The Effect of War Risks on the Petroleum and Petrochemical and Renewable Energy Industries: Evidence from Chinese Stock Market

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Abstract. This study explores the ramifications of war risks (Russo-Ukrainian Conflict specifically) on petroleum and renewable energy industries. Based on the stylized fact that war leads to spikes in oil prices, vector autoregressive (VAR) and autoregressive moving average-generalized autoregressive conditional heteroskedasticity (ARMA-GARCH) model analyses were conducted to evaluate stock return and volatility, respectively, in both sectors resulting from the change in Brent crude oil prices. The data in this study primarily encompasses Brent crude oil prices and the stock index for renewable energy and petroleum products in China. While the result of the VAR model analysis suggests that the increasing oil price has led to a positive effect on stock return for renewables and a trifling impact on stock return for petroleum products, the ARMA-GARCH model indicates that the change in Brent crude oil prices has exerted a negligible effect on stock volatility in both sectors. The positive stock return in the renewable energy sector caused by the increasing oil prices may incentivize more investors and promote the development of renewables in China. The government will also likely promulgate relevant policies to avert the risk of energy supply uncertainties and expedite the energy transition.

Keywords: Russia-Ukrainian Conflict, Petroleum, Renewable Energy, Time Series Model.

1. Introduction

The global energy supply chain, consisting of both conventional and renewable energy sources, has been primarily dictated by economic and political factors due to rapid economic development and globalization [1-2]. Such factors as political instability, financial crises, and natural disasters have resulted in significant fluctuations in oil prices, which would, in turn, cause vacillations in the petroleum product and renewable energy markets [1, 3, 4]. The Russo-Ukrainian Conflict, which began in 2014 and has intensified since Russia declared the "special military operation" in Ukraine on February 21, 2022, has led to skyrocketing oil prices as many countries started banning or restricting oil imports from Russia. The limitations imposed on oil trading resulting from the war have disrupted the energy supply, contributing to a sharp increase in global oil prices [5-6]. The striking fluctuation in global oil prices exerted by wars and other political events has manifested the critical roles of politics in determining oil prices [7-8]. Not only has the occurrence of war caused notable fluctuations in oil prices, but it is also altering the global landscape of the renewable energy industry [1]. The demand for renewables continuously reacts to the variations in energy supplies caused by the war in addition to the international exhortation to promote sustainable development through the big idea of Environmental, social, and corporate governance (ESG) [9]. The shift of energy dependence from oil to renewable energy would also result in environmental change because of the reduction in greenhouse gas (GHG) emissions caused by stimulation in energy transition and heavier investment in renewables [10].

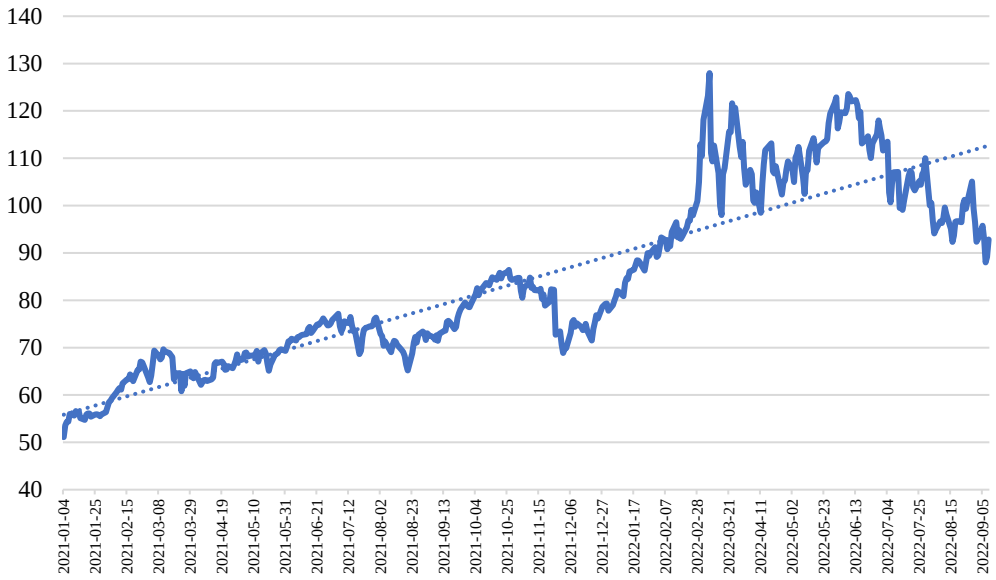


Figure 1. Brent Crude Oil Price ($USD) (Photo credit: Original)

The ongoing geopolitical conflicts between Russia and Ukraine have subverted the relatively stable global energy supply. Since the eruption of the conflict, the European Union (EU) has imposed a partial ban on Russian crude oil, petroleum products, and shipping insurance on Russia's oil exports, which has dramatically limited crude oil trading and urged many countries to look for alternatives. The Brent crude oil price has continued to increase since the beginning of 2021 and boomed in February 2022, when Russia declared and initiated a special military operation in Ukraine (Figure 1). While some European countries have redirected their focus to generating more nuclear energy by extending the lifespans of their nuclear plants, other countries have started investing heavily in renewable energy to promote energy transition or importing crude oil from Asia, Africa, and North America. Although it might seem clear that oil prices spike instantly in response to the change in supply and demand caused by the war, the implications of war risks on future oil prices and renewable energy remain nebulous.

While some existing studies investigated how such uncertainty risks as war, terrorist attacks, and other political events have impacted oil prices by applying different quantitative methods, the joint ramifications exerted by the war on both conventional and renewable energy sources remain unassessed [11-12]. For instance, the study by Song, Y., Chen, B., Wang, X. Y., Wang, P. P., which employs a time-varying parameter/stochastic volatility vector autoregression (TVP-SV-VAR) model to assess the impact of uncertainty risks on oil prices, suggests that the oil prices are primarily driven by economic policy uncertainties and geopolitical risks, in which the former exerts larger significance [1]. Though the study briefly discusses the possible implications of war risks on energy transition and environmental alteration, its data manipulation and analysis are performed based on monthly West Texas Intermediate crude oil futures price without the inclusion of the green energy stock index, therefore rendering no indication of war's potential impacts on renewable energy [1]. However, as the global community continues to advocate the idea of ESG and carbon neutrality to alleviate the ongoing climate crisis, renewable energy has been constituted as a critical substitute for oil to minimize GHG emissions [10, 13]. In addition, the spike in oil prices, making oil less affordable for the public, has accelerated the industrial movement toward renewable energy [13]. While the governments have started promulgating various policies to facilitate the energy transition, different funds have also begun heavily investing in relevant sectors to expand the capacity of renewables. The governments' and businesses' collaborative efforts have indicated the rising significance of green energy and underscored the need to consider the impact of war risk on renewable energy sectors.

This study explores the impacts of Russo-Ukrainian Conflict's risk parameters on petroleum and renewable energy industries in China. VAR and ARMA-GARCH models are conducted to evaluate

stock return and volatility in both renewable energy and petroleum products sectors resulting from the change in Brent crude oil. Specifically, the data reflects how the war has impacted global oil prices along with the stock returns of both petroleum and renewable energy industries and suggests potential future changes.

The rest of the paper is structured as follows: the second section provides an account of the data source and quantitative methods applied in the study; the third section elucidates the empirical results and implications; the fourth section interprets the findings and offers some speculative comments on the future volatility of oil price and stock returns potentially resulting from the Russian-Ukrainian conflict.

2. Method

2.1 Data Source

Choice Financial Terminal, which discloses financial information covering the stock, fund, and bond, serves as the primary database for the study to obtain Brent crude oil prices and stock price index for both petroleum and renewable energy industries in China [14-15]. The time frame of collected data ranges from June 2021 to September 2022. The scope of the data covers the beginning of rising tension between Russia and Ukraine, the initiation of Russian special military operations, and the ongoing conflict to provide a comprehensive recapitulation of oil prices and stock price index fluctuations caused by the Russo-Ukrainian war.

2.2 Augmented Dickey-Fuller (ADF) Unit Root Test

Prior to data manipulation and processing, testing the data's stationariness is essential to ensure data validity. In this study, based on the ADF test results performed using STATA shown in Table 1, the p-values for the log returns of Brent crude oil prices, green energy stock index, and petroleum stock index are 0, which is smaller than the 0.1 significance level (α). The p-values of 0 successfully reject the null hypothesis, which states that the variable possesses a unit root, a feature of the stochastic process that may result in problems relevant to statistical inference. Consequently, the model constructed based on the data is viable, and the data is stationary.

Table 1. ADF Test

Variables	t-statistic	p-value
Index or price		
Brent	-2.068	0.5637
Green energy	-2.461	0.3479
Petroleum products (China)	-2.404	0.3772
Yield		
Brent	-12.880	0.0000***
Green energy	-13.047	0.0000***
Petroleum products (China)	-11.622	0.0000***

2.3 Vector Autoregression (VAR) Model

In the study, the vector autoregression (VAR) model primarily functions to capture the dynamic relationship among different variables while circumventing the uncertainties inherent in the model [15-16]. The VAR model reflects the correlations among three variables: Brent crude oil prices, petroleum products stock price index, and renewable energy stock price index. The model assesses the impact of the rate of stock returns caused by the fluctuations in Brent crude oil prices. The model contains three separate time series variables, which are denoted by $x_{t,1}$, $x_{t,2}$, and $x_{t,3}$, yielding a triradiate VAR(p) model [17].

$$x_{t,1} = a_1 + \emptyset_{11}x_{t-1,1} + \cdots + \emptyset_{1p}x_{t-p,1} + \beta_{11}x_{t-1,2} + \cdots + \beta_{1p}x_{t-p,2} + \delta_{11}x_{t-1,3} + \cdots + \delta_{1p}x_{t-p,3} + e_{1t}. \quad (1)$$

$$x_{t,2} = a_2 + \emptyset_{21}x_{t-1,1} + \cdots + \emptyset_{2p}x_{t-p,1} + \beta_{21}x_{t-1,2} + \cdots + \beta_{2p}x_{t-p,2} + \delta_{21}x_{t-1,3} + \cdots + \delta_{2p}x_{t-p,3} + e_{2t}. \quad (2)$$

$$x_{t,3} = a_3 + \emptyset_{31}x_{t-1,1} + \cdots + \emptyset_{3p}x_{t-p,1} + \beta_{31}x_{t-1,2} + \cdots + \beta_{3p}x_{t-p,2} + \delta_{31}x_{t-1,3} + \cdots + \delta_{3p}x_{t-p,3} + e_{3t}. \quad (3)$$

$$\begin{bmatrix} x_{t,1} \\ x_{t,2} \\ x_{t,3} \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} + \begin{bmatrix} \emptyset_{11} & \cdots & \emptyset_{1p} \\ \emptyset_{21} & \cdots & \emptyset_{2p} \\ \emptyset_{31} & \cdots & \emptyset_{3p} \end{bmatrix} \begin{bmatrix} x_{t-1,1} \\ \vdots \\ x_{t-p,1} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \cdots & \beta_{1p} \\ \beta_{21} & \cdots & \beta_{2p} \\ \beta_{31} & \cdots & \beta_{3p} \end{bmatrix} \begin{bmatrix} x_{t-1,2} \\ \vdots \\ x_{t-p,2} \end{bmatrix} + \begin{bmatrix} \delta_{11} & \cdots & \delta_{1p} \\ \delta_{21} & \cdots & \delta_{2p} \\ \delta_{31} & \cdots & \delta_{3p} \end{bmatrix} \begin{bmatrix} x_{t-1,3} \\ \vdots \\ x_{t-p,3} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \end{bmatrix}. \quad (4)$$

2.4 ARMA-GARCHX Model

The ARMA-GARCHX model serves to assess the volatility of Brent crude oil prices to determine its impact on the return of petroleum products and green energy's stock price index. The model consists of two major counterparts: ARMA and GARCHX.

The autoregressive-moving-average (ARMA) model is primarily utilized to describe weakly stationary stochastic time series regarding two polynomials. The two polynomials, autoregressive polynomial and moving average polynomial, are represented by p and q in the model, respectively. While AR(p) makes predictions by applying previous values of the dependent variable, Ma(q) makes predictions by using the series mean and previous errors. As shown in the expression, AR(p) is represented by $\emptyset_0 + \sum_{i=1}^{p} \emptyset_i x_{t-i}$, and the remaining part denotes Ma(q). In this case, AR(p) projects the future value by using historical stock return of petroleum products and green energy index in China from June 2021 to September 2022, while Ma(q) predicts the future using the error term.

$$x_t = \emptyset_0 + \sum_{i=1}^{p} \emptyset_i x_{t-i} + a_i - \sum_{i=1}^{q} \emptyset_i a_{t-i} \quad (5)$$

The generalized autoregressive conditional heteroskedasticity (GARCH) model, a statistical model used to analyze time-series data, is a key statistical modeling tool derived from the ARCH model to predict the volatility of return [18]. Compared to GARCH, the ARCH model is the simplest GARCH model and possesses many similarities with the AR (1) model. This study primarily adopts the GARCH (1, 1) to extract the volatility of the Brent crude oil prices and uses it as an external explanatory variable to account for the change in stock returns of petroleum products and green energy index, which serve as response variables [19]. The usage of GARCH (1, 1) instead of ARCH(p) attributes to the fact that GARCH (1, 1) contains fewer parameters, which is more apposite for time series and adequate to recognize the volatility clustering in the data [20]. As shown in expression, $\alpha_1 \epsilon_{t-1}^2$ symbolizes ARCH, while $\gamma_1 \sigma_{t-1}^2$ represents GARCH. The remaining term acts as an additional explanatory variable in the model, which is the volatility of Brent crude oil prices during the period [19-20].

$$\sigma_t^2 = \alpha_{0,1} + \alpha_1 \epsilon_{t-1}^2 + \beta_t m_t + \gamma_1 \sigma_{t-1}^2 \quad (6)$$

3. Results

3.1 Order of VAR Model

In the VAR model, the LR statistic acts as the primary criteria to assess each lag to determine the optimal lag order, which is indicated by asterisk (*) symbols (Table 2). As displayed in the table, lags 0, 1, and 17 all contain asterisk symbols. As a result, it is critical to compare the AIC differences among the three lags to determine the desired lag order. While the difference in AICs between lags 0 and 1 is 0.0859, the difference in AICs between lags 17 and 18 is 0.0546. The smaller AIC difference between lags 17 and 18 unveils that lag 17 is a more suitable option as the starting lag.

Table 2. VAR model identification

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	2082.47				1.1e-10	-14.4400	-14.4255	-14.4026*
1	2105.16	45.39	9	0.000	9.8e-11*	-14.5359*	-14.4747*	-14.3832
2	2108.4	6.4689	9	0.692	1.0e-10	-14.4958	-14.3888	-14.2287
3	2111.14	5.4738	9	0.791	1.1e-10	-14.4523	-14.2994	-14.0708
4	2112.1	1.9336	9	0.992	1.1e-10	-14.3965	-14.1978	-13.9005
5	2117.79	11.374	9	0.251	1.1e-10	-14.3735	-14.1289	-13.763
6	2128.22	20.87	9	0.013	1.1e-10	-14.3835	-14.093	-13.6585
7	2134.14	11.827	9	0.223	1.2e-10	-14.3621	-14.0257	-13.5226
8	2136.39	4.5125	9	0.875	1.2e-10	-14.3152	-13.933	-13.3613
9	2143.74	14.693	9	0.100	1.2e-10	-14.3038	-13.8756	-13.2354
10	2148.4	9.328	9	0.408	1.3e-10	-14.2736	-13.7996	-13.0908
11	2155.89	14.973	9	0.092	1.3e-10	-14.2631	-13.7433	-12.9658
12	21621.12	10.461	9	0.314	1.3e-10	-14.237	-13.6712	-12.8252
13	2164.63	7.0138	9	0.636	1.4e-10	-14.1988	-13.5872	-12.6726
14	2169.86	10.469	9	0.314	1.4e-10	-14.1727	-13.5152	-12.532
15	2173.39	7.0631	9	0.631	1.5e-10	-14.1347	-13.4313	-12.3795
16	2180.82	14.859	9	0.095	1.5e-10	-14.1238	-13.3745	-12.2541
17	2189.46	17.271*	9	0.045	1.5e-10	-14.1212	-13.3261	-12.1371
18	2197.2	15.475	9	0.079	1.5e-10	-14.1125	-13.2715	-12.0139
19	2203.67	12.956	9	0.165	1.5e-10	-14.095	-13.2081	-11.8819
20	2209.11	10.865	9	0.285	1.6e-10	-14.0702	-13.1375	-11.7427
21	2213.96	9.697	9	0.376	1.6e-10	-14.0414	-13.0628	-11.5994
22	2217.94	7.9593	9	0.538	1.7e-10	-14.0065	-12.982	-11.4581
23	2220.63	5.395	9	0.799	1.8e-10	-13.9627	-12.8924	-11.2918
24	2223.52	5.7695	9	0.763	1.9e-10	-13.9203	-12.8041	-11.1349

After determining the optimal order for VAR model, it is essential to evaluate if the model is stable. If the VAR model turns out to be unstable, the impulse-response function will not converge to 0, meaning that the spike in Brent crude oil prices resulting from the Russo-Ukrainian Conflict has prolonged effect on stock returns of renewable energy and petroleum products. Subsequently, unit root test is conducted to assess the model's applicability by sketching a unit circle with the roots. As shown in Figure 2, all roots lie within the circle, demonstrating that the current lag order is valid, and triradiate VAR (17) is a stable model.

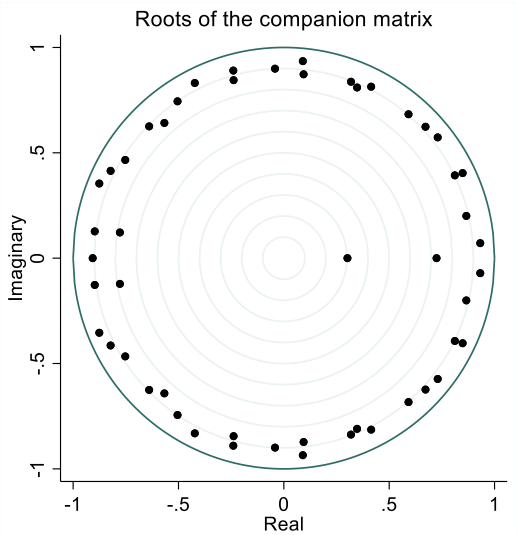


Figure 2. VAR stability (Photo credit: Original)

3.2 Impulse Response

Shortly after the outbreak of the Russo-Ukrainian War, global crude oil prices skyrocketed, and the entire stock market in China was extremely volatile and displayed a declining trend [20]. Nonetheless, as time moves on, most stock indexes have bounced back to the normalized range, similar to those before the war. This phenomenon infers that the war's impact on the Chinese stock market reflects a temporary shock rather than a long-term effect. In the overall energy industry, renewable energy acts as the primary substitute for fossil fuels [10]. The increasing oil prices, which would diminish the consumer demand for oil, will likely boost the consumption of renewables. However, the correlation needs to be constructed through models to quantify the impact.

Based on the impulse response diagram (Figure 3), when the Brent crude oil prices increase by 1% at t=0, the stock return for green energy shows a declining trend from t=0 to t=2, and the sharpest negative impact during the period was around 2.5%. At t=3, however, the ramifications posed by the spike in oil price on stock return for renewables mostly become positive, with the highest positive impact of 0.2% at t=11. Overall, the increase in oil prices resulting from the war has exerted a positive net impact on the stock return of renewable energy. The negative impact from t=0 to t=2 might attribute to the public's anxiety resulting from the outbreak of the war, which urged investors to be more risk-averse and transfer their assets to more secure investments.

On the other hand, the spurring crude oil prices exert a positive impact on stock return for petroleum products in China at t=0, and then the level of impact oscillates at around 0 in the following periods. The relatively stable and limited impact exerted by the spike in crude oil prices on the stock returns for petroleum products in China might result from the abundance of crude oil in China, which leads to a more elastic demand for oil import. The price elasticity of crude oil in China might lead to an initially favorable response in the stock market. However, as the crude oil price continues to go up or stays at a lofty range, consumers will likely reduce the frequencies of driving or switch to electric vehicles. Therefore, the rising oil prices' net impact on stock return for petroleum products in China still remains unclear based on the impulse response diagram.

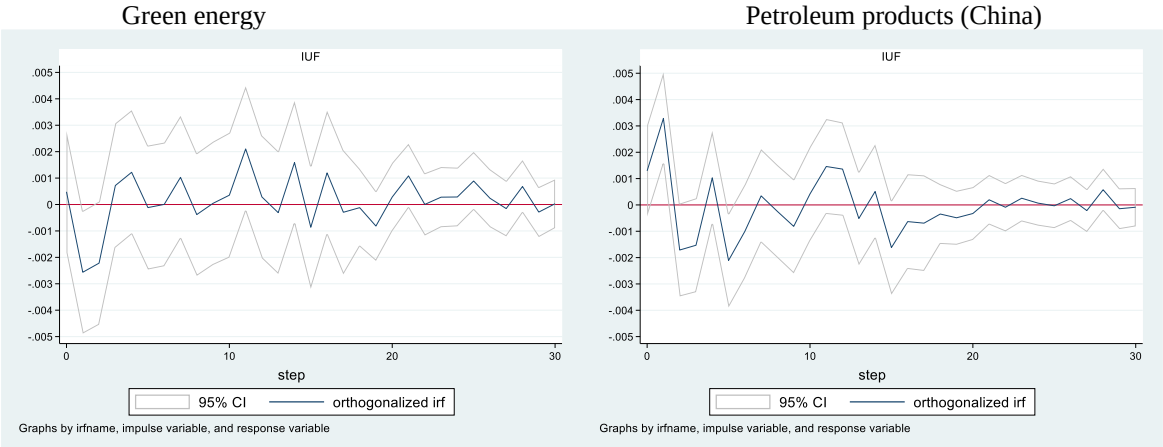


Figure 3. Impulse response (Photo credit: Original)

3.3 ARMA Specification

In terms of the order of stock returns in logarithms, PACF and ACF can serve as critical measures to derive the lag orders for AR(p) and MA(q). In both PACF and ACF plots for green energy displayed in Figure 4, every value lies within the critical value, indicating that AR(p) and MA(q) both have an order of 0, and the values of p and q equal 0. On the other hand, the only part below the critical value is 29 for both plots for petroleum products, unveiling that AR(p) and MA(q) both have an order of 29, with p and q values of 29.

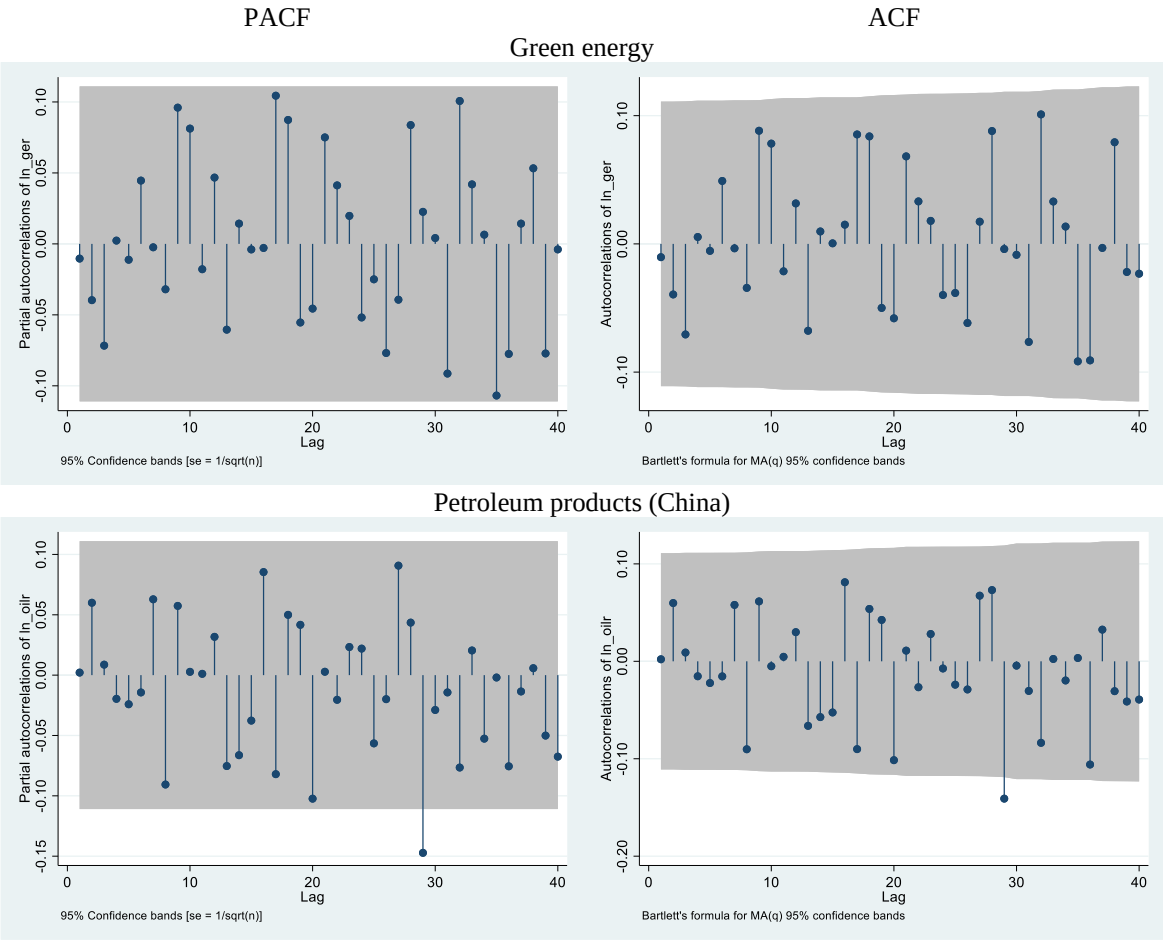


Figure 4. PACF and ACF (Photo credit: Original)

3.4 ARMA-GARCH Estimation Results and Variance Equation

As stated in section 2.4, conducting GARCH (1, 1) is sufficient to capture volatility clustering in time series. As a result, the ARMA-GARCHX model is constructed.

Based on the estimation results shown in Table 3, the ARCH and GARCH terms in the variance equation for both green energy and petroleum products have p-values smaller than 0.01, demonstrating that they are statistically significant. The presence of conditional heteroskedasticity satisfies the requirement to construct the GARCH model. According to the estimation result of the external explanatory variable, the change in Brent crude oil prices does not exert a significant impact on the stock return volatility for green energy and petroleum products in China.

Table 3. ARMA-GARCHX estimation results

Variables	(1)			(2)		
	Green Energy			Petroleum products (China)		
		Mean equation				
AR, L29				0.0881534	0.3875363	0.820
MA, L29				-0.2263091	0.3851382	0.557
Constant	-7.149629	0.1543793	0.000	-9.550871	0.6444483	0.000
		Variance equation				
Brent, sigma-sq	0.0005712	0.0015984	0.721	-0.0630633	0.0459133	0.170
		GARCH (1, 1)				
ARCH, L1	-0.0821739	0.0209659	0.000	0.1741784	0.0711318	0.014
GARCH, L1	0.5669989	0.1472773	0.000	0.6774348	0.1357367	0.000
Constant	-7.149629	0.1543793	0.000	-9.550871	0.6444483	0.000

4. Conclusion

Compared to existing studies in similar areas, this paper focuses on the impacts of war on stock return and volatility of petroleum and renewable energy in China, whereas other studies directly assess the ramifications of different uncertainty risks on oil prices' volatility or the stock market as a whole. Even though some studies briefly discuss the potential implications of the war on energy transition, the empirical data does not include the stock index for renewable energy and cannot suggest the actual impacts caused by risk factors on renewable energy sectors. One similarity, however, is that most studies investigating the subject matter construct similar models, such as TVP-SV-VAR, ARMA-GARCH, and DCC-GARCH, to determine the volatility and return.

Based on the stylized fact that the outbreak of war leads to rising oil prices, this study investigates the effects of change in oil prices on stock return and volatility, respectively. As indicated by the empirical results of the VAR model, the occurrence of the Russo-Ukrainian conflict has resulted in a positive impact on the stock returns of renewable energy but a negligible impact on the stock returns of petroleum products in China. On the other hand, according to the results of the ARMA-GARCH model, the fluctuations in Brent crude oil price have imposed nominal impacts on stock volatility in both industries.

The positive effect of the Russo-Ukrainian conflict on renewables' stock returns may promote the popularity of renewable energy in the market and stimulate more relevant investment. Besides, the government is likely to promulgate policies to provide more favorable conditions for investors and expedite the energy transition in China to accelerate carbon neutrality. On the other hand, since China has a comparatively large oil reservoir, its demand for oil imports is relatively elastic. As a result, the war and spike in oil prices have led to a slight impact on the stock returns of petroleum products in China, and the future outlook of the rising oil prices' net impact on stock return for petroleum products still remains nebulous.

References

[1] Song, Y., Chen, B., Wang, X. Y., Wang, P. P. Defending global oil price security: Based on the perspective of uncertainty risk. Energy Strategy Reviews, 2002, 41: 100858.

[2] Estrada, M., Park, D., Tahir, M., Khan A. Simulations of US-Iran war and its impact on global oil price behavior. Borsa Istanbul Review, 2020, 20 (1): 1-12.

[3] Bašta, M., Molnár, P. Oil market volatility and stock market volatility. Finance Research Letters, 2018, 26: 204-214.

[4] Zhang, Y. J., Yan, X. X. The impact of U.S. economic policy uncertainty on WTI crude oil returns in different time and frequency domains. International Review of Economics & Finance, 2020, 69: 750-768.

[5] Yuan, Y., Zhuang, X. T., Liu, Z. Y., Huang, W. Q. Analysis of the temporal properties of price shock sequences in crude oil markets. Physica: A: Statistical. Mechanics and its Applications, 2014, 394: 235-246.

[6] Degiannakis, S., Filis G., Panagiotakopoulou, S. Oil price shocks and uncertainty: How stable is their relationship over time? Economic Modeling, 2018, 72: 42-53.

[7] Cunado, J., Gupta, R., Lau, C. K. M., Sheng, X. Time-Varying Impact of Geopolitical Risks on Oil Prices. Defence and Peace Economics, 2020, 31(6): 692-706.

[8] Qian, L. H., Zeng, Q., Li, T. Geopolitical risk and oil price volatility: Evidence from Markov-switching model. International Review of Economics & Finance, 2022, 81: 29-38.

[9] Miller, J., Ratti, R. Crude oil and stock markets: Stability, instability, and bubbles. Energy Economics, 2009, 31(4): 559-568.

[10] Moriartry, P., Honnery, D. What is the global potential for renewable energy? Renewable and Sustainable Energy Reviews, 2012, 16 (1): 244-252.

[11] Coleman, L. Explaining crude oil prices using fundamental measure. Energy Policy, 2012, 40: 318-324.

[12] Kesicki, F. The third oil price surge – What's different this time? Energy Policy, 2010, 38(3): 1596-1606.

[13] Araújo, K. The emerging field of energy transitions: Progress, challenges and opportunities. Energy Research & Social Science, 2014, 1: 112-121.

[14] Zhang, B., Wang, P.J. Return and volatility spillovers between china and world oil markets. Economic Modeling, 2014, 42: 413-420.

[15] Eastmoney homepage. [EB/OL]. https://choice.eastmoney.com/.

[16] Sims, C. A. The Role of Approximate Prior Restrictions in Distributed Lag Estimation. Journal of the American Statistical Association, 1972, 67(337): 169-175.

[17] Mann, H. B., Wald, A. On the Statistical Treatment of Linear Stochastic Difference Equations. Econometrica, 1943, 11: 173-220.

[18] Franses, P. H., Ghijsels, H. Additive outliers, GARCH and forecasting volatility. International Journal of Forecasting, 1999, 15(1): 1-9.

[19] Ghani, I. M., Rahim, H.A. Modeling and Forecasting of Volatility using ARMA-GARCH: Case Study on Malaysia Natural Rubber Prices. IOP Conference Series: Materials Science and Engineering, 2019, 548: 012023.

[20] Engle, R. GARCH 101: The Use of ARCH/GARCH Models in Applied Econometrics. Journal of Economic Perspectives, 2001, 15 (4):157-168.