Russia Ukraine Conflict, Crude Oil Price and Dynamic Changes in Dow Jones Index

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Abstract. This study conducted a time series analysis of the Dow Jones Industrial Average's response to the Russia Ukraine conflict through the change in crude oil continuous contract price. The relevant data was derived from 1st November 2021 to 29th April 2022. The inputs were employed in the vector autoregressive model (VAR), autoregressive moving average models (ARMAX), and ARMA-GARCH model to quantitatively characterize the dynamic relationship between the daily rate of returns of DJI and crude oil price. The finding suggested that the stock market reacted volatilely during the early stages of the Russia Ukraine conflict, and later the market eased the volatility. The result provides critical implications for investors to hedge risks in their international portfolio diversification.

Keywords: Russia Ukraine conflict, Dow Jones Industrial Index, Crude Oil, Empirical research.

1. Introduction

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2. Introduction

On February 24, 2022, the Russian military initiated its invasion of Ukraine. Accordingly, the war could be the largest in Europe after World War II. As of the end of April, the war has resulted in a humanitarian crisis viewed by other parts of the world, causing over 2.9 million refugees. As the conflict continued, the value of the Russian ruble dropped to a historic low value against the U.S. dollar or euro. However, the invasion of Ukraine has not yet resulted in a loss of oil supply to the international market. Still, the conflict inevitably led to a surge in oil and gas prices, as the U.S. and EU countries committed to reducing their dependencies on Russian natural energy.

In the third quarter of 2021, Russian gas shipments passing the Ukraine transit route accounted for 11% of the EU's net extra-EU gas imports. Russia is the world's largest exporter and second-largest crude oil exporter among the markets worldwide. It exported 7.8 million barrels per day in December 2021, with crude and condensate accounting for 5 million barrels per day (64 percent). Exports of oil products totaled 2.85 million barrels per day, with 1.1 million barrels per day of gasoline, 650 barrels per day of fuel oil, 500 barrels per day of naphtha, and 280 barrels per day of vacuum gas oil (VGO) [1].

In 2021, the European Union and the United Kingdom imported crude oil, petroleum products, and natural gas from Russia for 147.8 billion dollars. The EU is heavily reliant on Russia for energy supplies, mainly natural gas delivered through pipelines. Following the Russia-Ukraine conflict, imports of petroleum goods and gas have been closely reviewed, with the EU attempting to prevent itself from excessive reliance on Russian oil and gas. The United States imported approximately 8.7 million barrels of crude oil and petroleum products from Russia in January 2022, a significant decline from the previous month. The amount in May 2021 was the highest in the fiscal year. Overall, imports in 2021 exceeded 245 million barrels, valued at about 4.7 million dollars [2].

As a result of the Russian invasion of Ukraine, the price of gasoline has increased tremendously and reached the highest level at around 5.83 U.S. dollars per gallon at the beginning of May. In other words, the war led to a crude oil price increase and caused volatile market uncertainty and gas price inflation.

Several studies have already provided different perspectives on how the conflict would influence the oil price and the market. The survey conducted by Jong-Min Kim and Hojin Jung concluded an inverse relationship between the U.S. crude oil prices and interest rates [3]. Their study used the Granger causality test and the BEKK representation of a multivariate GARCH process, a method this paper will also take part in. Another study was based on cointegrated VAR models, part of which model this paper will also address. The study indicated the relationship between the fluctuations in oil prices with the bulk of depreciation in the Ruble [4]. The study conducted by Alexey Mikhaylov used the FIGARCH model to predict the impact of oil prices on stock market indices for Russia and Brazil [5]. The study contributed to new methods for forecasting volatility, which can be utilized under the circumstance of the continually involved Russia and Ukraine conflict.

This paper aims to analyze the time-series impact of the Russia-Ukraine conflict, specifically in terms of fluctuations in crude oil settlement price and Dow Jones industrial average indexes. The visualization and demonstration of such influence require a timeline of the military conflict initiating from three months before the beginning to the end of April. To scientifically demonstrate the cause and effect, the paper will analyze the data derived from Dow Jones Industrial Average index using the econometrics model conducted in Stata, such as the ARMAX model, VAR model, and ARMA-GARCH model. The method of time-series evaluation showcased volatility in industrials corresponding to different landmarks of the conflict.

The rest of this paper is organized as follows: Part 2 is the research design, including data sources, unit root test, and model specification. Part 3 reports empirical results. Part 4 is the discussion, and part 5 is the conclusion.

3. Research Design

3.1 Data

This paper was primarily constructed based upon two indexes: Dow Jones Industrial Average and Crude Oil continuous contract settlement price. Since the objective is to evaluate the time series impact of Russia Ukraine conflict quantitatively, namely how did the fluctuation in crude oil price influenced the Dow Jones index, the model utilized the daily closed price from 1st November 2021 to 29th April 2022, three months before the beginning of the conflict to the end of April.

This paper’s data was derived from the official portal of MarketWatch, a website providing financial information, analysis, and stock market data, a subsidiary of Dow Jones & Company. The Dow Jones Industrial Average, Dow Jones, or the Dow, is a price-weighted measurement stock market index of 30 prominent companies listed on the United States stock exchange.

3.2 Initial Transformation

BP neural network is back-propagating, mainly composed of three parts: input layer, middle layer, and output layer. The number of nodes in the input and output layers is relatively easy to determine, but the determination of the number of nodes in the hidden layer is a very important and complex problem.

The first step of data transformation was to compute the logarithm of the Dow Jones Industrial Average (DJI) and Crude Oil Continuous Contract price (Oil) daily. Then, the logarithm versions were used to compute the daily rates of return.

$$\ln price = \ln(1 + price) \tag{1}$$

$$\ln yield = \ln(1 + yield) \tag{2}$$

in which price stands for the daily price of DJI or Oil index, so that equation (1) shows their logarithm, denoted as $\ln DJI$ and $\ln Oil$. In turn, equation (2) shows the daily rates of return of the index logarithm, denoted as $\ln DJIr$ and $\ln Oilr$.

3.3 Unit Root Test

To make time-series analysis effective and solid, the time-series data must be stable over time. Otherwise, there would be the no good or predictive relationship to be evaluated between exogenous and endogenous variables. Unit root test is a stability test method proposed for macro data series and economic time series data. It is the foundation for constructing ARMA, ARIMA, and cointegration analysis models because the unit root test examines the stationarity of time series data. To prevent certain circumstances, for instance, Pseudo regression, an Augmented Dickey-Fuller (ADF) test for unit root should be conducted to test for stationarity.

$$x_t = c_t + \beta x_{t-1} + \sum_{i=1}^{p-1} \phi_t \triangle x_{t-i} + e_t \tag{3}$$

The test hypothesis is:

$$H_0: \beta = 1$$
$$H_1: \beta < 1$$

The decision rule is to reject the null hypothesis if the t-statistic under the ADF test is sufficiently large; likewise, if the p-value is significantly large, it fails to reject the null hypothesis. DJI and Crude oil prices were tested using STATA with a lag of 1 term (results shown in Table 1).

Table 1 ADF-test

Variables	t-statistic	p-value
	Price	
DJI	-2.882	0.1685
Crude oil	-2.813	0.1922
	Rate of return	
DJI	-8.651	0.0000***
Crude oil	-8.078	0.0000***

According to the ADF test results for price indexes, $\ln DJI$ and $\ln Oil$, the MacKinnon approximate p-value for Z(t) is 0.1685 and 0.1922, respectively. The p-values are significantly greater than the significance level of 0.05. Thus, the test statistics for the price index are not sufficient to reject the null hypothesis at all given significance levels (none of 1%, 5%, 10%). This suggests that the log price of DJI and crude oil, $\ln DJI$ and $\ln Oil$, are not qualified for stationarity. Generally speaking, the results demonstrate the typical market efficiency that the past period index cannot sufficiently predict the future stock market performance.

On the other hand, according to the ADF test results for $\ln DJIr$ and $\ln Oilr$, the MacKinnon approximate p-value for Z(t) is zero, which demonstrates that the variables are both significant. The test statistics are sufficient to reject the null hypothesis at all given significance levels (1%, 5%, and

10%). This suggests that the logarithm of the rate of return of DJI and crude oil prices ($\ln DJIr$ and $\ln Oilr$) are qualified for stationarity.

3.4 ARMA (p, q) model

The foundation of the ARMAX model is the Autoregressive Moving Average Model (ARMA) model. An ARMA model is utilized to evaluate weakly stationary stochastic time series in terms of two polynomials in which the first is for autoregression, the second for the moving average. Normally, the model is referred to as the ARMA (p, q) model, where p is the order of the autoregressive polynomial, and q is the order of the moving polynomial. The equation is given by:

$$x_t = \phi_0 + \sum_{i=1}^{p} \phi_i \, x_{t-i} + a_t - \sum_{i=1}^{q} \theta_i \, a_{t-i} \tag{4}$$

Where p and q are all non-negative integers, $\sum_{i=1}^{p} \phi_i \, x_{t-i}$ is the autoregressive (AR) part, a_t is a white-noise series independent for all t, and $\sum_{i=1}^{q} \theta_i \, a_{t-i}$ is the moving average (MA) part.

This study demands that AR polynomial and MA polynomial do not have any common factors; otherwise, the order (p, q) will be lowered. As the AR model, the AR polynomial introduces the characteristic equation of the ARMA model. As long as the absolute value of the characteristic equations' solutions is lesser than 1, the ARMA model is weakly stable. The goal of ARMA model is to simultaneously use the past realized value and the past perturbation to predict the future values.

3.5 PACF Order Identification

The partial autocorrelation function (PACF) provides the partial correlation of a stationary time series with its corresponding lagged values. PACF regresses the time series values at shorter lags, contrasting with the autocorrelation function which does not control for other lags.

The PACF is a widely used tool for AR model order identification, and a simple yet effective way to introduce it is to consider a series of AR models sequentially:

$$\begin{gathered} x_t = \phi_{0,1} + \phi_{1,1} x_{t-1} + e_{1t} \\ x_t = \phi_{0,2} + \phi_{1,2} x_{t-1} + \phi_{2,2} x_{t-2} + e_{2t} \\ x_t = \phi_{0,3} + \phi_{1,3} x_{t-1} + \phi_{2,3} x_{t-2} + \phi_{3,3} x_{t-3} + e_{3t} \\ x_t = \phi_{0,4} + \phi_{1,4} x_{t-1} + \phi_{2,4} x_{t-2} + \phi_{3,4} x_{t-3} + \phi_{4,4} x_{t-3} + e_{4t} \end{gathered} \tag{5}$$

Thus, the equation (5) can be transformed into a general form:

$$x_t = \phi_{0,p} + \phi_{1,p} x_{t-1} + \phi_{2,p} x_{t-2} + \cdots + \phi_{p,p} x_{t-p} + e_{pt} \tag{6}$$

The PACF has the following properties:

1) As the sample size T increases towards infinity, $\hat{\phi}_{p,p}$ will converge to ϕ_p;

2) for l greater than p, $\hat{\phi}_{l,l}$ congers to zero;

3) for l greater than p, $\hat{\phi}_{l,l}$ has an asymptotic variance valued at $1/T$.

The above results demonstrate that the sample PACF of AR (p) series is censored at the p step.

3.6 ARMAX Model

The ARMAX models include two extensions and applications of the ARMA models: 1) a model may define various time series with different p and q values in different time series and 2) a time series is provided with the feasibility to apply additional dependencies on observations from related time series, the cross-predictors. Note that the additional dependencies should also be weakly stationary.

$$x_t = \phi_0 + \sum_{i=1}^{p} \phi_i\, x_{t-i} + a_t - \sum_{i=1}^{q} \theta_i\, a_{t-i} + \gamma_{11} x_{1,t-1} + \cdots + \gamma_{1q_1} x_{1,t-q_1} + \gamma_{K1} x_{K,t-1} + \cdots + \gamma_{Kq_K} x_{K,t-q_k} \tag{7}$$

The ARMAX model has a representation of time series similar to an ARMA model, equation (4). The only difference is that the dependent variable also depends on the vector of cross predictors. A full ARMAX model contains multiple time series which correlate through the cross predictors only, and thus the unobserved error variables are independent across time series in the model and can have various shared variances for multiple time series [6]. Basically, as an extension of ARMA model, ARMAX model simultaneously uses the past realized value and the past perturbation to predict the future values, while examining the contribution of other explanatory variables in affecting the dependent variable.

Specifically, after setting the $\ln DJIr$ as the dependent variable, the paper constructed three ARMAX models. The first step was to use PACF to determine the order for the model. Then, starting from only using $\ln Oilr$ as the explanatory variable, the model sequentially adds in two lagged terms as additional explanatory variables.

3.7 VAR Model

When predicting several economic variables, one way is to control for a simple time series variable to predict several variables respectively. Another way is to consider those variables altogether as a system and make a prediction, for the sake of mutual consistency, which is called multivariate time series. The vector autoregressive (VAR) model is used for multivariate time series, in which structure is constructed as each variable is a linear function of past lags of itself and past lags of the other variables.

Suppose there are two time series variables, $\{y_{1t}, y_{2t}\}$, and make them the dependent variables of two regression functions, respectively. The dependent variables for such regression functions are the lag p order of those two time series variables. Hence constructs a bivariate VAR (p) system.

$$\begin{aligned} y_{1\mathrm{t}} &= \beta_{10} + \beta_{11} y_{1,\mathrm{t}-1} + \cdots + \beta_{1\mathrm{p}} y_{1,\mathrm{t}-\mathrm{p}} + \gamma_{11} y_{2,t-1} + \cdots + \gamma_{1p} y_{2,t-p} + \varepsilon_{1t} \\ y_{2\mathrm{t}} &= \beta_{20} + \beta_{21} y_{1,\mathrm{t}-1} + \cdots + \beta_{2\mathrm{p}} y_{1,\mathrm{t}-\mathrm{p}} + \gamma_{21} y_{2,t-1} + \cdots + \gamma_{2p} y_{2,t-p} + \varepsilon_{2t} \end{aligned} \tag{8}$$

Allow for the contemporaneous correlation among the perturbation terms in the two dependent variables. Note that the two functions have identical explanatory variables, so to put them together. Make the contemporaneous variables into column vectors, and combine the corresponding coefficients into matrixes.

Define the corresponding coefficients concerning the terms sequentially as a matrix $T_0, T_1, \ldots, T_p$, have:

$$y_t = T_0 + T_1 y_{t-1} + \cdots + T_p y_{t-p} + \varepsilon_t \tag{9}$$

This form is very similar to AR (p), as defined as VAR (p). The term, $\{\varepsilon_t\}$, is an extension of a one-dimensional white noise process, the "vector white noise process".

In order to evaluate the impulse of one explanatory variable and the response of other variables with respect to the magnitude of time movement, the impulse response function was used. Specifically, the model computed 30 terms of impulse functions.

$$\frac{\partial y_{t+s}}{\partial \varepsilon'_t} = \psi_s \tag{10}$$

Which expresses the impact on the value of the i[th] variable in the (t + s) term, y_{t+s}, when the j[th] variable increases by 1 unit in the t[th] term; regarding $\frac{\partial y_{t+s}}{\partial \varepsilon'_t}$ as the function for time interval s, it thus is the Impulse and Response Function (IRF).

3.8 ARMA-GARCH Model

In general, cross-sectional data sets are considered to possess heteroskedasticity, and time-series data sets possess auto-correlation. However, in 1982, Engle pointed out that the cross-sectional data sets have a particular auto-correlation, namely "Autoregressive Conditional Heteroskedasticity" (ARCH) [7].

In econometrics, the ARCH model for time series data describes the variance of the current error term or innovation as a function of the actual volume of the error terms from previous periods. The ARCH model is considered appropriate as long as the error variance follows an autoregressive (AR) model.

For the general linear regression model:

$$y_t = x'_t \beta + \varepsilon_t \tag{11}$$

Denote the conditional variance for the error term ε_t as $\sigma_t^2 = Var(\varepsilon_t | \varepsilon_{t-1}, \ldots)$, where t stands for periods. Due to the volatility agglomeration, suppose that the conditional variance of the error term depends on the square of the last error term:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 \tag{12}$$

which stands for the error term of ARCH (1).

More generally, suppose the variance depends on the square of the last p periods of error terms, the error term for ARCH (p) is:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_p \varepsilon_{t-p}^2 \tag{13}$$

In the ARCH (p) model, a loss of sample volume could occur if it were to estimate too many parameters once p is large. In 1986, Bollerslev brought up the GARCH, which reduced the parameters required for estimation and made the prediction of future conditional variance more accurate [8].

If an autoregressive moving average model (ARMA) model is assumed for the error variance, the model is a generalized autoregressive conditional heteroskedasticity (GARCH) model. The idea was that, upon the foundation of ARCH model, GARCH added the section of autoregression of the errors themselves.

The setting of GARCH (p, q) is:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_q \varepsilon_{t-q}^2 + \gamma_1 \sigma_{t-1}^2 + \cdots + \gamma_p \sigma_{t-p}^2 \tag{14}$$

The conditional variance follows a process similar to ARMA (p, q) but without the random contemporaneous error term. The mean equation is the ARMA process, and the most frequently used GRACH model is GARCH (1,1):

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 \sigma_{t-1}^2 \tag{15}$$

GARCH model is widely used because it reduces the requirement of the number of parameters. In other words, since σ_{t-1}^2 already includes the information of $\{\varepsilon_{t-2}^2, \ldots, \varepsilon_{t-p-1}^2\}$, equation (15) can be transformed into:

$$\sigma_t^2 = \frac{\alpha_0}{1-\gamma_1} + \alpha_1(\varepsilon_{t-1}^2 + \gamma_1\varepsilon_{t-2}^2 + \gamma_1^2\varepsilon_{t-3}^2 + \cdots) \quad (16)$$

In a way, GARCH (1,1) is equivalent to the infinite order of ARCH model. Hence, if involved variance that is lagged 1 term as an explanatory variable, ARCH (p) model can be simplified as GARCH (1,1). GARCH (or ARCH) model is employed only if the conditional heteroskedasticity exists.

To assess the time-series influence of the Russia Ukraine conflict on the Dow Jones Industrial Average, this study will conduct the analysis based on the utilization of the autoregressive moving average (ARMA) model with various generalized autoregressive conditional heteroskedasticity (GARCH) methods, namely the ARMA-GARCH model.

The model is advanced both in its improved model precision, achieved through an ARMA model which includes strong correlations among adjacent measurements and in its extracted nonlinear characteristic that exhibits volatility clustering through a GARCH model [9]. The goal of employing ARMA-GARCH model is to simultaneously predict the rate of return and volatility.

As for the model setting, ARMA-GARCH is achieved by replacing the mean function in GARCH model with ARMA process. The conditional mean process due to ARMA has the same shape as the conditional variance process due to GARCH, while the lag order may differ. Specifically, a total of three ARMA GARCH models were conducted.

4. Empirical Results and Analysis

4.1 VAR Model: Lag Order Identification, Impulse, and Response

Table 2 indicates the generated named Selection-order criteria, in which LL is interpreted as log-likelihood function, while LR is utilized for likelihood test, namely for conducting likelihood ratio tests for joint significance of last-order coefficients. The model examined 12 lags for each explanatory time series variable. The optimal lag is considered the lag which has the greatest LR values. Hence, the optimal lag is lag 4.

Table 2 VAR Model Identification

Lag	LL	LR	df	p
1	563.98	1.8655	4	0.760
2	567.436	6.9127	4	0.141
3	569.461	4.0496	4	0.399
4	574.701	10.48*	4	0.033
5	577.727	6.0519	4	0.195
6	581.909	8.3639	4	0.079
7	583.709	3.5999	4	0.463
8	585.634	3.8512	4	0.427
9	587.741	4.2136	4	0.378
10	590.283	5.0842	4	0.279
11	591.542	2.5176	4	0.641
12	592.428	1.7709	4	0.778

To examine the VAR stability, this paper drew a varstable, roots of the companion matrix for visualization. The horizontal axis was labeled Real, and the vertical axis was labeled imaginary. According to Figure 1, since all the eigenvalues are inside the unit circle, the VAR model is considered to possess stationarity property.

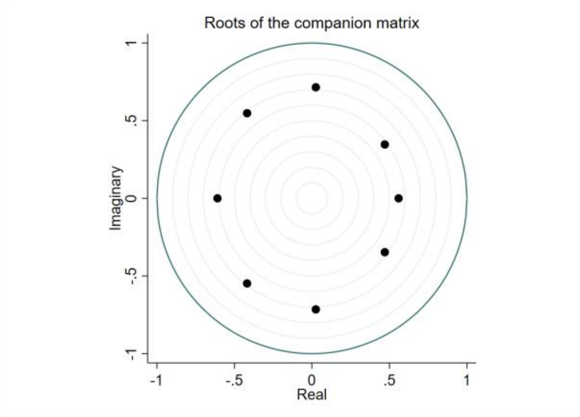

Figure 1 VAR stability

Figure 2 showcases the dynamic movement and effect of daily crude oil price rate of returns on the daily Dow Jones index daily returns. The impulse response functions are derived from the VAR model (designed in section 2.6) with an optimal lag determined as 4 (shown in Table 2). Specifically, 30 steps were used in the visualization of impulse response over 125 trading days from 1st November 2021 to 29th April 2022, three months before the beginning of the conflict to the end of April. Thus, each step represents approximately 4 trading days.

Derived from the estimation results shown in Figure 2, as illustrated in a perspective of the dynamic influence, the increase in the rate of return of crude oil continuous contract price will result in a temporary volatile fluctuation in the rate of return of the Dow Jones Industrial Average. Specifically, within the first two steps, namely the first 8 trading days, the crude oil continuous contract price increase lowered the DJI rate of return. Following was a radical increase in the Dow Jones rate of return as a response to the time series movement of crude oil contract rate of returns. The fluctuation persisted and did not ease nor disappear until passed step 10, which is 40 trading days.

The result suggests that what crude oil continuous contract price impacts DJI rate of return is more like a temporary external impulse. Either the positive or negative impulse on the DJI index is not persistent so that such a reduction in peak effects and dynamic fluctuation can be explained and supported by corresponding monetary and fiscal policies. Furthermore, the result also demonstrates that the stock market is relatively efficient and that all the shocks would be revealed by the market performance.

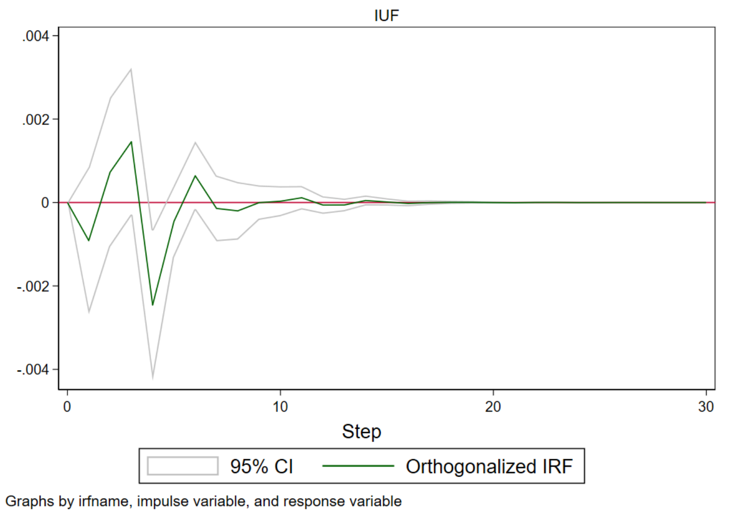

Figure 2 Impulse and response

4.2 ARMAX Model: Lag Order Identification and Estimation Results

This study used the autocorrelation function (ACF) and partial autocorrelation function (PACF) and the plots chart to identify the lag order for the ARMAX model. As shown in Figure 3, significant lags were found in lags 18, 24, 27, 37, and 40. For the application of ARMA-GARCH model, lag order 18 will be selected in constructing the AR- models. As shown in Figure 3, the PACF order identification approach resulted in that lag order 18 would be implemented in computing the ARMAX model.

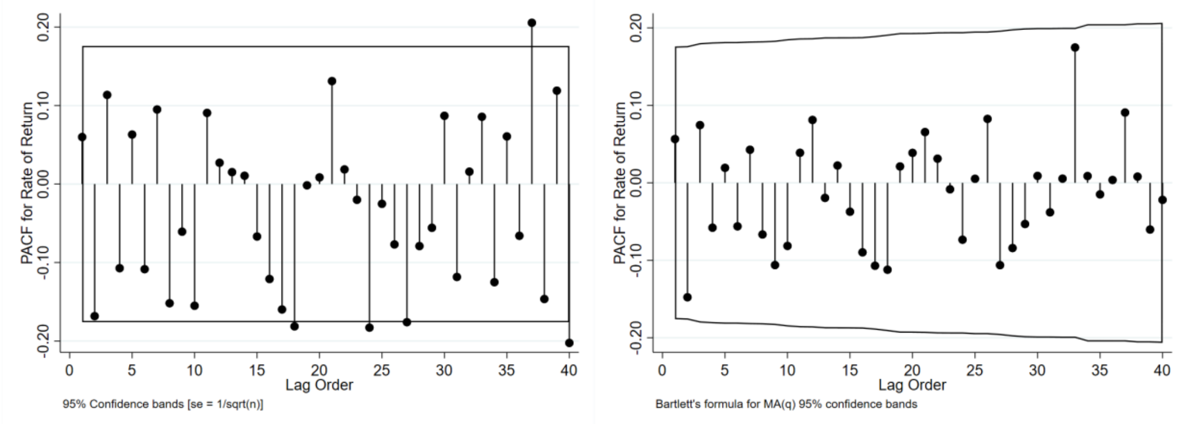

Figure 3 ARMA model identification

Table 2 is a summary of the estimated coefficients along with their standard deviation of three consecutive ARMAX models, each sequentially adding one more lagged term of crude oil rate of return logarithm as additional explanatory variables. From the estimation results from the ARMAX model, the crude oil continuous contract rate of return does not have a significant dynamic correlation with the Dow Jones Industrial Average rate of return, given that none of the coefficients in the model is marked as significant due to their relatively large p-value.

Theoretically, the goal of ARMAX model is to use the past realized value and the past perturbations to predict the future outcomes, while examining the effectiveness of other exogenous variables. In this study, however, the result suggests that, past realized values, and data of crude oil contract rate of return, cannot provide sufficient and solid prediction on future stock market performance, at least under the constraint of the estimation constructed by ARMAX model.

The finding aligns with the stock market efficient theories that in a relatively efficient market, information and analysis of past data would not be effective in predicting future prices and returns [10].

Table 2 ARMAX model estimation results

Variables	(1)	(2)	(3)
	Crude oil		
T=0	0.0203	0.0198	0.0207
	(0.0199)	(0.0196)	(0.0200)
T=-1		-0.0296	-0.0292
		(0.0279)	(0.0278)
T=-2			0.0200
			(0.0298)
	ARMA		
AR (-18)	-0.1376	-0.1408	-0.1425
	(0.1050)	(0.1058)	(0.1054)
Constant	-0.0006	-0.0006	-0.0006
	(0.0008)	(0.0008)	(0.0008)

None of the coefficients are significant.

4.3 ARMA-GARCH Model Empirical Results

Table 4 is a summary of the coefficients along with their standard deviation of three consecutive ARMA-GARCH models, each sequentially added one more lagged term of crude oil rate of return logarithm as additional explanatory variables.

Interpreted from the estimation results derived from the ARMA-GARCH model, the DJI rate of return possesses a significant GARCH effect, namely the conditional heteroskedasticity. Interpreted from the estimation results of exogenous variables, an increase in the crude oil continuous contract rate of return would not result in an increase in the daily fluctuation of DJI.

More specifically, for the crude oil explanatory variables in all of the three ARMA-GARCH models, variables with T=0 are all significant and effective in explaining the dependent variable, the log rate of return of the DJI index. Meanwhile, none of the variables with T= -1 or -2 have significance. The finding aligns with the result derived from ARMAX model as well as the Impulse and Response generated by the VAR model, that the past values are not sufficient nor supportive in explaining or predicting future returns. In summary, the past crude oil rate of return is not a significant exogenous explanatory variable to be input into the model, so it is reasonable to conclude that the crude oil rate of return does not have explanatory influence over the Dow Jones Index.

Associated with the estimation result from VAR model, it would reasonable to conclude that, the increase in crude oil continuous contract price only causes a temporary impact on the DJI rate of return. Although the Russia Ukraine conflict initially caused tremendous fluctuation in DJI returns, the stock market performance, revealed by DJI in this study, tended to ease and dispel the impact on the market return.

Table 4 ARMA-GARCH model estimation results

Variables	(1)	(2)	(3)
		Crude oil	
T=0	-24.4938**	-22.6610*	-22.1907**
	(12.2716)	(11.8003)	(11.0950)
T=-1		8.5823	8.2114
		(37.6971)	(46.012)
T=-2			16.4168
			(43.4073)
		ARCH	
ARCH (-1)	0.2284	0.2260	0.2124
	(0.1467)	(0.1567)	(0.1608)
GARCH (-1)	0.6976***	0.6761***	0.6946***
	(0.1762)	(0.2274)	(0.2226)
Constant	-11.8086***	-11.6133***	-11.7905***
	(1.1851)	(1.1991)	(1.3087)

The coefficients are marked with their significance (*** significance if $p<0.01$, ** significance if $p<0.05$, and * significance if $p<0.1$)

5. Discussion

This study contributes to analyzing the time series impact of crude oil price on the DJI index. The model has a GARCH effect that the time series involved have conditional heteroscedasticity. The result shows that the crude oil rate of return can only be regarded as a temporary factor. However, the past realized values do not possess explanatory power in either explaining or predicting the DJI index, an indicator of stock market performance.

The paper by Christian and other scholars examined a short schematic overview summarizing the relationship between exchange rate, oil prices, and sanctions [4]. Among the literature reviewed, the paper by Yahia and Saleh in 2008 analyzed the relationships between economic sanctions, oil price fluctuations, and employment [11]. While that study simultaneously considered sanctions and oil prices, this paper quantitatively examines the impact of crude oil rate of return on the DJI index.

In terms of using the conclusion of this study to make fiscal policy, the policymaker should aim at maintaining the short-term stability of the stock market rather than overestimating the crude oil rate of return impact on stock market performance. As the study pointed out, the crude oil rate of return has a temporary impulse caused, but it does not persist. In conclusion, the aim of fiscal policy should focus on providing crude oil supply and limiting the negative externalities of short-term fluctuations in the stock market. On the other hand, the investors should also use the conclusion of this study to diversify their portfolios further. In short, they should not lose confidence in the stock market's resilience and not overestimate the duration of volatility.

The study had certain drawbacks: it only took crude oil price and rate of return as explanatory variables and the DJI index as the dependent variable. The limitation on variables could potentially incur bias in the conclusion. The sample size could have been more prominent because this study only considered the data three months before the start of the conflict. Given that Russia and Ukraine had a hostile relationship way before, the model could use more data. In conclusion, future studies can simultaneously consider more explanatory variables and use more indicators to evaluate the stock market performance and select a larger sample size.

6. Conclusion

The study reported in this paper was conducted in the context of the Russia Ukraine conflict. This study aimed to quantitatively examine the time series impact of the conflict on the Dow Jones Industrial Average index through the change in crude oil continuous contract price from 1st November 2021 to 29th April 2022. The study found that the Dow Jones index showed an initial volatile fluctuation in response to the change in crude oil price. The early-stage volatility persisted within the first 40 days and then dispelled afterward. In conclusion, the finding suggested that the stock market reacted volatilely during the early stages of the Russia Ukraine conflict, and later, the market eased the volatility.

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