Risk of spillovers between the Chinese and international crude oil futures' markets: A dynamic Copula-CoES approach

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Abstract. To overcome the limitations of conditional value-at-risk (CoVaR), the upside conditional expected shortfall (CoES) is proposed and used as a measure of the extreme risk spillover effect between the Chinese and international crude oil futures markets. Then, the calculation formula of the upside CoES is given under the semiparametric dynamic Copula model, which does not need to set the specific evolution equation of the Copula parameters. The empirical results show that there is a strong positive correlation between Chinese and international crude oil futures, and the correlation gradually increases when oil prices rise. There is a significant two-way risk spillover effect for both of them, and the average risk spillover intensity between Chinese crude oil futures (INE) and West Texas intermediate crude oil futures (WTI) is the highest. Moreover, INE is not always the recipient of the price fluctuation risk. In particular, INE has played the role of risk spillover most of the time after 2019. This study provides new ideas for the measurement of risk spillovers.

1. Introduction

In the international crude oil trade, the trading price of crude oil is priced based on the crude oil futures price. Therefore, crude oil futures are in an extremely important position in the international crude oil pricing system. The world's three major crude oil futures, West Texas intermediate crude oil futures (WTI), Brent crude oil futures (BRT), and Oman crude oil futures (OMN) provide price benchmarks for crude oil trade in North America, Europe and the Asia-Pacific region, respectively. On March 26, 2018, Chinese crude oil futures (INE) denominated in RMB were officially listed for trading. Less than one year after trading, INE surpassed OMN and became the world's third-largest crude oil futures in terms of trading volume. The linkage between the Chinese and international crude oil futures markets is becoming an important issue for researchers to study urgently. Therefore, this paper attempts to quantitatively study the risk spillover effect between the Chinese crude oil futures and the three major international crude oil futures markets. It can not only reveal the direction, intensity and dynamic change process of risk spillovers, but also provide effective information reference for crude oil futures investors and market regulators.

The risk spillover effect refers to the transmission mechanism of risk between different markets. In the early days, the commonly used risk spillover measurement method assumed that there was only a
linear relationship between the markets, which was often inconsistent with reality, so it was gradually replaced by methods such as GARCH model, tail correlation coefficient, and conditional value-at-risk (CoVaR). Among them, CoVaR has been most widely used in recent years (Jin, 2018; Warshaw, 2019; Ji et al., 2020), but CoVaR has a design flaw that does not meet the consistency. Adrian and Brunnermeier (2016) proposed that CoVaR can be extended to conditional expected shortfall (CoES) to overcome this defect. Subsequently, Zhao et al. (2017), Su and Wong (2018), Zhu et al. (2020) used quantile regression to calculate CoES and measured the risk spillover effect in different markets. They believe that CoES has more advantages in consistency and robustness. However, quantile regression can only reflect the linear relationship between the regression variable and the quantile, which makes CoES insufficient for the calculation method.

In view of above, we propose the risk spillover measure of the upside CoES, and then employ the semiparametric dynamic Copula function to calculate the upside CoES that can overcome the limitations of the existing calculation methods of CoES. Our empirical results indicate that there are significant two-way risk spillover effects between INE and WTI, BRT, and OMN. Specially, the average risk spillover intensity between INE and WTI is the highest. Moreover, INE has played the role of risk spillover for most of the time after 2019. Our studies enrich the findings in the existing literature by proposing the dynamic Copula-CoES approach and revealing the present situation of risk spillovers between the Chinese and international crude oil futures markets.

2. Methodologies

2.1. Definition of the upside CoES

For the general financial market, financial assets are more likely to cause the herding effect when prices fall than when prices rise, but for crude oil futures markets, the opposite is true. Therefore, the traditional downside risk spillover measurement is not suitable for measuring the risk spillover effect between crude oil futures markets. Let \( R^1_t \) and \( R^2_t \) respectively denote the yields of China crude oil futures and international crude oil futures at time \( t \), then the upside CoES can be defined as:

\[
CoES_{a,b,5.0}^{1,2,\alpha,} = E[R^1_t \mid R^1_t \geq CoVaR_{a,b,\alpha}^{1,2,\alpha} \mid R^2_t = VaR_{a,b,\alpha}^{1,2,\alpha}] = \frac{1}{\beta} \int_{-\infty}^{\infty} CoVaR_{a,b,\alpha}^{1,2,\alpha} dq
\]

where \( VaR_{a,b,\alpha}^{1,2,\alpha} \) and \( CoVaR_{a,b,\alpha}^{1,2,\alpha} \) are the upside VaR and the upside CoVaR respectively, satisfying

\[
P(R^2_t \geq VaR_{a,b,\alpha}^{1,2,\alpha}) = \alpha \quad \text{and} \quad P(R^1_t \geq CoVaR_{a,b,\alpha}^{1,2,\alpha} \mid R^2_t = VaR_{a,b,\alpha}^{1,2,\alpha}) = \beta
\]

Furthermore, the upside risk spillover intensity of international crude oil futures to China crude oil futures is defined as:

\[
\Delta CoES_{b,5.0,\alpha}^{1,2,\alpha} = CoES_{b,5.0,\alpha}^{1,2,\alpha} - CoES_{b,5.0,\beta}^{1,2,\alpha}
\]

where \( CoES_{b,5.0,\alpha}^{1,2,\alpha} \) is the conditional expected shortfall of \( R^1_t \) when \( R^2_t \) is in a normal state (i.e., \( \alpha = 0.5 \)).

2.2. Calculation of the upside CoES

It can be seen from Eq. (1) that the premise of calculating the upside CoES is to calculate the corresponding upside CoVaR. To overcome the limitations of the existing CoES calculation method, the Copula model is employed to calculate the upside CoVaR and CoES.

Let \( F(\cdot,\cdot) \) be the joint distribution function of \( (R^1_t, R^2_t) \), and its marginal distribution functions are \( F_{R^1_t}(x) \) and \( F_{R^2_t}(y) \) respectively. According to the Sklar’s theorem, there must be a Copula function that makes \( F(x,y) = C(F_{R^1_t}(x), F_{R^2_t}(y)) \). Therefore, the Copula form of CoVaR can be written as:

\[
P(R^1_t \geq CoVaR_{a,b,\alpha}^{1,2,\alpha} \mid R^2_t = VaR_{a,b,\alpha}^{1,2,\alpha}) = \frac{\partial C(F_{R^1_t}(CoVaR_{a,b,\alpha}^{1,2,\alpha}), F_{R^2_t}(y))}{\partial F_{R^2_t}(y)}_{y=VaR_{a,b,\alpha}^{1,2,\alpha}} = \beta
\]
To describe the dynamic characteristics of the dependency structure between crude oil futures markets and to accurately measure the risk spillover effect, we employ the semiparametric dynamic Copula model proposed by Hafner and Reznikova (2010) to construct the dynamic dependence structure between the Chinese and international crude oil futures markets. The semiparametric dynamic Copula model not only does not need to set the specific evolution equation of the Copula parameters, but also can estimate multiple parameters at the same time, and the parameter estimation results are also highly stable.

Taking $t$-Copula as an example, the semiparametric dynamic $t$-Copula model assumes that the parameters $\rho$ and $\upsilon$ of $t$-Copula are both second-order continuous and differentiable functions with respect to $t$. Then the parameters can be assumed to be unchanged in a small time frame. Therefore, the local pseudo-likelihood function at any time $t_0$ can be obtained as:

$$
\bar{L}(\theta; h, t_0) = \sum_{i=1}^{T} \log \tilde{c}(F_{i,t}(x), F_{2,t}(y); \theta(t))K_{\tilde{h}}\left(\frac{t - t_0}{T}\right)
$$

where $\theta = \{\rho, \upsilon\}$ is the parameter set of $t$-Copula, $\tilde{c}(.\cdot)$ is the density function of $t$-Copula, $h$ is the window width ($h > 0$), $K(.)$ is the kernel function, and $K_{\tilde{h}}(\cdot/\tilde{h})$. The estimation of $\theta$ at time $t_0$ can be obtained by maximizing the local likelihood function:

$$
\hat{\theta}(t_0) = \arg \max_\theta \bar{L}(\theta; h, t_0)
$$

The marginal GARCH(1,1) models are selected to fit $F_{1,t}(x)$ and $F_{2,t}(y)$ respectively, because they can effectively characterize the heteroscedasticity of the crude oil futures returns. The expression of the GARCH(1,1) model is:

$$
R_t^i = \mu_i + \epsilon_{i,t} \\
\epsilon_{i,t} = \sigma_{i,t}z_{i,t}, \quad i = 1,2 \\
\sigma_{i,t}^2 = \omega_i + \alpha_i\epsilon_{i,t-1}^2 + \beta_i\sigma_{i,t-1}^2
$$

where $z_{i,t}$ denotes the standardized residual following the normal distribution.

Substituting all the estimation $\hat{\theta} = \{\hat{\rho}, \hat{\upsilon}\}$ into the analytical formula of the upside CoES, the expression of it under the semiparametric dynamic Copula model can be obtained:

$$
CoES_{ud,H} = \frac{1}{\hat{\beta}} \int_0^1 \int_0^1 F_{1,t}\left(T_{\hat{\rho}}\hat{T}_{\hat{\upsilon}}(1-\alpha) + \sqrt{(1-\hat{\rho}^2)(\hat{\upsilon}^2+1)}(\hat{\upsilon}T_{\hat{\upsilon}}^{-1}(1-\alpha)^2)T_{\hat{\upsilon}}^{-1}(q)\right) dq
$$

3. Data and preliminary analysis

This paper selects the daily settlement price of INE from the Shanghai International Energy Exchange, WTI from the New York Mercantile Exchange, BRT from the London International Petroleum Exchange, and OMN from the Dubai Commodity Exchange, respectively. The data are obtained from the Wind financial data base. The sample span is from March 26, 2018 to September 30, 2019. After excluding the data with different transaction dates, a total of 353 sets of data are obtained. Since INE is priced in RMB, and the other crude oil futures are priced in U.S. dollars, the settlement price of INE is converted using the central parity rate of RMB against U.S. dollars announced by the People’s Bank of China daily. Take the logarithm of the daily settlement price and perform the first-order difference to obtain the daily returns. The summary statistics for the return series are presented in Table 1.

All the means and standard deviations of the crude oil futures return series in Table 1 are very close. According to the skewness and kurtosis, all the return series exhibit obvious peak and thick tails and are rejected obeying a normal distribution verified by Jarque-Bera statistics (J-B). The Lagrange multiplier test results (ARCH-LM) show a significant ARCH effect for all the return series at the significance level of 5%. The ADF unit root test results imply that all the return series are stationary time series. Therefore, it satisfies the conditions for modeling the marginal distribution of each crude oil futures returns using the GARCH(1,1) model.
Table 1. Summary statistics for the crude oil futures returns.

|       | Mean  | Std. Dev. | Skewness | Kurtosis | J-B   | ARCH-LM | ADF   |
|-------|-------|-----------|----------|----------|-------|---------|-------|
| INE   | -0.0002 | 0.0193    | -0.5563  | 6.3578   | 184.04** | 3.28*   | -17.50** |
| WTI   | -0.0005 | 0.0222    | 0.0350   | 7.9102   | 354.70** | 6.13**  | -20.87** |
| BRT   | -0.0004 | 0.0212    | -0.0119  | 8.6868   | 475.66** | 4.34**  | -21.27** |
| OMN   | -0.0002 | 0.0202    | -0.4050  | 4.2740   | 345.20** | 33.39** | -19.32** |

Notes: ** and * denote significance at the 1% and 5% level respectively.

4. Empirical results

4.1. Marginal models’ estimations

Table 2 presents the parameter estimations for the marginal GARCH(1,1) model. Most of the parameters are significantly not 0 at the 1% significance level. \( \alpha + \beta \) is close to 1, indicating that the GARCH(1,1) model can characterize the volatility clustering of the crude oil futures return series. Kolmogorov-Smirnov (KS) test results show that the marginal distribution is uniformly distributed on \([0,1]\) at a significance level of 1%. Therefore, the Copula model can be used to construct dependence structure between the Chinese and international crude oil futures markets.

Table 2. Estimations for the GARCH (1,1) model.

|       | \( \mu \)     | \( \omega \)   | \( \alpha \) | \( \beta \) | KS    |
|-------|----------------|----------------|-------------|-------------|-------|
| INE   | -6.90E-5       | 1.17E-5        | 0.0434**    | 0.9286**    | 0.9691|
| WTI   | -1.79E-4       | 7.13E-6        | 0.0340**    | 0.9566**    | 0.8549|
| BRT   | 2.58E-4        | 1.02E-5        | 0.0487**    | 0.9340**    | 0.9883|
| OMN   | 2.09E-4        | 7.29E-5        | 0.1402**    | 0.6825**    | 0.5807|

Notes: ** denotes significance at the 1% level.

4.2. Semiparametric dynamic t-Copula models’ estimations

A variety of Copula models are used to respectively fit the dependence structure between INE and WTI, BRT, and OMN. The results show that t-Copula has the highest goodness of fit. The goodness-of-fit test results of t-Copula in Table 3 also show that t-Copula can well describe the dependence structure of the crude oil futures markets.

Table 3. Estimations for the t-Copula model.

|       | \( \rho \)    | \( \nu \) | p-value |
|-------|---------------|----------|---------|
| INE & WTI | 0.2236 | 29.5571 | 0.1696 |
| INE & BRT | 0.3086 | 14.6747 | 0.1079 |
| INE & OMN | 0.2183 | 29.6190 | 0.7313 |

Considering that \( t_\nu \) is too small to be of no practical meaning, we calculate parameter estimations of semiparametric dynamic t-Copula parameter values based on each trading day, and regard each parameter series obtained as a smooth function of \( t \). In addition, the choice of window width should not be too large, otherwise it will cause a large fitting error, and it should not be too small, otherwise the sample information cannot be fully utilized, so 20 trading days are selected as the window width based on experience. Moreover, the commonly used Epanechnikov kernel function, \( K(u)=0.75(1-u^2)(-1 \leq u \leq 1) \), is selected in the dynamic parameter estimation.

Figure 1 shows the dynamic correlation coefficients of INE and WTI, BRT, and OMN fitted by the semiparametric dynamic t-Copula model. The dynamic correlation coefficients have changed...
drastically, but the trend are roughly the same. In April 2018, crude oil prices continued to rise due to market concerns about the uncertainty of U.S.-Iranian relations; on May 4, the U.S. announced its withdrawal from the Iran nuclear agreement, bringing oil prices to recent highs. Subsequently, oil prices fell in June until the first round of sanctions on Iran was initiated by the U.S. in August, and oil prices resumed. In November 2018, the U.S. launched a second round of sanctions against Iran, but the sanctions were lower than expected and oil prices fell. In April 2019, the exemption period of the US sanctions on Iran ended. The crude oil market had expressed concern about the incident since the beginning of the year. Oil prices continued to rise until May, when global trade frictions intensified, crude oil demand decreased, and oil prices declined. Affected by the detention of Iranian oil tankers, oil prices resumed their rise in August. It can be seen that the dynamic correlation between the Chinese and international crude oil futures markets is pro-cyclical, that is, when oil prices are high, the correlation is strong, and when oil prices fall, the correlation also weakens.

Figure 1. Dynamic correlation coefficients of the Chinese and international crude oil futures returns.

4.3. Risk spillover measure
Figure 2 shows the dynamic changes of ES, VaR, the upside CoVaR and the upside CoES for crude oil futures market returns. CoVaR is generally smaller than the corresponding CoES, indicating that CoVaR underestimates the conditional risk of crude oil futures when oil prices rise in other markets compared to CoES. CoES is almost always greater than ES, indicating that when the price of crude oil in one market rises, it will boost the price in other markets, that is, there is a positive risk spillover effect between the Chinese and international crude oil futures markets. Compared with international crude oil futures, the risk of INE fluctuates the most, that may be related to the setting of INE trading rules such as short trading hours, high trading margins, and restrictions on intraday fluctuations.

Figure 2. VaR, ES, CoVaR and CoES for crude oil futures returns.
To further analyze the intensity of risk spillovers between the Chinese and international crude oil futures, delta CoESs are calculated according to Eq. (2). The average risk spillover intensity between INE and WTI is the highest in Table 4, followed by INE and BRT, and finally INE and OMN. The main reason for the above phenomenon is that WTI is the world's most traded crude oil futures, and its price discovery ability is stronger than that of BRT and OMN. Furthermore, the risk spillover intensity from INE to international crude oil futures is on average higher than that from international crude oil futures to INE, indicating that there are asymmetric risk spillovers between the Chinese and international crude oil futures markets. In other words, INE has not always played the role of risk taker.

Table 4. Descriptive statistics for delta CoESs.

|          | Mean  | Maximum | Minimum | Std. Dev. |
|----------|-------|---------|---------|-----------|
| WTI→INE  | 0.0325| 0.0582  | 0.0205  | 0.0064    |
| BRT→INE  | 0.0323| 0.0601  | 0.0202  | 0.0064    |
| OMN→INE  | 0.0320| 0.0489  | 0.0212  | 0.0052    |
| INE→WTI  | 0.0367| 0.0662  | 0.0201  | 0.0080    |
| INE→BRT  | 0.0349| 0.0676  | 0.0229  | 0.0077    |
| INE→OMN  | 0.0328| 0.0605  | 0.0210  | 0.0053    |

5. Conclusions
In view of the risk characteristics of the crude oil futures markets, we propose and use the upside CoES as a measure of the risk spillover effect between the Chinese and three major international crude oil futures markets. To improve the rationality and accuracy of the measurement results, we employ the semiparametric dynamic Copula model to calculate the upside CoES. Based on empirical research, we draw the following conclusions. First, there is a strong positive correlation between the Chinese and international crude oil futures markets, and the correlation will gradually increase when oil prices rise. Second, there is a two-way risk spillover effect between the Chinese and international crude oil futures markets, and the risk spillover intensity between INE and WTI is the highest. Third, the risk spillover effect is asymmetric, and INE has not always played the role of risk taker. Our findings therefore have important implications for crude oil futures investors and market regulators.

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