energy market.

Finally, it is critical to keep in mind how dependent China's domestic energy markets are on global crude oil markets, which lack the capacity to bear the dangers posed by global crude oil futures markets. In order to prevent serious risk transmission through inter-market chains and thereby increase market efficiency for China, regulators should encourage the improvement of market mechanisms, such as licensing price constraints and bank restrictions.

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