

Analysis on Risk Spillover Effect of Oil Price and China's Stock Market before and after Negative Oil Price Shock based on GARCH-CoVaR Model

Xingzu Chen

School of Insurance, University of International Business and Economics, Beijing, 210009, China

Abstract

With people's growing attention to international oil prices after the impact of negative oil prices, this paper chooses data from March 1, 2019 to May 20, 2020. Taking the impact events as the segmentation point, the paper uses GARCH-COVAR model based on student t distribution to analyze the risk spillover effect between China's stock market and international oil price. The empirical results show that: (1) The CSI 300 Index and WTI have the characteristics of aggregate volatility. The CSI 300 Index has risk premium and WTI has leverage effect. (2) The risk degree of international oil price is greater than that of China's stock market. (3) There is a two-way risk spillover effect between China's stock market and international oil price, and the two-way risk spillover effect is enhanced after the negative impact event of oil price.

Keywords

China's Stock Market; Risk Spillover Effects; Oil Price; GARCH-CoVaR.

1. Introduction

Oil is an important raw material and an important energy source to maintain the smooth operation of a country's economy. Among them, crude oil as an important raw material for oil has attracted much attention. Because China is the largest importer of crude oil, crude oil price fluctuations have a great impact on the Chinese economy. As a barometer of a country's economy, the stock market has a great reference value to the economic situation of a country. In addition, fluctuations in market sentiment caused by changes in crude oil prices will also cause changes in the stock market. Therefore, the correlation between the fluctuation of the crude oil price and that of China's stock market is worth discussing. Every abnormal fluctuation of crude oil prices has a drastic impact on the global stock market. For example, on April 20, 2020, the US crude oil futures prices reaching a negative value caused sharp fluctuations in the international stock market. China's stock market also reacted strongly because of the market transmission. What's more, the negative price caused people to pay more attention to the change of crude oil prices. Therefore, this paper proposes to explore the correlation between the fluctuation of China's stock market and that of the crude oil prices.

2. Literature Review

2.1. Foreign Literature

The impact of oil prices on the stock market has attracted the attention of scholars as early as in the 1980s, and Chen et al. (1986) [1] research found that the risk of changes in oil prices was not reflected in the stock market. At the end of the 20th century, AYG et al. (1999) [2] studying economic data from Norway through the VAR model found that the stock market responded accurately to changes in oil prices, identical to the US and Japan. Faff et al. [3] (2005) through

the analysis of Australian stock data and oil price sensitivity found that there were different oil price sensitivity in different industries. In the 21st century, Limin et al (2015) [4] and Juan C et al(2016) [5] used the financial crisis to split up the risk spillover effects of the crude oil and stock markets. In more detail, Limin et al.(2015) measures the risk by VaR, while Juan C et al.(2016) obtains the quantile dependence under different stock market conditions through the copula function. In conclusion, the combining of foreign literature has found that in addition to the early belief that oil price changes had nothing to do with the stock market, most scholars believe that the stock market will respond to the changes of oil prices, so it is meaningful to explore the relationship between China's market oil price changes and the fluctuations of the stock market.

2.2. Chinese Literature

By combing the relevant Chinese literature, it is found that Chinese scholars in the early stage believed that the two were irrelevant. For example, Jin and Jin(2008) [6] found that there was no yield spillover effect in any direction between China's stock market price and the international oil price. With the development of time, Chinese scholars have found a correlation between China's stock market and international oil price. Liu and Fang (2013) [7] found the asymmetric influence of international oil prices on China's stock market index based on the CGARCH model analysis. Zhu et al. (2016) [8] by the AR(p)-GARCH (1,1)-Copula model found that China's earnings related international crude oil prices compared to the rest of the BRICS countries. Ding et al. (2017) [9] used the VAR method to find that the prices of international oil have a negative impact on the stock market. Zhu and Yuan (2019) [10] believe that the international interpretation of crude oil prices on China's stock market is 1.2%, so that the impact of crude oil price impact on China's stock market cannot be ignored. Zhou et al. (2020) [11] took the "market-oriented reform" as the segmentation point, using the time-varying parameter vector autoregression model and found that the connection between the crude oil market and China's stock market was small before the reform was before 2018, while the spillover effect of crude oil price gradually increased and the influence of crude oil price on China's stock market was strengthening after the reform. Zhong et al. (2020) [12] found that extreme changes in international crude oil prices are an important source of tail risk in China's stock market based on the time-varying POT model. Wang et al. (2020) [13] used the calculation and analysis of binary Copula-GARCH model and CoVaR to get the large risk overflow of international oil price fluctuation and the different industries.

After sorting out literature that summarized above, although the current research on the relationship between the international oil price and China's stock market is rich, there is no inquiry on the special time of the negative oil price, so this paper plans to analyze the risk spillover strength of China's stock market and the international oil price before and after the negative value of the oil price.

3. Research Methods

3.1. GARCH Class Model Establishment

(1) GARCH model principle

The GARCH model is the generalized autoregressive condition heterovariance model, and the GARCH (1,1) model is expressed as:

$$r_t = \gamma + u_t \quad (1)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \times u_{t-1}^2 + \beta \times \sigma_{t-1}^2 \quad (2)$$

r_t represents the yield; γ represents the mean of yield; σ_t^2 represents a conditional variance, and u_t represents the disturbance term. according to the characteristics of financial data, the disturbance term generally conforms to the student t distribution or GED distribution, and this paper assumes that the disturbance term conforms to the student t distribution. $\alpha_1 u_{t-1}^2$ is ARCH item, and $\beta \sigma_{t-1}^2$ is GARCH item.

(2) ARCH-M model principle

A model introduced by Engle, Lilien and Robins (1987) that utilizes the conditional variance to represent the expected risk, the "ARCH-in-Mean model" (ARCH-M model). The model is generally used to measure the risk premium, expressed as:

$$r_t = \gamma + \rho \times \sigma_t^2 + u_t \quad (3)$$

$\rho \sigma_t^2$ is ARCH-M item.

(3) TARCH model principle

The TARCH model was proposed by Zakoian(1990) and Glosten et al. (1993). The model is generally used to measure the "leverage effect", namely whether there is an asymmetric effect. Then, the representation of conditional variance in this model is that:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \times u_{t-1}^2 + \alpha_2 \times u_{t-1}^2 d_{t-1}^2 + \beta \times \sigma_{t-1}^2 \quad (4)$$

Among them, d_{t-1} is a virtual variable. When u_{t-1} is less than 0, d_{t-1} is equal to 1, otherwise d_{t-1} is equal to 0. $\alpha_2 u_{t-1}^2 d_{t-1}$ is the asymmetric effect term (TARCH term).

3.2. CoVaR Model Establishment

(1) VaR model

The Value at Risk Method (VaR) as published by J.P Morgan in 1997. Value of risk refers to the maximum loss that a financial asset may suffer within a given future period under normal market conditions and at a given confidence level, and the formula is:

$$\text{Prob}(\Delta P > \text{VaR}) = 1 - c \quad (5)$$

ΔP is the loss of the financial assets during the holding period and the c is a given confidence level. For easy calculation and general consideration, 95% is the confidence level.

(2) CoVaR model

The definition of CoVaR was first proposed by Adrian and Brunnermeier (2008) as a conditional risk value with the specific formula:

$$\text{Prob}(\Delta P^x \leq \text{CoVaR}_q^{x,y} | \Delta P^y = \text{VaR}_q^y) = c \quad (6)$$

$$\Delta \text{CoVaR}_q^{x,y} = \text{CoVaR}_q^{x,y} - \text{VaR}_q^x \quad (7)$$

Among them, ΔP^x , ΔP^y represents losses from x, y financial markets, while $\text{CoVaR}_q^{x,y}$ represents that the risk the financial market y may face when the financial market x is in the extreme loss of VaR_q^y at a given confidence level of c . $\text{CoVaR}_q^{x,y}$ is the spillover risk value of the y market to the x market. To facilitate the comparison, the overflow risk value is standardized, and the formula is:

$$\%CoVaR_q^{x,y} = \frac{\Delta CoVaR_q^{x,y}}{VaR_q^x} \times 100\% \quad (8)$$

(3) The GARCH model introduces the VaR and CoVaR models

This paper calculates the VaR and CoVaR values based on the student t distribution-GARCH model method. When calculating the VaR value, the equation set yield to formula (1) where a market yield is only related to its own yield fluctuations. When calculating the CoVaR, the yield of a market is not only related to its own yield fluctuation, but also related to the risk change in another market, and the formula is:

$$r_{x,t} = \gamma_x + \tau VaR_{y,t} + u_{x,t} \quad (9)$$

$r_{x,t}$, γ_x and $u_{x,t}$ is the corresponding value of the x financial market respectively. $VaR_{y,t}$ represents the tail risk of the y financial markets. After the mean equation is obtained, the separation value of the corresponding t distribution is obtained with the corresponding degrees of freedom, and the VaR and CoVaR values are calculated combined with the predicted mean and the standard difference.

4. Empirical Analysis

4.1. Sample Selection and Descriptive Statistics

The paper selects the Shanghai and Shenzhen CSI 300 Index of the Shanghai Stock Exchange to indicate China's stock market. The West Texas Intermediate Light Oil (WTI) is taken in this paper to represent international crude prices. The above data sources are all from the Wind database. This paper selects the date of the negative oil price, April 20, 2020, as the time segmentation point, and keeps the two sets of data volumes same, thus select the daily data for the trading day of 2019/3/1-2020/4/19 and 2020/4/21-2021/5/20 for analysis, with a total of 543 sets of data for analysis. This paper identifies the CSI 300 Index and WTI prices as phs and pw.

The yield selected in this paper is a logarithmic yield and increases it by 100 times for easy comparison and calculation, namely:

$$r_{x,t} = 100 \times \ln \frac{p_{x,t}}{p_{x,t-1}} = 100 \times (\ln p_{x,t} - \ln p_{x,t-1}) \quad (10)$$

Among them, $r_{x,t}$ is the logarithmic yield of the x index at the t moment, and is the price for the x index at t moments.

The yield of CSI 300 and WTI according to the yield formula (9) are recorded as rhs and rw. A descriptive statistical analysis of the total sample data of rhs and rw yields shows in Table 1.

Table 1. Descriptive Statistical Results of the CSI 300 Index and WTI Yields

Sequence	Mean	Std	Skewness	Kurtosis	ADF	ARCH-LM
rhs	0.060	1.337	-0.732	7.222	-23.485***	7.007*
rw	0.019	4.313	-0.811	21.578	-22.853***	76.746***

(Note: ***, **, * are significant at 1%, 5%, 10% confidence levels, respectively.)

Table 1 shows that both the CSI 300 Index yield's and international oil yield's skewness are less than 0 and kurtosis are greater than 3. It indicates that their distributions have characteristics of left side and spike thick tail, and their distributions are consistent with the case of general financial data. The JB statistics indicate that both yields do not obey the normal distribution hypothesis. Compared to the standard difference at the 1% significant level, both the ADF unit root test is less than that, thus obeying the unit root test, indicating that the return sequence is stable. The results of order three lag of ARCH effect LM test show that the logarithmic yields of both the CSI 300 Index and the WTI have conditional isovariance at a significant level of 90%, which means that the data meets the use of GARCH class models.

Moreover, the corresponding price and yield situation of the total sample data of the CSI 300 Index and WTI are drawn in Figure 1.

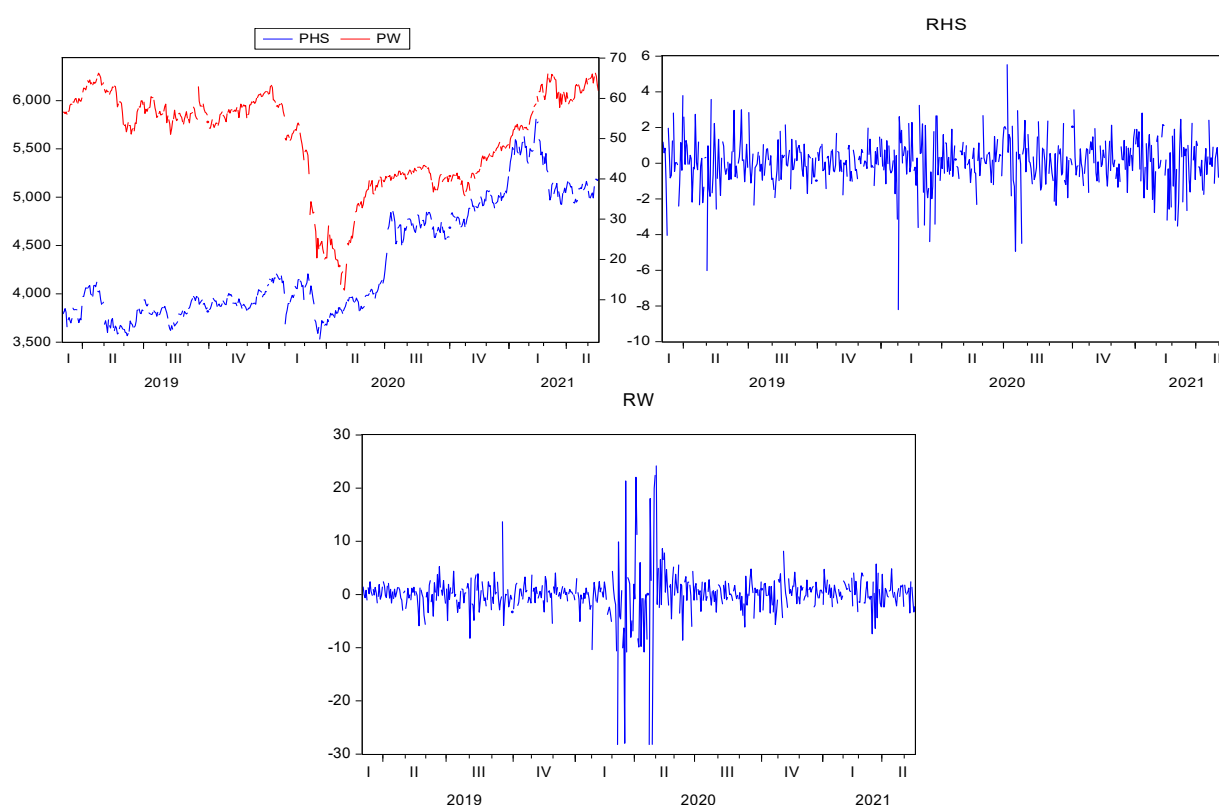


Figure 1. Price Fluctuation of the CSI 300 Index and WTI and their Return Rate Sequence Diagram

As can be seen from the price timing chart of Figure 1, the change trend of the CSI 300 Index is basically the same as that of the WTI, and the fluctuation of the WTI is more intense than that of the CSI 300 index before the negative oil price, while the volatility of the CSI 300 index after the negative price was more dramatic than before. It can be seen from the rhs timing diagram in Figure 1 that it has a relatively obvious aggregation fluctuation. The aggregation fluctuation of WTI yield shown in the timing diagram of rw is more obvious, and it is obvious that the fluctuation is concentrated in the period before and after the negative value of the oil price. The results of the rhs and rw timing diagram also intuitively support the results of its ARCH-LM test that meet the use conditions of GARCH class models.

4.2. Analysis of risk premium and asymmetric characteristics

The ARCH-M model and the TAR model are established to analyze the risk premium and leverage effect of the total sample data of the CSI 300 Index and WTI, and due to the characteristics of the data, this paper set the yield sequence to obey the student t distribution,

that is, the disturbance items obeys the student t distribution. The parameters obtained through the Stata software are shown below.

Table 2. Results of GARCH Class Model Parameters Estimation under Student t Distribution

Sequence	Model	α_0	α_1	α_2	β	ρ
rhs	GARCH	0.112	0.079**		0.870***	
	ARCH-M	1.941***	0.001*			20.540***
	TARCH	3.567***	0.020	-0.010	-0.872***	
rw	GARCH	0.529**	0.206**		0.802***	
	ARCH-M	14.307	1.539			0.006
	TARCH	0.374**	0.251*	-0.182**	0.837***	

(Note: ***, **, * are significant at 1%, 5%, 10% confidence levels, respectively.)

According to the above results, ρ (ARCH-M item) of the CSI 300 yield is 20.540 and is significant at the 99% level, indicating that the CSI 300 index has a relatively significant risk premium, while the ρ value of WTI yield is positive but not significant, which means that although WTI is also high risk and high profit, its risk premium is not obvious. In the asymmetric analysis, α_2 (TARCH item) of the CSI 300 Index yield is not significant, so there is no asymmetric effect, while the asymmetric term of WTI yield is -0.182 and significant at the 95% significance level, which shows that for international oil prices, "good news" has less impact on price fluctuations than "bad news", namely, it has a leverage effect.

4.3. Analysis of the Risk Spillover Strength

Since the purpose of this article is to compare the difference of risk spillover intensity between international crude oil and China's stock market before and after the negative oil price, this section analyses two samples which are 2019/3/1-2020/4/19 date called previous-segment data and 2020/4/21-2021/5/20 data called back-segment data by comparing the total data. Through Eviews software, the separation value and tail risk values under the t distribution of each yield sequence are shown in Table 3.

Table 3. Separation Values and Tail Risk Values of Each Study Sequence

Date Range	Variable	t distribution (95% confidence level)		VaR	
		Degree of Freedom	Fractional Value	Mean	Std
Total Data	The CSI 300 Index	4.752	2.039	-2.575	0.743
	WTI	3.310	2.266	-7.492	6.144
Previous-segment Data	The CSI 300 Index	3.970	2.136	-2.770	0.743
	WTI	2.733	2.450	-9.083	6.906
Back-segment Data	The CSI 300 Index	5.368	1.985	-2.397	0.239
	WTI	6.647	1.910	-5.405	5.603

(Note: The risks shown in the table are the lower tail risks)

According to the results of Table 3, the risk degree of CSI 300 Index and WTI both decreased after the negative price and the decline of WTI was large. By comparing the risks of CSI 300 Index and WTI, we could find that the risk of international oil price is both higher than that of China's stock market whether before and after the impact. A possible explanation for this might be that the changes in international oil prices are affected not only by macro factors, but also

by the oil producing countries, and then the risk of international oil prices may be greater. In addition, due to China's macro-control policies which stabilize the market and positive epidemic prevention and control measures which make the market sentiment relatively stable, the impact of the epidemic on international oil prices is higher than on China's stock market.

It can be seen from Figure 1 that the price change interaction between the CSI 300 Index and WTI, especially since the II quarter of 2020, indicates a correlation between the two. In order to further investigate the overflow direction and intensity of the risk of China's stock market and international oil market, this paper uses the Student t-GARCH-CoVaR model and combines the formula of CoVaR, Δ CoVaR and %CoVaR to calculate conditional risk series values based on obtaining VaR sequence of the CSI 300 Index and WTI. Fractional values under the t distribution and conditional risk series values computed through EvIEWS are summarized in Table 4.

Table 4. Fractional Value and Conditional Risk Values

Data Range	Variable	t Distribution (95% Confidence level)		Mean of CoVaR Series		
		Degree of Freedom	Fractional Value	CoVaR	Δ CoVaR	%CoVaR
Total Data	CSI 300 Index→WTI	3.308	2.267	-7.494	-0.002	0.034
	WTI→CSI 300 Index	4.748	2.039	-2.576	-0.001	0.039
Previous-segment Data	CSI 300 Index→WTI	2.732	2.451	-9.086	-0.003	-0.025
	WTI→CSI 300 Index	3.972	2.136	-2.771	-0.001	0.008
Back-segment Data	CSI 300 Index→WTI	6.602	1.912	-5.408	-0.003	0.093
	WTI→CSI 300 Index	5.364	1.985	-2.396	0.001	-0.051

(Note: CSI 300 Index→WTI represents the risk spillover effect of the CSI 300 Index on WTI, with the rest.).

According to the results of the total data of Table 4, both the spillover effect of the CSI 300 Index on the WTI and the spillover effect of the WTI on the CSI 300 Index are positive spillover effects. A possible explanation for this might be that this paper select a relatively small sample interval, and some special risk events may similarly affect the fluctuations of the CSI 300 Index and WTI. Besides, the result of the sample data shows that the spillover effect of the CSI 300 Index on the WTI is negative spillover effects and the spillover effect of the WTI on the CSI 300 Index is positive effect before the oil price impact, while it's exactly the opposite after the oil price impact. From the perspective of risk spillover intensity, the risk spillover intensity in any direction after the negative impact of oil prices is greater than the intensity before the impact of oil prices. Possible reasons for this might be that more attention to international oil price of China's stock market after the impact, Chinese unconventional measures and oil production reduction after the impact. Moreover, whether before and after the impact, the CSI 300 index has a stronger risk spillover on the WTI than its impact on the CSI 300 index, which may be related to the increased influence of the Chinese economy on the world economy, and the CSI 300 index under China's stronger macro-control role.

5. Conclusion and Policy Suggestions

Based on the data of CSI 300 Index and WTI, this paper establishes a GARCH class model to study the risk characteristics of the CSI 300 Index and WTI. Secondly, dividing the sample data with negative oil price as the impact event, the GARCH-CoVaR model is established to analyze and compare the risk spillover state and intensity of China's stock market and international oil price before and after the impact of negative oil price. The concrete empirical analysis conclusions are as follows:

First, the total sample shows that both the CSI 300 Index and WTI have obvious aggregation fluctuation characteristics. The CSI 300 index has a significant risk premium and WTI has a leverage effect. Secondly, through the comparison of the sample data, we can get the conclusion that under the severe influence of oil prices by the oil producer and the macro-control action of the Chinese government, the risk degree of international oil prices is greater than the risk degree of China's stock market. Finally, in terms of risk spillover effect analysis, there is a two-way risk spillover effect between China's stock market and international oil price. Moreover, due to the rising concern on oil prices after negative oil prices, producer control over oil production and China's unconventional measures, the two-way risk spillover intensity after the impact is enhanced.

In summary, China should further stabilize operation of the national economy under the epidemic situation, weaken the impact of international oil price on China's market, and enhance investors' confidence in the Chinese market. Besides, China should also build more oil storage facilities and improve the oil pricing mechanism and oil storage and transportation systems to weaken the impact of the strong fluctuation of oil prices in the international market on the Chinese economy.

References

- [1] Economic Forces and the Stock Market[J]. The Journal of Business, 1986, 59(03):383-403.
- [2] AYG,BFS. Causal relations among stock returns and macroeconomic variables in a small, open economy - ScienceDirect[J]. Journal of International Financial Markets, Institutions and Money, 1999, 9(01):61-74.
- [3] Faff R W, Brailsford T J . Oil price risk and the Australian stock market[J]. Journal of Energy Finance & Development, 2005, 4(01):69-87.
- [4] Limin, Du, Yanan, et al. Extreme risk spillovers between crude oil and stock markets[J]. Energy Economics, 2015, 51(08):455-456.
- [5] Jcr A , Au B . Quantile dependence of oil price movements and stock returns - ScienceDirect[J]. Energy Economics, 2016, 54(11):33-49.
- [6] Jin Hongfei, Jin Luo. Overflow effect of oil price and stock market based on comparative analysis of Chinese and American data[J]. Journal of Financial Research, 2008, (02): 83-97.
- [7] Liu Ling, Fang Yan. Analysis of asymmetric impact of international oil Impact on chinese stock market based on the CGARCH model[J]. Inquiry into Economic Issues, 2013, (12): 120-125
- [8] Zhu Huiming, Dong Dan, Guo Peng. Study on the correlation between international crude oil price and stock market income based on the Copula function[J]. The Theory and Practice of Financial and Economics, 2016,37 (02): 32-37.
- [9] Ding Xuhui, Wang Liuyuan, He Juhua. Linkage effect of international oil price and Chinese stock market based on VAR model[J]. Enterprise Economy, 2017,36 (07): 167-173.
- [10] Zhu Xiaoneng, Yuan Jingfa. Oil price trends and the stock market: empirical evidence from 35 countries along "the Belt and Road" [J]. Journal of Financial Research, 2019, (09): 131-150.

- [11] Zhou Donghai, Chen Binxia, Jiang Yuanying. Research on the relationships between interest rate, exchange rate marketization, International Crude Oil and China's Stock Market[J]. Statistics & Information Forum, 2020,35 (02): 47-58.
- [12] Zhong Wanling, Li Haiqi, Yang Shenggang. Tail risk spillover effects among crude oil price, macroeconomic variables and China's stock market[J/OL]. Chinese Journal of Management Science,: 1-13
- [13] Wang Sanxing, Li Huiyu, Chen Tiantian, Song Ran. An analysis of risk spillover effects between international oil price and industry stock market[J]. Macroeconomics, 2020, (08): 166-175.