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The Impact of International Oil Price Fluctuations on China's Stock Performance of Clean Energy Industry: Under the Russia-Ukraine Conflict

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Abstract: Crude oil is an important component of the global energy market, and its price fluctuations have a huge impact on the economy and the environment. As a large oil consumer, China has a great demand for non-renewable resources such as crude oil. With the sustainable and stable development of China's economy, its dependence on imported crude oil is deepening, and the impact of international crude oil price fluctuations on China's energy industry is also gradually deepening. In addition, with the impact of epidemic, geopolitical, environmental crisis and financial crisis in recent years, the international crude oil price has produced drastic fluctuations, so the study of the relationship between the international crude oil futures price fluctuations and the stock prices of clean energy companies is of great significance for the development of new energy industry and domestic energy security. This paper applies the VAR model to examine the links between Brent crude oil index, WTI crude oil index and China's Clean Energy Theme Index (CET), and the ARMA-GARCHX model to investigate the impact of international oil price on China's clean energy market after the Russia-Ukraine conflict. The empirical results show that international crude oil price fluctuation has a short-term alternating impact on China's clean energy theme index yield and provides useful insights to investors.

Keywords: Russia-Ukraine conflict, clean energy industry

1. Introduction

Clean energy, also known as green energy or renewable energy. In the past few decades, the consumption of fossil energy has brought huge environmental pollution problems to various countries, and has produced a large negative external effect. In order to protect the environment, countries have shifted their attention to the development of clean and environmentally friendly energy resources, and have begun to vigorously develop clean new energy resources.

Even though clean energy is gradually taking over the fossil fuel, the global economy is still highly dependent on tradition energy. China as the world's second largest economy, are heavily dependent on imported oil. According to the forecast of the International Energy Agency: If the growth rate of China's crude oil demand remains unchanged in the future, the dependence on oil imports will increase to 80% in 2035. The extremely high dependence on foreign oil not only shows that China

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might face a huge risk on oil security in the future, but also shows that the impact of international crude oil price fluctuations on China's energy market as well as financial market is gradually deepening. Therefore, the volatility of global crude oil prices could have a large impact on China's economy and the performance of almost all companies. And because there are obvious income effects and substitution effects between clean energy and traditional fossil energy, the stock returns of clean energy companies must be affected by oil price changes as well. Therefore, the relationship between international oil prices and new energy prices has become a hot spot in related research fields.

Kumar, Singhal & Ghosh and Reboredo & Ugolini studied the relationship between different traditional energy price fluctuations and new energy companies' stock prices, and they found that crude oil prices have the most significant impacts on new energy stock price volatility [1-3]. Henriques & Sadorsky adopted the first-order VAR model to study the crude oil price and the energy market, and found that the increase of international crude oil prices will aggravate the stock price fluctuations of energy companies and technology companies [4]. In Sadorsky's research, he found that oil price fluctuations has a one-way volatility spillover effect on renewable energy stock price [5]. Subsequently, Kumar et al further conducted an in-depth research on the relationship between three clean energy indices and the crude oil price. The results showed that oil prices and technology stock prices separately affect the stock prices of clean energy firms and there is an alternative relationship between crude oil and renewable energy.

In addition, renewable energy companies in different regions are affected differently by the volatility of oil prices. Baars selected a sample of 85 representative renewable energy companies from different regions and found there is a significantly lower impact of oil price fluctuations on companies in the American region, compared to Europe and Asia [6]. Reboredo & Ugolini conducted the corresponding research on the new energy stock market in the United States and the European Union by using the quantile analysis method, and concluded that the price fluctuation of new energy stocks is mainly affected by the fluctuation of crude oil price.

Wen et al adopted the asymmetric GARCH model and found that there was volatility spillover effect between China's new energy stocks and WTI crude oil futures [7]. Wang and Ma established a VAR model and DCC-GARCH model to analyze the relationship between the international crude oil yield and the new energy and high-tech industry stock index yield in China. The research shows that the international crude oil yield only has a significant impact on China's new energy stock index yield, while there is no significant influence on China's high-tech industry [8]. Wang et al found that the international crude oil price has a one-way mean spillover effect on China's new energy stock price, and the fluctuation of the international crude oil price has a significant impact on the price of China's new energy stock, whereas the international crude oil price is not affected by China's new energy stock price fluctuation [9]. Huang, Ye and Huang reveals the spillover effect of international crude oil futures price on China's new energy stocks shows alternating time-varying and significant asymmetry, that is, the spillover effect of falling oil price is more obvious than that of rising oil price. In the long run, crude oil has a significant positive risk spillover to new energy stocks. These previous researches highlighted the fluctuation of international crude oil price will certainly lead to an impact on the China's new energy industry [10].

In 2022, the conflict between Russia and Ukraine has triggered a global energy crisis, with extensive and persistent shocks on world energy development. After the outbreak of the conflict (2022.2.24), both Brent and New York crude futures prices broke through the $100/BBL, the highest price in more than 7 years, and have remained in the high range of $100-130/BBL (please see Figure 1).

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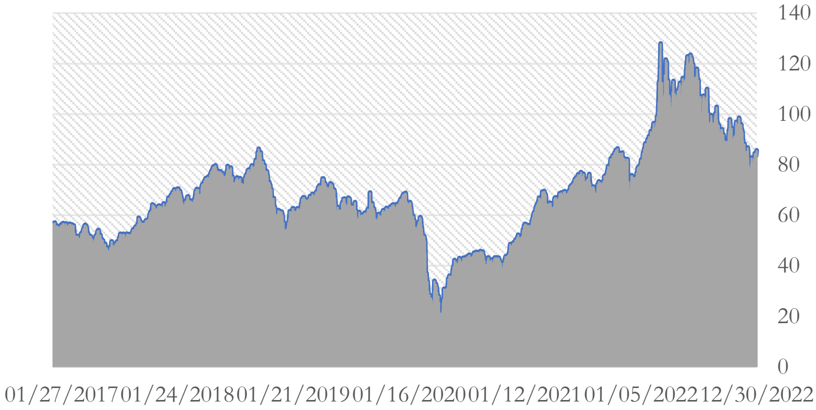

Figure 1: Crude Oil Brent Daily Price (USD/ Bbl).
Photo credit: Original
Data source: Investing.

The Russia-Ukraine conflict has severely changed the global energy structure, coupled with the dramatic world economy crisis caused by the COVID-19 epidemic. The change of the global environment may also make the previous research conclusions lose their validity. However, there are few studies on the correlation between the international crude oil market and China's new energy stock market after the Russia-Ukraine conflict. To fill the void, this paper will use econometrics method, the empirical analysis is carried out by VAR model and ARMA-GARCH mode to study the dynamic relationship between international crude oil price fluctuation and Chinese new energy stock market under the influence of Russia-Ukraine conflict. In this research, WTI crude oil price, Brent oil price and China's clean energy theme index (CET) were selected as the research object and we investigated on how CET yield in China respond to international oil price impulses, and to provide relevant advice to investors and organizations.

The introductory chapter of this thesis is followed by the second chapter that gives a brief description of data source, ADF test and the models. The third chapter is a full discussion of empirical analysis results. And then follows with discussion part and final conclusion part.

2. Research Design

2.1. Data Source

The study uses the Investing.com, a web, in conjunction with Choice financial terminal to search and extract daily closing price of WTI and Brent Oil price, and China's Clean Energy Price (CET) from December 9, 2020 to December 6, 2022, excluding missing data caused by holidays, weekends and different trading times.

2.2. ADF Test

A unit root test is performed on the both stock price and stock yield models. The test statistic from Table 1 shows that the p-values for the price data are bigger than 0.1, which means the time series are non-stationary. While, the p-values of WTI, Brent and CET index's yield data are all equal to 0, implying the yield data are stationary. Therefore, this study will use the yield of three indexes as the research object to build the model.

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Table 1: ADF test.

Variables	t-statistic	p-value
Price		
WTI	-1.538	0.8157
Brent	-1.622	0.7835
CE index	-1.995	0.6044
Yield		
WTI	-16.945	0.0000***
Brent	-16.222	0.0000***
CE index	-15.582	0.0000***

2.3. Vector Autoregression Model

VAR model studies the dynamic relationship between multivariate stationary time series and the impact effect of a random disturbance on variables, because the change of a variable may not only be affected by other variables but also by its own past value. The main feature of the VAR model is to match each endogenous variable with the lagged item of each variable and construct a function, so as to convert multiple variables into vectors for regression analysis, which not only includes more lagged values, but also excludes endogenous and exogenous factors' interference. The mathematical equation of general VAR(p) model is as follows:

$$y_t = \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \alpha_p y_{t-p} + \beta_1 x_t + \cdots \ldots + \beta_r x_{t-r} + \varepsilon_t \tag{1}$$

Where y_t is the m-dimensional endogenous variable vector, x_t is the n-dimensional exogenous variable vector, α and β are m*m dimensional and n*n dimensional coefficient matrices, p and r are the lag intervals of exogenous and endogenous variable respectively, and ε_t is a random disturbance. After obtaining a stable VAR model, Granger causality test, impulse response function, variance decomposition and other tools can be used to further observe the dynamic process between variables.

There are three separate time series variables representing CET yield, WTI yield and Brent yield in this research, denoted by $x_{t,1}$, $x_{t,2}$, $x_{t,3}$, the VAR(p) model is shown below,

$$x_{t,1} = \alpha_1 + \emptyset_{11} x_{t-1,1} + \cdots + \emptyset_{1p} x_{t-p,1} + \beta_{11} x_{t-1,2} + \cdots + \beta_{1p} x_{t-p,2} + \delta_{11} x_{t-1,3} + \cdots + \delta_{1p} x_{t-p,3} + e_{1t} \tag{2}$$

$$x_{t,2} = \alpha_2 + \emptyset_{21} x_{t-1,1} + \cdots + \emptyset_{2p} x_{t-p,1} + \beta_{21} x_{t-1,2} + \cdots + \beta_{2p} x_{t-p,2} + \delta_{21} x_{t-1,3} + \cdots + \delta_{2p} x_{t-p,3} + e_{2t} \tag{3}$$

$$x_{t,3} = \alpha_3 + \emptyset_{31} x_{t-1,1} + \cdots + \emptyset_{3p} x_{t-p,1} + \beta_{31} x_{t-1,2} + \cdots + \beta_{3p} x_{t-p,2} + \delta_{31} x_{t-1,3} + \cdots + \delta_{3p} x_{t-p,3} + e_{3t} \tag{4}$$

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$$\begin{bmatrix} x_{t,1} \\ x_{t,2} \\ x_{t,3} \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} + \begin{bmatrix} \emptyset_{11} \dots \emptyset_{1p} \\ \emptyset_{21} \dots \emptyset_{2p} \\ \emptyset_{31} \dots \emptyset_{3p} \end{bmatrix} \begin{bmatrix} x_{t-1,1} \\ \dots \dots \\ x_{t-p,1} \end{bmatrix} + \begin{bmatrix} \beta_{11} \dots \beta_{1p} \\ \beta_{21} \dots \beta_{3p} \\ \beta_{31} \dots \beta_{3p} \end{bmatrix} \begin{bmatrix} x_{t-1,2} \\ \dots \dots \\ x_{t-p,2} \end{bmatrix} + \begin{bmatrix} \delta_{11} \dots \delta_{1p} \\ \delta_{21} \dots \delta_{2p} \\ \delta_{31} \dots \delta_{3p} \end{bmatrix} \begin{bmatrix} x_{t-1,3} \\ \dots \dots \\ x_{t-p,3} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \end{bmatrix} \tag{5}$$

And the equation (5) is in matrix form.

2.4. ARMA-GARCH Model

The general expression of ARMA(p,q) model is shown below,

$$r_t = \varphi_0 + \sum_{i=1}^{p} \varphi_i r_{t-i} + a_t - \sum_{i=1}^{q} \theta_i a_{t-i} \tag{6}$$

Where $\{a_t\}$ is white noise series, $\phi_0 + \sum_{i=1}^{p} \phi_i r_{t-i}$ is the AR(p) whereas the rest of the equation is MA(q). AR(p) estimates future value applying past clean energy index returns, whilst MA(q) forecasting using an error item.

Proposed by Bollerslev, GARCH model is derived from ARCH by adding the p-order autoregressive, which can effectively fit the heteroscedasticity function with long-term memory [11]. The general expression of GARCH(m,s) model should be,

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i \alpha_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2 \tag{7}$$

For modern high-frequency financial time series, the data often has the characteristics of volatility aggregation, but the data is stable in the long run, that is, the long-term variance (unconditional variance) is a constant value, but the variance is non-stationary in the short term. For this conditional heteroscedasticity, GARCH model can accurately describe the volatility of the clean energy index returns.

3. Empirical Results and Analysis

3.1. Order of VAR Model

In order to find out the optimal lag order for explaining the interaction relationship between the endogenous variables, the LR likelihood method, AIC and other information criterion of each lag should be assessed. Table 2 reveals the desired lag orders by giving an asterisk sign (*) after the statistic which are lag 1, 2 and 11. The FPE, AIC and SBIC values of three lags are quite close, except for the LR value. It is obvious that the lag 11 has the smallest LR value which is 18.91, while the lag 1's is 87.664 and lag 2's is 22.528. As a result, lag 11 is the best option to perform the VAR model (see Table 2).

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Table 2: VAR model identification.

Lag	LL	LR	p	FPE	AIC	HQIC	SBIC
0	3596.91			4.00E-11	15.4245	-15.414	-15.3978
1	3640.74	87.664	0.000	3.50E-11	-15.574	-15.532*	-15.4673*
2	3652	22.528	0.007	3.4e-11*	-15.5837*	-15.5102	-15.397
3	3660.83	17.651	0.039	3.40E-11	-15.583	-15.478	-15.3162
4	3662.25	2.8386	0.970	3.50E-11	-15.5504	-15.4139	-15.2036
5	3668.8	13.094	0.158	3.60E-11	-15.5399	-15.3719	-15.113
6	3678.18	18.772	0.027	3.60E-11	-15.5416	-15.342	-15.0346
7	3682.26	8.1619	0.518	3.60E-11	-15.5204	-15.2894	-14.9335
8	3686.15	7.7746	0.557	3.70E-11	-15.4985	-15.236	-14.8315
9	3693.37	14.447	0.107	3.80E-11	-15.4909	-15.1969	-14.7439
10	3699.1	11.445	0.246	3.80E-11	-15.4768	-15.1513	-14.6497
11	3708.55	18.91*	0.026	3.80E-11	-15.4788	-15.1218	-14.5717
12	3715.01	12.92	0.166	3.80E-11	-15.4679	-15.0794	-14.4807

After determining the order of VAR model, it is crucial to test the stationary of the model. If the VAR model is non-stationary, indicating that the international oil price has long lasting impact on the CET yield. By applying unit root test, it is obvious that all the roots fell within the circle in Figure 2, implying that VAR (11) is stationary.

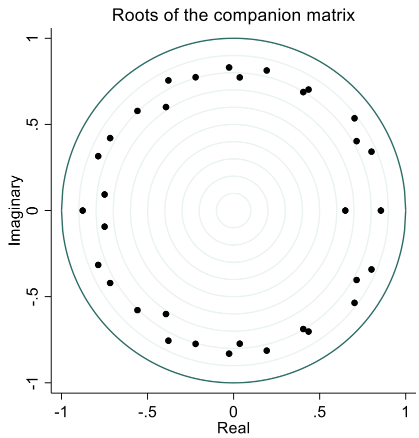

Figure 2: VAR stability.
Photo credit: Original

3.2. Impulse Response

Within a short period of time after the outbreak of the Russia-Ukraine conflict, along with the sharp rise in oil prices, China's entire financial market fluctuated violently and declined rapidly in a short period of time. But as time went on, the stock indexes basically recovered to the level before the Russia-Ukraine conflict. This situation shows that the Russia-Ukraine conflict is more of a short-term shock to the entire financial market. In the medium and long term, the financial market reflects its fundamentals more than short-term shocks.

As far as the energy industry is concerned, clean energy is a substitute for traditional energy. Previous researchers found that the fluctuation of international crude oil price has a certain spillover

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effect on the green energy stock prices (Henriques and Sadorsky; Baars) , and certainly leads to an increase in the consumption of clean energy, but this impact needs to be quantified by building a model.

From the impulse response diagram (Figure 3), the impact of 1 unit of oil price change at t=0 will have alternating positive and negative effects on the clean energy industry in the next 20 steps, floating within the bounds of plus or minus 0.20%, and then the shock gradually diminishes and the shock converges to zero.The author believes that the phenomenon of alternating positive and negative effects simultaneously reveals the short-term panic in the financial market and the positive prospects of the clean energy industry.

WTI Brent

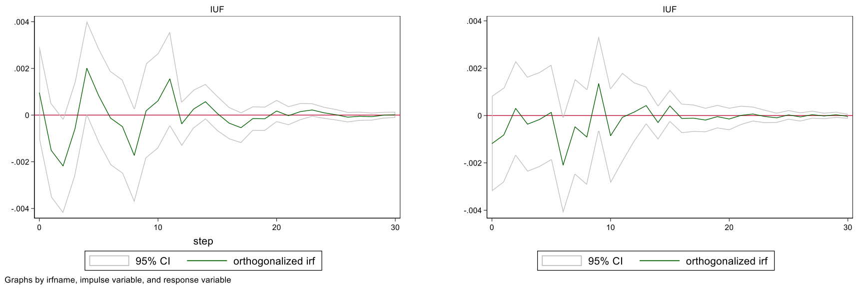

Figure 3: Impulse and response.
Photo credit: Original

However, it is difficult to observe the net impact of current oil price changes on future clean energy from the impulse response graph. Therefore, this paper further calculates the cumulative response function. From the estimated results of the cumulative response function, the net impact of 1 unit of WTI oil price shock in the period t=0 on CET yield in the next 30 steps is slightly less than 4%. Correspondingly, the cumulative effect of changes in Brent oil prices is about 2%.

WTI Brent

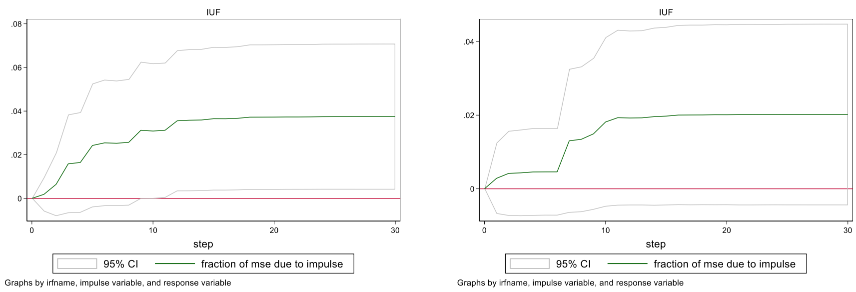

Figure 4: Cumulative response.
Photo credit: Original

According to the model estimation results, this paper predicts the CET yield in the next 30 periods (Figure 4), and the predicted values are all within the 95% confidence interval. It can be found that the yield of the clean energy industry has no obvious increase or decrease with the development of time except a small fluctuation up and down within 10 days. It can be seen from the prediction results that under the influence of the Russia-Ukraine conflict (Figure 5), the yield of China's clean energy industry first fell slightly, then rebounded rapidly, and gradually converged to 0.00% and shows no obvious trend in the long term.

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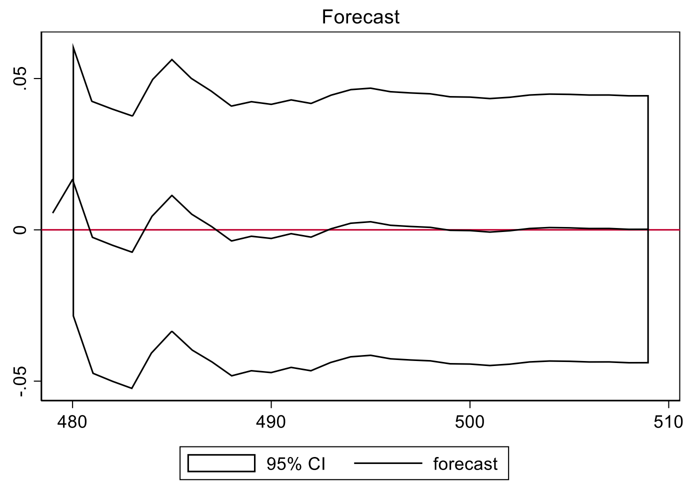

Figure 5: Forecast.
Photo credit: Original

3.3. ARMA Specification

Figure 6 is the ACF and PACF diagrams of the CET yield, which can be helpful to derive the lag orders for AP(p) and MA(q). It is clear that the first part beyond the critical values is 9 for both PACF and ACF plots, demonstrating that the value of p and q are equal to 9.

PACF ACF

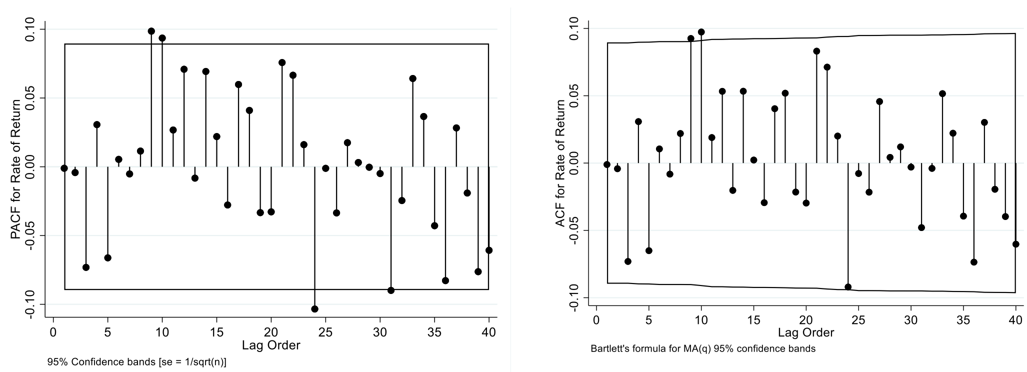

Figure 6: PACF and ACF.
Photo credit: Original

3.4. ARMA-GARCHX Estimation Results and Variance Equation

Generally, GARCH (1,1) model is adequate to capture volatility clustering in time series, so we use GARCH (1,1) and ARMA (9,9) to establish ARMA-GARCH joint estimation model.

Figure 7 depicts the characteristics of CET yield volatility. This time series data clearly exhibits conditional heteroskedasticity, while it would be more logical and reasonable to further examine whether this effect is statistically significant in the model estimation results.

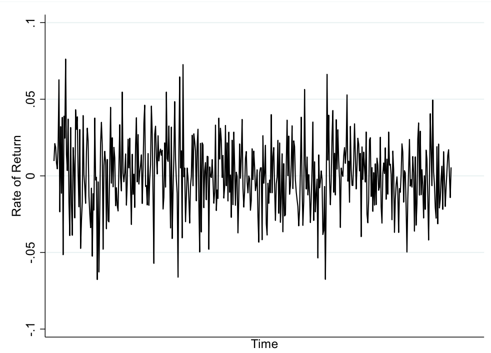

Figure 7: Return.
Photo credit: Original

Table 3 shows ARMA-GARCH model estimation results as wells as the variance equation. The ARCH and GARCH terms in the variance equation both have p-value smaller than 0.05 meaning that they are significant. This indicates that after the mean equation controls the autocorrelation of the clean energy yield, it has significant conditional heteroscedasticity. And p-values of both coefficients for the AR and MA model are greater than 0.05, implying that they are insignificant and reject the null hypothesis that the coefficients are 0. Judging from the estimation results of external explanatory variables, changes in the logarithmic return of WTI and Brent crude oil have no significant impact on the volatility of the clean energy industry.

Table 3: ARMA-GARCH estimation results.

	(1)			(2)		
	Coef.	Std. Err.	P>|z|	Coef.	Std. Err.	P>|z|
Mean Equation						
AR, L9	0.3417	0.3806	0.369	0.3374	0.3799	0.374
MA, L9	-0.2437	0.3930	0.535	-0.2388	0.3918	0.542
Constant	0.0005	0.0011	0.626	0.0007	0.0011	0.526
Variance Equation						
WTI	-0.1929	1.56778	0.902			
Brent				-1.0266	1.7097	0.548
ARCH, L1	-0.0978	0.0235	0.000	-0.0932	0.0238	0.000
GARCH, L1	-0.4187	0.1917	0.029	-0.4112	0.2076	0.048
Constant	-7.1101	0.1313	0.000	-7.1191	0.1436	0.000

4. Discussion

In comparison to other studies, this paper focuses on how the international oil price affect the yield of clean energy companies in China under the impact of the Russian-Ukraine conflict. This paper found that the fluctuation of international oil price caused by Russian-Ukraine conflict has an alternating positive and negative effect on China’s clean energy industry in a short-term, whereas other articles found that the international crude oil price plays a positive role in promoting the price of China’s new energy stocks, and the rise of international crude oil price could lead to the rise of China’s clean energy stock price.

This may be a result of China's vigorous push for clean energy reform from policy, finance and market in recent years. By 2019, China's non-fossil energy consumption ratio had reached the target

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of about 15 percent set in the Strategic Action Plan for Energy Development (2014-2020) ahead of schedule. Meanwhile, the installed power capacity of four types of non-fossil energy -- hydro, wind, solar and nuclear -- increased from 28.51% in 2012 to 39.69 % in 2019. It also indirectly proves that clean energy reform can successfully reduce China's dependence on oil energy and improve its robustness to global energy risk. And for the investors, even though the black swan events such as the Russia-Ukraine conflict could cause panic and affect domestic financial temporarily, China’s new energy market is more dependent on marco-fundamentals such as policy adjustments, new green financial instruments in the long term.

5. Conclusion

The objective of this study is to look into how international crude oil price changes correlate to China’s clean energy industry in terms of stock return and stock volatility after the Russia-Ukraine conflict. The VAR and ARMA-GARCH models are introduced for this purpose, with the VAR model exploring impulse response and the ARMA-GARCH model assessing yield and conditional variances. The results demonstrate that after the Russia-Ukraine conflict, the crude oil has a certain substitution effect on clean energy market in China, the rise in the international oil price yield will lead to a decline in the CET yield, but only in the short term. This could be explained as the development of the new energy industry in China is largely relied on the promotion of government policies and the support of the financial industry, thus the impact of traditional energy prices on China’s clean energy market is less profound and important.

Never the less, this research only selects the crude oil price as the main reference for traditional energy, but the Russia-Ukraine war also has a huge impact on the price of natural gas and other traditional energy, so a variety of energy price indexes can be selected for further exploration in the subsequent research. The findings of this research not only reveal the correlation between international oil price and China’s clean energy market but also indirectly prove the energy transformation strategy of Chinese government is effective and successful.

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