The Yield and Volatility of Financial Markets in the UK and China under the Russia-Ukraine Conflict

Haoyu Liu*

Department of Economics, University of Birmingham, Birmingham, The United Kingdom

*Corresponding author: HXL137@student.bham.ac.uk

Abstract: The Russia-Ukraine conflict was officially fought on 24 February 2022, heightening international tensions and causing externalities to the global economy, resulting in the ensuing volatility of crude oil prices. Based on the broader context that the Russia-Ukraine conflict imposes significant downward pressure on international financial markets, this paper aims at finding the potential tie between stock markets volatility and increasing crude oil prices based on the timeline of this regional conflict and analyses the logic behind the relationship, using evidence from the UK and China as well as VAR and ARMA-GARCH models. The findings show that in terms of the fundamentals of stock market operations, in the short period following the outbreak of the Russia-Ukraine conflict, accompanied by a surge in oil prices, both in the UK and China markets, stock markets fluctuated dramatically and moved downwards rapidly over a short period of time. However, over time it is not possible to intuitively judge the medium to long-term impact on equity markets of the rise in oil prices caused by this situation. For policy makers, there is a package of monetary, fiscal and tax policies that can be implemented to counter the externalities caused by the Russia-Ukraine conflict. It is worth noting, however, that any policy has a corresponding cost. For investors, investment behavior depends on one's level of risk appetite, but the general advice is to avoid relevant investments in the short term in the event of an outbreak of the Russia-Ukraine conflict.

Keywords: Russia-Ukraine conflict; Externalities; Crude Oil; VAR; ARMA-GARCH.

1. Introduction

On 24 February 2022, Russian President Vladimir Putin declared war on Ukraine, indicating that the Russia-Ukraine conflict was formally launched. Just two days later, on 26 February 2022, a number of Western countries decided to impose massive sanctions on Russia, while providing military, economic, and humanitarian aid to Ukraine. Following this, on 18 May 2022, Sweden and Finland applied to join NATO, further deteriorating relations between NATO and Russia. Until 17 July 2022, the UN Office of the High Commissioner for Human Rights (OHCHR) has estimated that the Russia-Ukraine conflict has resulted in 5,110 civilian deaths and 6,752 injuries [1]. The Russia-Ukraine conflict has created an unprecedentedly tense and dangerous international situation.

The Russia-Ukraine conflict has had a dramatic negative influence on the international economy. According to Liadze et al.'s global econometric model NiGEM, the Russia-Ukraine conflict is estimated to cause a 1% decline in global GDP, approximately US$1 trillion, by 2023, and cause a 3% in global inflation in 2022 and a 2% increase approximately in 2023 [2].

The conflict has caused incalculable damage to both sides. The projections for the Russian economy are more significant considering that Russia is one of the main import partners for nations such as China, the United States, Germany, France, and Italy. In contrast, none of the major economies have a significant trade relationship with Ukraine. Western countries' trade restrictions with Russia are estimated to cause a 9.71% decline in Russian annual long-term GDP in 2022, according to a model simulation of doubling of non-tariff trade barriers [3].

The conflict has also caused a degree of economic shock to other major countries. An analysis done by Yousaf et al of countrywide Cumulative Abnormal Returns (CARs) shows that equity markets in Hungary, Poland, Slovakia, France, Germany, Italy, Romania, and Spain, among other EU countries, were negatively affected in the aftermath of the events [4]. At the same time, higher inflation, higher import prices, reduced household consumption, supply chain disruptions, uncertainty, barriers to growth, reduced investment, and global (especially European) stock market volatility triggered by the crisis will pose significant challenges to the US and UK economies [5].

Crude oil, one of Russia's most important exports, has seen its market take a dramatic hit. Considering that Russia is the world's third-largest oil producer, the Russia-Ukraine war would lead to an international shortage of crude oil [6]. On 8 March 2022, international oil prices reached new highs since 2014: Brent crude oil futures settled at US$127.9 per barrel, up 62% from the beginning of the year; WTI crude oil futures settled at US$123 per barrel, up 63% from the beginning of the year; OPEC crude oil basket price was US$127.9 per barrel, up 64% from the beginning of the year [7]. 30 May 2022 saw the EU impose a partial ban on most imports of Russian oil, driving crude oil prices up again.

Research by Ahmed et al. shows that European stock markets have performed an apparent negative trend since 21 February 2022, as two Ukrainian states are acknowledged as independent by Russia. [8]. Research by Federle et al. shows that there is a “proximity penalty” in European market reactions to the military war: the closer the countries or companies are to Ukraine, the more negative their stock returns will be [9]. Research by Adekoya et al. shows that the wartime link between crude oil and major financial assets (i.e., bonds, Bitcoin, USD, gold, and stocks) is stronger than before the war [10]. Most studies have generally looked at the influence of the regional military conflict on the international financial market and crude oil prices, but few have delved into the impact of crude oil change caused by the conflict on the stock market. Based on the broader context of the apparent negative influence of the Russia-Ukraine conflict on international financial markets, this paper aims at finding the potential tie between stock markets volatility and increasing crude oil prices based on the timeline of the conflict and analyses the logic behind this relationship, using evidence from the UK and China.

The following structure of this paper is organized: Section 2 is research design, containing a description of the background and data, model specification; Section 3 is empirical results, containing the estimation results of the VAR and ARMA-GARCH models; Section 4 is discussion, providing suggestions for both policymakers and investors; and Section 5 is conclusion of this paper.

2. Research Design

2.1 Sources of Data

The chosen financial data (WTI crude oil futures prices, FTSE 100 Index, and SSE Composite Index) were downloaded from the Yahoo Finance website. The high quality of the data on this site supports countless articles and reports each year. Adjusted closed prices were selected once per day from three months before the start of the Russia-Ukraine war (24 November 2021) to the day the paper was written (11 July 2022). Data that are missing for holidays or other reasons are excluded. It is worth noting that in the analysis that follows, all data are in logarithmic form, i.e., data for WTI crude oil futures prices are logarithms of WTI crude oil futures prices, data for stock prices are logarithms of stock prices, etc. In subsequent studies, these data names were abbreviated to WTI, FTSE 100, and SSEC.

2.2 ADF-Test

To ensure the validity of the model, the stationarity of these variables should be tested.

Suppose x_t is a time series. The following regression model provides base for the Augmented Dickey-Fuller (ADF) test [11]:

$$\Delta x_t = \mu + \gamma t + \alpha x_{t-1} + \sum_{j=1}^{k-1} \beta_j \Delta x_{t-j} + u_t \tag{1}$$

In (1), Δ is the difference operator and u_t is white-noise. The ADF test is then carried out under the null hypothesis $H_0: \alpha = 0$ against the alternative hypothesis $H_1: \alpha < 0$.

Table 1. ADF test

	Variables	t-statistic	p-value
Price			
	WTI	-2.379	0.3909
	FTSE 100	-2.779	0.2047
	SSEC	-1.362	0.8717
Yield			
	WTI	-8.006	0.0000^{***}
	FTSE 100	-7.565	0.0000^{***}
	SSEC	-7.238	0.0000^{***}

As can be seen from Table 1, since the p-values are all less than 0.05, the yield of WTI, FTSE 100, and SSEC all pass the ADF test, indicating that they are all stationary.

Since the yield of WTI, FTSE 100, and SSEC are stationary, they are all qualified as introduced variables of the ARMA-GARCH model.

2.3 Model Specifications: VAR

In this section, a VAR model is built in order to estimate the dynamic influence of the Russia-Ukraine conflict and the volatility of crude oil prices on the FTSE 100 and the SSEC.

This model is defined by the following function:

$$y_t = \begin{pmatrix} \beta_{10} \\ \beta_{20} \end{pmatrix} + \begin{pmatrix} \beta_{11} & \gamma_{11} \\ \beta_{21} & \gamma_{21} \end{pmatrix} y_{t-1} + \cdots + \begin{pmatrix} \beta_{1p} & \gamma_{1p} \\ \beta_{2p} & \gamma_{2p} \end{pmatrix} y_{t-p} + \varepsilon_t \tag{2}$$

In (2), $y_t = \begin{pmatrix} \beta_{1t} \\ \beta_{2t} \end{pmatrix}$ is the two-time series vector, ε_t is the disturbance term and p is the chosen time lag.

The impulse response function tests the extent to which the influence of a unit disruption will change other variables over time.

This model is defined by the following function:

$$\frac{\partial y_{t+s}}{\partial \varepsilon_t} = \varphi_s \tag{3}$$

This equation calculates how much the value of the variable y_{t+s} is affected in (t+s)-th period given that the disturbance term in t-th period ε_t increases by one unit, while the variables and the disturbance term in other periods remain constant.

2.4 Model Specifications: ARMA-GARCH

In this part, an ARMA-GARCH model is built in order to predict the yield and volatility of the FTSE 100 and SSEC together. WTI is chosen to be an exogenous variable.

Hence, it is possible to evaluate the correlation between the consequences of the Russia-Ukraine conflict and the yield and volatility of the stocks.

In particular, each part of the mixed model can be designated as a standard ARMA series [12]:

$$y_t = \sum_{r=1}^{R} b_r \, y_{t-r} + \sum_{s=1}^{S} a_s \, \varepsilon_{t-s} + \varepsilon_t \tag{4}$$

Meanwhile, the assumption of Gaussian white noise applies to each of the disturbance terms, whose variance is defined by the GARCH-X model with the exogenous variable WTI [13]:

$$\sigma_t^2 = \delta_0 + \sum_{q=1}^{Q} \delta_q\, \varepsilon_{t-q}^2 + \sum_{p=1}^{P} \beta_p\, \sigma_{t-p}^2 + \sum_{k=1}^{K} \pi_k \mathrm{WTI}_{t-k} \tag{5}$$

In (5), the term $\sum_{q=1}^{Q} \delta_q\, \varepsilon_{t-q}^2$ is ARCH part and the term $\sum_{p=1}^{P} \beta_p\, \sigma_{t-p}^2$ is GARCH part.

The GARCH model focuses on reducing the number of parameters. ARCH(p) can be simplified to GARCH (1,1) through iteration method.

3. Empirical Results

3.1 VAR

Several methods can be applied when determining the lag order of the VAR model

Firstly, the likelihood ratio (LR) test evaluates the fit quality of two competing statistical models based on the ratio of their likelihoods:

$$LR = -2(logL_k - logL_{k+1}) \tag{6}$$

The lag order of the VAR model is considered appropriate until the LR statistic is lower than a specific critical value.

Secondly, Akaike's Final Prediction Error (FPE) criterion is another approach. It selects the model with the lowest, i.e., the most accurate, FPE by comparing how well the model is tested on different data sets. [14].

Thirdly, the Akaike information criterion (AIC) is a good symbol of prediction error. Assume that k is the number of estimated parameters, and $\hat{L}$ is the maximum value of the likelihood function of the model. Thus,

$$AIC = 2k - 2ln(\hat{L}) \tag{7}$$

The lag order of the VAR model is considered appropriate when the AIC statistic is the least.

Fourthly, the Schwarz-Bayesian information criterion (SBIC) is a good symbol of prediction error. Assume that k is the number of estimated parameters, n is the sample size and $\hat{L}$ is the maximum value of the likelihood function of the model. Thus,

$$BIC = kln(n) - 2ln(\hat{L}) \tag{8}$$

The lag order of the VAR model is considered appropriate when the AIC statistic is the least.

Fifthly, the Hannan–Quinn information criterion (HQIC) is an alternative to AIC and SBIC. Assume that k is the number of estimated parameters, n is the sample size and $\hat{L}$ is the maximum value of the likelihood function of the model. Thus,

$$HQIC = 2kln\big(ln(n)\big) - 2ln(\hat{L}) \tag{9}$$

The lag order of the VAR model is considered appropriate when the AIC statistic is the least.

Table 2. VAR model identification

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	251.615				1.3e-11	-16.5743	-16.5295	-16.4342
1	255.996	8.7625	9	0.459	1.7e-11	-16.2664	-16.0871	-15.7059
2	261.395	10.797	9	0.290	2.3e-11	-16.0263	-15.7125	-15.0455
3	275.129	27.469	9	0.001	1.7e-11	-16.3419	-15.8937	-14.9407
4	280.643	11.028	9	0.274	2.4e-11	-16.1096	-15.5268	-14.288
5	291.253	21.22	9	0.012	2.6e-11	-16.2169	-15.4997	-13.975
6	300.088	17.688	9	0.039	3.6e-11	-16.2058	-15.3542	-13.5436
7	314.68	29.185	9	0.001	4.3e-11	-16.5787	-15.5925	-13.496
8	332.643	35.925	9	0.000	6.2e-11	-17.1762	-16.0555	-13.6732
9	920.223	1175.2	9	0.000	1.1e-26*	-55.7482	-54.4931	-51.8249
10	3118.67	4396.9	9	0.000	.	-201.912	-200.567	-197.708
11	3206.32	175.3*	9	0.000	.	-207.755	-206.41	-203.551
12	3210.56	8.4701	9	0.488	.	-208.037*	-206.693*	-203.834*

As can be seen from Table 2, AIC, HQIC, and SBIC reach the minimum at lag=12, LR reaches the minimum at lag=11, while FPE reaches a minimum at lag=9.

Therefore, lag=9 is considered an appropriate order of the VAR model.

The stationarity of the parameters should be examined before estimation.

This model is defined by the following function, for p>1:

$$VAR(p): y_t = c + Ay_{t-1} + e_t \tag{10}$$

The criterion for determining that a VAR system is stationary is that all roots of the characteristic equation $|A - \lambda I| = 0$ are in the unit circle.

As can be seen from Figure 1, the VAR system is stationary because all the black dots are contained within the unit circle.

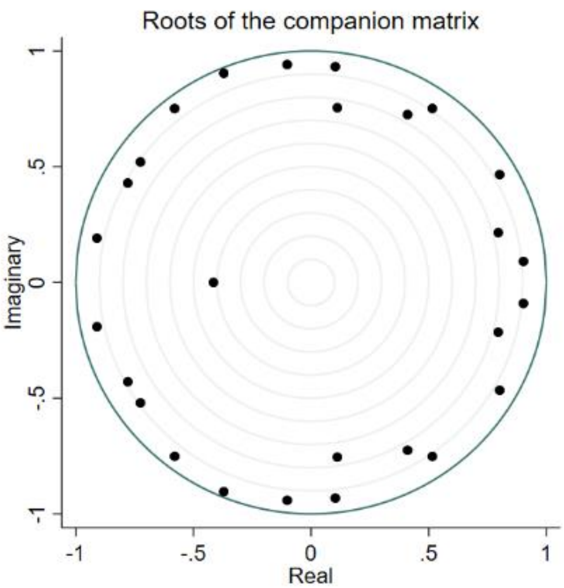

Figure 1. VAR stability

3.2 Impulse Responses

Take the FTSE 100 and SSEC as the response variables and the WTI as the impulse variable. The impulse responses of the FTSE 100 and SSEC are plotted separately.

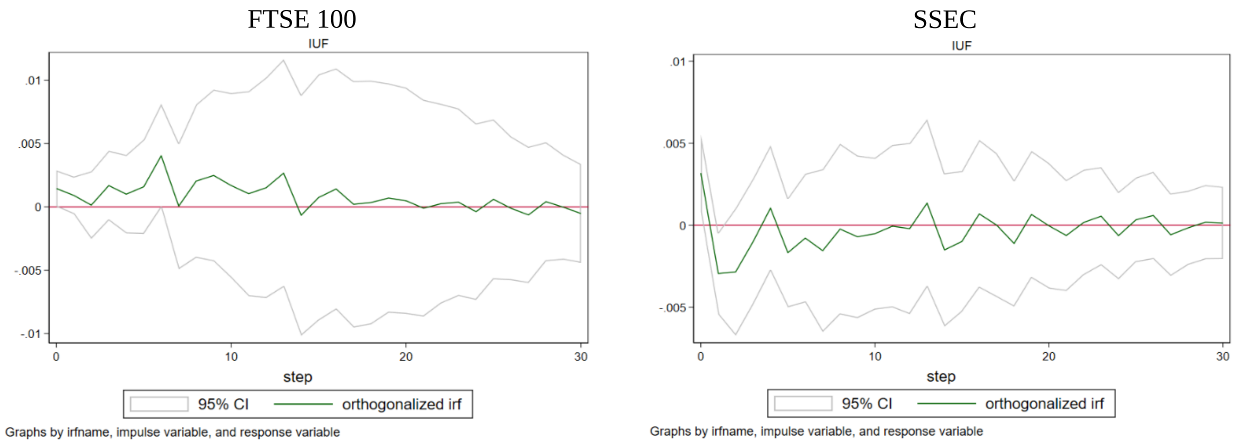

Figure 2. Impulse and response

Note: The Y-axis represents the pulse of the conflict on the rate of return for FTSE 100 and SSEC, while the X-axis represents the change in period.

Looking at the fundamentals of stock market operations, in the short period following the outbreak of the Russia-Ukraine conflict, accompanied by a surge in oil prices, both in the UK and the Chinese markets, stock markets fluctuated violently and quickly to the downside for a short period of time. However, over time, it is not possible to intuitively determine the medium to long term effects of the oil price increase due to the military conflict on the UK and the Chinese markets.

Starting from the impulse response estimation results, this paper finds that the effect of oil prices on stock index returns is relatively small in order of magnitude for both the UK and Chinese stock markets. Specifically, a 1% change in oil prices is associated with small fluctuations in UK and Chinese stock market returns over the next 20 to 30 periods, with an amplitude of about 0.25%. Moreover, the effect would fade over time.

There are two possible reasons for this: firstly, in response to the shock to equity markets created by the external risk, the monetary authorities of both countries have taken action to avoid the transmission of that risk to the domestic level, which would create systemic financial risk. Secondly, there is no medium to long-term impact of this external time shock on equity markets, which remain responsive to their fundamentals in the medium to long term.

Accordingly, this paper concludes that the medium to long term influence of the Russia-Ukraine war on equity markets is not significant in either the UK or Chinese markets.

3.3 Lag Order for ARMA

Firstly, the lag order of the ARMA model for the FTSE 100 was decided through the PACF and ACF.

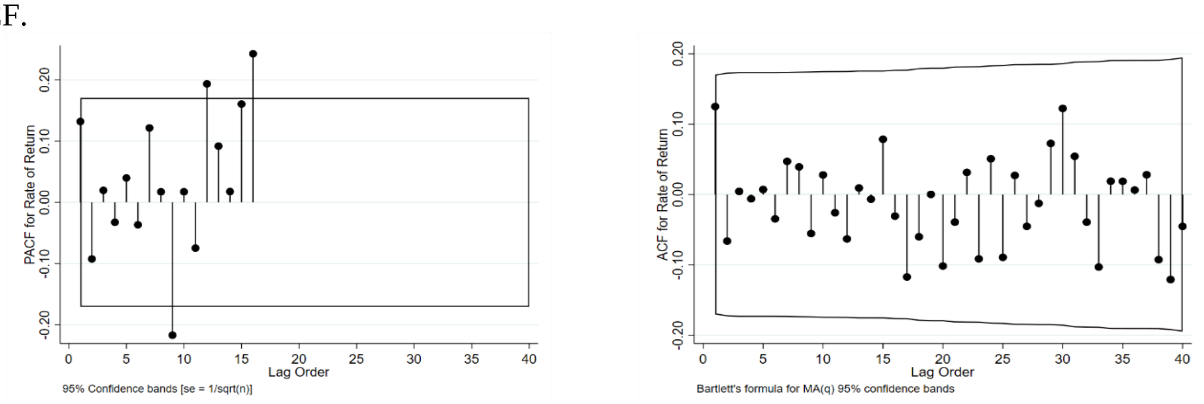

Figure 3. PACF and ACF, FTSE 100

Note: These two graphs have the time lag order as the X-axis, and the dependent variables PACF and ACF of the FTSE 100's rate of return as the Y-axis. The 95% confidence interval for AR(p) and MA(q) is the bounding area.

As shown in Figure 3, when lag=9, the value of PACF lies outside the 95% confidence interval for the first time, which means the lag order for AR is 9. However, the lag order for MA cannot be determined, since the ACF function is not significant.

Similarly, the lag order of the ARMA model for the SSEC was decided through the PACF and ACF.

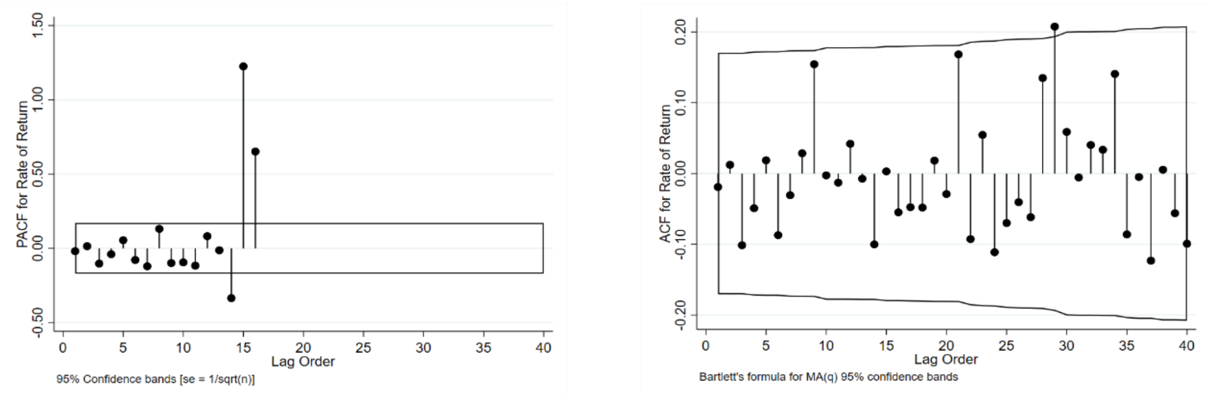

Figure 4. PACF and ACF, SSEC

Note: These two graphs have the time lag order as the X-axis, and the dependent variables PACF and ACF of the SSEC's rate of return as the Y-axis. The 95% confidence interval for AR(p) and MA(q) is the bounding area.

As shown in Figure 4, when lag=14, the value of PACF lies outside the 95% confidence interval for the first time, which means the lag order for AR is 14. Also, when lag=29, the value of ACF lies outside the 95% confidence interval for the first time, which means the lag order for MA is 29.

3.4 ARMA-GARCH

This section of the paper uses an ARMA-GARCH model to estimate the potential influence of increasing crude oil prices on daily stock market volatility.

It is important to note that the FTSE 100 return AR order is 9 and there is no MA term in the mean equation as the ACF function is not significant.

In addition, when modeling SSEC returns, the log-likelihood function does not converge in the process of numerically modeling the maximum value, and for this model of SSEC returns only, the mean equation is set to a constant in this paper.

Table 3. ARMA-GARCH estimation results, variance equation

	(1)	(2)	(3)	(4)	(5)	(6)
		FTSE 100			SSEC	
			Crude oil			
T=0	-8.2985	-9.7070	-9.6622	-12.8630**	-14.4853**	-28.1299***
	(6.2707)	(7.1705)	(13.3193)	(5.7247)	(6.8405)	(9.4120)
T=-1		-2.7388	-0.0874		-5.0172	-3.6632
		(6.2627)	(15.0161)		(6.1736)	(11.8133)
T=-2			7.8955			23.1796*
			(15.3359)			(12.7633)
			GARCH			
ARCH (-1)	0.3209***	0.2778**	0.3795***	0.2092	0.1780	0.0670
	(0.1091)	(0.1125)	(0.1415)	(0.1296)	(0.1306)	(0.0740)
GARCH (-1)	0.0833	0.0738	0.3627**	0.3209	0 .2070	0.4896***
	(0.2777)	(0.4491)	(0.1761)	(0.2594)	(0.2953)	(0.1408)
Constant	-9.4629***	-9.3331***	-10.2194***	-9.6735***	-9.3818	-10.2243***
	(0.4857)	(0.7243)	(0.7101)	(0.6012)	(0.5718)	(0.5512)

Note: Standard errors are reported in parentheses, and the estimated results are rounded-up to 4 digits after the decimal point. ***, **, and * indicate the level of significance of 1%, 5%, and 10%, respectively.

As shown in Table 3, the results of the variance equation show that the ARCH terms in columns (1), (2), and (3) are significant. The GARCH terms in columns (3) and (6) are significant, according to which the conditional heteroskedasticity model can be constructed. Neither of the two terms in columns (4) and (5) is significant, so the other coefficients of the model are not statistically significant.

Estimates of the explanatory variables suggest that in the medium to long term, changes in crude oil prices do not in fact exacerbate the daily volatility of the stock markets of the two countries.

4. Discussion

Compared to previous studies, this paper fills a gap in this area by focusing on the influence of the increasing crude oil prices on the UK and Chinese stock markets due to the Russia-Ukraine conflict using a VAR model and an ARMA-GARCH model.

Similar to the results derived previously, in the short period following the outbreak of the Russia-Ukraine conflict, accompanied by a surge in oil prices, both the UK and Chinese markets experienced short-term sharp stock market volatility and rapid downward movements. However, in the medium to long term, the magnitude of the stock market shocks will diminish over time, suggesting that the impact of the regional conflict is waning.

For policymakers, the corresponding actions taken by the monetary authorities of the two countries following the outbreak of the conflict deserve in-depth examination. A number of measures, such as monetary, fiscal, and tax policies, should be implemented in response to the shocks to equity markets created by external risks [15]. However, any policy has a cost. If the government takes actions to curb inflation, assumed that wages are stick down, greater unemployment and a decline in real GDP growth are both expected. If the government implements accommodative policies to offset the losses in real GDP, greater inflation will occur, and transient increases in GDP growth will balance this. [16].

For investors, it is best not to get involved in investments in the short term of the Russia-Ukraine conflict. However, investment decisions during a conflict depend on the degree of individual risk appetite. Interestingly, the measurement of risk aversion depends on the environment. In the case of external shocks, it is possible that this phenomenon exists, with expected utility maximizers being very averse to individual-specific risk and very tolerant of market risk [17]. The behavior of investors also merits in-depth study.

5. Conclusion

The global economy has been significantly impacted by the Russia-Ukraine conflict, which has also negatively impacted equities returns in the UK and Chinese markets.

This paper aims at figuring out the influence of the Russia-Ukraine conflict on stocks and volatility in the UK and China markets and provides further evidence on how the Russia-Ukraine conflict has affected equity markets through its impact on crude oil prices. We find that while in the short term, the surge in oil prices was accompanied by sharp volatility and rapid downside movements in both the UK and Chinese stock markets, in the medium to long term, the influence of the Russia-Ukraine conflict on stock markets was not significant in either the UK or Chinese markets, and changes in crude oil prices did not increase the daily volatility of stock markets in either country.

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