Fluctuations of Oil Price and China's Stock Market

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Abstract. The Russia-Ukraine conflict broke out in February 2022 and oil prices fluctuated heavily with the deterioration of the conflict. This paper evaluates the causes of oil price fluctuations and their effects on China's stock market in value and volatility. We build the ARMAX and ARMA-GARCH models to analyze the impact of fluctuations of oil price on the stock price. According to the results of empirical analysis, the paper finds that oil price fluctuations can negatively influence China's stock price. We hope to bring some investment and management suggestions to investors, firms and policy makers in China's stock market respectively according to our conclusion.

Keywords: Russia-Ukraine conflict, oil price fluctuations, China's stock market.

1. Introduction

According to the statistics of the International Energy Agency (IEA) and Wood Mackenzie, Russia is the third-largest oil producer in the world and second only to the United States and Saudi Arabia. In 2021, Russia's oil production was 11.06 million barrels per day, of which crude oil production was 10.68 million barrels per day. Since 2022, the Russia-Ukraine conflict has gradually deteriorated, which caused oil price fluctuations significantly. The price of WTI crude oil futures has increased by $15 / barrel from January to February. On January 26, the United States and North Atlantic Treaty Organization (NATO) submitted a reply on the bilateral security guarantee to Russia, rejecting Russia's request to "not include Ukraine in NATO", which aggravated tension heavily. On February 24, Russia launched a special military operation in Ukraine. On February 28, the United States, the United Kingdom, and other countries committed to ensuring selected Russian banks are removed from the Society for Worldwide Interbank Financial Telecommunication (SWIFT) messaging system, and then the price of WTI crude oil futures exceeded 100 dollars. On February 27, British Petroleum (BP), Shell, ExxonMobil, and other oil companies successively announced their withdrawal from Russian business, which led to concerns about insufficient supply and oil prices. On March 8, the United States announced a ban on the import of Russian oil and gas. After that, the United Kingdom announced that it would gradually stop importing Russian oil and related products by the end of the year. WTI crude oil futures price reached US $123.70/barrel, the highest value after 2015.

The Russia-Ukraine conflict triggered sanctions against Russia by the United States, the United Kingdom, and other countries, which deeply affected Russian oil exports and oil prices. These countries have cut off the use of the SWIFT messaging system by some Russian banks and sanctioned Russian financial institutions, making bilateral transactions more difficult and costly. If a large number of Russian oil traders cannot obtain dollars through trade, they will reduce oil exports to avoid losses. What's more, people will not change the habit of driving cars and enterprises will not suddenly reduce the use of oil in a short time. Therefore, the reduction of oil supply will lead to a rise of oil prices.

The paper written by Xin Gu, Weiqiang Zhang, and Sang Cheng discusses the impact of Sino-US trade and non-trade disputes on the Chinese stock market.[1] They research a number of affected industries, including media, computer applications, and electronic equipment. We learn from their methods and study the different influences on related industries. The standard story is that the price of oil influences the costs of other production and manufacturing. For example, there is presumed to be a direct relationship between a rise in oil prices means higher transport costs leaving less disposable income in people's wallets. Also, the rise in oil prices serves as an obstacle to the auto industry. Consumers can't afford high oil prices so they are not willing to buy cars. At the same time, the real estate market is also affected because of the decline in purchasing power and the rise in unemployment caused by high oil prices, and consumers' willingness to buy houses has been greatly weakened. On the contrary, domestic enterprises which mine oil can make profits from the sharp rise in oil prices. For the chemical industry, though many industrial chemicals are refined from oil, Chemical enterprises can also raise product prices to balance the rise in costs. Pesticides, chemical fertilizers, and chemical fibers are produced by the enterprises, which have a profound impact on the agriculture and garment production industry. People will not reduce their spending on agriculture and clothing in a short time, so the chemical industry can benefit from a higher oil prices.

Oil price fluctuation has a direct impact on China's energy and machinery industries. In 2019, China's dependence on foreign oil has reached 72%. Therefore, international oil price fluctuations will seriously affect China's stock market. However, as mentioned above, oil price fluctuations have different effects on different industries. So it is difficult to judge profits and stock fluctuation. Generally speaking, the impact of oil prices on China's stock market is complex. Based on this idea, this paper tries to look out for further corresponding relationships between the oil price fluctuations and China's stock market.

This paper discusses oil price fluctuation and its influence on China's stock market. Firstly, we use WTI crude oil futures price as an indicator to measure oil price fluctuations and use Shanghai Securities Composite Index (SSEC) and Shenzhen Securities Component Index (SZI) as indicators to measure China's stock market. Secondly, we build an ARMAX model to find out whether oil price fluctuations have an influence on the stock price and how serious this impact is. In the next part, the paper builds an ARMA-GARCH model. Based on the conditional heteroscedasticity found in the stock price series, the research lays great importance on the result of the GARCH part and draws conclusions based on the model performance.

2. Research Design

2.1 Data Source

Data of WTI crude oil futures price in this paper is derived from New York Mercantile Exchange (NYMEX). NYMEX is the world's largest physical commodity futures exchange and is today part of the Chicago Mercantile Exchange Group (CME Group), which is the world’s leading and most diverse derivatives marketplace. It mainly involves two categories of products: energy and rare metals, but the trading of energy products accounts for the largest proportion. What’s more, it lists global benchmarks for these futures products, commodities.

The data of SSEC and SZI is obtained from Shanghai Stock Exchange and Shenzhen Stock Exchange respectively. Shanghai Stock Exchange and Shenzhen Stock Exchange are the major stock exchanges in China. They are also the most well-known and active stock exchanges in the world. To reflect the real stock market, the paper chooses closing price as an indicator.

This paper matches oil price data with the stock price data according to the date. Since the stock price data changes only on the trading day, the paper ignores the oil price data on non-trading days and sorts the remaining data by date. In this research, we will use Stata for regression analysis to solve the problems that may be encountered in further study.

2.2 Unit Root Test

The unit root test is also called the ADF test, which is a good way to check out whether a time series is stationary. When using ARMA, ARIMA, and other models, the time series are required to be stationary. Therefore, the ADF test is used to test the stationarity of the time series. If the time series is not stationary, we will use other methods to transform the series to make it stationary.

The function of the unit root test can be written as:

$$x_t = c_t + \beta x_{t-1} + \sum_{i=1}^{p-1} \emptyset_i \Delta x_{t-i} + \varepsilon_t \tag{1}$$

Wherex_t refers to time series, β is the lag term coefficient.

If β equals 1, it becomes the unit root and the relationship between independent variables and dependent variables is deceptive, which means that the effect of residual in the model is permanent. The null hypothesis of the ADF test is that β equals 1, which indicates that the series has a unit root and is not stationary. Therefore, if we want to acquire a stationary series, we must order β to be less than 1.

In the research, we construct logarithmic rate of return as the stock yield, which can be calculated as:

$$Simple\ Rate\ of\ Return = \frac{Price_t - Price_{t-1}}{Price_{t-1}} \tag{2}$$

$$\textit{Logarithmic Rate of Return} = \textit{ln(1+Simple Rate of Return)} \tag{3}$$

Table 1 gives us the test results of the price series and their rate of returns:

Table 1 results of the stationarity test

Variables	t-statistic	p-value
	Price series	
SSEC	-2.895	0.1577
SSZI	-2.914	0.1285
WTI	-3.846	0.0144
	Rate of return	
SSEC	-7.150	0.0000***
SZI	-7.203	0.0000***
WTI	-4.092	0.0065***

Note: ***, **, and * indicate the level of significance of 1%, 5%, and 10%, respectively.

It shows that the price series is not stationary because SSEC and SZI series are not significantly stationary under 90% confidence intervals. However, the rate of return series is significantly stationary under 99% confidence intervals, which means they perform very well in the stationarity. When it comes to data of WTI, though its price series can be trusted under 95% confidence intervals its rate of return series has a higher significance. Based on the results, we can build ARMAX and other models which suppose the time series is stationary.

2.3 ARMAX Model Specification

ARMAX model is an autoregressive moving average model with external interference term, which combines regression analysis and time series analysis. It is composed of an autoregressive model (AR model for short), moving average model (MA model for short) and an X Distributed Lag (ADL) term.

AR model offers a statistical method for processing time series. It has an assumption that the past and future data series are linear. The core idea of AR modal is that it can use past data to predict the future. If we need data for multiple periods, we have to introduce a variable "p", which refers to the largest lag order of all lag terms. AR(P) function can be written as:

$$y_t = c + \sum_{i=1}^{p} \varphi_i\, y_{t-i} + \varepsilon_t \tag{4}$$

Where c is a constant and y_t is the value of the series, while ε_t is the error term.

MA model is another way to predict future value while it pays more attention to error terms. The core idea of MA model is that it can make use of past error terms to predict future values. It can be written as:

$$y_t = c + \sum_{i=1}^{q} \theta_i \, \varepsilon_{t-i} + \varepsilon_t \tag{5}$$

Where c is a constant and y_t is the value of the series, while ε_t is the error term series.

To build an ARMAX model, we have to introduce an X term, which is derived from an Autoregressive Distributed Lag (ADL) model. ADL model can be shown as:

$$y_t = c + \sum_{i=1}^{p} \varphi_i \, y_{t-i} + \sum_{k=0}^{l} \omega_k \, x_{t-k} + \varepsilon_t \tag{6}$$

Where c is a constant and y_t is the value of the series, while ε_t is the error term series and x_{t-k} is the value of another series.

As mentioned above, an ARMAX model is formed by an AR model, a MA model, and an X term. So it can be shown as:

$$y_t = c + \sum_{i=1}^{p} \varphi_i \, y_{t-i} + \sum_{j=1}^{q} \theta_j \, \varepsilon_{t-j} + \sum_{k=0}^{l} \omega_k \, x_{t-k} + \varepsilon_t \tag{7}$$

Where c is a constant and y_t is the value of the series, while ε_t is the error term series and $\sum_{k=0}^{l} \omega_k \, x_{t-k}$ can be considered as the X term of the model.

To fully consider the relationship between oil price fluctuations and China's stock market, we choose to build an ARMAX model to consider the impact of the past value and error term. So in this paper, y_t is the yield of SSEC or SZI, x_{t-k} is the value of the X variable in period t-k. φ_i, θ_i, ω_k are corresponding coefficients.

2.4 ARMA-GARCH Model Specification

Based on ARMA model, ARMA-GARCH model introduces the GARCH model. GARCH model is a regression model specially tailored for financial data. GARCH further models the variance of error based on the ordinary regression model. It is especially suitable for the analysis and prediction of volatility. A GARCH(p,q) can be written as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2 \tag{8}$$

Where σ_t^2 is the variance of the series in the period t and α_0 is a constant, while ε_{t-j}^2 is the square of the error term in the period t-j.

Markets' returns are positively correlated with the risks they contain so we must consider risks. Compared with the previous ARMA model, ARMA-GARCH model takes risk into account based on value, which plays an essential role to analyze the fluctuation of stock value. To discuss the risk of return, we build an ARMA-GARCH model which considers both value and variance.

3. Empirical Result

3.1 ARMAX Model Result

To build an ARMAX model, the paper first finds out the suitable AR and MA part of SSEC and SZI.

Check the partial autocorrelation plot (PACF plot) of the series in Stata, the result is shown in Figure 1. The black rectangle is the benchmark to find out the statistically significant term in the AR model, from which it could be seen that the lag 11 and 15 terms of the original series may have a significant impact on the current data for both SSEC and SZI.

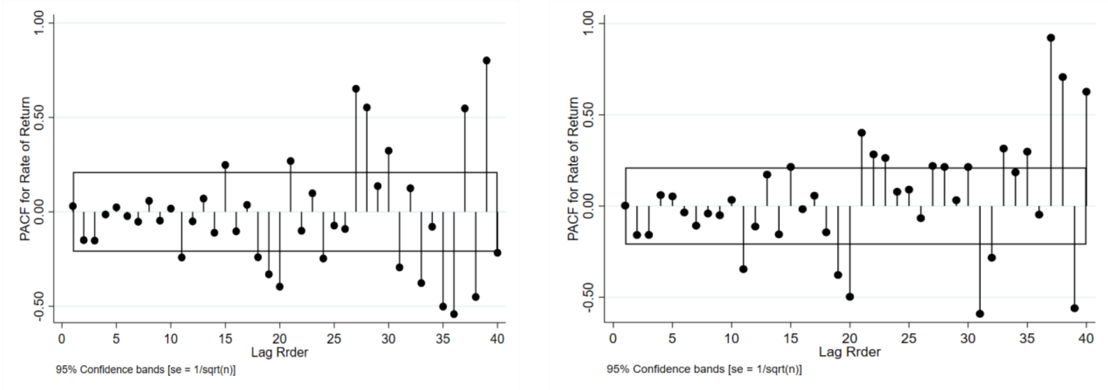

Figure 1 PACF for AR order identification

To further confirm the result, the research uses a white noise test to find out the proper order p of the AR model. According to the results of the test, it shows that the feasible order of the AR model for both two indicators is 11.

Autocorrelation Plot (ACF Plot) is used in this paper to determine the MA part of the series, a plot drawn by Stata is shown in Figure 2. It can be seen from the result that there are no fit lag terms for SSEC and lag 11 terms are a good choice for the moving average process.

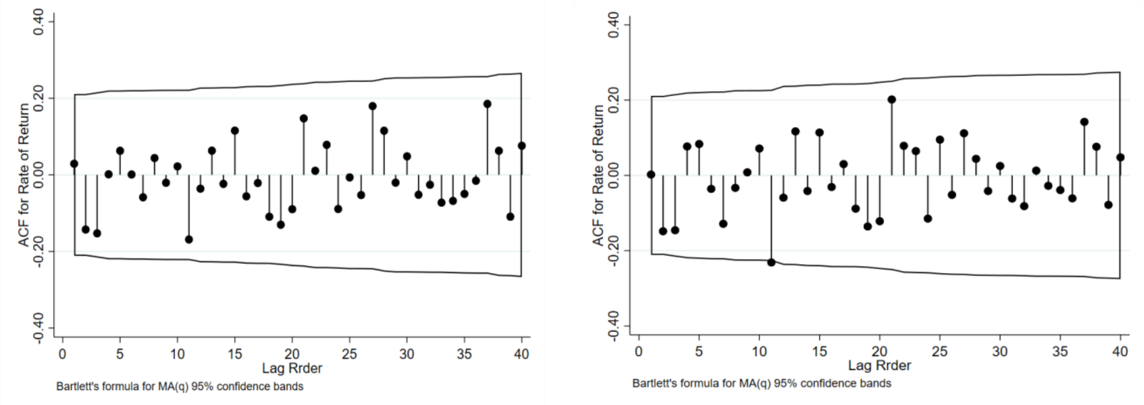

Figure 2 ACF for MA order identification

To further confirm the result, the research uses a white noise test to find out the proper order p of the MA model. The test results show that the feasible order of the MA model for SZI is 11.

After testing the several models built with different AR and MA terms, the paper finally finds the best ARMA term of ARMA which contains the AR terms of lag 11 as well as the MA term of lag 11.

Table 2 ARMAX model estimation results

Variables	SSEC			SZI		
	(1)	(2)	(3)	(4)	(5)	(6)
			WTI			
T=0	-0.0079	0.0567	0.0561	-0.0099	0.0518	0.0799*
	(0.0080)	(0.0381)	(0.4266)	(0.0089)	(0.0475)	(0.0463)
T=-1		-0.0664*	-0.0616		-0.0634	-0.1506**
		(0.0375)	(0.0605)		(0.0488)	(0.0699)
T=-2			-0.0041			0.0570
			(0.0280)			(0.0369)
			ARMA			
AR (-11)	-0.2046	-0.2007	-0.2096	-0.4481	-0.4685	2.2038***
	(0.1321)	(0.1529)	(0.1572)	(0.5795)	(0.5881)	(0.6372)
MA (-11)				0.1766	0.1980397	-2.2008***
				(0.6455)	(0.6455)	(0.6302)
Constant	0.0341	0.0416	0.0412	0.4186***	0.0489	0.0587
	(0.03650)	(0.0351)	(0.0358)	(0.0403)	(0.0414)	(0.0604)

Note: T indicates the lag order. In the two rows of each lag, the first one indicates the estimated coefficient of the term, and the second is the standard error of the estimated result. ***, **, and * indicate the level of significance of 1%, 5%, and 10%, respectively.

From estimation results in table 2, the second column of estimates shows that there is a significant negative correlation between the yield of crude oil futures lagging behind the first period and the yield of SSEC at a degree of significance of 1%. Specifically, for every 1% increase in the yield of crude oil futures lagging behind the first period, the yield of SSEC would decrease by 6.64%.

From the ARMA (11,11) estimation results, the sixth column of estimates explains that there is a negative correlation between the yield of crude oil futures lagging behind the first period and the yield of SZI at a degree of significance of 5%, and there is a positive correlation between the yield of crude oil futures in the current period and the yield of SZI at a degree of significance of 10%. Because the yield in the current period has a lower significance, the rise of crude oil futures price can explain the decline of SZI yield.

3.2 ARMA-GARCH Model Result

Based on what has been done in building the ARMAX model, this paper uses an ARMA-GARCH model. We use GARCH model to consider the variance equation and find out whether the change of oil price leads to the change of stock volatility. The results are shown in Table 3.

Table 3 ARMA-GARCH model estimation results

Variables	SH index			SZ index		
	(1)	(2)	(3)	(4)	(5)	(6)
T=0	2.3933	-0.8706	-1.4712	3.0320**	-4.7282	-4.5527
	(1.5865)	(7.4469)	(7.1649)	(1.4761)	(6.5110)	(7.6258)
T=-1		3.3913	1.9414		7.8590	5.8870
		(6.8717)	(8.7531)		(6.6644)	(13.2892)
T=-2			2.0800			1.6583
			(7.0006)			(7.4932)
Constant	-20.6425***	-21.1254***	-21.1963***	-22.8780***	-22.9437***	-22.1958***
	(6.9007)	(7.2080)	(7.2214)	(6.5872)	(6.1650)	(6.2306)

Note: T indicates the lag order. In the two rows of each lag, the first one indicates the estimated coefficient of the term, and the second is the standard error of the estimated result. ***, **, and * indicate the level of significance of 1%, 5%, and 10%, respectively

Based on the result of columns (4), the increase of crude oil yield leads to the fluctuation of SZI and has no significant impact on the SSEC. According to the research by Mork et al, Lee et al., Hooker, Hamilton, et al, oil prices shocks can affect the discount rate for cash flow by affecting the expected inflation rate and the expected real interest rate, which will influence the corporate investment decision as well.[2-7] By the normal logic, big firms have more human, material, and financial resources which can help them predict the expected real interest rate and the expected rate of inflation so they will be better prepared than small or medium firms.

As of November 2021, the Shanghai Stock Exchange has a total market value of 7.7 trillion dollars and more than 2000 listed enterprises mostly with large market values. Thus, the total market value of Shenzhen Stock Exchange is 5.9 trillion dollars and there are 2550 listed companies, which mainly have medium market value. Because the Shanghai Stock Exchange has a larger size, which means a higher anti-risk ability, external risk factors such as oil price fluctuations will have less impact on it. But for those medium firms in Shenzhen Stock Exchange, are more affected by external risk factors and have to respond more violently to oil price fluctuations. Therefore, SZI fluctuates more dramatically than SSEC under the influence of oil price fluctuations.

4. Discussion

According to the empirical results of the two models, the paper finds that the yield of SSEC and SZI is negatively correlated with the yield of crude oil futures lagging behind the first period. In addition, oil price fluctuations would surprisingly repress the volatility of Shenzhen Stock Exchange but have no significant influence on Shanghai Stock Exchange.

There are plenty of issues about the effect of oil price fluctuations on the stock market. Jones and Kaul report a significant negative connection.[8] Park and Ratti prove that oil price fluctuations have a significantly negative impact on stock returns in the U.S. and 12 European oil-importing countries.[9] These papers have similar results to our research. But some theses provide evidence for the findings that the connection is not so significant. Huang et al. conclude that oil futures returns are not correlated with stock market returns, even contemporaneously.[10] Chang et al use the VARMA-GARCH and VARMA-AGARCH models to provide little evidence of dependence between the crude oil and the financial market.[11] The reason why our results are different from theirs may come from the different times of the data. The data used by us is under the Russian-Ukrainian conflict in 2022, while the data used by most of the previous research comes from the 1990s or the early 20th century. Moreover, we evaluate the impact on the Chinese market, while other literature mostly discusses the impact on the United States or European countries.

For investors, the decline of stock returns and the increase in risks make it a wise choice to reduce or avoid buying stocks when oil prices rise. They can choose to store assets by means of bonds or bank deposits, which are security assets and better than cash. investment organizations, according to the research by Fabio Zona,[12] organizations with slack resources may invest in innovation tp respond to a crisis. If you want to invest in stocks, you can choose Shanghai Stock Exchange, which has more companies with large market value and strong anti-risk ability. So, the volatility of Shanghai Stock Exchange is less affected by the fluctuation of oil price. For policymakers, it is very important to encourage companies to improve their anti-risk ability. They can choose to reward companies that do better in the aspect by reducing taxes or giving preferential conditions, which provides a positive incentive to all firms. After most companies improve their anti-risk ability, the anti-risk ability of the whole market will be strengthened, so that it can deal with sudden external factors better.

Further research can be carried out from two aspects: First, the ARMAX model can be improved with the same GARCH term to make a more precise analysis of the stock price. Second, this paper uses SSEC and SZI as indicators to measure China's stock market, but we can use more optimized indicators to consider investor sentiment and market sentiment.

5. Conclusion

The Russia-Ukraine conflict has had a great impact on international oil prices, which results in an insufficient oil supply and a rise in the oil price. The research builds the ARMAX model and ARMA-GARCH model to focus on the stock return and volatility sector. According to the analysis of empirical results, the correlation coefficient between oil price fluctuation and China's stock market is negative under a high significance. Additionally, oil price fluctuations have impact on Shenzhen Stock Exchange, but no impact on Shanghai Stock Exchange. The paper finds that conclusions vary considerably from different stock exchanges. For Shanghai Stock Exchange, higher oil prices will result in lower yields. However, volatility will not increase significantly. But for Shenzhen Stock Exchange, a rise in oil prices will not only reduce its yield but also increase its volatility.

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