# The Time-Varying Impact of Oil Price Changes on the Consumer Sector: Evidence from the Russia-Ukraine Conflict

Xinjie Li*

Department of Mathematics, Tianjin Normal University, Tianjin, China

*Corresponding author: 2773587B@student.gla.ac.uk

**Abstract.** The impact of changes in oil prices has always had a more or less significant impact on various industries, often affecting the whole body, so the impact of oil price changes has been a hot topic of research. There is still a gap in the literature in terms of the statistically significant impact of oil price changes caused by the large-scale war between Russia and Ukraine, which radiates to the consumer sector. This paper collects WTI and Brent crude oil settlement prices, as well as consumption indices, from three months before the outbreak of the Russia-Ukraine conflict to the present. To achieve smoothness, a VAR model is built using the log-return series of the three data sets, and impulse response plot analysis concludes that there is indeed a significant correlation between the two crude oil prices and the consumption index. An ARMA-GARCH model was later developed to quantify the correlation and derive specific values for the volatility brought about by changes in the prices of the two crude oils on the consumer sector returns.

**Keywords:** Changes in oil prices; Russia-Ukraine conflict; Consumption.

## 1. Introduction

As one of the most important sources of energy for modern industry, oil is an important safeguard for the development of science, technology, and finance. As an important strategic commodity, oil is the focus of competition between various countries and regions in the world. Russia, one of the world's largest crude oil producers, has stabilized at over 10 million barrels per day since 2009 and has shown a steady growth trend [1]. Russia's domestic demand is small in comparison to its large crude oil production, with Russian crude oil consumption accounting for less than a third of its production, and the excess of supply and demand means that Russia is an exporting country in terms of crude oil resources. Russian crude oil exports have evolved in two phases since 2000: from 2000 to 2007, exports grew at a high rate, with annual growth rates of up to 15% on several occasions [2] Exports fell sharply after the financial crisis in 2008 and did not turn positive until after 2010. Russian crude oil exports have maintained steady growth in recent years as infrastructure has improved [3]. 2017 Russia's crude oil exports to China have gradually increased, even surpassing Saudi Arabia as by far the largest supplier of crude oil to China [4].

International crude oil prices after the outbreak of the Russo-Ukrainian war. continued to fluctuate at high levels from US$87/barrel in early February 2022 to US$139/barrel in March 2022. The huge changes in international oil prices pose a huge challenge to the world's economic security, and as the world's largest oil consumer, producer, and net importer, it is of practical guidance to study the impact of the real changes in oil prices on consumption due to the Russia-Ukraine conflict.

International crude oil prices are affected by factors such as supply and demand and the geopolitical environment [5]. The influences of such factors are complex and diverse, from a historical perspective, the fourth Middle East war that broke out in 1973 allowed the OPEC member countries to regain their oil pricing power, which in turn triggered the first oil crisis, during which the international crude oil price rose from $3/barrel to $12/barrel and the high price lasted until 1979 [6]. The Iran-Iraq War, which broke out in September 1980, severely damaged the oil production capacity of both Iran and Iraq, and in the fourth quarter of 1980, Iranian oil exports ceased and Iraqi oil fell to 500,000 barrels per day, and international crude oil prices again rose [7]. When Iraq invaded Kuwait in 1990 and the Gulf War broke out, the UN imposed a total embargo on crude oil exports from Iraq and Kuwait, resulting in world crude oil supplies falling by 4.7 million barrels per day and international crude oil prices rising from $14 to $40 per barrel [8]. The outbreak of 9/11 caused the international price of crude oil to rise again, reaching a peak of nearly $150 per barrel in 2008 [9].

The outbreak of the Russia-Ukraine war in 2022, the largest war in Europe since the Second World War, has had a current impact on world financial and oil markets. Following the outbreak of the war, the international price of crude oil has continued to increase, spiking to almost US$140 per barrel in March 2022, the highest level since 2014. For various reasons, it is important to look at the Russo-Ukrainian war in terms of the performance of the consumer market. Firstly, although the Russo-Ukrainian war is bilateral, several countries, led by the US, have imposed severe sanctions on Russia. Secondly, because of the high dependence of European countries on Russian crude oil and gas [10], the war has sent crude oil prices to their highest level in eight years. But the impact of this rise in crude oil prices is again different from previous crude oil crises. With the global consumer market continuing to be depressed due to the New Coronavirus, the large increase in the price of crude oil, which had fallen sharply during the virus pandemic, meant that it could have a further impact on the world's already depressed consumer market. Thirdly due to the economic importance of crude oil, he has long-standing links with many financial and commodity markets [11]. In the past, since the energy crisis of the last century, it has been widely accepted in academic circles that the rising price of crude oil, an important key raw material for industrial production, drives inflation, which in turn leads to a decline in consumer demand [12].

The world economy is on a clear downward trend amidst the epidemic, high oil prices, and an increasingly volatile geopolitical landscape, although much research has been done in the field of economics on the impact of crude oil prices on consumption [13]. However, in the new era of globalization and protectionism, it is particularly important and relevant to examine the time-varying impact on world consumption of the high crude oil prices triggered by the Russian-Ukrainian war.

This paper uses three sets of data, WTI and Brent crude oil futures closing prices and the SSE Consumer Sector Index, to conduct data correlation analysis, model construction and testing. The impact of international oil price volatility on the consumer sector is investigated in the context of the Russia-Ukraine conflict from both qualitative and quantitative perspectives respectively. Specifically, we first examine whether there is a statistically significant impact and, when this is confirmed, proceed to examine how large the impact is mathematically.

The subsequent content of this paper is organised as follows: Part 2 is research design, which includes data sources, unit root test, and model specification; Part 3 is the empirical result, which includes VAR Identification, Impulse Response, ARMA Identification, and ARMA-GARCH Model Result; Part 4 is discussion; Part 5 is conclusion.

## 2. Research Design

### 2.1 Data sources

The data collected in this paper are from Choice Financial Terminal, where the two sets of international crude oil futures closing prices are WTI crude oil and Brent crude oil, and the consumer sector index is the daily SSE consumer closing prices. The intercept period for the three sets of data is from 3 months before the outbreak of the Russia-Ukraine conflict to the present, i.e. 24 November 2021 to 8 July 2022. As the closing times of the three are not the same, only data for the overlapping dates are retained.

WTI is the benchmark for all crude oil produced in or destined for the United States. Brent crude oil, which is traded on the Intercontinental Exchange in London and the New York Mercantile Exchange, is also the benchmark for oil prices in the market. Unlike WTI, this is a futures based on the Brent index and is financially settled. The SSE Consumer Index refers to a composite share price index of 30 major consumer sector companies selected from the Shanghai market. It reflects the trend and level of price changes of daily necessities and services ordered by urban residents over a certain period of time.

This paper uses the WTI and Brent oil settlement prices and the consumer sector indices to generate three sets of time series and generates the corresponding log original series and log return series based on the time series to conduct a series of model construction and result analysis. The relationship between the Russian-Ukrainian conflict and oil price changes and the consumer sector index is investigated, thus exploring the time-varying impact on the consumer sector. In this thesis, a series of studies are carried out mainly using Stata to analyse data and construct models.

### 2.2 Unit Root Test

Unit Root Test is used to test whether a time series has a unit root. The assumption that the series is stationary is the basis for quantitative analysis of time series. If a time series is not smooth, it is very difficult to use a model to reflect its past and future. Therefore, it is important to confirm the smoothness condition of the data before starting the study. Where there are non-stationary time series, this paper will also treat them accordingly.

Before conducting the unit root test, it is necessary to assume that the time series $x_t$ can be written as follows:

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

In equation (1), $c_t$ is the deterministic component. $e_t$ is a stationary error process (white noise). The null hypothesis of this test is that the coefficient $\beta = 1$, which implies that there is a unit root in the time series, at which point it is an unsteady series. The alternative hypothesis is $\beta < 1$, which means that the series is stationary.

Table 1 illustrates the ADF test results of the logarithmic original series and logarithmic yield series:

**Table 1.** ADF test

| Variables | | t-statistic | p-value |
|---|---|---|---|
| Price | | | |
| | WTI | -2.3250 | 0.4199 |
| | Brent | -2.4340 | 0.3619 |
| | Consumption | -1.2170 | 0.9069 |
| Yield | | | |
| | WTI | -9.4360 | 0.0000*** |
| | Brent | -9.5020 | 0.0000*** |
| | Consumption | -8.9700 | 0.0000*** |

Note: ***, **, and * denote 1%, 5%, and 10% significant levels respectively.

From the above results it can be seen that all the logarithmic original series do not perform too well in the smoothness tests, being insignificant at 90% confidence intervals. However, their corresponding three log-return series are all highly significant at 99% confidence interval, which is a good reason to reject the original hypothesis and thus obtain three sets of well-smoothed series. Based on these results, the paper can then use these smooth series to construct the following model for further investigation.

### 2.3 VAR Model Specification

The vector autoregressive model, introduced by Sims in 1980 [14], puts together several economic variables of simultaneous interest and forecasts them as a system so that the forecasts are self-consistent with each other, this is called a "multivariate time series".

Suppose there are two time series variables as the explanatory variables for each of the two regression equations, and the explanatory variables are the order lagged values of these two variables, forming a bivariate $\mathrm{VAR(p)}$ system:

$$\begin{cases} y_{1t} = \beta_{10} + \beta_{11} y_{1,t-1} + \cdots + \beta_{1p} y_{1,t-p} + \gamma_{11} y_{2,t-1} + \cdots + \gamma_{1p} y_{2,t-p} + \varepsilon_{1t} \\ y_{2t} = \beta_{20} + \beta_{21} y_{1,t-1} + \cdots + \beta_{2p} y_{1,t-p} + \gamma_{21} y_{2,t-1} + \cdots + \gamma_{2p} y_{2,t-p} + \varepsilon_{2t} \end{cases} \tag{2}$$

Where 1 and 2 are both white noise processes (so there is no autocorrelation), but a "contemporaneous correlation" between the perturbation terms of the two equations is allowed:

$$Cov\left(\varepsilon_{1t}, \varepsilon_{2s}\right) = \begin{cases} \sigma_{12}, & \text{if } t = s \\ 0, & \text{other} \end{cases} \tag{3}$$

Write out the column vectors for the contemporaneous variables and combine the corresponding coefficients into a matrix:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} \beta_{10} \\ \beta_{20} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \gamma_{11} \\ \beta_{21} & \gamma_{21} \end{bmatrix} \begin{bmatrix} y_{1.t-1} \\ y_{2.t-1} \end{bmatrix} + \cdots + \begin{bmatrix} \beta_{1p} & \gamma_{1p} \\ \beta_{2p} & \gamma_{2p} \end{bmatrix} \begin{bmatrix} y_{1.t-p} \\ y_{2.t-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \tag{4}$$

Where $\mathrm{y_t} = \begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix}$ , $\varepsilon_t = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$,

Defining the corresponding coefficient matrix as $\Gamma_0, \Gamma_1, \ldots, \Gamma_p$ , can get

$$y_t = \Gamma_0 + \Gamma_1 y_{t-1} + \cdots + \Gamma_p y_{t-p} + \varepsilon_t \tag{5}$$

Where $\{\varepsilon_t\}$ is a generalization of the one-dimensional white noise process known as the "vector white noise process".

### 2.4 VAR Model Specification

With respect to time series variables, the second assumption of traditional econometrics is that their variance is fixed. The ARCH model is also known as the "autoregressive conditional heteroskedasticity model". This model solves the problems associated with the above assumptions and makes such methods more feasible.

The ARCH model, known as the "Autoregressive conditional heteroskedasticity model", solves the problems associated with the second assumption of traditional econometrics for time series variables and becomes more feasible.

Denoting returns or return residuals by $\{\varepsilon_t\}$, suppose $\varepsilon_t = \sigma_t z_t$ , where $z_t \sim \mathrm{iidN}(0,1)$ (i.e. independent identically distributed, all conforming to an expectation of 0 distribution) where the sequence $\sigma_t^2$ is modeled as

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_p \varepsilon_{t-p}^2 \tag{6}$$

Where $\alpha_0 > 0, \alpha_i \geq 0, i > 0$ ,i.e., returns for each period are linearly combined with non-negative numbers and the constant term is positive.

In an ARCH(p) model, if $p$ is large, there will be many parameters to be estimated. This means that sample size will be lost. In contrast, the GARCH proposed by Bollerslev can reduce the number of parameters to be estimated. In this way, predictions of future conditional variance are more accurate. Actually, the GARCH model is an ARCH model with the autoregressive part of $\sigma_t^2$ added to it. $\sigma_t^2$ is still a function of $\{\sigma_{t-1}^2, \ldots, \sigma_{t-p}^2\}$. The model of GARCH(p,q) is set as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \underbrace{\varepsilon_{t-1}^2 + \cdots + \alpha_q}_{ARCH} \varepsilon_{t-q}^2 + \gamma_1 \underbrace{\sigma_{t-1}^2 + \cdots + \gamma_p}_{\mathrm{GARCH}} \sigma_{t-p}^2 \tag{7}$$

The most commonly used GARCH model is GARCH (1,1):

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_0 + \gamma_1 \varepsilon_{t-1}^2 \tag{8}$$

This paper uses the ARMA-GARCH model to forecast both return and volatility, putting the WTI log return series and Brent log return series as exogenous variables in the variance equation respectively.

# 3. Empirical results

## 3.1 VAR Identification

To confirm the correct order $p$ of the $VAR(p)$ model, the paper use VARSOC selection-order criteria in Stata. As can be seen from table 2 below, the most appropriate order of VAR is 6.

Only two things need to be determined to build a VAR model: the variable under study and the other is the maximum order of the lag. And the former is clear: a series of three log returns. In this paper, the maximum lag order k is first determined using the AIC (Akaike Information Criterion) statistic. the formula for the AIC statistic is as follows:

$$AIC = log\left[\frac{\sum_{t=1}^{T} e_t^2}{T}\right] + \frac{2k}{T} \tag{9}$$

$$min\{AIC\} = log\left[\frac{\sum_{t=1}^{T} e_{kt}^2}{\sum_{t=1}^{T} e_{(k+1)t}^2}\right] - \frac{2}{T} \tag{10}$$

Where $T$ is the sample size.

Two VAR models with lag orders of $k$ and $k+1$, respectively, indicate a more moderate lag order as long as their AIC statistics are closer.

The Great Likelihood Estimation for Logistic Regression is then used to check whether the maximum lag order $k$ obtained is moderate based on the relationship between the LR statistic and the critical value. The formula for the LR statistic is as follows:

$$LR = -2(LogL_k - LogL_{k+1}) \tag{11}$$

Where the $LogL_k$ is the logarithmic rate of return series.

When the sample size is sufficiently large compared to the number of parameters being estimated, LR asymptotically follows a chi-square distribution with degree of freedom $N^2$, i.e.

$$LR \sim \chi_{(N^2)}^2 \tag{12}$$

When the LR statistic is less than the critical value, the lag order of the VAR model is considered to be moderate. When the LR statistic is greater than the critical value, the lag order of the VAR model is considered not high enough, and more lagged variables need to continue to be added as explanatory variables.

**Table 2.** VAR model identification

| Lag | LL | LR | df | p | FPE | AIC | HQIC | SBIC |
|---|---|---|---|---|---|---|---|---|
| 0 | 1092.43 | | | | 2.0e-11* | -16.1397* | -16.1134* | -16.0751* |
| 1 | 1099.41 | 13.966 | 9 | 0.124 | 2.0e-11 | -16.1098 | -16.0048 | -15.8515 |
| 2 | 1101.32 | 3.8216 | 9 | 0.923 | 2.2e-11 | -16.0047 | -15.8211 | -15.5528 |
| 3 | 1107.07 | 11.506 | 9 | 0.243 | 2.4e-11 | -15.9566 | -15.6943 | -15.311 |
| 4 | 1109.27 | 4.3953 | 9 | 0.884 | 2.6e-11 | -15.8559 | -15.5148 | -15.0166 |
| 5 | 1117.87 | 17.196 | 9 | 0.046 | 2.6e-11 | -15.8499 | -15.4301 | -14.8169 |
| 6 | 1128.94 | 22.142* | 9 | 0.008 | 2.6e-11 | -15.8806 | -15.3821 | -14.6539 |
| 7 | 1131.85 | 5.8274 | 9 | 0.757 | 2.8e-11 | -15.7904 | -15.2132 | -14.3701 |
| 8 | 1136.47 | 9.2268 | 9 | 0.417 | 3.0e-11 | -15.7254 | -15.0695 | -14.1114 |
| 9 | 1143.87 | 14.808 | 9 | 0.096 | 3.1e-11 | -15.7018 | -14.9672 | -13.8941 |
| 10 | 1146.12 | 4.5028 | 9 | 0.875 | 3.4e-11 | -15.6018 | -14.7885 | -13.6004 |
| 11 | 1153.75 | 15.249 | 9 | 0.084 | 3.5e-11 | -15.5814 | -14.6894 | -13.3863 |
| 12 | 1156.16 | 4.8174 | 9 | 0.850 | 4.0e-11 | -15.4838 | -14.5131 | -13.0950 |

This paper uses Stata to build VAR(6) model, and then check whether the VAR estimates are stable. This means analyzing whether the effect of a pulsating shock on the VAR model will fade out over time. If it fades away, the VAR model is stationary; otherwise, it is unstable. A VAR model with a unit root is non-stationary, i.e. the responses of the endogenous variables in the VAR model do not disappear over time when there is a pulsating shock in the new interest. It is clear in Figure 1 that, none of the eigenvalues are outside the unit circle. So the VAR system developed in this paper is smooth.

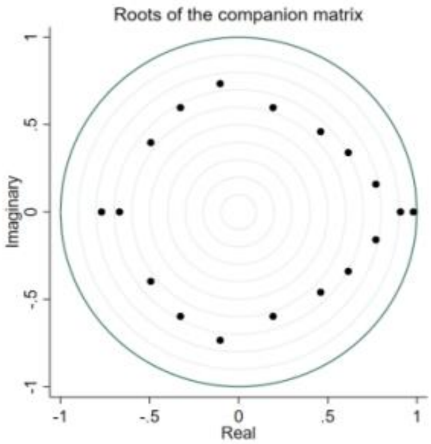


**Figure 1.** VAR stability

### 3.2 Impulse Response

WTI Brent

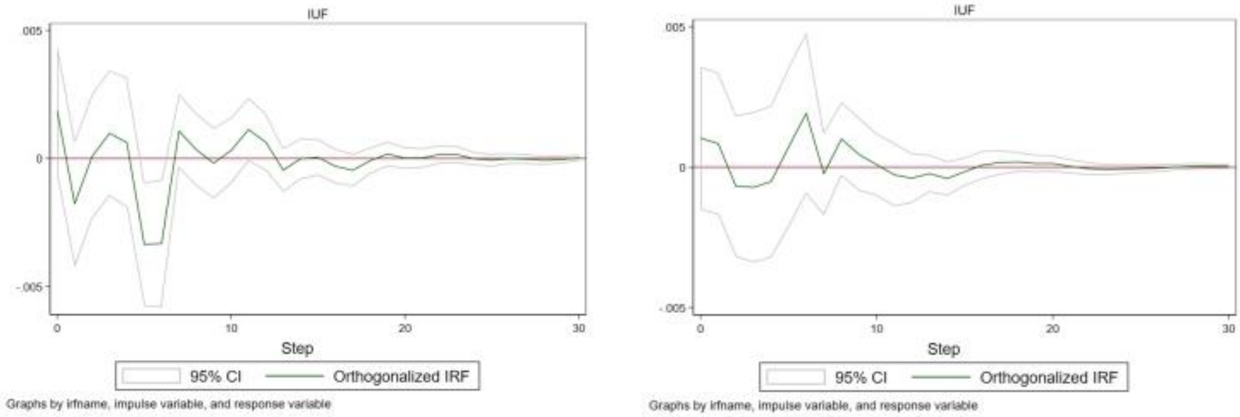


**Figure 2.** Impulse and response

Figure 2 contains two impulse response plots where the impulse variables are WTI log returns and Brent log returns, and the response variables are both consumption index log returns.

The estimated results from the impulse responses show that the net effect of higher WTI crude oil prices on consumer sector returns is negative, with no similar effect for Brent. Specifically, a 1% increase in WTI crude oil returns in period t=0 oscillates consumer sector returns over the next 10 periods, with the maximum of the negative effect occurring in periods 5 and 6, with a magnitude of approximately 0.4%. After period 10, the effect decays rapidly and eventually disappears.

However, the impact of higher crude oil prices on the consumer sector is not particularly large in order of magnitude. The likely reason for this is that, as the blood of modern industry, higher crude oil prices must lead to higher production and transport costs for companies, which have to undergo a series of transmission before eventually leading to higher prices for consumer goods, and this takes some time to be transmitted and adjusted. It is difficult to see a significant impact in the short term.

### 3.3 ARMA Identification

To determine the order of the AR and MA components, this paper uses PACF and ACF to order the log-return series of the CPI.

A partial autocorrelation plot (PACF plot) of the series is viewed in Stata, and the results are shown in the left-hand panel in Figure 3. The black rectangle is the key to finding statistically significant terms in the AR model. Thus based on the position of the bars in relation to the matrix, it is obtained that the lagged 24 and 30 terms of the original series have a significant effect.

This paper uses an autocorrelation plot (ACF Plot) to determine the MA portion of the series, which is plotted by Stata as shown in the right-hand panel in Figure 3. As can be seen from the results, all but the 24th order fall within the 2 times standard deviation range, making the lagged 24 terms a suitable order.

PACF ACF

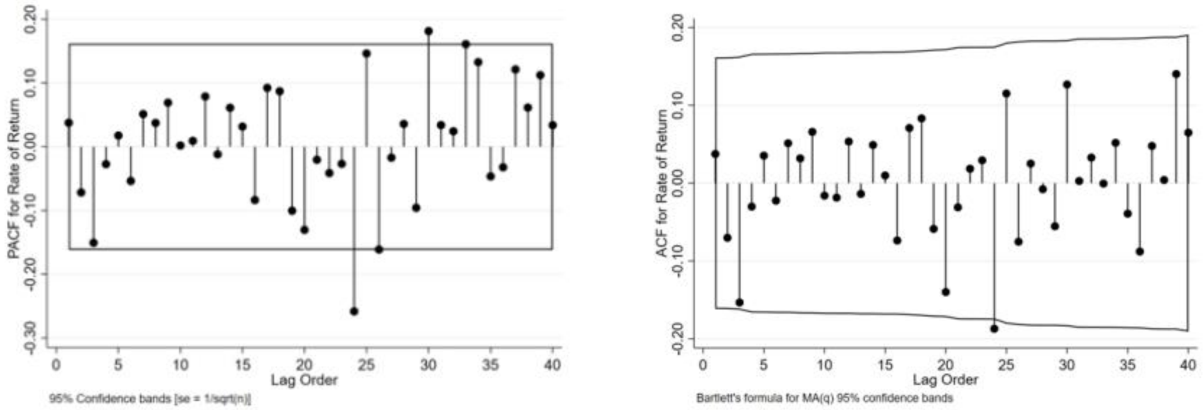


**Figure 3.** PACF and ACF, consumption

### 3.4 ARMA-GARCH Model Result

From the estimation results of the variance equation, both the ARCH and GARCH terms of the consumer sector returns are significant, indicating that the time series has significant conditional heteroskedasticity and can be modeled as GARCH.

**Table 3.** ARMA-GARCH model estimation

| | (1) | | (2) | |
|---|---|---|---|---|
| | Coef. | Std. err | Coef. | Std. err |
| WTI | 0.0121*** | 0.0018 | | |
| Brent | | | 0.0091*** | 0.0021 |
| ARCH (-1) | 0.4230*** | 0.0891 | 0.2207*** | 0.0943 |
| GARCH (-1) | 0.2121** | 0.0883 | 0.4654*** | 0.1377 |
| Constant | -8.4637*** | 0.4524 | -8.8371*** | 0.5021 |

In addition, WTI and Brent crude oil returns have a significant impact on the daily volatility of the consumer sector with coefficients of 0.0121, and 0.0091, respectively, significant at the 1% level. This means that a 1 unit increase in the log return of WTI crude oil is associated with a 0.0121 unit increase in the volatility of consumer sector returns and a 1 unit increase in the log return of Brent crude oil is associated with a 0.0091 unit increase in the volatility of consumer sector returns.

## 4. Discussion

In contrast to the existing literature, this paper uses two specific sets of data on international crude oil prices to analyse the impact of oil price changes on the consumer sector, in turn, from a qualitative and quantitative perspective. Unlike most of the literature, this paper uses data from three months before the outbreak of the Russian-Ukrainian conflict to the present, which provides a clearer picture of the impact of the Russian-Ukrainian conflict on oil prices and the impact that this has had on the consumer sector, allowing the reader to see more clearly the volatility of the consumer index due to changes in oil prices.

Based on the analysis of the impulse response results, this paper concludes that the Russian-Ukrainian conflict and higher crude oil prices have not had much impact on the consumer sector. Based on the ARMA-GARCH model constructed, it appears that WTI and Brent crude oil yields have a significant effect on the daily volatility of the consumer sector at the 1% confidence level. The above results are since the supply fundamentals of crude oil had been tight for a long time before the outbreak of the Russia-Ukraine conflict, and the Russia-Ukraine conflict acted as a trigger to cause a spike in crude oil prices, thus putting pressure on energy and commodity prices, which took some time to be transmitted to the consumer sector, and the price pressure would gradually weaken during the transmission process. The Russian-Ukrainian conflict and changes in crude oil prices will therefore have a significant impact on the consumer sector, but not to a significant degree. During the transmission process, the increased costs are partly absorbed by producers, who do not choose to transfer cost pressures to consumers by raising prices. It can be seen that against the backdrop of a weak economy due to the novel coronavirus pneumonia epidemic, producers were afraid to raise prices for fear of losing market competitiveness and had to bear the pressure of rising costs themselves. To avoid such a passive situation, China should vigorously pursue technological innovation and strive to become fully oil-free and change its dependence on crude oil, so that it can comfortably face the medium and long-term risks arising from price fluctuations in the international crude oil market. At the same time, we should vigorously support small and micro enterprises, broaden financing channels and lower the threshold for bank loans, to help them survive the impact of multiple factors and continue to improve their vitality.

## 5. Conclusion

The Russian-Ukrainian conflict, which was the trigger for the spike in crude oil prices, together with changes, has had a significant impact on various sectors, adding to the already weak global economy. This paper focuses on the time-varying impact of the Russia-Ukraine conflict and changes in crude oil prices on the consumer sector and concludes that the fact that both have had an impact on the consumer sector is significant but not significant in order of magnitude, contrary to one's intuition.

## References

[1] Outlook A E. Energy information administration. Department of Energy, 2010, 92010(9): 1-15.

[2] Pirog, Robert. Russian oil and gas challenges. Connections 2007, 6(3): 82-99.

[3] Popkova, Elena G., et al. Innovations as a basis for marketing strategies of Russian oil companies in the conditions of oil prices reduction. overcoming Uncertainty of Institutional Environment as a Tool of Global Crisis Management. springer, Cham, 2017. 449-455.

[4] Falkowski, Krzysztof. Trade interdependence between Russia vs. the European Union and China within the context of the competitiveness of the Russian economy. Equilibrium. Quarterly Journal of Economics and Economic Policy, 2018, 13(4): 667-687.

[5] Du, W. The determinant and the future trend of international oil price. Economic Theory and Business Management, 2006, 9: 70.

[6] Abdelaziz, Mohamed, Georgios Chortareas, and Andrea Cipollini. Stock Prices, Exchange Rates, and Oil: Evidence from Middle East Oil-Exporting Countries. 2008.

[7] Takeyh, Ray. The Iran-Iraq War: A Reassessment. The Middle East Journal, 2010, 64(3): 365-383.

[8] Leigh, Andrew, Justin Wolfers, and Eric Zitzewitz. What do financial markets think of war in Iraq? 2003.

[9] Sari, Ramazan, Shawkat Hammoudeh, and Ugur Soytas. Dynamics of oil price price, precious metal prices, and exchange rate. Energy Economics, 2010, 32(2): 351-362.

[10] Reed, Stanley, Melissa Eddy, and Benjamin Novak. But the punitive move may come with costly disruptions. The New York Times, 2022: B1-L.

[11] Oberholzer, Basil. Monetary policy and crude oil: prices, production and consumption. Edward Elgar Publishing, 2017.

[12] Fan Y, Jiao J, Liang Q, et al. The impact of rising international crude oil price on China's economy: an empirical analysis with CGE model. International Journal of Global Energy Issues, 2007, 27(4): 404.

[13] Hamilton J D. Oil and the Macroeconomy. The new Palgrave dictionary of economics, 2008.

[14] Qin D. Rise of VAR modelling approach. Journal of Economic Surveys, 2011, 25(1): 156-174