Regional Conflict and Financial Market Reaction: Evidence from China and US

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Abstract. The conflict between Russia and Ukraine at the start of 2022 has largely influenced the global market, both the commodity market and stock market. Russia, as a major exporter of oil, has been sanctioned by the western countries which led to a sharp rise in the price of the crude oil. And the global capital market was affected consequently. This paper uses the Shanghai Stock Exchange Composite and the Shenzhen Stock Exchange Component Index in the Chinese market, and the Dow Jones Industrial Average, the Standard & Poor's, and the National Association of Securities Dealers Automated Quotations in the American market to assess the impact of the geopolitical risk. Using these indices, this paper builds a VAR model to analyze the interaction of the index value and the oil price within a system, and to predict the further influence of the fluctuation in the price of the crude oil on the security market. An ARMA-GARCH model is also built to find out the change in stock market volatility induced by the oil price. This paper finds that the war-induced rise in the price of crude oil has a negative impact on the return of the security market both in China and the US while having little influence on the volatility.

Keywords: Geopolitical risk; time series; ARMA-GARCH; VAR; oil price.

1. Introduction

In February 2022, the outbreak of the conflict between Russia and Ukraine gave a big shock to the world and the capital market. The Ministry of Defense of Russia had announced to partly withdraw the land force which had been involved in a large-scale military exercise on the Ukraine border on Feb 15th, which seemed to be a signal that the crisis in Ukraine has eased. Two days later, however, the situation suddenly deteriorated and on Feb 24th, the war began, which was far beyond investors' expectations and has become a black swan event that sharply influenced the capital market in the short term. The CBOE Volatility Index significantly rose on Feb 24th, to 33.91 with an increased rate of over 12%.

Moreover, besides the war itself, Russia as a major energy exporter has faced sanctions from the western country which raised concerns about supply disruption and pushed WTI crude oil prices up. The price went up from $93 on Feb 24th to $124 on Mar 8th, when President Biden signed an Executive Order to ban the import of Russian oil, liquefied natural gas, and coal to the United States. The European Union and the United Kingdom followed up and the oil price remained fluctuated at a high level of over $100 for almost 4 months after the announcement, which has had a profound impact on the capital market around the world. Oil as a crucial non-renewable energy resource, due to the geographical unbalanced distribution, needs to trade frequently and thus has a great spill-over effect on the capital market of the exporting and importing countries. [1] As the conflict heated up and the sanction from western countries escalated, there has been increased volatility in the financial market.

Literature shows that geopolitical conflicts have a great impact on the global stock market. From a microscopic perspective, the results show that the geopolitical conflict leads to a decline in the price of corporate securities and an increase in asset volatility, and therefore leads to a higher default probability and greater turmoil and uncertainty in the financial market [2]. As researchers had pointed out, the war-induced shock had a remarkable negative impact on major financial markets with a greater effect on volatility than returns, and the effect increased with the countries' increasing dependence on Russian commodities [3, 4]. Researchers used the Geopolitical Risk Index (GPR) to analyze the geopolitical risk events' influence on global economy, and have found that the geopolitical turmoil has a significant short-term impact on the global stock market overall. However, the impact was more remarkable on European market for its reliance on the trading and energy market in Asia and eastern Europe. Due to the scale of the US market and the global influence of the US dollar, American market performs a better anti-risk advantage over the other countries. Chinese market, with high resilience in economy and independence in macro-economic policy, was also less affected by geopolitical events [5].

Both Russia and Ukraine are the most important commodity exporters in the world, and the war largely affected the world's commodity market supply chain. The war exacerbated the energy dilemma after Covid-19 pandemic all around the world, the price increased dramatically and many people in many areas cannot afford to pay their electricity bills [6, 7]. Literature shows that the sanction on the energy exportation of Russia has triggered panic in the market and led to an increase in the probability of outbreak of the fourth energy crisis. Furthermore, the rise in oil prices may lead to global inflation and may spill over to the global capital market in the long term [8]. Researchers have found that economics experts increase short-run inflation expectations for 2022 by around 0.75% after the conflict between Russia and Ukraine, for many of them believed that the Russian invasion had intensified global supply bottlenecks [9].

There are several researches on the transmission mechanism of the price fluctuation of crude oil onto the security market. Sun found out the spill-over effect the price of the oil has on the security market is time-varying, the risk contagion of the extreme market period is significantly greater than that of the normal market period, and the financial crisis has helped the two-market link closer [10]. Researchers constructed VAR Model and analyzed the impact of the supply shock and demand shock of oil on different countries, finding that oil market shock has little impact on the developed market[11].

All these findings research the short-term shock on the security market and the long-lasting impact on the oil market of the Russian and Ukraine conflict. Previous findings have pointed out the spillover effect of the crude market has on stock price. This paper aims to connect the impact of the war on the oil market and the spillover effect of the oil price fluctuation on the stock price, to find out the long-term effect of the war on the capital market in China and America.

The paper researches on the return and volatility both in the Chinese market and the American market, using 2 indices from the Chinese security market and 3 indices from the American security market. Firstly, the research calculates the return of the index using the close price and prepares the data to build further models. The paper builds a VAR model, creating a system containing the return of the 5 indices and the WTI crude oil return. The paper draws the impulse response graph to visualize the WTI oil price-induced shock on the 5 indices and to further predict how the oil price will affect the American and Chinese security markets. Finally, the paper moves on to the volatility of the market, which indicates the risk of the stock market. Based on the conditional heteroscedasticity of the stock returns, this paper builds an ARMA-GARCH model, using the WTI oil price as an exogenous variable to analyze the volatility that the oil price brings to the stock market.

2. Research Design

2.1 Data Source

The paper uses the price data of security index to represent the performance of the market, and all the price data are obtained by the Choice Financial Terminal. This paper chooses the Shanghai Stock Exchange Composite (SSEC) and the Shenzhen Stock Exchange Component Index (SZSE) in the Chinese market, while the Standard & Poor's (S&P 500), Dow Jones Industrial Average (DJI), and the National Association of Securities Dealers Automated Quotations (NASDAQ) in the American market. And the closing price of West Texas Intermediate oil (WTI) is used in the paper to represent the crude oil market.

This paper matches Chinese market indices and the American market indices together, since the indices and the WTI crude oil only trade on trading days and there is a time difference between the two markets, the paper fills the non-trading days' price with the price on the last trading day before it.

When considering the return of the index, the paper uses logarithm form of return to make sure that the time series data is stationary, and the equation is:

$$Return = \ln\left(\frac{P_t}{P_{t-1}}\right) = \ln(P_t) - \ln\,(P_{t-1}). \tag{1}$$

where P_t stands for the closing price on the time *t*.

To analyze the impact of the sanction on oil exportation, the paper chooses data from 2021-11-24 (3 months before the conflict) to 2022-08-01, for a total of 166 observed values. Stata is the most used tool to build time series models and do further analysis.

2.2 Unit-Root Test

This paper used the augmented Dickey-Fuller (ADF) test to check whether the time series is stationary. An ADF test is also known as the unit root test, the test is employed in this paper for its convenience and simplicity in use, and its accuracy in the results.

The fundamental equation of the ADF test is given as equation 2:

$$x_t = c_t + \beta x_{t-1} + \sum_{i=1}^{t-1} \phi_i \Delta x_{t-i} + \varepsilon_t. \tag{2}$$

where x_t stands for the variable at time *t*, c_t stands for a constant, β is the coefficient of time trend, Δx_{t-i} is the first order difference of x_t at time *t-1* and ε_t is an exogenous variable.

The null hypothesis is that the coefficient $\beta = 1$, which means the time series has a unit root and is not stationary, while the alternative hypothesis is that $\beta < 1$, meaning that there is no unit root in the time series. If $p \geq \alpha$, the null hypothesis that $\beta = 1$ cannot be rejected and which means the unit root exists, the time series is not stationary; in the contrast, the null hypothesis can be rejected and the time series is stationary.

The ADF test results are given in Table 1.

Table 1. ADF test

Variables	t-statistic	p-value
Close price		
SSEC	-1.615	0.7865
SZSE	-1.024	0.9408
S&P 500	-2.375	0.3931
NASDAQ	-8.677	0.0000***
DJI	-2.674	0.2470
WTI	-1.744	0.7311
Yield		
SSEC	-9.375	0.0000***
SZSE	-9.373	0.0000***
S&P 500	-8.783	0.0000***
NASDAQ	-15.741	0.0000***
DJI	-8.854	0.0000***
WTI	-9.923	0.0000***

It can be concluded from the table that except for the NASDAQ close price, all the other close price series are not significantly stationary under 95% confidence intervals. When it comes to the logarithm series of the index yields, all the series are significantly stationary under 99% confidence intervals. Based on the ADF test results, the paper could build the following time series models with these stationary series.

2.3 VAR Model Specification

Sims introduced the Vector Autoregression (VAR) Model in 1980[12]. Sometimes many economic variables can affect each other at the same time. The VAR model can be used to predict several variables simultaneously and to find the relationship among them as a system, instead of building time series models for each variable, by putting the variables together and making predictions that are mutually consistent.

To illustrate, firstly considering a two-variable-model (x_1, x_2) with only one lag ($p = 1$), the equations are given below:

$$x_{1,t} = c_{11}x_{1,t-1} + c_{12}x_{2,t-1} + \varepsilon_{x_1 t} \tag{3}$$

$$x_{2,t} = c_{21}x_{1,t-1} + c_{22}x_{2,t-1} + \varepsilon_{x_2 t} \tag{4}$$

It can be compactly written a vector group like:

$$X_t = CX_{t-1} + E_t \tag{5}$$

where $X_t = \begin{bmatrix} x_{1,t} \\ x_{2,t} \end{bmatrix}$, $C = \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix}$, $X_{t-1} = \begin{bmatrix} x_{1,t-1} \\ x_{2,t-1} \end{bmatrix}$, $E_t = \begin{bmatrix} \varepsilon_{x_1 t} \\ \varepsilon_{x_2 t} \end{bmatrix}$.

To generalize the two-variable model, this paper uses a n-variable model with p lags to construct a VAR(p) Model:

$$Y_t = \Gamma_0 + \Gamma_1 Y_{t-1} + \cdots + \Gamma_p Y_{t-p} + E_t \tag{6}$$

where $Y_t = \begin{bmatrix} y_{1,t} \\ \cdots \\ y_{n,t} \end{bmatrix}$, $\Gamma_0 = \begin{bmatrix} \beta_{1,0} \\ \cdots \\ \beta_{n,0} \end{bmatrix}$, $\Gamma_1 = \begin{bmatrix} \beta_{1,1} & \cdots & \lambda_{1,1} \\ \vdots & \ddots & \vdots \\ \beta_{n,1} & \cdots & \lambda_{n,1} \end{bmatrix}$,…, $\Gamma_p = \begin{bmatrix} \beta_{1,p} & \cdots & \lambda_{1,p} \\ \vdots & \ddots & \vdots \\ \beta_{n,p} & \cdots & \lambda_{n,p} \end{bmatrix}$.

In this equation, Y_t stands for the n response variables in the system. $\Gamma_0 \ldots \Gamma_p$ are the coefficient matrix for the corresponding terms. E_t stands for the vector white noise process.

To indicate how one unit of shock leads to the change in other variables over time, the paper used the Impulse Response Function (IRF) to draw an impulse response graph.

The IRF can be defined as follows:

$$\Psi_t = \frac{\partial Y_{t+s}}{\partial E_t'} \tag{7}$$

It calculates how the value, represented by $y_{i,t+s}$, of variable i changes at the time $t + s$ when the ε_{jt} in variable j increased by one unit at the time t. The IRF is a function of the time interval s.

2.4 ARMA-GARCH Model Specification

2.4.1 ARMA Model Specification

Linear time series regression models are always used to model asset return series, including Autoregressive (AR) Model, Moving Average (MA) Model, and ARMA Model.

An AR(p) model assumes that the conditional expectation of current return is determined by the past p periods of values, it can be written as:

$$y_t = \phi_0 + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \varepsilon_t \tag{8}$$

where y_t stands for the variable value at the time t and ε_t is the error term.

A MA(q) model can be seen as an AR model of infinite order with the coefficient restricted in some way[13]. It assumes that the current return may be influenced by the random shock and its lag terms, which can be written as:

$$y_t = c_0 + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \epsilon_{t-q} \tag{9}$$

When considering the financial market, it is found that the return of the asset can be influenced by the historical series itself, as well as the random shock from the market. Box, Jenkins, and Reinsel proposed the ARMA (p, q) model based on this idea, which can be written as follows[14]:

$$y_t = \phi_0 + \sum_{i=1}^{p} \phi_i \, y_{t-i} + \varepsilon_t - \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{10}$$

2.4.2 GARCH Model Specification

It is usually agreed that panel data may easily be subject to heteroskedasticity, while time series data was presumed to have a constant variance. However, there is a phenomenon where the stock index return fluctuates drastically in a period while remaining almost still in another period, which is known as volatility clustering. Engle proposed the ARCH model in 1982, pointing out that there's a special heteroskedasticity in time series, which is known as the Autoregressive Conditional Heteroskedasticity (ARCH)[15].

The ARCH model has the assumption that the last period variance of a time series can be used to predict the next period, using the same autoregressive logic as in AR model. The ARCH(p) model is given as follows:

$$\sigma_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + \cdots + a_p \varepsilon_{t-p}^2 \tag{11}$$

where σ_t^2 is the forecast variance at the time t. ε_t^2 stands for the actual observed value of variance at the time t.

The GARCH model can be seen as an improved ARCH model of infinite order proposed by Bollerslev. GARCH (p, q) can be written as follows[16]:

$$\sigma_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + \cdots + a_p \varepsilon_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_q \sigma_{t-q}^2 \tag{12}$$

2.4.3 ARMA-GARCH Model Specification

The ARMA-GARCH model is the combination of ARMA and GARCH model with two equations of both return and variance. In the efficient market with rational investors, the return of a risky asset is positively related to the risk it bears. Thus, the variance (GARCH) part is the decisive part and should be put more attention to when analyzing the risk of the market.

3. Empirical Result

3.1 VAR Order Selection

As the paper has mentioned and explained in the above part, the paper put the logarithm return of 5 indices, the SSEC, SZSE, S&P 500, DJI, NASDAQ, and WTI oil into the VAR(p) system. First, the suitable order p was determined by the VARSOC selection-order criteria in Stata. The model identification results are displayed in Table 2:

Table 2. VAR model identification

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	2538.46				2.60E-22	-32.677	-32.6291*	-32.5591*
1	2588.88	100.83	36	0	2.2e-22*	-32.8629*	-32.528	-32.0383
2	2618.41	59.065	36	0.009	2.30E-22	-32.7795	-32.1574	-31.2479
3	2638.86	40.9	36	0.264	2.90E-22	-32.5788	-31.6696	-30.3404
4	2660.4	43.089	36	0.194	3.50E-22	-32.3923	-31.196	-29.4471
5	2681.98	43.154	36	0.192	4.30E-22	-32.2062	-30.7228	-28.5541
6	2708.35	52.74	36	0.035	5.00E-22	-32.082	-30.3114	-27.723
7	2728.76	40.809	36	0.267	6.30E-22	-31.8807	-29.8231	-26.8149
8	2752.63	47.751	36	0.091	7.70E-22	-31.7243	-29.3795	-25.9516
9	2823.51	141.75	36	0	5.20E-22	-32.1743	-29.5424	-25.6947
10	2847.93	48.854	36	0.075	6.50E-22	-32.025	-29.106	-24.8385
11	2883.61	71.345	36	0	7.20E-22	-32.0207	-28.8147	-24.1275
12	2919.86	72.507*	36	0	8.10E-22	-32.024	-28.5308	-23.4239

Different criteria can be used to determine the order such as LR, FPE, AIC, HQIC, and SBIC. Since the autocorrelation of the error term cannot be eliminated when lags period is not sufficient, this paper uses LR criteria to determine the order.

LR-statistics is defined as follows:

$$LR = -2\left(logL_{(p)} - logL_{(p+1)}\right) \sim \chi^2(N^2) \quad (12)$$

where $logL_{(p)}$ and $logL_{(p+1)}$ are the maximum likelihood estimation of VAR (p) and VAR $(p+1)$, where p stands for the max lag period of the model. The LR statistics correspond to $\chi^2(N^2)$ distribution and it shows that when the increase of p doesn't lead to a significant increase in the $logL_{(p+1)}$, the new lag variable will not contribute to the VAR model.

Table 2 shows that a VAR model with 12 lags can be considered. After building a VAR (12) model, the paper used a unit circle with a semidiameter of 1 to check the eigenvalue stability condition. If all the dots indicating the eigenvalues are in the unit circle, then the VAR model can be verified as a stable model. The result of our VAR (12) model is plotted in Figure 1, which tells that the stability condition of this system is satisfied.

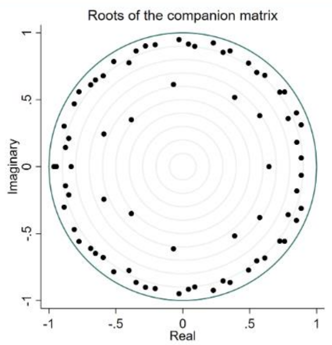


Fig. 1 VAR stability

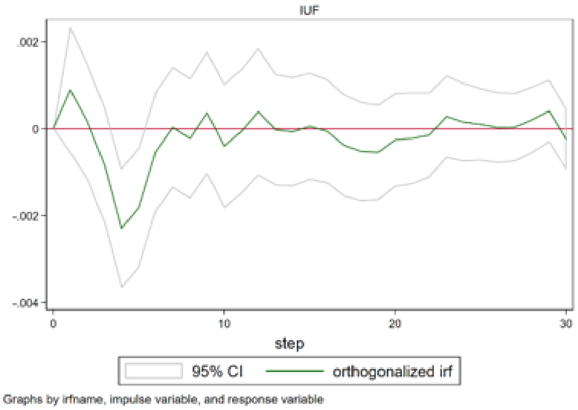
3.2 Impulse Response

The impulse response results of the indices in the American market and Chinese market to the change in WTI oil price are shown in Figure 2. It can be concluded that one unit of shock induced by the oil price at time t=0 would cause a short-term negative net effect in both markets, especially for the S&P 500, DJI, SSEC, and the SZSE. The maximum negative effect shows up at t=4, t=4, t=9, and t=9 respectively and the value is 0.2%, indicating that there's a time lag in the transmission mechanism from oil-price-undulation induced shock to the stock price. Differences between the time lag shows that the transmission chain in the Chinese market is longer than that in the American market.

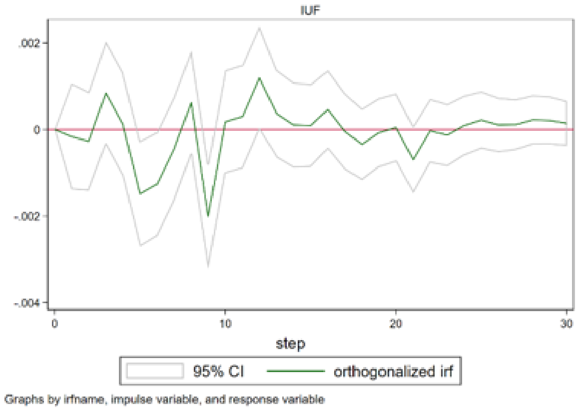
It shows that the negative impact of the oil price shock would gradually decrease and for all the 5 indices, the impact from one shock will disappear in around 2 weeks.

For the NASDAQ index, the negative effect is not as significant as the other 4 indices, showing a sudden drop at time t=1 with a quick rebound and remaining fluctuating around 0. This would probably be because the market volume of the NASDAQ is the biggest among the 5 indices, contributing a lot to its risk-resilient ability.

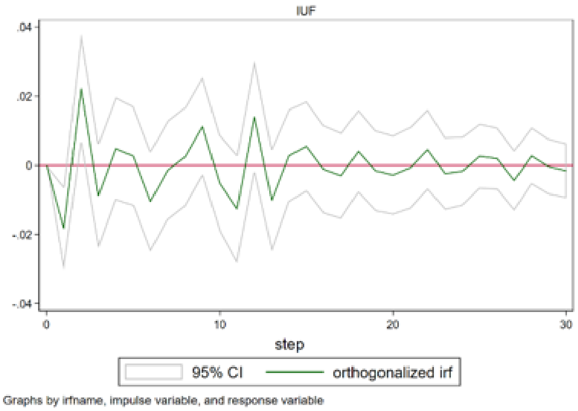
The US
S&P 500



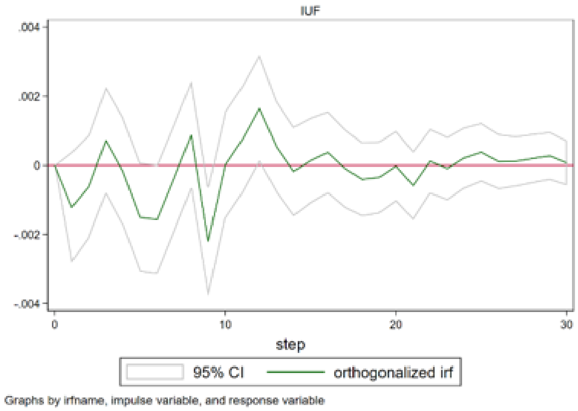
China
SSEC



NASDAQ



SZSE



DJI

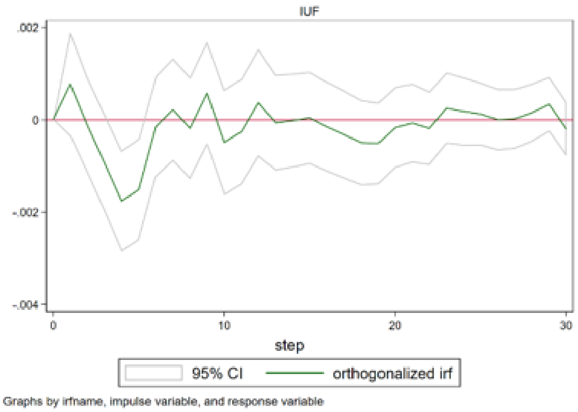


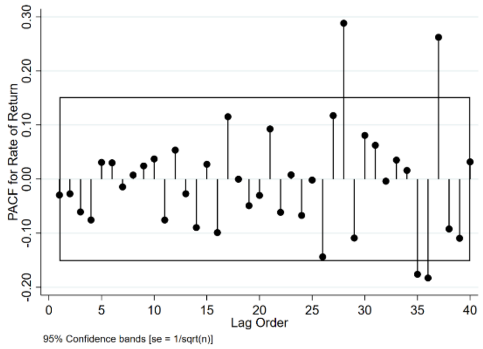
Fig. 2 Impulse and response

3.3 ARMA Order Selection

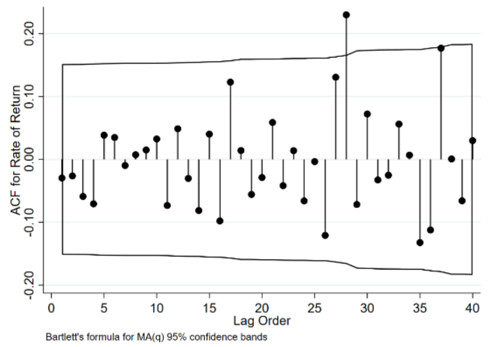
The partial autocorrelation plot (PACF Plot) and the autocorrelation plot (ACF Plot) are used to determine the AR and MA order of the time series. The results are shown in Figure 3.

The black rectangle is the benchmark to find the significant term of the coefficient of the AR and MA model. From figure 3, it can be found that the significant coefficients for SSEC in AR model are 28, 35, 36, 37, while the lag 28 term has a significant impact on current data, and this paper chooses ARMA (28, 28) for SSEC. The model suitable for SZSE is AR(26), for there is no significant coefficient in the MA model. And AR (8) can be a good model for the S&P 500, as well as ARMA (9, 10) for the NASDAQ and AR (8) for DJI.

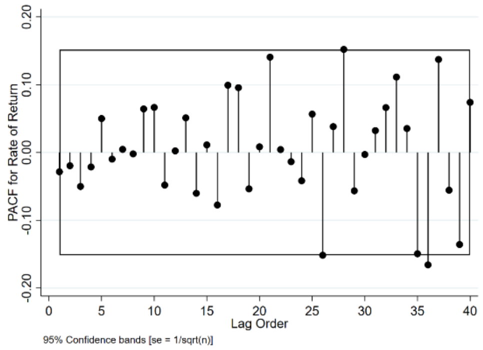
PACF
SSEC



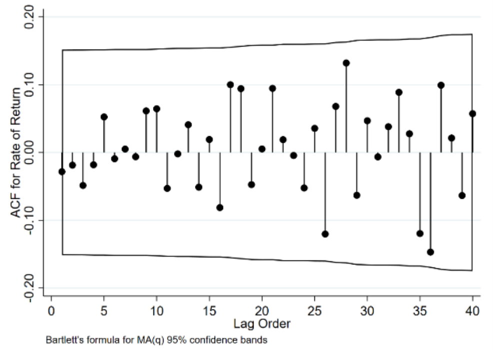
ACF
SSEC



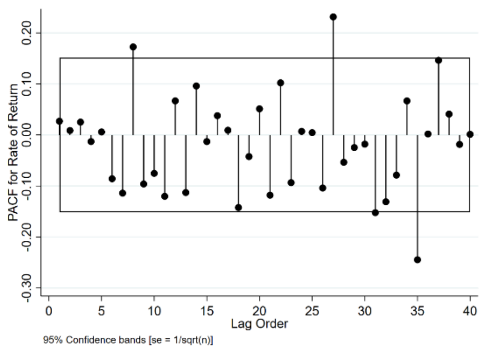
SZSE



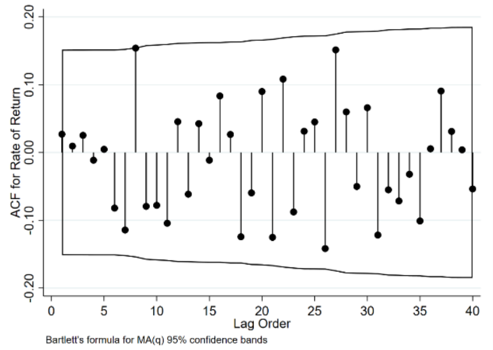
SZSE



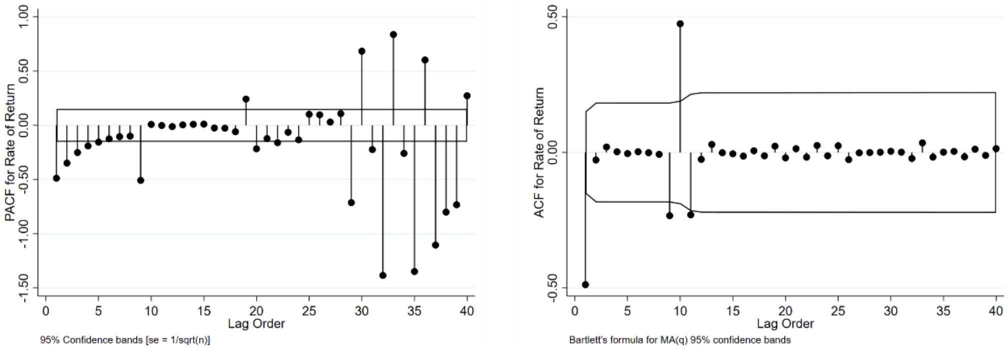
S&P 500



S&P 500



NASDAQ NASDAQ



DJI DJI

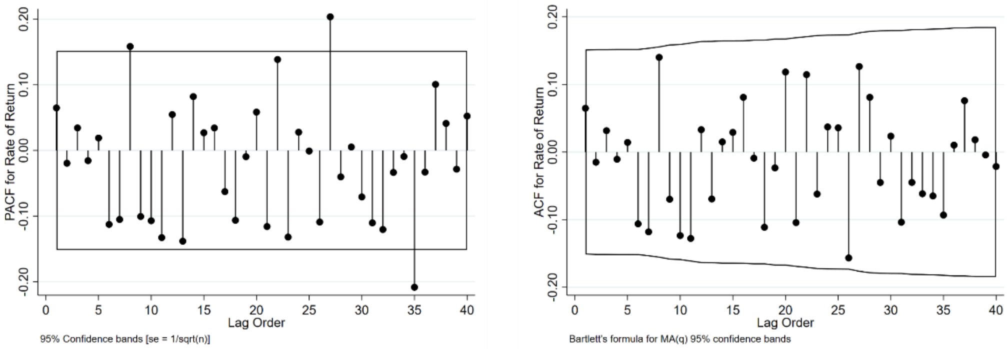


Fig. 3 PACF and ACF

3.4 ARMA-GARCH Estimation Result

This paper constructed an ARMA-GARCH (1,1) model with an exogenous variable of WTI oil price to train it. In order to analyze whether the fluctuation of the crude oil price has led to the increase in volatility in stock market. The results are given in Table 3.

Table 3. ARMA-GARCH estimation results

	(1)	(2)	(3)	(4)	(5)
	SSEC	SZSE	S&P 500	NASDAQ	DJI
WTI	-5.0341	207.2738	-2.3009	-85.5390***	-10.0713
	(9.1353)	(2066.912)	(3.0944)	(4.9036)	(9.5675)
ARCH (-1)	0.2299**	-0.0258**	0.0609	0.8610***	0.1028
	(0.1060)	(0.0123)	(0.0722)	(0.2136)	(0.0878)
GARCH (-1)	0.5344**	1.0069***	-0.6626	0.2296***	0.6986***
	(0.2152)	(0.0084)	(0.5040)	(0.0317)	(0.2525)
Constant	-10.4134***	-29.1449	-8.0474***	-8.2611	-10.5523
	(0.6721)	(214.8028)	(0.3646)	(0.2850)	(1.0502)

It can be concluded that the S&P 500, the SSEC, SZSE, NASDAQ, and DJI have a significant coefficient in the GARCH model, which means the return series of them have conditional heteroscedasticity.

The result of the exogenous variable of WTI has negative or insignificant coefficients which means the rise in WTI oil price didn't increase the volatility of the stock market. It is kind of counter-intuitive, and it can be partly due to the indirect influencing mechanism of the oil price to the stock market. On the other hand, the spillover effect has an apparent time lag as this paper have found in the last part, and the period chosen in this paper may be not long enough.

4. Discussion

This paper uses VAR model to find that the oil price raised by the conflict between Russia and Ukraine and the sanction of the western countries have a significant negative spillover effect on both American and Chinese security markets, and the impact has a time lag and gradually decreasing effect. This coincides with much research done by former researchers. Due to the scale of the NASDAQ market, it has a better risk resilient ability over other markets which enables the index to quickly rebound to a normal level, which is just in accordance with Apergis & Miller in 2009 [12].

The ARMA-GARCH result shows that conditional heteroscedasticity characteristics exist in the series of return of SSEC, SZSE, NASDAQ, and DJI, while no such property has been found in the S&P 500. There’s no significant relationship between the oil price volatility and the stock price volatility, which is kind of different from the conclusion drawn by Jouini & Harrathi in 2014. They pointed out the fluctuation in crude oil price has great influence on the stock market of GCC countries, and the volatility spillover effect is greater than the return spillover effect[17]. The 6-year-long period they used from 2005 to 2011 may be attributed to the result.

From the conclusions, investors should invest in securities or portfolios that are of large scale, which means they are well diversified and have a greater ability to resist the risk from the outer world. Policymakers should remain independent when making macroeconomic policies, which will help them to be immune from the turbulence in global market.

5. Conclusion

The geopolitical conflict has become a rising concern all over the world. Global market is getting more turbulent under this situation, including the commodity market, the oil market, and capital market. This paper researches how the geopolitical conflict affects the oil market and consequently affects the stock market, focusing on the oil price and indices in American and Chinese markets. Finally, the conclusion shows that the war raised oil prices and then had a negative effect on the return of the stock market in both Chinese and American markets, except for the NASDAQ, which has the largest market and the best anti-risk ability. It shows that the impact will gradually wear off in around two weeks after one shock. However, there seems to be not much increase in the volatility brought by the fluctuation of oil price, which could probably be due to the time lag and the indirect influencing mechanism of the spillover effect.

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