Changes in Crude Oil Price under the Russia-Ukraine Conflict and Dynamics of Stock Market in G7 Countries

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Abstract. On 24 February 2022, the conflict between Russia and Ukraine, due to the war, caused the stock market with greater sensitivities to the change of crude oil prices. This paper studies the effect of crude oil on G7 countries' stock markets before and after the Russian-Ukrainian conflict. Using a VAR model, impulse response plots are constructed to measure the extent of crude oil price impacts on stock prices in seven countries, and an ARMA-GRCH-X model is applied to measure the correlation between the prices of crude oil and stocks in seven countries. This study shows that variations in crude oil prices have the greatest influence on the stock markets of France, German, and Italy, with the UK following. The impact on the stock markets of Japan, Canada, and the US is relatively small. The results of the ARMA-GARCH-X model examination demonstrate that the prices of crude oil have a remarkable positive correlation with the stock markets of France, Germany, and Italy. This study shows that during the Russia-Ukraine conflict, stock markets were more influenced by the prices of crude oil and stock investors are advised to invest with caution during war.

Keywords: Russia-Ukraine Conflict, Stock Market, VAR model, ARMA-GARCH-X model.

1. Introduction

1.1. 1.1 Background

Previous research has shown that the prices of crude oil have a greater effect on world stock markets during war relative to peacetime, especially when the country engaged in the war is an exporter of crude oil. In January 2022, Russia launched separate dialogues with the US and NATO to demand that the US and NATO exclude the possibility of eastward expansion, but no substantial progress was made. On 2 February 2022, the US Department of Defense announced that additional troops would be sent to Europe in response to the tensions in the Russian-Ukrainian border region. February 17, 2022, Tensions continue to escalate in the East Ukraine region. On 23 February 2022, the EU officially adopted the sanctions imposed on Russia, with Japan, Canada and Australia announcing sanctions against Russia. On 24 February 2022, at 10am, Putin approved a special military operation by Russian troops in the Donbass region; at 12pm, Russian troops broke through the Kharkiv oblast border in eastern Ukraine and rockets were fired at Ukrainian command posts in Kiev and Kharkiv. The Russia-Ukraine conflict, in which Russia is a crude oil exporting country, has caused strong volatility in the crude oil market, which has spilled over into the world stock markets.

The purpose of this paper is to inspect the effect of crude oil prices on the G7 countries' stock markets from six months prior to the Russia-Ukraine conflict (August 2021) to the present (August 2022). A standard VAR model was used, and impulse response plots were used to detect the extent to which the seven countries were affected by crude oil prices. The ARMA-GARCH-X model is adopted to measure the correlation that exists between crude oil and the G7 countries' stock markets.

1.2. 1.2 Literature Review

The purpose of this study is to examine whether crude oil prices during the Russian-Ukrainian conflict influenced the stock markets of the G7 countries. A review of previous literature is used to discuss the existing research relating to the effect of the variations in crude oil prices on stock markets during the war/non-war periods and an attempt is made to supplement the existing research in this study that may have been overlooked. Themes of this literature review analyse the effect of the prices of crude oil on stocks according to influencing factors such as war, politics, and epidemics.

Ftiti et al. and Diaz et al. show that stock markets in the G7 countries were significantly influenced by the period of crisis (or war) stemming from the demand shock of crude oil [1, 2]. And when crude oil prices are at high levels it pushes stocks into a bear market, with the length of time that the stock market stays in a bear market depending on how long crude oil prices fall from their high levels [3]. This view is supported by Lee and Chiou who show that S&P 500 returns were negatively impacted by the prices of crude oil [4]. A study by Jammazi attributes the difference in the degree of stock market exposure to the source of crude oil, noting that stock markets response to crude oil shocks depends on the region of the main sources of supply and that external sources of crude oil can trigger stock markets collapse even though some countries have lower crude oil imports from overseas. And while the price of crude oil from non-European countries and North America had a stronger effect on stock markets, stock markets in Japan and the UK were less affected [5].

But Balcilar et al. show that it is not feasible when using crude oil prices to predict stock prices [6]. Attaie uses Granger causality tests to validate the view that crude oil prices are not Granger causal to stock prices [7]. And Khalfaoui et al. state that the prices of crude oil and stocks are affected directly by their own variations, indirectly affected by the variations in the prices of each other [8]. Therefore, the association between crude oil and stocks requires considering the effect of a number of additional factors.

Kollias et al., Gordon and Recio, Aloui and Jammazi, Zhang and Bittlingmayer with emphasis on the effect of crude oil on stocks during the war and show that the war can have impacts on the association between crude oil and stock returns [9-13]. Kollias et al. point out that crude oil shocks to stock returns are concentrated in the preparation phase of war [9]. The geographical location made the European crude oil market more affected in the early stages of the war [10], while the US was more affected in the months before the cease fire and less affected on the prices of crude oil and stocks during the war [10, 11]. Kollias et al. and Zhang in their research on the association between crude oil and stock prices in the two wars, it was demonstrated that the association between the prices of crude oil and stocks was more affected in the country which was involved in the war [9, 12].

Another major factor that cannot be ignored in the influence of the prices variations of crude oil on the stock market is the political factor [9, 13]. Furthermore, during a pandemic, as the number of infected people increases it also reduces stock returns and the prices of crude oil [14].

In summary, previous studies have concentrated on the implications from crude oil on the stock market during economic crises or wars. And indicated the existence of the influence from crude oil on the stock market during these periods, but more scholars have tended to study individual countries and this paper will concentrate on the effect of crude oil on the G7 countries' stock markets during the Russia-Ukraine conflict.

The remaining parts of this study are organised as follows: Part 2 is methodology, including data sources, ADF test, VAR model setting and ARMA-GARCH-X model setting. Part 3 is the empirical results and analysis, including the results of the ADF test, selection of the lag of VAR model, impulse response plots, selection of the lag of ARMA model and the results of the ARMA-GARCH-X estimation.

2. Methodology

2.1. Data Sources

Data for this study are all taken from the same financial platform [15], based on the daily prices of WTI and the daily prices of the G7 countries' stock markets (CAC 40 (French), DAX 30 (Germany), MIB (Italy), Nikkie 225 (Japan), S&P 500 (US), SPTSX (Canada), FTSE 100 (UK)). The data spans the period from six months prior to the Russia-Ukraine conflict to the present (August 2022). The above data is used to inspect the effect of the prices of crude oil on the G7 countries' stock markets before and after the Russia-Ukraine conflict.

2.2. ADF Test

The VAR (Vector Autoregressive) model is constructed on the assumption that all time series data are stable. The ADF (Augmented Dickey-Fuller) Test was used as a method to examine the existence of unit roots in the time series to prevent the occurrence of the pseudo-vector autoregression.

The eight data were individually built into a model for unit root testing, the null hypothesis was that the model had a unit root, meaning that the model was not smooth. After putting the data into Stata for ADF testing, the results for all eight data sets do not reject the null hypothesis, which indicates that all the data are not smooth.

After first-order differencing of the eight data, ADF tests were performed on each of the eight data sets and found that the p-value of all models was zero and the null hypothesis was rejected for all eight data sets tested, which indicated that all data were stationary.

2.3. VAR Model Setting

VAR (Vector Autoregression) model is commonly applied in the research of time series to investigate the relationship that exists between the dynamics of interacting variables.

A vector autoregressive model for a single variable can be written as:

$$y_t = \alpha + A_1 y_{t-1} + \cdots + A_p y_{t-p} + \varepsilon_0 \tag{1}$$

In equation (1), (1, 2, 3, …, p) is the lag. ε_0 is the white noise process.

In this paper, the daily data of WTI and the daily data of stock market returns of G7 countries are put into a VAR model (Equation (2)).

$$\begin{pmatrix} y_{1t} \\ y_{2t} \\ . \\ . \\ . \\ y_{8t} \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ . \\ . \\ . \\ \alpha_8 \end{pmatrix} + \begin{pmatrix} A_{1,1,1} & \cdots & A_{1,8,1} \\ \vdots & \ddots & \vdots \\ A_{8,1,1} & \cdots & A_{8,8,1} \end{pmatrix} \begin{pmatrix} y_{t-1} \\ y_{2t-1} \\ . \\ . \\ . \\ y_{8t-1} \end{pmatrix} + \cdots + \begin{pmatrix} A_{1,1,p} & \cdots & A_{1,8,p} \\ \vdots & \ddots & \vdots \\ A_{8,1,p} & \cdots & A_{8,8,p} \end{pmatrix} \begin{pmatrix} y_{t-p} \\ y_{2t-p} \\ . \\ . \\ . \\ y_{8t-p} \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ . \\ . \\ . \\ \varepsilon_8 \end{pmatrix} \tag{2}$$

In equation (2), (1, 2, 3, …, p) is the lag and the unit of lag is days. ε_1, ε_2, ε_3, …, ε_8 are white noise processes and there is no autocorrelation between them.

2.4. ARMA-GARCH-X Model Setting

In the ARMA (Autoregressive-Moving-Average) model (Equation 3).

$$y_t = \varepsilon_t + \sum_{i=1}^{p} \varphi_i y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{3}$$

Equation (4) represents the AR (p) (Autoregressive) model, with p as the lag coefficient. Models use the historical returns of the WTI and G7 countries stock markets to forecast their future returns separately.

$$y_t = \sum_{i=1}^{p} \varphi_i y_{t-i} + \varepsilon_t \tag{4}$$

Equation (5) represents the MA (q) (Moving-Average) model, with q as the lag coefficient, which use the past error terms of each of the eight data to forecast their future returns.

$$y_t = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{5}$$

This study constructs AMRA-GARCH-X models with returns and volatilities in stock markets in seven countries. This study uses the return on WTI as an external variable to measure the correlation between the volatility of WTI and stock markets of seven countries.

In general, an ARCH model is used to examine the properties of the perturbation term, with p as the lag coefficient (Equation 6).

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

However, in the ARCH (p) model, the sample size could be lost if the lag coefficient p is too large. Bollerslev proposed a model based on the ARCH model with autoregressive component of the sample variance, the GARCH (p, q) model (Equation 7).

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_p \varepsilon_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_q \sigma_{t-q}^2 \tag{7}$$

Equation 8 demonstrates the GARCH (1, 1) model.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{8}$$

In Equation 8, "$\alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_p \varepsilon_{t-p}^2$" is the ARCH component and "$\beta_1 \sigma_{t-1}^2 + \cdots + \beta_q \sigma_{t-q}^2$" is the GARCH component. The GARCH-X model, by contrast, is dependent on the GARCH model with the addition of an external covariate. In this study, WTI returns are added to the model as an external covariate.

Equation 9 is an ARMA-GARCH-X model of stock market returns of a single country, X_t is log return of WTI as an external explanatory variable.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma X_t \tag{9}$$

3. Empirical Results and Analysis

3.1. Result of ADF Test

Data in this study were taken from six months prior to the Russia-Ukraine conflict (August 2021) to the present (August 2022). The purpose is to research the effect of crude oil on the G7 countries' stock markets before and after the Russia-Ukraine conflict. The methodology of this study was to place all the data into one VAR model for testing. To avoid the occurrence of pseudo-vector autoregression, the data was tested using the ADF test, which in Table 1 shows that all models have unit roots, meaning that all models are not smooth. Each of the eight sets of data was first order differenced and then put into the models separately for re-testing. Table 1 shows that all the data after first-order differencing were smooth.

Table 1. ADF Test

Variables	t-statistic	p-value
	Price	
CAC 40	-2.561	0.2982
DAX 30	-3.065	0.1147
MIB	-2.619	0.2712
Nikkie 225	-2.547	0.3048
S&P 500	-3.234	0.0779
SPTSX	-2.170	0.5067
FTSE 100	-3.165	0.0916*
WTI	-1.662	0.7671
	Yield	
CAC 40	-11.517	0.0000***
DAX 30	-11.272	0.0000***
MIB	-11.495	0.0000***
Nikkie 225	-9.659	0.0000***
S&P 500	-11.445	0.0000***
SPTSX	-9.912	0.0000***
FTSE 100	-12.654	0.0000***
WTI	-10.677	0.0000***

3.2. VAR Lag Selection

The VAR lags are estimated using LL, LR, FPE, AIC, and HQIC tests after constructing the VAR model, but FPE, AIC, and HQIC recommend lag order 1 as the lag of this VAR model, but fewer lags would cause larger errors in the model results, and the possible explanation for this phenomenon is that the stock markets respond rapidly to the variations of the prices of crude oil. Therefore, the 1st order lag is the most significant in the test results (please see Table 2). Based on the stability condition of the model, this experiment tried the 7^{th}, 8^{th}, 11^{th} and 12^{th} order as the lag of the model, and finally the 8^{th} order was chosen as the lag of the model.

Table 2. VAR model identification

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	5326.96				3.6e-32	-49.7099	-49.659	-49.584*
1	5450.02	246.14	64	0.000	2.1e-32*	-50.2619*	-49.8043*	-49.1294
2	5504.8	109.55	64	0.000	2.2e-32	-50.1757	-49.3113	-48.0366
3	5545.64	81.676	64	0.067	2.8e-32	-49.9592	-48.688	-46.8134
4	5591.22	91.17	64	0.014	3.4e-32	-49.7871	-48.1092	-45.6347
5	5634.21	85.987	64	0.035	4.2e-32	-49.5908	-47.5061	-44.4317
6	5661.39	54.357	64	0.799	6.0e-32	-49.2467	-46.7552	-43.081
7	5733.59	144.39	64	0.000	5.8e-32	-49.3232	-46.425	-42.1509
8	5785.32	103.46	64	0.001	6.9e-32	-49.2086	-45.9035	-41.0296
9	5826.87	83.098	64	0.055	9.1e-32	-48.9988	-45.2869	-39.8131
10	5867.12	80.507	64	0.080	1.2e-31	-48.7768	-44.6582	-38.5845
11	5925.77	117.3	64	0.000	1.5e-31	-48.7268	-44.2014	-37.5279
12	5981.35	111.16*	64	0.000	1.8e-31	-48.6481	-43.716	-36.4425

This VAR model was represented as stable with all unit roots within a circle centered at the origin and with a radius unit of 1 (please see Figure 1).

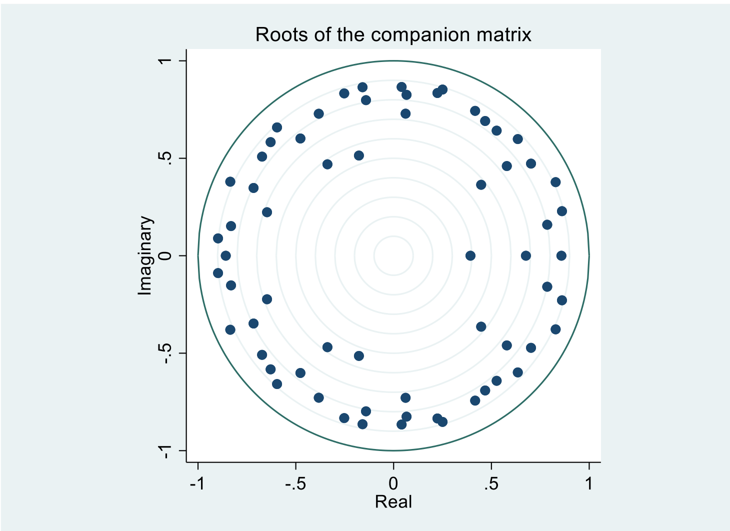


Figure 1. VAR stability
Photo credit: Original

3.3. Impulse Response

Impulse response analysis found that the variations in the price of crude oil due to the Russia-Ukraine conflict had a greater impact on the European equity markets among the G7 countries (apart from the UK) and a relatively smaller impact on Japanese, Canadian and US markets.

This study uses the DAX 30 (Germany stock market) as a specific illustration. From the impulse response analysis plots (Figure 2), it is found that shocks of one-unit crude oil price in period t = 0 are quickly reflected in the financial markets, with a negative effect on the DAX 30 reaching a maximum value of slightly more than 0.2% in the period and the second-highest value of the negative effect occurring at t = 4, with a magnitude of approximately 0.1%. The CAC 40, MIB, and Nikkie 225 performed in a similar pattern, with the prices of crude oil all having a positive effect on those stock markets in the later period.

Significantly, only the UK was the least affected of the European countries. Meanwhile, the US and Canada were affected minimally. The positive and negative impacts of the variations in the prices of crude oil on the stock markets of their two countries can be counteracted.

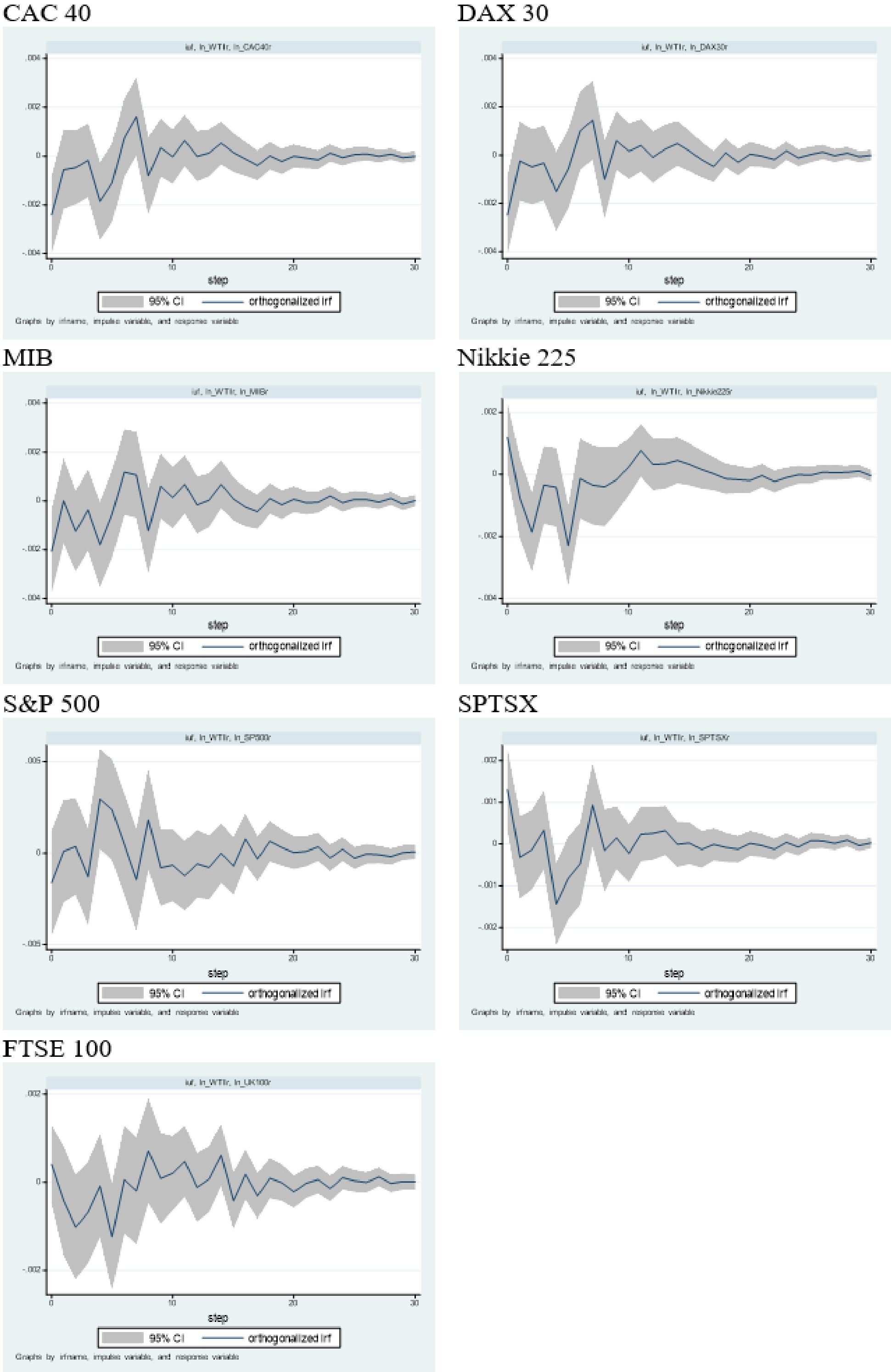


Figure 2. Impulse and response
Photo credit: Original

3.4. ARMA Lag Selection

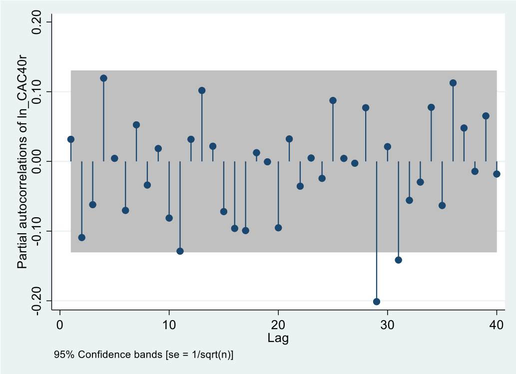
PACF and ACF estimation results are shown in Figure 3.

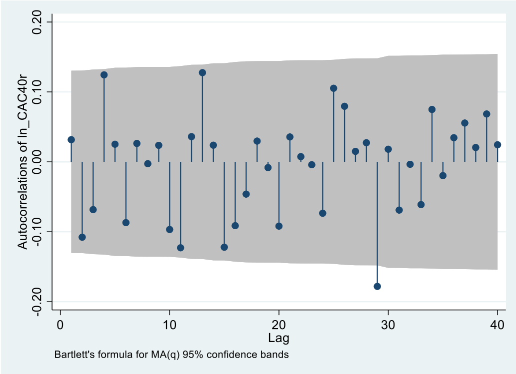
AR lag using PACF were significant at 29th in CAC 40, 29th in DAX 30, 11th in MIB, 18th in Nikkie 225, 7th in S&P 500, 1st in SPTSX and 17th in FTSE 100.

MA lags using ACF were significant at 29th in CAC 40, no significant autocorrelation order was found in DAX 30, so the lag was set in 0, significant at 11th in MIB, significant at 18th in Nikkie 225, 7th in S&P 500, 1st in SPTSX, 17th in FTSE 100.

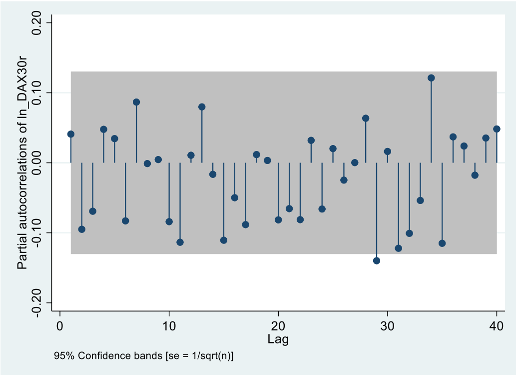
PACF ACF

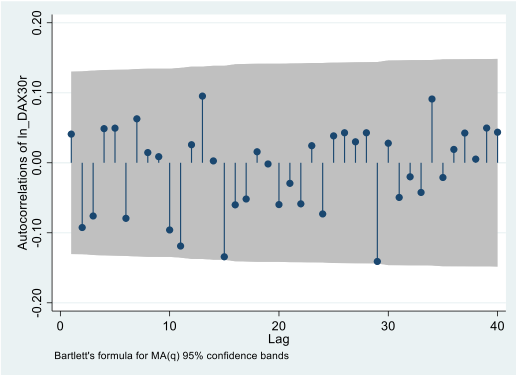
CAC 40



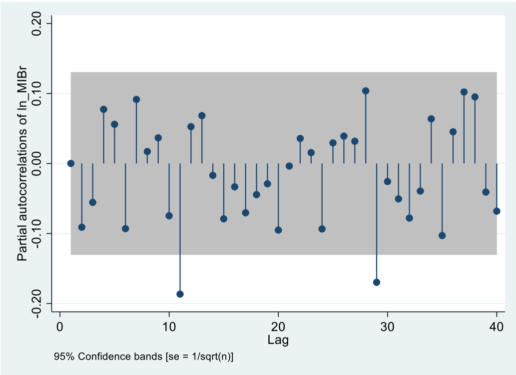


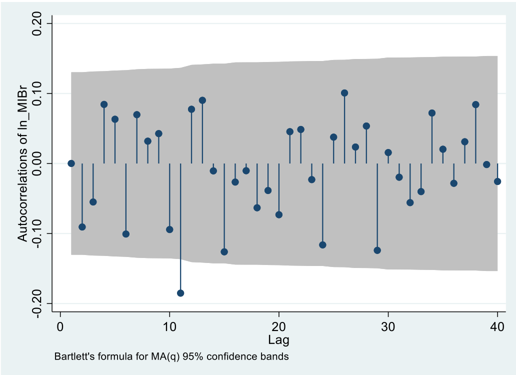
DAX 30



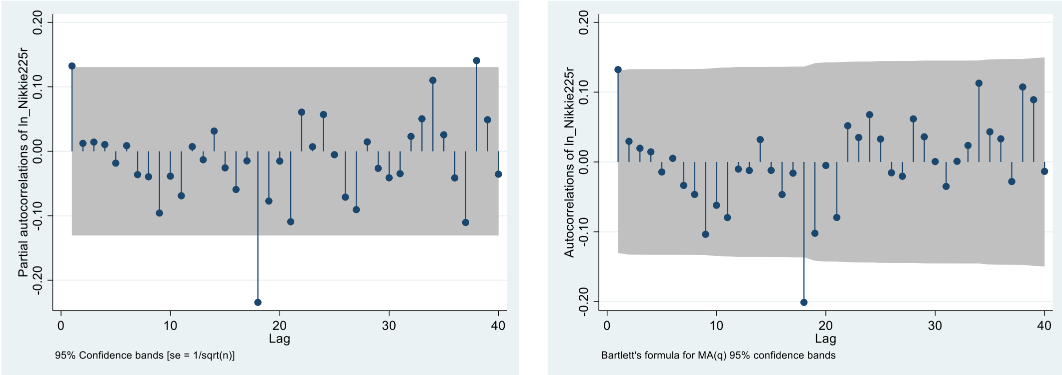


MIB

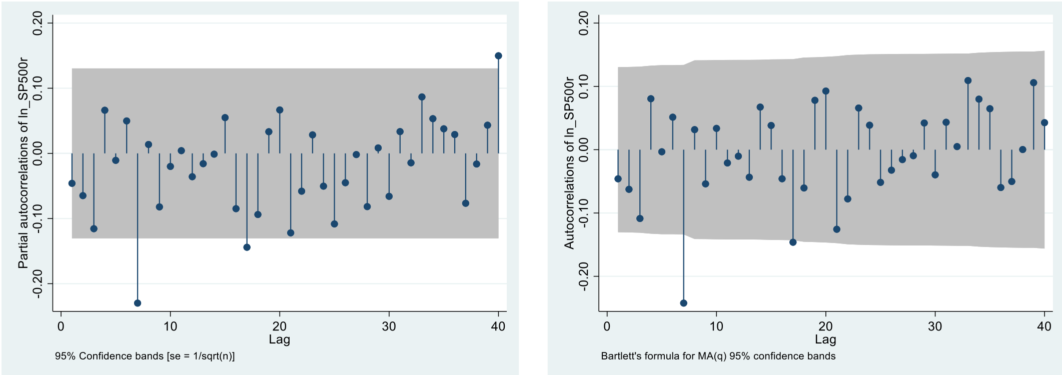




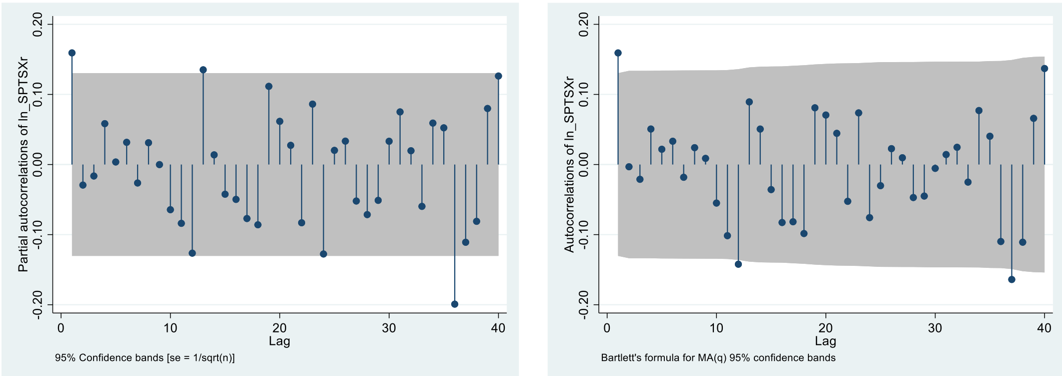
Nikkie 225



S&P 500



SPTSX



FTSE 100

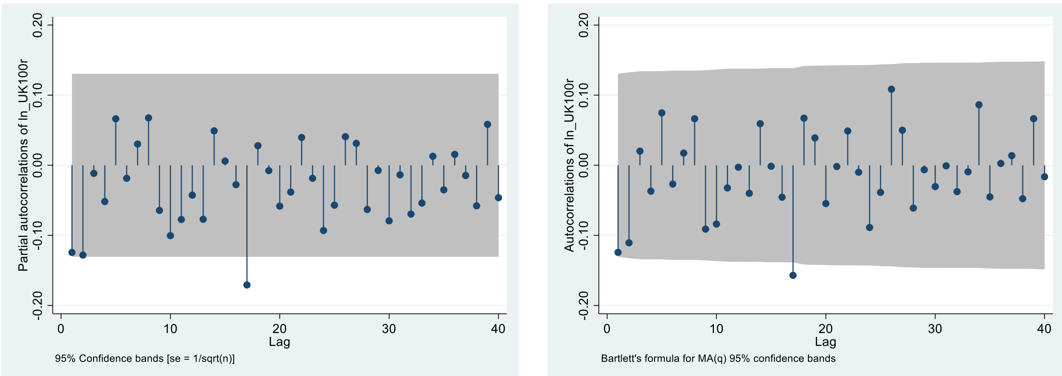


Figure 3. PACF and ACF

Photo credit: Original

3.5. Results of ARMA-GARCH-X Estimation

From the outcome of the ARMA-GARCH-X model estimation (Table 3), it is found that the G7 stock market returns all demonstrate statistically significant ARCH effects and GARCH effects and satisfy the basic conditions of GARCH modelling.

The estimation results from the external covariates reveal that crude oil returns have a significantly positive correlation with volatility for CAC 40, DAX 30, MIB but have a negative effect for other countries, particularly the FTSE 100, with a more significant negative effect.

Table 3. ARMA-GARCH-X estimation result

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CAC 40	DAX 30	MIB	Nikkie 225	S&P 500	SPTSX	FTSE 100
WTI	29.0637	25.7399	20.5217	-1.1996	-3.7685	-4.9119	-31.3591
	(0.0000)	(0.0020)	(0.0010)	(0.0730)	(0.8610)	(0.6800)	(0.0000)
ARCH	0.1572	0.1323	0.2593	-0.0749	0.1495	0.2711	0.3538
	(0.0390)	(0.0440)	(0.0000)	(0.0070)	(0.0210)	(0.0150)	(0.0020)
GARCH	0.6305	0.7120	0.5790	-0.7204	0.7980	0.5805	0.5541
	(0.0000)	(0.0000)	(0.0000)	(0.0010)	(0.000)	(0.0000)	(0.0000)
Constant	-10.5894	-10.7367	-10.2797	-8.3033	-10.2808	-11.3188	-11.3759
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

4. Discussion

This study validates the research results from Kollias et al., where this research shows that the variations in the prices of crude oil has the largest influence on the stock market of Europe among the G7 countries and the smallest impact on the stock markets of Japan, Canada, and the US. It is notable that among the European countries (France, Germany, Italy, and the UK), the stock market in the UK is the least affected due to the fact that the UK currently produces more indigenous crude oil than it imports crude oil, and that France, Germany and Italy are closer to war zones.

From the outcome of the ARMA-GARCH-X model it is concluded that the variations in the prices of crude oil has a significant negative relationship on the volatility of the UK, Japan, Canada, and the US. The interpretation of this result is supported by the view of Ftiti et al. and Diaz et al., which indicates that higher prices of crude oil push the stock markets of there four countries into a bear market.

Gordon and Recio investigated the effect of the prices of crude oil on the stock markets by dividing it into two parts before the war and after the start of the war, while this study only studied the prices of crude oil and stocks before and after the war by putting them into one time series, which is a limiting part of this study. Future studies may divide the time into two parts and increase the capacity of the sample countries to inspect the effect of crude oil on stock markets in countries close to or far from the war zones before and after the war.

The most complicated part of this study is the selection of the VAR lag. This study uses LL, LR, FPE, AIC, HQIC and SBIC tests to detect the best lag of the VAR model in this study, but the tests of FPE, AIC, and HQIC indicate that the best lag is 1st, which indicates that the 1st-order lag is most significant, but the VAR model with low lag order is prone to cause the autocorrelation of the residual term. To keep the model stable, this study tries multiple lags and finally chose the 8th order as the lag of the model.

Secondly, all data in this study does not include data from weekends (legal holidays). For example, the data for Thursday and Friday can be considered as a continuous time series, but the data for Friday and the following Monday cannot be considered as a continuous time series. However, all data are considered as a continuous time series.

Furthermore, for the purpose of this paper, the influence of crude oil on the stock markets in the phase of preparation of the war / at the war is only statistically relevant conclusion, whereas other influences exist in the real world. These factors may include political, pandemic influences. People were panicked by the effects of the war and frantically sold stocks in the early stages of the war to minimise their losses. Moreover, six months before the Russia-Ukraine conflict (August 2021) to the present (August 2022), the world is still in the midst of the pandemic and infections continue to increase. This has led people to be concerned about the market economy and the potential impact that continued rise in infections on the stock market, and this factor has also led people to sell their stocks to prevent themselves from losing money if stock markets collapse.

5. Conclusion

This study uses daily data for WTI and G7 countries' stock markets from six months (August 2021) prior to the Russia-Ukraine conflict to the present (August 2022) to inspect the shocks of crude oil prices on G7 countries' stock markets. This study adopts a standard VAR model and plots seven impulse responses of WTI on G7 countries, where daily data of the G7 countries' stock markets are the response variables. And the ARMA-GARCH-X model is used to detect the effect of crude oil prices on the stock prices of G7 countries.

Impulse response analysis revealed that the variations in the prices of crude oil caused by the Russia-Ukraine conflict had a significant impact on the European stock markets (except in the UK) among the G7 countries, and a comparatively smaller impact on Japan, Canada, and the US markets.

The results from the ARMA-GARCH-X model indicate that volatility in the crude oil returns has a significant positive impact on the stock markets returns in France, Germany, and Italy, but a smaller negative effect on the stock markets returns in Canada, Japan, and the US. Remarkably, returns in the UK stock market were most negatively affected.

Overall, this study indicates that during war preparations or during the war, volatility in crude oil prices could extend to the stock markets. This study advises investors to be cautious in investing in stocks during the war.

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