The Impact of 2022 Russia-Ukraine Conflict on the Financial Market: Evidence from China

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Abstract. This paper concerns the effect of the 2022 Russia-Ukraine conflict on the Chinese stock market. The event has caused chain reactions on a global scale, among which the soaring energy prices caught the most attention for having the most significant influence. Using the international crude oil futures' settlement prices and two market indexes as indicators of energy prices and Chinese stock market performance, this paper mainly focuses on their changes before and after Russia-Ukraine War. The data covers the period from 25 November 2021 to 14 April 2022, and time series analysis methods, including the Vector autoregression (VAR) model and ARMA-GARCH model, are used in the analysis process. Also, this paper conducts impulse response to examine the impact of one unit oil price change on the Chinese stock market index over time. As a result, a significant correlation between the upsurge in the energy prices and the downtrend of Chinese stock market performance can be found after the breakout of the Russia-Ukraine conflict, suggesting that international incidents can cause global turmoil. Nevertheless, for a mature market with good resilience, the influence of the strike would gradually evaded.

Keywords: Russia-Ukraine conflict, Economic impact, Chinese stock market, Energy prices.

1. Introduction

On 24 February 2022, Russia officially invaded Ukraine, triggering extensive collateral influences, including the refugee crisis, upsurging energy prices, and global financial market upheaval. Since then, energy prices have soared to a new level in history, and a continuous downtrend in the Chinese stock market has been observed. The occurrence of these two phenomena is in no way a coincidence. Although officially, China claims to be an anti-war country that stands for neither party, it is generally considered Russia's supporter for maintaining a peaceful relationship with Russia, thus receiving hostility from many European countries. Most investors believe that the conflict between Russia and Ukraine (along with the reoccurring Covid-19 pandemic) indirectly damaged China's economy, causing its stock market return to drop sharply [1].

To analyze the energy price change caused by the Russia-Ukraine conflict, the paper uses global crude oil futures' settlement prices as indicators. Especially, this paper chooses futures contrasts' settlement prices of Brent crude oil, as it is one of the most actively and massively traded types of crude oil in the global market. Brent crude oil is extracted in the North Sea, and its futures are traded at London Intercontinental Exchange (ICE, London) and New York Mercantile Exchange (NYMEX). This paper uses ICE Brent Crude futures, whose contrast is a deliverable contract based on EFP delivery with an option to cash settle. Its settlement price change can reflect the general energy price change on a global scale.

On China's mainland, there are two types of stocks traded on both the Shanghai Stock Exchange and the Shenzhen Stock Exchange, called A shares and B shares. The Shanghai Stock Exchange was established on 19 December 1990, while the Shenzhen Stock Exchange was established on 2 July 2, 1991. To analyze Chinese stock market performance, this paper takes Shanghai Securities Exchange Composite Index (SHA: 000001, later referred to as SH index) and Shenzhen Component Index (SHE: 399001, later referred to as SZ index) as an example. SH Index is a market capitalization weighted-average index, while the SZ index is a weighted stock price index calculated by taking the stocks of 40 listed companies with market representativeness from among all listed stocks and using the outstanding shares as weights. These two indexes are commonly used in the news and investing practices to represent the performance of Chinses stock market.

Because the Russia-Ukraine conflict is quite a recent issue, few pieces of research have been published. The existing studies related to the Russia-Ukraine conflict mainly concern its economic cost and consequences, but none relate to the Chinese stock market. This paper is an attempt to fill this gap.

Nevertheless, we can still review some papers about other exogenous affairs' impact on the financial market to make analogies. For example, according to a study about the Covid-19 pandemic in 2020, there is a negative association between crude oil returns and stock returns [2]. What is more, the pandemic caused the energy market to plunge, leading to an oil supply surplus and a decline in the price [3], which is just the opposite of what the Russia-Ukraine conflict has caused. So, by intuition, their impact on the financial market should also be the opposite: only considering the influence of energy prices, the stock market returns would be higher after the 2020 Covid-19 pandemic and lower after the Russia-Ukraine conflict.

As for Chinses stock market, after years of development and internationalization, it has become increasingly bound to the global economy. A study done in 2018 claimed that global economic policy uncertainty has a positive and significant influence on the volatility of the Chinese stock market, which reflects that the Chinese stock market has been gradually integrated into the global economy [4]. Therefore, it is assumed that the Russia-Ukraine conflict may play a big part in the downward sloping trend of Chinese stock market performance.

Apart from the introduction, this paper mainly has three components. The first part is the data processing procedure and model explanation. Next, the paper conducts empirical analysis using VAR and ARMA-GARCH models. Finally, it comes to discussion and conclusion.

The result of this paper is meaningful in at least two aspects. First, it helps investors, portfolio managers, and even policymakers to make possible predictions about the economic consequences of the ongoing conflict between Russia and Ukraine. Second, the conclusion can be extended to broader circumstances: how political conflicts intrigue turmoil in countries that are not even directly involved in the events. We should always consider the world as a whole.

2. Data and research design

2.1 Data source and pre-possessing

The daily brent oil futures price and stock index data were obtained from https://cn.investing.com/, consisting of 110 daily observations. Because the London Intercontinental Exchange has different holidays than Shanghai and Shenzhen Stock Exchanges, the dates with vacant values were deleted, so there was a total of 98 daily observations at last. These data were turned into time series ranging from 1 to 98.

Firstly, the paper conducted the heteroskedasticity test on raw series using White Test:

Table.1. Heteroskedasticity results on raw series

Source	chi2	df	p
Heteroskedasticity	15.73	5	0.0077***
Skewness	11.95	2	0.0025***
Kurtosis	0.64	1	0.4225
Total	28.32	8	0.0004***

The p-value of heteroskedasticity is less than 0.01, suggesting that heteroskedasticity exists in raw series. Thus, we should perform logarithmic variation to eliminate heteroskedasticity. The paper used the daily log data for price series and return series. Firstly, the paper got the price series from the raw series:

$$ln(1 + P_t) \quad (1)$$

And then differentiated the price series to get the return series:

$$ln(1 + P_t) - ln(1 + P_{t-1}) \tag{2}$$

Therefore, these would be the series that are used in the following data analysis process.

2.2 Unit root test

The paper tested the stationariness of both the price and return series. Graphs were drawn with time on the horizontal axis and series data on the vertical axis, as shown below:

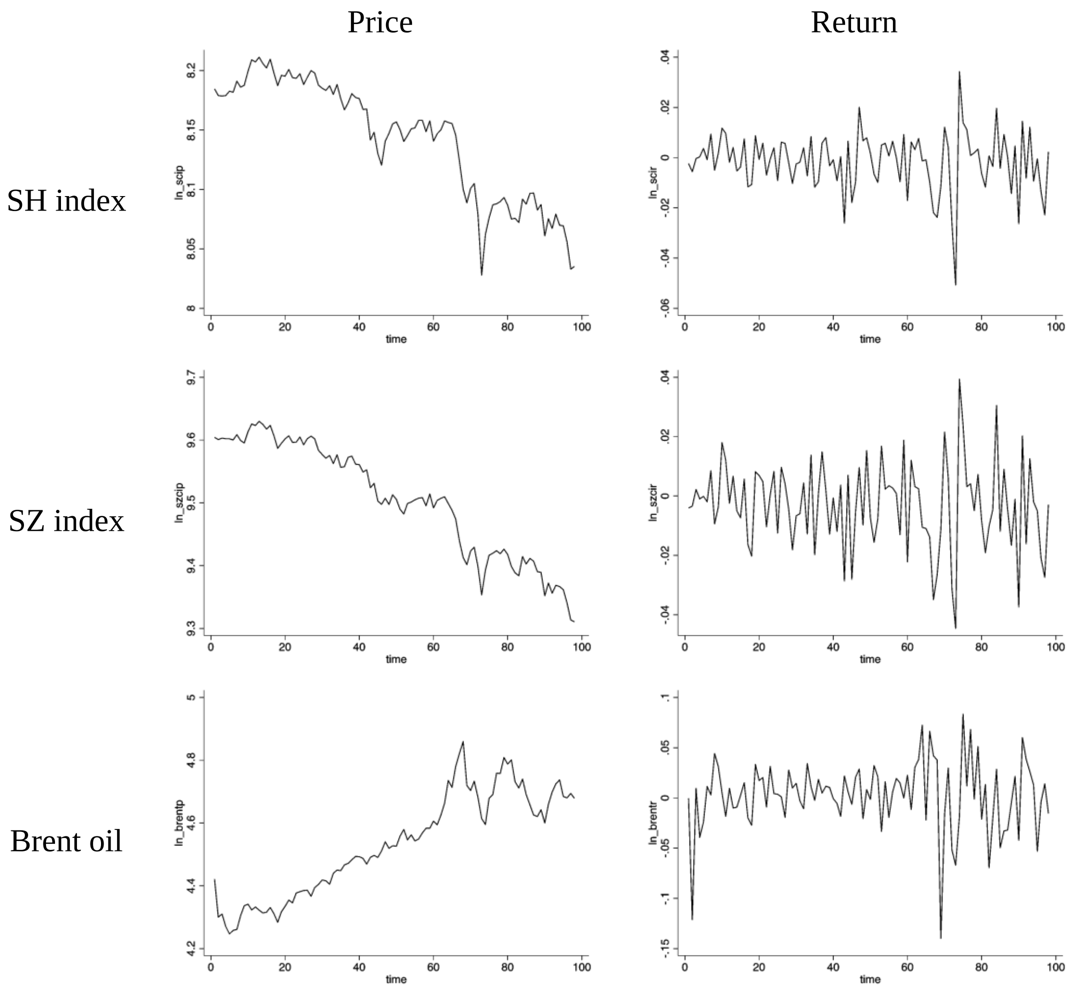

Figure 1. Time-series graphs

By visual inspection, it could be observed that all the price series are non-stationary, and the return series are stationary.

To get proof for the observation, we needed to conduct the unit root test. The paper used the ADF test with a 1-lagged period containing a time trend term and got the results shown in the following table:

Table.2. ADF-test

Variables	t-statistic	p-value
Price		
SH index	-3.160	0.0927*
SZ index	-3.126	0.1001
Brent oil	-2.424	0.3668
Return		
SH index	-7.343	0.0000***
SZ index	-7.471	0.0000***
Brent oil	-6.968	0.0000***

It can be seen that the p-values of raw series are all above 0.01, suggesting that the price series are non-stationary series. However, for the return series, the Z-test values are less than the critical values of each test, and the p-values are all less than 0.01. These observations suggested that the return series are stationary, further confirming the observation. So, further analysis would be based on the return series.

2.3 VAR model

1) Model and order identification

In forecasting several economic variables, one method is to forecast each variable separately by the univariate time series method. Another method is to forecast these variables together as a system so that the forecasts are mutually consistent, called 'multivariate time series' (MTVS). Since we have three series to analyze, we should choose the latter method. Vector autoregression (VAR) was first proposed by Sims (1980). It is a statistical model used to capture the relationship between multiple quantities as they change over time.

As we know, a k-variant time series $\{\boldsymbol{X_t}\}$ satisfies $VAR(p)$ if:

$$\boldsymbol{r}_t = \boldsymbol{\phi}_0 + \boldsymbol{\Phi}_1 \boldsymbol{r}_{t-1} + \cdots + \boldsymbol{\Phi}_p \boldsymbol{r}_{t-p} + \boldsymbol{a}_t \tag{3}$$

, where ϕ_0 is a k-dimensional constant vector, $\{a_t\}$ is a weak smooth series that is not related to $\{r_t\}$ with $E\boldsymbol{a}_t = \boldsymbol{0}$, $\mathrm{Var}(\boldsymbol{a}_t) = \boldsymbol{\Sigma} > 0$; $\boldsymbol{\Phi}_l (l = 0,1, \ldots, p)$ is a k-order square matrix.

2) Estimation

Suppose the $VAR(p)$ model is stationary, we can forecast $\{r_t\}$ l steps ahead by the following equation:

$$r_t(l) = E(r_{t+l}|F_t) = \boldsymbol{\phi}_0 + \sum_{j=1}^{p} \boldsymbol{\Phi}_j \boldsymbol{r}_t(l-j) \tag{4}$$

, where F_t denotes the information contained in $\boldsymbol{r}_s, s < t$ up to time t, so $E(a_t|F_{t-1}) = 0$.

3) Impulse response

To examine how much a unit shock causes other variables to change over time, we can estimate the impulse response. $VAR(p)$ model can also be written as:

$$\boldsymbol{r}_t = \boldsymbol{\mu} + \sum_{l=0}^{\infty} \boldsymbol{\Psi}_l \, \boldsymbol{a}_{t-l} \tag{5}$$

, so $\boldsymbol{\Psi}_l$ is the coefficient of the impact of the past information to $\boldsymbol{r}_t$, and its elements are the coefficients of the pulse response function of time series $\boldsymbol{r}_t$.

2.4 ARMA-GARCH Model

1) AR, MA, and ARMA models

When the time series is stationary, we can model it using three types of time series processes: autoregressive (AR), moving average (MA), and mixed autoregressive and moving- average (ARMA). An autoregressive model of order p denoted as $AR(p)$, can be expressed as:

$$X_t = \phi_0 + \phi_1 X_{t-1} + \cdots + \phi_p X_{t-p} + \varepsilon_t \tag{6}$$

, where $\{\varepsilon_t\}$ is a zero-mean independent identically distributed white noise series with variance equal to σ^2, and ε_t is independent from $X_{t-1}, X_{t-2}, \cdots$.
The moving average of order q, denoted as $MA(q)$, can be expressed as follows:

$$X_t = \theta_0 + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} \tag{7}$$

, where $\varepsilon_t\ (\mathrm{t} = 1,2,3, \dots)$ is a white noise disturbance term with $\mathrm{E}(\varepsilon_t) = 0$ and $\mathrm{var}(\varepsilon_t) = \sigma^2$. The combination of $AR(p)$ model and $MA(q)$ model formed of $ARMA(p, q)$ the model which expressed as:

$$X_t = \phi_0 + \phi_1 X_{t-1} + \cdots + \phi_p X_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} \tag{8}$$

or in sigma notation:

$$X_t = \phi_0 + \sum_{i=1}^{p} \phi_i X_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \tag{9}$$

, where $\mathrm{X_t}$ is the return time series of the SH index or SZ index, ϕ_0 is a constant term, ϕ_i are the parameters of the autoregressive components of order p, θ_j are the parameters of the moving average component of order q, and ε_t is the error term at time t. The order p and q are non-negative integers.

Whether the time series complies with AR, MA or ARMA can be determined by the partial autocorrelation function (PACF) and autocorrelation function (ACF).

Define $L(X_t | X_{t-1}, \dots, X_{t-n})$ as the optimal linear prediction with $X_{t-1}, \dots, X_{t-n}$ to X_t, then for a stationary time series, $\{\phi_{nn}\}$ is the PACF of the time series $\{X_t\}$, if:

$$L(X_t | X_{t-1}, \dots, X_{t-n}) = \phi_{n0} + \phi_{n1} X_{t-1} + \cdots + \phi_{nn} X_{t-n} \tag{10}$$

, where $\phi_{nj}\ (j = 0,1, \cdots n)$ is unrelated to t.

If $\{X_n\}$ satisfies:

$$X_t = \phi_0 + \phi_1 X_{t-1} + \cdots + \phi_p X_{t-p} + \varepsilon_t\ (\phi_p \neq 0) \tag{11}$$

, it means that only $X_{t-1}, \dots, X_{t-p}$ are used when estimatingX_t and adding $X_{t-p-1}, X_{t-p-2}, \dots$ will not make a difference. This property is called the truncated tailing of the partial autocorrelation function of the AR model, and this p is the optimal order for $AR(p)$.
As for ACF, $\{\rho_k\}$ is the ACF of the time series $\{X_t\}$, if:

$$\rho_k = \rho(X_{t-k}, X_t) = \frac{\mathrm{Cov}(X_{t-k}, X_t)}{\sqrt{\mathrm{Var}(X_{t-k})\mathrm{Var}(X_t)}} = \frac{\gamma_k}{\sqrt{\gamma_0 \gamma_0}} = \frac{\gamma_k}{\gamma_0}\ (k = 0,1, \dots, \forall t) \tag{12}$$

Similar to the truncated tailing property of PACF, ACF's tail truncates after q if:

$$\rho_q \neq 0,\ \rho_k = 0, \text{ and } k > q \tag{13}$$

And this q is the optimal order for $MA(q)$.

Moreover, suppose the observed time series has properties similar to that of AR and MA but is not possible to implement partial autocorrelation function truncation or correlation function truncation at low order. In that case, it is an ARMA model. $ARMA(p,q)$ can be seen as combination of $AR(p)$ and $MA(q)$.

2) ARCH and GARCH models

For financial time series, due to its volatility clustering characteristics, the volatility of the time series (second-order moments) is not a constant. In that case, AR, MA, and ARMA models cannot portray this conditional heteroskedasticity characteristic, but ARCH and GARCH models can solve this problem. The Autoregressive conditional heteroscedastic (ARCH) model aims to predict the conditional variance of return series. It can be expressed as:

$$y_t = C + \varepsilon_t, \text{ and } \varepsilon_t = \sigma_t z_t \tag{14}$$

, where y_t is the observed time series, C is a constant value, ε_t is residual, z_t is the standardized residual satisfying $z_t \sim i$id N(0,1), and σ_t satisfies:

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \cdots + \alpha_p\varepsilon_{t-p}^2\ (\alpha_0 > 0, \alpha_i \geq 0, i > 0) \tag{15}$$

The general form of $\mathrm{ARCH(q)}$ the model can be written as follows:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \cdots + \alpha_q y_{t-q} + \varepsilon_t \tag{16}$$

If σ_t^2 is represented by the ARMA model, and the deformation of the ARCH model is the GARCH model (Bollerslev,1986). The generalized autoregressive heteroscedastic (GARCH) model uses fewer parameters than the ARCH model. The general form of $\mathrm{GARCH(p,q)}$ the model can be written as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \cdots + \alpha_q\varepsilon_{t-q} + \beta_1\sigma_{t-1}^2 + \cdots + \beta_p\sigma_{t-p}^2 \tag{17}$$

For simplicity, the paper uses $\mathrm{ARCH(1)}$ and $\mathrm{GARCH(1,1)}$ in our further modeling:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \varepsilon_t \tag{18}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \tag{19}$$

3. Empirical results and analysis

3.1 VAR order identification

The paper conducted lag periods identification to get the optimal lag order for $VAR(p)$ model. In order to save degrees of freedom, the paper chose the maximal lag order of 12.

Table.3. VAR model identification

Lag	LL	LR	p
1	761.994	24.563	0.003
2	762.933	1.8776	0.993
3	765.616	5.3662	0.801
4	770.687	10.142	0.339
5	789.896	38.418	0.000
6	799.778	19.765	0.019
7	805.119	10.681	0.298
8	808.845	7.4515	0.590
9	814.248	10.806	0.289
10	817.047	5.5979	0.779
11	825.651	17.208	0.046
12	838.051	24.8^{*}	0.003

Note: *, **, *** Statistically significant at the 10%, 5% and 1% significant level

The program result shows that the optimal lag order for the return series is 12. Then the paper tested the result1 using the following methods:

1) Granger's causality test

Table.4. Granger causality Wald tests

Equation	Excluded	chi2	df	Pb>chi2
	SZ index	9.7709	12	0.636
SH index	Brent oil	33.834	12	0.001^{***}
	ALL	50.704	24	0.001^{***}
	SH index	15.835	12	0.199
SZ index	Brent oil	34.647	12	0.001^{***}
	ALL	53.656	24	0.000^{***}
	SH index	25.693	12	0.012^{**}
Brent oil	SZ index	23.676	12	0.023^{**}
	ALL	64.783	24	0.000^{***}

P-value less than 0.05 is accepted as Granger cause, and most p-value satisfies this standard. Therefore, Granger cause is accepted under lag order 12.

2) Unit circle test

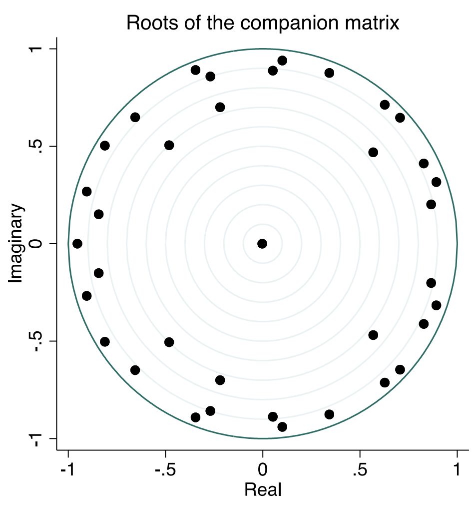

Figure 2. Unit circle test result

The characteristic roots are all within the unit circle, indicating stable $VAR(12)$ model.

In conclusion, lag order 12 is acceptable under both tests, so all subsequent operations would be performed under lag order 12.

3.2 Impulse response

After setting the optimal lag order, the paper estimated the return series of SH index and SZ index for the following 60 days and did the impulse response. The paper got the following results:

SH Index SZ Index

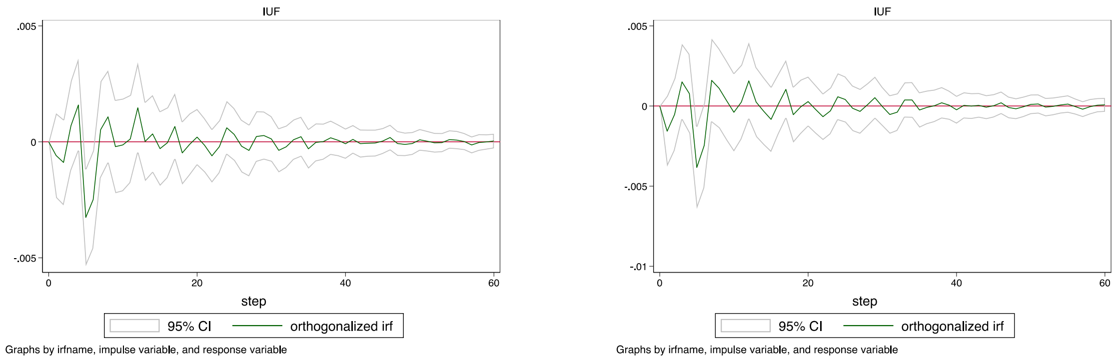

Figure 3. Impulse and response

From the graphs above, it can be told that an increase in international futures crude oil returns in the current period will simultaneously lead to a downward movement in both market returns in the next period. This finding could explain the performance of the Chinese stock market after the Russian-Ukrainian conflict causing a significant increase in the international crude oil prices.

In addition, the shock to the Chinese stock market caused by the change in crude oil prices gradually becomes smaller over time and eventually disappears in 60 days, suggesting that the Chinese economy is resilient from a long-term perspective.

3.3 ARMA-GARCH estimation results

Firstly, we should recognize which kind of model do the index series follow:

SH Index SZ Index

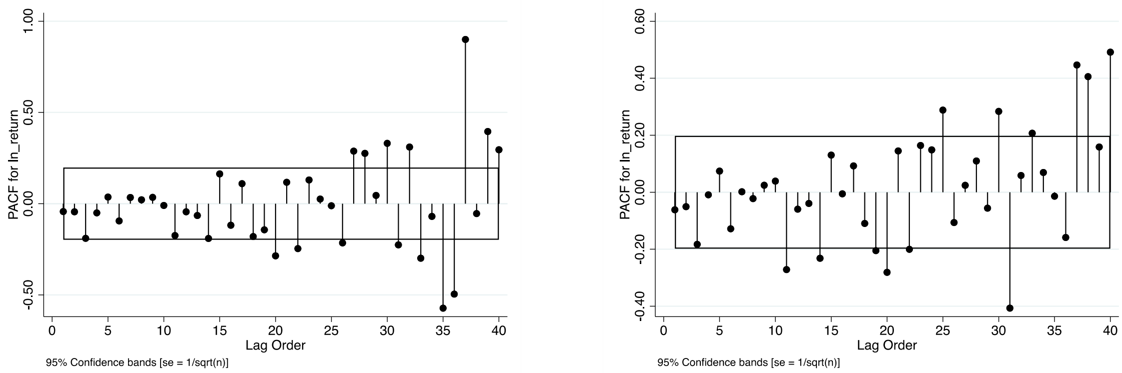

Figure 4. PACF for AR identification

The graphs above show that the SH index and SZ index have lag orders of 20 and 11 respectively, indicating that the SH index complies with $AR(20)$ and the SZ index with $AR(11)$.

SH Index SZ Index

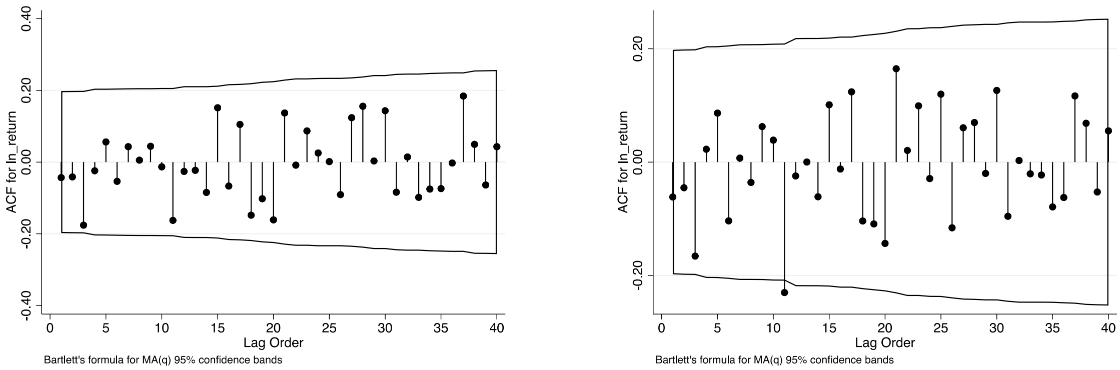

Figure 5. ACF for MA identification

The graphs above show that the SH index and SZ index have lag orders of 0 and 11 respectively, indicating that the SH index does not satisfy MA model while the SZ index complies with $AR(11)$.

Moreover, the paper chose $ARCH(1)$ and $GARCH(1,1)$ for simplicity. In this case, the paper established the ARMA-GARCH model accordingly for SH and SZ index, using Brent oil as the impulse variable:

Table.5. ARMA-GARCH model estimation results, variance equation

Variables	(1)	(2)	(3)	(4)	(5)	(6)
		SH index			SZ Index	
			Brent oil			
T=0	-3.9017	2.1422	-10.0525	-8.8958**	-17.7921***	-24.0327***
	(7.4943)	(13.5177)	(12.3687)	(4.5059)	(5.8292)	(5.6792)
T=-1		-22.6947***	-20.0175**		30.0431**	20.2112
		(7.5305)	(8.8247)		(13.5711)	(12.6600)
T=-2			17.7746			10.7043
			(14.1873)			(14.4202)
			GARCH			
ARCH (-1)	0.3135**	0.2469*	0.1133	0.1696	-0.0039	-0.0219
	(0.1397)	(0.1394)	(0.1360)	(0.1549)	(0.0885)	(0.0874)
GARCH (-1)	0.2488	0.4033**	0.5600**	0.1360	0.8217***	0.6634***
	(0.3148)	(0.1649)	(0.2684)	(0.3921)	(0.1611)	(0.1768)
Constant	-9.8681***	-10.3104***	-10.5999***	-8.9725***	-10.9303***	-10.1747***
	(0.6224)	(0.4730)	(0.7234)	(0.5741)	(1.0660)	(0.5119)

Note: *, **, *** Statistically significant at the 10%, 5% and 1% significant level

As the autocorrelation in the mean equation is under control, the variance serves as a combination of conditional heteroskedasticity and external factors driving the variance.

The ARCH terms and GARCH are significant in the models in columns (1) to (6), indicating that stock market returns have significant ARCH and GARCH effects. A large disturbance tends to be followed by another significant disturbance, namely ‘volatility aggregation’.

The above shows that the international crude oil price change has caused dramatic changes in stock market returns. However, from the estimation results of the ARMA-GARCH exogenous variables, the increase in international crude oil prices did not lead to more dramatic daily volatility in the Chinese stock markets from the full model in columns (3) and (6).

This evidence suggests that the volatility in the Chinese stock market is more likely to be driven by other factors.

4. Discussion

From the case study of China about the impact of the 2022 Russia-Ukraine conflict on global financial markets, we can derive some general regularities about the financial world. A mature and competitive market is resilient to strikes and can respond quickly. However, in a short period, possible negative consequences of strikes must be considered to avoid loss. Everything in the real world is interlocked, and even a minor incident may cause butterfly reactions.

Compared with other research, this paper's distinctive feature lies in its approach to representing the Russia-Ukraine conflict with data. From a macro perspective, it can be extrapolated that what is behind the Russia-Ukraine conflict is fierce competition for energy markets. That means the conflict directly caused the upsurge in global energy prices. So, the paper used crude oil futures' settlement price to represent the conflict's impact. This is quite novel.

For professional investors and portfolio managers, this paper serves as a warning sign for those who ignore international issues. Chinese investors should pay more attention to global incidents to catch up with the everchanging business environment.

For the Chinese government, it should work with Europe to put forward a peace proposal and form an anti-war alliance with Europe. Strategically, China must avoid being kidnapped by Russia and isolated from the international community. China should strive to restore normal economic and trade relations with the US and Europe to minimize the impact of the energy crisis. These suggestions also provide a reference for other countries worldwide in their response to the international chaos and resume economic vibrancy.

And finally, future researchers can explain the downtrend of the Chinese stock market performance on a more comprehensive scale. They can take other exogenous factors (e.g., the recurring Covid-19 pandemic, tightening regulations towards Chinese high-tech companies, as mentioned before) into consideration and strip out the effects of these factors to get a more unbiased analysis of the Russia-Ukraine conflict's influence.

5. Conclusion

Several conclusions can be derived from both the VAR model's impulse response and the ARMA-GARCH results.

First, the Russia-Ukraine conflict is one of the triggers of the following poor performance of the Chinese stock market. From the previous result, it is shown that the rising international crude oil prices led to a subsequent decline in Chinese stock market returns, which means there is a negative correlation between the international crude oil prices and the Chinese stock market indexes. As the Russia-Ukraine conflict directly tightened the energy supply, causing the upsurging energy prices, this will have ripple effects on the Chinese stock markets.

Second, the shock will continue for several months, and its effect will be weaker and weaker as time passes. The previous results show that in the long run, the shock to the Chinese stock market caused by changes in crude oil prices gradually becomes more negligible over time and eventually disappears. This is common sense, as most shocks cause intermediate influences and eventually vanish. Nevertheless, the reason why the Chinese stock market will gradually get back to normal is something worth discussing. The paper suggests it is due to the resilience of Chinese stock markets. After decades of development and improvement, Chinese stock markets have become more mature and fairer, indicating that the stock prices are more likely to be fair value. So, no matter what strikes the market, it will eventually get back to equilibrium.

Finally, the impact of the conflict evaded after estimation of 40 days. Although empirical evidence shows a continuing downtrend of the Chinese market indexes, it is more likely to be affected by other factors except for the Russia-Ukraine conflict, such as the recurring Covid-19 pandemic. This finding implicated that rational investors can take less consideration of the Russia-Ukraine conflict's impact when making investment decisions after about two months.

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