IMPACT OF RUSSIAN-UKRAINE CONFLICT ON LOCAL FINANCIAL MARKETS: APPLICATION OF GARCH VOLATILITY MODELLING

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Abstract

The Russian-Ukraine conflict started February 24, 2022 and has been labeled as one of the biggest military assaults on the European soil since World War II. It is therefore important to understand the impact these crises as had on various financial markets, most especially European stock markets. This study therefore carried out volatility modelling on 3 major European stock markets namely: NASDAQ, NYSE and IMOEX. Daily closing prices of these markets were collected for a period of 3 months before the conflict and 3 months during. Stationarity, normality and auto-correlation tests were carried out to ensure these assumptions are met by the data being studied. GARCH models were then applied to measure the extent of volatility. Results explains that there already existed a low-level volatility before the crises started, this increased at the start of the conflict.

Keywords: Conflict, Econometrics, Financial Markets, GARCH, Stock Index, Volatility

Introduction

The first conflict in Europe since the Second World War broke out when Russia invaded Ukraine on February 24, 2022. The Russia-Ukraine conflict, which the international community viewed as an act of aggression, was the biggest military assault on a European state since World War II and resulted in the largest influx of refugees into Europe since that conflict, with more than 3.4 million Ukrainians fleeing their homeland. Brunnermeier, & Landau, (2022) examined the potential for "greening" monetary policies as well as the scope and boundaries of green finance. It does not offer any clear conclusions or recommendations for policy. Instead, it provides a framework for considering the problem and identifies some crucial trade-offs and options. The economic effects of the global withdrawal from Russia are not likely to be offset by rising oil revenues. Given that the two nations are major exporters of important commodities, this is looking to be the market's worst period since the global financial crisis (GFC) of 2008, and it appears to be outside the scope of Covid's impact. 75% of the wheat that is imported by nations in Europe, Central Asia, the Middle East, and Africa comes from Russia and Ukraine (World Bank, 2022). Ukraine is the world's largest exporter of sunflower oil, accounting for 40% of all seed oil exports worldwide. Ukraine is also the source of almost 13% of corn exports and 5% of wheat exports. 25 percent of the world's natural gas, 18 percent of the coal, 11 percent of the crude oil, 18 percent of the wheat, and 14 percent of the fertilizers are exported by Russia. (2022, World Bank). Pestova et al., (2022) revealed that the United States, Europe, and numerous other nations placed further economic sanctions on Russia as a result of its invasion of Ukraine on February 24, 2022. Using a structural vector auto-regression model of the Russian economy, this column evaluates the financial impacts of these sanctions. The results point to a fall in industrial production, consumption, and investment as well as a -12.5 percent to -16.5 percent contraction in Russian GDP in 2022. Even with probable oil and gas embargoes, the Russian economy will nonetheless continue to rely on its current export model, which might be challenging to overturn. The conflict in Ukraine and the epidemic have once again demonstrated how crises may have a significant negative impact on the economy and reverse years of progress in per capita income and growth.

This paper contributes to the fast-emerging literature on the impact of the Russian -Ukrainian conflict upon economic and financial outcomes. Thus, in this paper, we strategically steer away from the sanctions-based literature and examine the possible effects of this conflict on various economies financial markets by modeling the volatility of various financial indexes both before and during the conflict.

Huisman, R., & Mahieu, R. (2003) became aware of the deregulation of global energy markets and proposed a regime-switching model that forecasted price spikes distinct from regular average –reverting prices to capture price spikes.

Yarovaya, L et al (2021) looked at the impact of human capital efficiency (HCE) on equity fund performance during three stages of the COVID-19 pandemic by collecting data from 799 open-ended equity funds across five EU countries, categorizing them into five HCE categories, and comparing risk-adjusted performance across these categories. The findings imply that during the COVID-19 epidemic, equities funds with better HCE rankings outperformed their peers. The research proposed that fund managers invest in human capital to boost their funds' ability to cope and adapt during times of great tension.

Chan, K. F (2011) et.al examined the correlations between returns across three asset classes: financial assets (US equities and Treasury bonds), commodities (oil and gold), and real estate assets (US Case–Shiller index) using a general Markov switching model. In the process, two distinct regimes emerged: a "calm" regime with periods of economic expansion and a "crisis" regime with periods of economic decline. Higher volatility and dramatically negative stock returns, as well as evidence of contagion across stocks, oil, and real estate, characterize the crisis regime. Kam therefore provided considerable evidence of a flight to quality – from stocks to Treasury bonds – throughout these periods.

Hamilton, J. D. (1990). introduced an EM algorithm for obtaining maximum likelihood estimates of parameters for processes subject to discrete shifts in autoregressive parameters, with the shifts themselves modeled as the outcome of a discrete-valued Markov process. The simplicity of the EM algorithm permits potential application of the approach to large vector systems.

Hamilton, J. D. (1989). proposed a relatively simple method for modeling regime shifts. An autoregression's parameters are considered as the result of a discrete-state Markov process. A nonstationary series' mean growth rate, for example, may be subject to periodic, discontinuous shifts. The study describes an approach for using the maximum likelihood method to estimate population parameters and lays the groundwork for projecting future values of the series. An empirical application of this technique to postwar US real GDP reveals that the periodic shift from a positive to a negative growth rate is a recurrent feature of the US business cycle, and might even be used as an objective criterion for defining and assessing recessions. According to the aforementioned predicted parameter tenets, a normal economic recession is associated with a 3% permanent decline in GNP.

With the help of a summing autoregressive restrictive, heteroscedasticity model, Bora, & Basistha, (2021) investigated the influence of COVID-19 on the unpredictability of stock costs in India.The financial exchange in India experienced uncertainty during the pandemic period, according to the findings. We discovered that the profit from the files is higher in the pre-COVID-19 period than in the COVID-19 period when we compared the results from the COVID and pre-COVID periods.

2.0 Methodology

Dataset

For this research, daily closing price of 3 stock markets and exchanges was considered. These are United States (NASDAQ and NYSE) and a Russian Stock market (MOEX). These data were pulled in R statistical software using its pre-built $getSymbols$ function. Data was split into two: 3 months before the conflict and 3 moths after the conflict. This are then compared to understand the effect of the conflict on the selected markets. GARCH volatility modelling was carried out on the daily returns of the stocks to understand the volatility before and during the conflict. For each of the stocks being studied, the closing price of the current day is defined as P_t and the one for the day before as P_{t-1}. This therefore helps us define the daily returns by:

$$R_t = In(P_t) - In(P_{t-1})$$

Stationarity Process

In order to reparametrize the modeling process in this study, an Augmented Dickey-Fuller (ADF) and Lomnicki-Jarque-Bera was adopted such as;

Augmented Dickey-Fuller (ADF):

$$\Delta y_t = \phi y_{t-1} + \sum_{j=1}^{p-1} \alpha_j^* y_{t-j} + \varepsilon_t$$

Where, $\phi = -\alpha(1)$ and $\alpha_j^* = -(\alpha_{j+1} + \cdots + \alpha_p)$.

Lomnicki-Jarque-Bera (LJB):

$$LJB = \frac{T}{6}[T^{-1}\sum_{t=1}^{T}(\hat{u}_t^s)^3]^2 + \frac{T}{24}[T^{-1}\sum_{t=1}^{T}(\hat{u}_t^s)^4 - 3]^2$$

Where $T^{-1}\sum_{t=1}^{T}(\hat{u}_t^s)^3$ shows a measure for the skewness of distribution and $T^{-1}\sum_{t=1}^{T}(\hat{u}_t^s)^4$ measures the kurtosis.

Model Specification and Estimation

This study focuses on the GARCH (1,1) or ARMA-GARCH model that turned out to be extremely useful in forecasting the volatility of financial time series data. According to Ngozi (2019) ARMA-GARCH specification is adopted in an effort to model the volatility (conditional mean and variance) of any financial time series because of its superiority in modeling such series.

That is;

$$y_t = E_{t-1}(y_t) + u_t \qquad 1$$

Where, $E_{t-1}(y_t)$ is expectation conditional on information available at time $t-1$, u_t is error generated from the mean equation at time t.

Equivalently, a GARCH process u_t can be written as:

$$u_t = \varphi_t \sigma_t,\ \varphi_t \sim iid\ N(0,1) \qquad 2$$

$$\sigma_t^2 = \gamma_0 + \gamma_1 u_{t-1}^2 + \gamma_2 u_{t-2}^2 + \cdots + \gamma_q u_{t-q}^2 + v_1\sigma_{t-1}^2 + \cdots + v_p\sigma_{t-p}^2 \qquad 3$$

From equation (2), u_t becomes;

$$u_t = z_t'\theta \qquad 4$$

In which, $\varphi_t$is deduced as a sequence of independent, identically distributed (iid) random variables with zero mean and unit variance. While the compact notation, $z_t' = (1, u_{t-1}^2, \ldots u_{t-p}^2)$ and the $p+q+1$ vector $\theta = (\gamma_0,\ \gamma_1, \ldots \gamma_q, v_1, \ldots, v_p)'$ collects the parameters of interest. Hence, the sufficient conditions for the conditional variances σ_t^2 in equation (3) positively are expressed as; $\gamma_0 > 0, \gamma_i, v_j \geq 0, i = 1, \ldots, q, j = 1, \ldots, p$.

Using lag-polynomials, equation (3) becomes;

$$(1 - v_1 L - \cdots - v_p L^p)\sigma_t^2 = \gamma_0 + (\gamma_1 L + \cdots + \gamma_q L^q)u_t^2 \qquad 5$$

Since,

$(1 - v_1 L - \cdots - v_p L^p)\sigma_t^2 = (1 - v(L))\sigma_t^2$ and

$\gamma_0 + (\gamma_1 L + \cdots + \gamma_q L^q)u_t^2 = \gamma_0 + \gamma(L)u_t^2$, then;

$$(1 - v(L))\sigma_t^2 = \gamma_0 + \gamma(L)u_t^2 \quad 6$$

If the roots of the polynomial $(1 - v(z)) > 1$ in absolute value, the GARCH (q, p)process has an ARCH representation of infinite order:

$$\sigma_t^2 = (1 - v(L))^{-1}\gamma_0 + (1 - v(L))^{-1}\gamma(L)u_t^2 \quad 7$$

Where equation (7), deduced as;

$$\sigma_t^2 = \gamma_0^* + \sum_{i=1}^{\infty}\gamma_i^* u_{t-i}^2 \quad 8$$

Applying volatility forecasting, that is; zero-mean process in equation (9), where the GARCH (q, p) model yields a representation of squared observations u_t^2 in equation (10)

$$\pi_t = u_t^2 - \sigma_t^2 \quad 9$$

$$u_t^2 = \gamma_0 + \sum_{i=1}^{\max(p,q)}(\gamma_i + v_i)u_{t-i}^2 + \pi_t - \sum_{i=1}^{p} v_i \pi_{t-i} \quad 10$$

hence; $\gamma_i = 0, i > q \text{ or } v_i = 0, i > p$ are set implicitly if $q < p \text{ or } p < q$ respectively, π_t as the error process which is uncorrelated, u_t^2 as an autoregressive representation, σ_t^2 as the corresponding conditional expectation which is also autoregressive.

However, by convolution, equation (8) and (10) turns:

$$\sigma_t^2 = \gamma_0^* + \sum_{i=1}^{\infty}\gamma_i^* u_{t-i}^2 + \sum_{i=1}^{\infty}\gamma_i^* \pi_{t-i} \quad 11$$

Therefore, equation (11) above is deduced as the Autoregressive Moving Average and Generalized Autoregressive Conditionally Heteroskedastic (ARMA-GARCH) as a model employed for the study.

3.0 Analysis

Summary Statistics

Table 1: Summary statistics of the indexes being studied

Index	Mean	Median	Min	Max	Sta. Dev.	Skewness	Kurtosis
NASDAQ before the conflict	14832.52	15083.17	13352.78	15871.26	786.88	-0.34	-1.34
NASDAQ during the conflict	13095.32	13322.9	11354.62	14619.64	922.94	-0.42	-0.88
NYSE before the conflict	16787.06	16797.02	16133.89	17353.76	318.14	-0.15	-0.88
NYSE during the conflict	16087.05	16124.64	14902.14	17014.76	593.79	-0.43	-1.03
MOEX before the conflict	3646.34	3671.89	3036.88	3960.33	208.14	-0.69	0.24
MOEX during the conflict	2436.93	2424.1	2058.12	2787.69	150.74	0.24	0.13

Table 1 above shows a descriptive summary statistic of the daily closing prices before and during the conflict, we observe that there exists a wide variance between the minimum and maximum values, as well as that all the indexes are negatively skewed for the time period under consideration and only MOEX happens to be positively skewed and

platykurtic. This means most of the indexes both before and during the conflict have their daily closing prices mostly concentrated towards the right-hand side of the distribution curve.

Augmented Dickey Fuller Test

For each of the indexes considered in this paper, ADF tests were carried out as it is always helpful in time series and econometrics modelling to first confirm the stationarity status of the data being studied.

Table 2: Augmented Dickey Fuller test on the indexes

Index	Dickey-Fuller Statistics	P-value
NASDAQ before the conflict	-4.7448	0.01
NASDAQ during the conflict	-3.802	0.02
NYSE before the conflict	-4.2909	0.01
NYSE during the conflict	-4.1437	0.01
MOEX before the conflict	-4.0259	0.01
MOEX during the conflict	3.6305	0.04

Table 2 highlights the p-values and estimates of the ADF test statistics for the indexes daily return prices. We observe that for all the indexes both before and during the conflict, their p-values are all less than 0.05, we therefore fail to accept Augmented Dickey Fuller test's null hypothesis which states that the distribution returns are not stationary since the p-value for the daily returns of all the indexes are all less than 0.05, meaning they are statistically significant. We can therefore conclude that daily return for all indexes under study are stationary.

JARQUE-BERA NORMALITY TEST

There is need to as well confirm the normality status of our indexes daily return prices. We do this using the Jarque-Bera normality test. The Jarque-Bera test is a goodness-of-fit test that determines if the sample data have skewness and kurtosis that matches a normal distribution.For the indexes under study, the test statistics are represented below.

Table 3: Jarque-Bera test on the indexes

Index	Jarque-Bera Statistics	P-value
NASDAQ before the conflict	1.313	0.519
NASDAQ during the conflict	1.401	0.496
NYSE before the conflict	0.682	0.711
NYSE during the conflict	0.911	0.634
MOEX before the conflict	42.302	6.52e-10
MOEX during the conflict	200.32	2.2e-16

Table 3 above shows that most of the daily returns of the stock indexes being studied are not normally distributed as they have p-values greater than 0.05 at 5% significance levels. We therefore can accept the null-hypothesis of this test and conclude that the daily returns are not normally distributed.

Autocorrelation

Autocorrelation or lagged correlation are quite common in time series as the residuals of the daily returns might not be entirely independent of one another. To highlight the correlation between the observations of time □ and time □ + □ i.e the returns on a daily bases, we use an autocorrelation plot which is important when modelling financial econometrics. As shown in fig 1, the first bar shows us the correlation at lag = 0 is 1 andexplained by the fact that the correlation of a residual against itself would be one. If there existno autocorrelation, the followinglog bars would fall quickly to about zero.

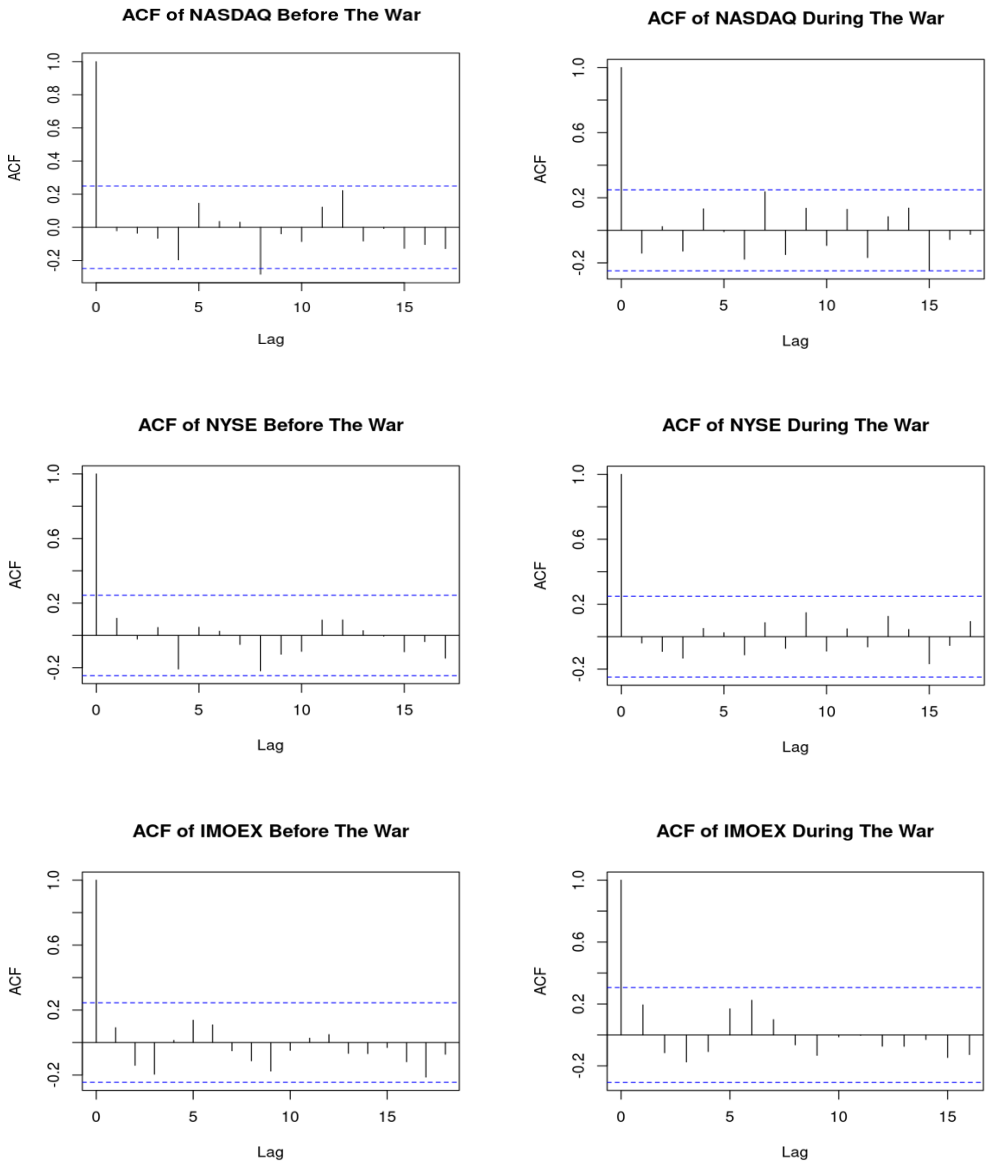


Figure 1: Autocorrelation plots

Volatility Modelling Using Garch

This work uses the GARCH model with an order of p = 1 and q = 1 as these are the best order used for modelling econometrics and time series. This model evaluates the change in volatility before and during the Russian-Ukraine

conflict. With reference to table 4 below which shows the significance of the estimated parameters, it can be explained that there exists a low level of volatility in the period preceding the conflict, this is explained by the ARCH (□) and we can see that the estimates of the indexes being studied are all positive and only few are significant statistically, judging by the p-values in bracket. To measure the overall persistent volatility for the period before the conflict, we add the ARCH and GARCH and observe that only NYSE has a lower volatility compared to that of NASDAQ and MOEX at over 0.99, which explains that there exists a significant effect of the current days return on variance of future period returns. Comparing to the period during the conflict, we see a decline which can be as a result of any other factor not related to the conflict.

And to measure the volatility of the period during the conflict, we can still see from table 4 below how volatility responded to the effect of the ongoing conflict. Comparing the difference of the ARCH effect for each of the indexes before the conflict and during the conflict, we can explain that the conflict had an effect on the volatility of the indexes causing an increase in its value during the conflict.

Table 4: GARCH estimate on the time period before the conflict

Parameters	**NASDAQ before the conflict**	**NYSE before the conflict**	**MOEX before the conflict**
Intercept (□)	0.000001 (0.486)	0.000002 (0.00)	0.000067 (0.334)
ARCH (□)	0.000000 (1.00)	0.000001 (0.99)	0.347496 (0.045)
GARCH(□)	0.999000 (0.00)	0.973859 (0.00)	0.643743 (0.00)
□ + □	0.990	0.974	0.991

From equation above, the model specifications for the GARCH (1,1) conditional volatility modelling for the 3 indexes before the start of the conflict are represented by;

$$\square_{\square}^{2} = 0.000001 + 0.999\,\square_{\square-\square}^{2} \quad 12$$

$$\square_{\square}^{2} = 0.000002 + \sum_{\square=1}^{\square} 0.000001\,\square_{\square-\square}^{2} + \sum_{\square=1}^{\square} 0.974\,\square_{\square-\square}^{2} \quad 13$$

$$\square_{\square}^{2} = 0.000067 + \sum_{\square=1}^{\square} 0.347\,\square_{\square-\square}^{2} + \sum_{\square=1}^{\square} 0.644\,\square_{\square-\square}^{2} \quad 14$$

Table 5: GARCH estimate on the time period during the conflict

Parameters	**NASDAQ during the conflict**	**NYSE during the conflict**	**MOEX during the conflict**
Intercept (□)	0.000049 (0.501)	0.000012 (0.006)	0.000006 (0.708)
ARCH(□)	0.106541 (0.421)	0.141295 (0.00)	0.000000 (1.00)
GARCH(□)	0.802283 (0.00)	0.804107 (0.00)	0.959059 (0.00)
□ + □	0.909	0.945	0.959

And that of the period during the conflict for the 3 indexes are given by:

$$\square_{\square}^{2} = 0.000049 + 0.1065\square_{\square-\square}^{2} + 0.8022_{\square-\square}^{2} \quad 15$$

$$\square_{\square}^{2} = 0.000012 + \sum_{\square=1}^{\square} 0.1413\ \square_{\square-\square}^{2} + \sum_{\square=1}^{\square} 0.8041\ \square_{\square-\square}^{2} \quad 16$$

$$\square_{\square}^{2} = 0.000006 + \sum_{\square=1}^{\square} 0.959\ \square_{\square-\square}^{2} \quad 17$$

This model can further be used for further analysis such as forecasting future volatility in these indexes studied.

Conclusion

This study aimed to measure and understand the level of volatility of 3 major financial markets namely: NASDAQ, NYSE (United States of America) and IMOEX (Russia) with respect to the ongoing Russian-Ukraine conflict. Daily closing prices of these markets were collected and divided into the period before the conflict and the period during the conflict, 3 months before the conflict and the first 3 months during the conflict. Various test analysis was carried out on the data in order to understand the status of the data being studied. Tests including stationarity test, normality test and auto-correlation tests were carried out on the data, and it was confirmed that all assumptions regarding these tests were satisfied before being used for modelling.

The GARCH(1,1) volatility modelling carried out on NASDAQ, NYSE and IMOEX shows that there already exist volatility in the indexes even before the start of the conflict. This was probably caused by news of the impending crises by the media and series of threats being exchanged by both countries' leaders. NASDAQ and IMOEX already had very high volatilities and only NYSE had a low volatility. In comparison to the period during the conflict, we see from the GARCH(1,1) results that there exist a high persistence for the indexes daily returns and that the impact of this volatility spillovers are very much significant and positively correlated.

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