INSTITUTO POLITÉCNICO DE LISBOA
INSTITUTO SUPERIOR DE CONTABILIDADE E ADMINISTRAÇÃO DE LISBOA

THE IMPACT OF THE WAR IN UKRAINE ON IMPLIED VOLATILITY INDICES: VIX, VSTOXX, JNIV AND RVI

Telmo Neves

Lisbon, April 2025

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Resumo

Em fevereiro de 2022, a Rússia invadiu a Ucrânia desencadeando uma crise energética, que resultou no aumento da inflação, das taxas de juro e numa queda significativa no mercado acionista americano e europeu.

Esta investigação tem como objetivo analisar o impacto que a guerra na Ucrânia causou na volatilidade das rendibilidades dos índices de volatilidade implícita: VIX, VSTOXX, JNIV e RVI, utilizando o modelo EGARCH. O horizonte temporal considerado na amostra inclui o período de estabilidade entre 2017 e 2019, e o período da guerra na Ucrânia entre 21/02/2022 e 06/10/2023.

Os resultados indicam que o choque causado pela guerra na Ucrânia aumentou a incerteza, afetando significativamente a volatilidade futura das rendibilidades em todos os índices analisados, tendo tido maior impacto no RVI. No período inicial da guerra o índice que teve a sua volatilidade mais afetada foi o RVI e os menos afetados foram o VSTOXX e o JNIV. Enquanto que no período em que o mercado estava a subir o JNIV e o VSTOXX mostraram-se mais sensíveis às más notícias do que o VIX.

Palavras-chave: Guerra na Ucrânia, Mercados Financeiros, Volatilidade, Índices de Volatilidade Implícita e Modelo EGARCH

Abstract

In February 2022, Russia invaded Ukraine, triggering an energy crisis that resulted in increased inflation, interest rates, and a significant decline in the American and European stock markets.

This investigation aims to analyze the impact of the war in Ukraine on the volatility of returns of the volatility indices: VIX, VSTOXX, JNIV, and RVI, using the EGARCH model. The time horizon considered in the sample includes the stability period between 2017 and 2019, and the period of the war in Ukraine from 21/02/2022 to 06/10/2023.

The results indicate that the shock caused by the war in Ukraine increased uncertainty, significantly affecting the future volatility of returns across all analyzed indices, with the greatest impact on the RVI. During the initial period of the war, the RVI was the index whose volatility was most affected, while the VSTOXX and JNIV were the least affected. In contrast, during the period of market recovery, the JNIV and VSTOXX were more sensitive to bad news than the VIX.

Keywords: Ukraine War, Financial Markets, Volatility, Implied Volatility Indices, and EGARCH Model.

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List of Abbreviations

ADF - Augmented Dickey Fuller

DW - Durbin-Watson

VIX - CBOE Volatility Index

VSTOXX - STOXX 50 Volatility Index

JNIV - NIKKEI Volatility Index

RVI - Russian Volatility Index

ARCH - Autoregressive Conditional Heteroskedasticity

GARCH - Generalized Autoregressive Conditional Heteroskedasticity

EGARCH - Exponential Generalized Autoregressive Conditional Heteroskedasticity

1. Introduction

The topic of this dissertation is based on the impact that the war in Ukraine had on the volatility of the returns of four implied volatility indices, which are the CBOE Volatility Index (VIX), STOXX 50 Volatility Index (VSTOXX), NIKKEI Volatility Index (JNIV), and Russian Volatility Index (RVI).

This topic was chosen because this macroeconomic event generated a sense of uncertainty and fear among investors, leading to a significant decline in the capital markets in 2022.

According to Taera et al. (2023), all financial and alternative assets, including Islamic, ESG, conventional, crypto, fintech, and commodities, experienced increased volatility during the Ukraine war, with the exception of Bitcoin.

The impact of the war in Ukraine depends on its geographical proximity to, and trade relations with, Russia and Ukraine (Mishra et al., 2024). The geographical proximity to the battlefield of the Russia-Ukraine conflict is associated with a greater risk of the spread of war, which leads investors to shift away from the risky European markets (Wang et al., 2023).

The research objectives are:

1. Investigate the impact that the war in Ukraine has had on the future volatility in the four implied volatility indices under study.
2. Analyze which indices show volatility that is most sensitive to the magnitude of this shock caused by the war in Ukraine.
3. Analyze the leverage effect of the Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model on the various volatility indices.

Research questions:

1. What was the impact of the war in Ukraine on the volatility of the returns of the four implied volatility indices under study?
2. What was the impact on the volatility of the returns of the analyzed indices during the initial period of the war in Ukraine, when the American and European markets were declining, and in the subsequent period when the markets were rising?

This study is relevant because it helps explain the impact that an "extreme" macroeconomic event, involving the third most powerful country in the world, has on financial markets in terms of expected volatility. Through a volatility study, we can observe how investors react to this type of event.

The investigation model that will be used to analyze the volatility of the returns of the four implied volatility indices is the EGARCH model, as it overcomes the limitations presented by the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and Autoregressive Conditional Heteroskedasticity (ARCH) models.

After this brief introduction, in chapter 2, we will present the literature review, in which we analyze some scientific investigations conducted with volatility models on various assets during the period of the war in Ukraine. In chapter 3, we define the analyzed sample, explain the time horizons used, and analyze the returns of the time series, we also present the research methodology and justify the choice of the model used, and we validate the assumptions of the EGARCH model. In chapter 4, we present and analyze the results obtained in our research. And in chapter 5, we draw the appropriate conclusions.

2. Literature Review

In this chapter, we will analyze various scientific studies that investigated the impact of the war in Ukraine on financial markets.

2.1 Impact of the War in Ukraine on Financial Markets

On February 24, 2022, Russia invaded Ukraine. The impact on financial markets was immediate accordingly to Martin (2022), the Moscow's Moex index has dropped almost 9 per cent in the first week of war. Being one of the worst months in the market since 2009, well beyond the scale of COVID-19 impact.

(Taera et al.,2023) applied a GARCH model to assess the volatility and persistence of the shock caused by COVID-19 and the war in Ukraine, the analysis encompassed various asset classes such as Islamic, ESG, conventional, crypto, fintech, and commodities.

The results revealed that, across all time frames, nearly all financial and alternative assets experienced an increase in volatility, with the exception of Bitcoin. The Islamic equities and ESG indexes showed relatively lower risk compared to conventional stocks and other alternative assets during the war. (Mishra et al., 2024) corroborates this idea saying that, the equity indices of global markets were heavily influenced.

To analyze the stability, the instantaneous shock, and short-term impact of the war in Ukraine, empirical methods were applied using data from the Shanghai Composite Index, S&P 500 index, WTI oil price, and LBMA gold price.

The results show that only the Shanghai Composite Index is relatively stable, while the S&P 500 index, WTI oil price and LBMA gold price are unstable. These three unstable assets all suffered positive shocks in their price levels within several days after the Russia-Ukraine conflict broke out. The rise in the S&P 500 index can be explained from the perspective of international capital flow (Wang et al., 2023).

To compare the war response of European and global stock markets against the COVID-19 pandemic and the 2008 global financial crisis response, a Markov-switching HAR model was applied on volatility proxies, alongside with a representative sample of commodities.

The results show an instantaneous reaction of global stock markets to the war in Ukraine, which suggests that the invasion was interpreted by investors as real news. This contrasts markedly with the 2008 global financial crisis and the COVID-19 pandemic, where there was a lagged response. However, the post-invasion crisis intensity was noticeably smaller compared to both the COVID-19 pandemic and the 2008 global financial crisis (Izzeldin et al., 2023). (Mishra et al., 2024) corroborates this idea saying that the impact of the war in Ukraine is stronger during a shorter window surrounding the event date but diminishes over the extended period.

Granat (2023) also studied the timing reaction of the equity market, he used the adjusted returns of 62 country level stock market data, using a nonlinear model and rolling-window regressions, to investigate whether the expectations began to be priced in the equity markets before the operations of the war in Ukraine.

The results show that the equity markets started to price the conflict at least 50 days before the invasion, and the impact of the event on the financial markets on the event day was approximately one-third of the full impact.

To examine the impact of the breakout of the conflict between Russia and Ukraine on the G20 and other selected stock markets, they analyzed the abnormal returns before and after the start of the war. The aggregate stock market analysis indicates a significant and negative impact of the Russia–Ukraine conflict on the event day and post event days.

The results show that the stock markets of Hungary, Russia, Poland, and Slovakia were first to react in anticipation of the military actions in Ukraine, showing negative returns in pre-event days already, whereas the stock markets of Australia, France, Germany, India, Italy, Japan, Romania, South Africa, Spain, and Turkey were adversely affected in the post-invasion days (Yousaf et al., 2022).

(Mishra et al., 2024) to investigate regional and periodic asymmetries in the impact of the Ukraine war outbreak on global equity markets, MSCI equity indices from 47 sample countries were utilized, and this study examines global stock market reactions within a 61-day window centered around the event day.

The research delineates regional and periodic asymmetries, suggesting that the impact of the war in Ukraine depends on its geographical proximity to, and trade relations with, Russia and Ukraine. (Wang et al., 2023) corroborates this idea, saying that the geographical proximity to the battlefield of the Russia-Ukraine conflict is associated with a greater risk of the spread of war, which leads investors to shift away from the risky European markets.

(Assaf et al., 2023) investigate the effect of the ongoing war between Russia-Ukraine on the global financial market, by using the event study method to assess the impact of the Russia-Ukraine war on global stock markets. The results reveal that the developed countries experienced more negative price reactions compared to emerging countries. Geographically, Europe, the Middle East, and Africa are the most affected regions, whereas the American division does not show significant price reactions. (Yousaf et al., 2022) note that the regional analysis indicates that the European and Asian markets have been significantly and negatively impacted by the war in Ukraine.

(Li et al., 2024) examines the impact of the Russia-Ukraine war on global commodity and financial markets by analyzing the volatility and return spillovers of 26 assets across the indexes, S&P500, Dow Industrial Average, Europe STOXX 600, FTSE100, CAC40, DAX, SMI index, and RTS Index (Russia).

The results show significant increases in volatility spillovers after the invasion although increases in return spillovers were milder. Stock and currency markets were the leading spillover transmitters and receivers. Investor attention to the conflict played a large role in driving market spillovers, particularly in extreme quantiles. Meanwhile, uncertain market conditions seem to provide significant feedback to investor attention, resulting in amplified market risk.

(Blasco et al, 2024) investigates the influence of the Russia-Ukraine conflict on herding behavior in global stock markets. By analyzing the MSCI World and MSCI Emerging indexes along with the Russian market, it examines patterns of investor imitation before the invasion, immediately after the onset of the war, and throughout a prolonged conflict period.

The results reveal that emerging markets facing heightened geopolitical risk, either due to their proximity to the conflict or to commercial interests in energy markets, exhibit herding during the initial war phase. This analysis sheds light on the impact of geopolitical events on financial market dynamics, particularly in emerging economies.

(Félix et al., 2024) examine the dynamic behavior of the US stock market due to the subsequent impact of the COVID-19 outbreak and the war in Ukraine. To that end, they analyze daily data of Dow Jones Industrial Average returns from 2 January 1900 to 31 October 2022.

The results suggests that the consecutive occurrence of these unexpected events has had more severe adverse effects on the US stock market than those recorded in similar past episodes. Additionally, the events are highly correlated with indicators of economic policy uncertainty and financial market fear.

Ukraine and Russia have a significant presence in the global economy. Some developing economies are heavily reliant on Russia and Ukraine for food. These two countries supply more than 75 percent of the wheat imported by a handful of economies in Europe and Central Asia, the Middle East, and Africa (Gill, 2022).

Russia is also a major force in the market for energy and metals: It accounts for a quarter of the market for natural gas, 18 percent of the coal market, 14 percent of the market for platinum, and 11 percent for crude oil (Gill, 2022).

Investigate the event-based geopolitical shocks from the Russian-Ukraine war on agricultural and energy commodities using daily event-based structural vector autoregression. The results show that the geopolitical shock affects the markets of wheat (2%), corn (1%), and European natural gas (7.5%). However, substantial heterogeneity is observed among the agricultural and energy markets. The geopolitical risk stemming from the Russia-Ukraine conflict affects the European natural gas market more strongly than the United States and Asian markets. The analysis of financial variables contributes to the literature by showcasing increased volatility in the European stock market (Aizenman, 2024).

2.2 Volatility

Volatility measures the risk of a given asset, there are two types of volatility: historical and implied.

Historical volatility is a statistical measurement of how much a given stock moves up and down and measures a stock's price as compared to its average or mean. The most popular way to calculate a stock's historical volatility is by calculating the standard deviation of a stock's price movements over a period.

Implied volatility is another type of volatility and attempts to quantify a stock's volatility going forward. Implied volatility reflects the prices of the options contracts associated with a particular stock.

2.3 Implied Volatility Indices

2.3.1 VIX

Volatility indices allow for the estimation of implied volatility. The first and most widely followed volatility index is the VIX.

The VIX was introduced in 1993 with two purposes in mind, accordingly to Whaley (2009). First, it was intended to provide a benchmark of expected short-term market volatility. Second, VIX was intended to provide an index upon which futures and options contracts on volatility could be written.

The level of VIX is implied by the current prices of options on the S&P 500 Index and represents expected future stock market volatility over the next 30 calendar days.

The VIX is often regarded as the stock market's “fear index”. This index usually spikes when there is turbulence in the markets. Quotes above 30 indicate heightened investor anxiety, while levels above 50 signal panic.

2.3.2 VSTOXX

The VSTOXX measures expected volatility in the EURO STOXX 50 index of 50 Eurozone blue-chip stocks over the next 30 days (Dennison, 2021).

The VSTOXX reflects investors fear or uncertainty about the European market.

Calculation of the VSTOXX index is quite similar to calculation of the VIX. Two "sub-indices" are calculated as implied variance from a wide range of eligible options with two different expirations. These two subindices are then interpolated to get constant 30-day maturity.

2.3.3 JNIV

JNIV estimates the degree of expected fluctuation in the Nikkei Stock Average (Market News Insights, 2023).

The index is calculated using prices of Nikkei 225 futures and Nikkei 225 options on the OSE, taking the near-term future price as the basis of at the money. The volatility of the near-term option and next-term option are calculated using the out of the money option prices of each delivery month.

The index value is then calculated by linear interpolation or linear extrapolation between the volatilities of each delivery month for a time to expiration of 30 days.

2.3.4 RVI

The RVI measures the market's expectation of the 30-day volatility, calculated from real prices of near and next series RTS Index options.

The RVI is an aggregated indicator that tracks the performance of the futures and options market. And is calculated based on volatility levels of the nearby and next series of options on RTS Index futures.

3. Sample and Methodology

In this chapter, we will define the sample, explaining the reasons for choosing the different time horizons, and we will conduct a statistical analysis of the returns of the time series. We also present in this chapter the research methodology and justify the choice of the model used, and we validate the assumptions of the EGARCH model

3.1 Sample

The sample data correspond to the daily closing prices of the indices under study: VIX, VSTOXX, JNIV and RVI. We cannot analyze the Ukrainian market because it does not have an implied volatility index.

The historical data for the index quotes were extracted from the website investing.com.

The time horizon considered for the sample includes the following periods: 01/01/2017 - 31/12/2019, 21/02/2022 - 14/10/2022, and 17/10/2022 - 06/10/2023.

The period from 2017 to 2019 is characterized by the stability lived before the war in Ukraine and the COVID-19 pandemic. Economies were growing, inflation and interest rates were low, and there was an upward trend in the European and American stock markets.

To avoid distortions in the results, we did not consider the period of 2020 and 2021 due to the COVID-19 pandemic.

The period 21/02/2022 - 14/10/2022, corresponds to the period in which there was a significant decline in the American and European stock markets, influenced by the war in Ukraine.

The Russian military began to move and position troops in eastern Ukraine on February 21, 2022, and launched an attack on February 24, 2022.

During the period 17/10/2022 - 06/10/2023, there was a reversal of the downward trend in the European and American stock markets, caused by the war in Ukraine.

On October 7, 2024, the conflict between Israel and Palestine began, with approximately 2200 missiles fired in Gaza on that day. To ensure that this macroeconomic event does not impact our results, we have decided to limit the sample data related to the war in Ukraine up to October 6, 2023.

3.2 Statistical Analysis of Time Series Returns

Statistical analysis is crucial, as it is based on the daily returns of the implied volatility indices that we will estimate the model.

The daily returns were calculated using the following expression:

$R_t = \ln P_t - \ln P_{t-1}$ (3.1)

R_t corresponds to the return at the moment t, P_t is the closing price value at the moment t, and P_{t-1} is the closing price value at the moment t - 1.

Let's analyze individually the returns of the 3-time series of the four implied volatility indices.

Table 3.1 Statistical indicators of the daily returns of the implied volatility indices for the period 01/01/2017 - 31/12/2019

	VIX	VSTOXX	JNIV	RVI
Minimum	-0,2998	-0,4344	-0,2274	-0,5211
Maximum	0,7682	0,4701	0,4166	0,7357
Median	-0,0057	-0,0047	-0,006	-0,0021
Standard Deviation	0,0823	0,0744	0,0635	0,0721
Skewness	1,7315	0,4392	1,1811	1,0911
Kurtosis	15,0846	8,7611	8,3401	29,9872
Jarque-Bera	4.964,79 ***	1.076,87 ***	1.040,23 ***	23.122,19 ***
N	754	761	732	757

Note: Statistically significant at the confidence level * P < 0,1 ** P < 0,05 *** P < 0,01

When analyzing Table 3.1, we find that the VIX exhibits the highest standard deviation, and both the VIX and RVI have a significantly higher maximum compared to the JNIV and VSTOXX. The JNIV has the smallest maximum and standard deviation, and the largest minimum (which is negative). The RVI has the smallest minimum (which is negative).

Table 3.2 Statistical indicators of the daily returns of the implied volatility indices for the period 21/02/2022 - 14/10/2022

	VIX	VSTOXX	JNIV	RVI
Minimum	-0,1403	-0,1715	-0,1617	-0,3306
Maximum	0.2182	0,2047	0,1927	0,3387
Median	-0,0131	-0,005	-0,0051	-0,0041
Standard Deviation	0,0667	0,0638	0,0586	0,0926
Skewness	1,0145	0,312	0,4817	0,6115
Kurtosis	4,2355	3,3288	3,7328	5,6528
Jarque-Bera	39,74 ***	3,50	9,71 ***	54,04 ***
N	169	169	159	152

Note: Statistically significant at the confidence level * P < 0,1 ** P < 0,05 *** P < 0,01

We can observe in Table 3.2 that the RVI has the highest maximum and standard deviation, with a standard deviation 38.83% higher than VIX, and it has the smallest minimum (which is negative). The JNIV has the lowest maximum and standard deviation.

Table 3.3 Statistical indicators of the daily returns of the implied volatility indices for the period 17/10/2022 - 06/10/2023

	VIX	VSTOXX	JNIV	RVI
Minimum	-0,1559	-0,1836	-0,184	-0,3105
Maximum	0,01682	0,3414	0,1986	0,3214
Median	-0,0065	-0,0066	-0,0049	-0,0054
Standard Deviation	0,0529	0,0619	0,0456	0,0749
Skewness	0,2815	1,1089	0,5177	0,4676
Kurtosis	3,3598	7,4964	5,8859	6,665
Jarque-Bera	4,72 *	263,93 ***	94,78 ***	147,84 ***
N	254	252	242	248

Note: Statistically significant at the confidence level * P < 0,1 ** P < 0,05 *** P < 0,01

The values shown in Table 3.3 indicate that VSTOXX and RVI exhibit significantly higher maximums compared to the other two indices. RVI has the highest standard deviation and JNIV the lowest. VIX has the lowest maximum and highest minimum.

Based on the analyses of the three-time series for the four indices, we conclude that:

- JNIV consistently exhibits the smallest standard deviation across all three-time series.

- RVI has the highest standard deviation during the two periods of the Ukraine war.

- VSTOXX shows slightly lower maximum and standard deviation compared to VIX in the initial period of the Ukraine war, but in the subsequent period, VSTOXX has higher maximum and standard deviation than VIX.

The kurtosis value is always higher than 3 for all-time series of the four implied volatility indices. So, we conclude that the time series exhibit a non-normal distribution and have fat tails, apart from the VSTOXX time series in the period 21/02/2022 - 14/10/2022 and the VIX time series in the period 17/10/2022 - 06/10/2023, because the probability of the Jarque-Bera test is higher than 5%, we can conclude that these two series have a normal distribution.

3.3 Methodology

In this chapter, we will analyze the volatility models: ARCH, GARCH, and EGARCH with the objective of identifying the best model to analyze the volatility of the returns of the four implied volatility indices.

3.3.1 ARCH Model

Traditional econometric models assume a constant one-period forecast variance. To generalize this implausible assumption, a new class of stochastic processes called ARCH processes was introduced by Engle (1982). For such processes, the recent past gives information about the one-period forecast variance.

While conventional time series and econometric models operate under an assumption of constant variance, the ARCH allows the conditional variance to change over time as a function of past errors leaving the unconditional variance constant. Bollerslev (1986) considered this type of model behavior has already proven useful in modelling several different economic phenomena.

Despite its usefulness, the ARCH model is rarely used, Brooks (2008) presents the limitations of this model:

- The number of lags of the squared error that are required to capture all the dependence in the conditional variance, might be very large.
- Non-negativity constraints might be violated. Everything else equal, the more parameters there are in the conditional variance equation, the more likely it is that one or more of them will have negative estimated values.

3.3.2 GARCH Model

The ARCH model had some limitations that were studied and overcome by the GARCH model, developed by Tim Bollerslev.

GARCH was introduced by Bollerslev (1986) allowing for a much more flexible lag structure. The extension of the ARCH process to the GARCH process bears much resemblance to the extension of the standard time series AR process to the general ARMA process and permits a more parsimonious description in many situations.

Unlike the ARCH model, the GARCH model is still widely used, Lindström et. al (2015) present two limitations of the GARCH model:

- It is symmetric, because it does not predict the volatility to behave differently depending on the sign of variance, contrary to empirical observations on real data.
- Another problem is the requirements on the parameters, making the numerical optimization difficult.

Nelson (1991) presents another limitation:

- Interpreting whether shocks to conditional variance persist or not is difficult, because the usual norms measuring persistence often do not agree.

3.3.3 EGARCH Model

The EGARCH model was studied by Nelson, aiming to overcome the limitations of the GARCH model.

Lindström et. al (2015), refers to the limitations that the EGARCH model allows to overcome:

- The EGARCH process addresses the symmetry problems.
- Impose less restrictions on the parameters, as the exponent of the conditional variance equation is an ARMA process.

There are several ways to express the conditional variance equation of the EGARCH model, Brooks (2002) but one possible specification is given by:

$$Ln\ \sigma_t^2 = \omega + \beta\ Ln\ (\sigma_{t-1}^2) + \gamma\ \frac{\mu_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|\mu_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \quad (3.1)$$

ω – constant; β, γ and α are the parameters; σ_t^2 – variance; μ – error

The conditional variance clearly must be nonnegative with probability one. The EGARCH model adopt a different device than the GARCH model, to ensure that σ_t^2 remains nonnegative, by making ln (σ_t^2) linear in some function of time and lagged (Nelson, 1991).

Accordingly with Nelson (1991) the parameter β represents the effect of past volatility on future volatility. A high β value (close to 1) indicates that past volatility has a significant impact on the prediction of future volatility.

Nelson (1991) says that the parameter α represents the impact of the magnitude of past shocks on future volatility. A higher value of α indicates that volatility is more sensitive to the magnitude of these shocks.

Nelson (1991) defends that if γ is statistically significant and has a negative sign, this implies that a fall in returns results in greater volatility than an increase in returns of the same magnitude (leverage effect).

The research model that will be used to analyze the volatility of the returns of the four implied volatility indices is the EGARCH model, as it overcomes the limitations presented by the GARCH and ARCH models.

3.4 Validation of the Assumptions of the EGARCH Model

To ensure the accuracy of the results obtained, it is essential to validate the assumptions established by Nelsson (1991) for the EGARCH model.

3.4.1 Stationarity

We will use the Augmented Dickey-Fuller (ADF) and the Philipps-Perron test to check the stationarity of the time series of returns for each of the studied implied volatility indices.

A stationary series is defined by Brooks (2002) as one with a constant mean, constant variance and constant autocovariances for each given lag.

The ADF test has two hypotheses:

H0: series contains a unit root versus H1: series is stationary

The objective is for the time series to be stationary, to reject H0 the estimated values must be smaller than the critical values defined by Fuller (1976).

Table 3.4 Critical values for ADF tests

Significance Level	1%	5%	10%
Critical Values for Constant and Trend	-3,96	-3,41	-3,12

Source: Fuller (1976, p. 373)

The results obtained from the ADF test on the time series of returns for the four considered implied volatility indices are presented in four figures from appendix 1 to appendix 4.

We present these results in the following summary table:

Table 3.5 Results of the ADF test conducted on the returns of the four volatility indices

Volatility Indices	VIX	VSTOXX	JNIV	RVI
T-Statistic of ADF test	- 36,4381	- 36,0319	- 36,0876	- 41,5582

Given the results presented in Table 3.5, we conclude that the T-Statistic values estimated through the ADF test are lower than the critical values shown in Table 3.4.

We reject H0 and conclude that the time series of the four indices are stationary at the 1% significance level.

To corroborate these results, we will also employ the Phillips-Perron test to assess the stationarity of the time series of returns for each of the implied volatility indices under study.

The Phillips-perron test has two hypotheses:

H0: series contains a unit root versus H1: series is stationary

The results obtained from the Philipps-Perron test on the time series of returns for the four implied volatility indices are presented in four figures from appendix 5 to appendix 8.

We present these results in the following summary table:

Table 3.6 Results of the Phillips-Perron test conducted on the returns of the four volatility indices

Volatility Indices	VIX	VSTOXX	JNIV	RVI
T-Statistic of Philips-Perron test	-37,8975	-37,0219	-37,1396	-41,7639

Given the results presented in Table 3.6, we conclude that the T-Statistic values estimated through the Phillips-Perron test are lower than the critical values shown in Table 3.4.

We reject H0 and conclude that the time series of the four indices are stationary at the 1% significance level.

The results show that the time series for the four implied volatility indices are stationary at the 1% significance level, as confirmed by both the ADF test and the Phillips-Perron test, thereby validating the assumption of stationarity.

3.4.2 Heteroscedasticity

We will use the ARCH-LM test and the White test to check the heteroscedasticity in the time series of returns for each of the studied implied volatility indices.

If the errors do not have a constant variance, they are said to be heteroscedastic (Brooks, 2002).

The hypotheses of the ARCH-LM test are:

H0: series is homoscedastic versus H1: series is heteroscedastic

To reject H0, the estimated values must be lower than the significance levels: 1%, 5%, or 10%.

The results obtained from the ARCH-LM test, applied to the returns of the time series of the four indices, are shown in appendices 9 to 12. These results are presented in the following summary table:

Table 3.7 Results of the ARCH-LM test conducted on the returns of the four volatility indices

Volatility Indices	VIX	VSTOXX	JNIV	RVI
Prob. Chi-Square of ARCH-LM test	0,0006	0,0075	0,0115	0,0028

The results in Table 3.7 indicate that the time series of the VIX, VSTOXX, and RVI indices exhibit heteroscedasticity at the 1% significance level, while the JNIV index shows heteroscedasticity at the 5% significance level.

To corroborate these results, we will also employ the White test to assess the heteroscedasticity of the time series of returns for each of the implied volatility indices under study.

The White test has two hypotheses:

H0: series is homoscedastic versus H1: series is heteroscedastic

The results obtained from the White test on the time series of returns for the four implied volatility indices are presented in four figures from appendix 13 to appendix 16. We present these results in the following summary table:

Table 3.8 Results of the White test conducted on the returns of the four volatility indices

Volatility Indices	VIX	VSTOXX	JNIV	RVI
Prob. Chi-Square of White test	0,0002	0,0006	0,0006	0,0003

The results in Table 3.8 indicate that the time series of the all four volatility indices exhibit heteroscedasticity at the 1% significance level.

The results show that the time series for the four implied volatility indices are heteroscedastic at the 1% significance level, as confirmed by both the ARCH-LM test and the White test, thereby validating the assumption of heteroscedasticity.

3.4.3 Absence of Autocorrelation

We will use the Ljung-Box test to check the absence of autocorrelation in the time series of returns for each of the implied volatility indices.

The hypotheses of the test are:

H0: No autocorrelation Vs H1: Autocorrelation

The objective is to demonstrate that the original series does not exhibit autocorrelation when compared to the same series with a one-day lag.

The results obtained from the Ljung-Box test on the time series of returns for the four considered implied volatility indices are presented in four figures from appendix 17 to appendix 20.

The results show that only the JNIV returns have a Prob>Q greater than 0,05 at all estimated lags. Therefore, the VIX, VSTOXX, and RVI time series exhibit autocorrelation.

We validated the stationarity of the returns of the four time series through the ADF and Phillips-Perron tests. Heteroscedasticity was tested and validated through the ARCH-LM and White tests. And we were only able to validate the absence of autocorrelation in the JNIV time series using the Ljung-Box test.

4. Results

Our results were obtained using the EGARCH model, as explained in the previous section, and were analyzed with the EViews software.

4.1 Analysis of the Results for the Periods: 2017 - 2019 and 21/02/2022 - 06/10/2023

We start by conducting an individual analysis of the results obtained using the EGARCH model, employing a student's t-distribution, for the period 2017-2019 and for the period of the war in Ukraine: 21/02/2022 - 06/10/2023.

Table 4.1 Results of the EGARCH model estimation for the period 2017 - 2019

	VIX	VSTOXX	JNIV	RVI
ω	-0,6316 ***	-0,5643 ***	-0,9387 ***	-1,3935 ***
β	0,8945 ***	0,9031 ***	0,8674 ***	0,8162 ***
γ	-0,3275 ***	-0,1865 ***	-0,2688 ***	-0,1573 ***
α	0,0731 ***	0,0592 ***	0,2212 ***	0,5836 ***

Note: Statistically significant at the confidence level * P < 0,1 ** P < 0,05 *** P < 0,01

The results of the EGARCH model parameters for the period 2017-2019, presented in Table 4.1, are statistically significant at the 1% confidence level across all four implied volatility indices.

The value of the α parameter for the RVI is significantly higher than the value of the other indices. Although the JNIV has a considerably lower value than the RVI, its α value is much higher compared to the VIX and VSTOXX. This indicates that, during this period, a shock in variance has a much greater impact on the future volatility of the RVI and JNIV returns than on the VIX or VSTOXX.

The VSTOXX and VIX exhibit very similar β values, which are higher than the values of the JNIV and RVI. This indicates that, during the period under analysis, the results of the VSTOXX and VIX have a greater persistence of past volatility, whereas in the JNIV and RVI, past volatility contributes less to the prediction of future volatility.

The value of the γ parameter for the VIX and JNIV is considerably more negative than the values of the other indices. This indicates that, in the VIX and JNIV, bad news increases volatility more than good news, compared to the increase in the VSTOXX and RVI.

Table 4.2 Results of the EGARCH model estimation for the period 21/02/2022 - 06/10/2023

	VIX	VSTOXX	JNIV	RVI
ω	-1,0861 ***	-0,9737 ***	-1,5541 ***	-1,9685 ***
β	0,8377 ***	0,8617 ***	0,7986 ***	0,6973 ***
γ	-0,2087 ***	-0,1964 ***	-0,2298 ***	-0,1685 *
α	0,2399 ***	0,2678 ***	0,4769 ***	0,7248 ***

Note: Statistically significant at the confidence level * P < 0,1 ** P < 0,05 *** P < 0,01

The results of the parameters presented in Table 4.2 for the EGARCH model during the period of the war in Ukraine are statistically significant at the 1% confidence level for all four implied volatility indices, except for the parameter γ of the RVI, which is statistically significant at the 10% confidence level.

The RVI shows a much higher α parameter value compared to the other indices. Although the JNIV has a lower α value than the RVI, it is still significantly higher than those of the VIX and VSTOXX. This indicates that a shock in variance affects the future volatility of the RVI and JNIV returns much more than it does for the VIX and VSTOXX.

The VSTOXX and VIX exhibit higher β values compared to the other indices. This suggests that, during the period under analysis, the VSTOXX and VIX show greater persistence of past volatility, whereas in the JNIV and RVI, past volatility has a smaller contribution to the prediction of future volatility.

During this period, the index with the most negative γ parameter value is the JNIV. The values for the VIX and VSTOXX are similar, and the RVI is the index with the least negative γ. This indicates that, in the JNIV, bad news increases volatility more than good news, compared to the increase that occurs in the other indices.

After performing the individual analysis of the two periods, we will next conduct a comparative analysis of the results from both periods to assess the impact caused by the war in Ukraine.

Starting with the analysis of the α parameter, we observe that during the period of the Ukraine war, there was a significant increase in value in all four implied volatility indices. The VIX saw an increase of 228%, the VSTOXX 352%, the JNIV 116%, and the RVI 24%. The VIX and VSTOXX experienced the largest increases, but their absolute values were much lower during the 2017-2019 period compared to the RVI and JNIV.

These results reveal that the magnitude of the shock caused by the war in Ukraine significantly affected the future volatility of returns across all the indices analyzed.

Examining the β parameter, we observe a decrease in all four implied volatility indices during the period of the Ukraine war. Compared to the 2017-2019 period, the VIX decreased by 7%, the VSTOXX by 5%, the JNIV by 9%, and the RVI by 17%. The RVI experienced the largest decline both in relative and absolute terms.

The results indicate that the persistence of past volatility decreased, and past volatility contributed less to the prediction of future volatility. This suggests that the Ukraine war contributed to an increase in volatility, making it more challenging to forecast future volatility across all four implied volatility indices, with the greatest impact on the RVI.

Finally, we analyzed the γ parameter, which is the most relevant in the results of an EGARCH model. We observed a different reaction in this parameter compared to the other two parameters. The γ value of the VIX increased by 36% and in the JNIV by 15%, while the γ value of the VSTOXX decreased by 5% and by 7% in the RVI.

This analysis of the γ parameter suggests that, during the Ukraine war period, in the VSTOXX and RVI, bad news will increase volatility more than good news of the same magnitude. In contrast, in the VIX and JNIV, bad news will increase volatility (but to a lesser extent compared to the 2017-2019 period) relative to good news.

4.2 Analysis of the Results for the Periods: 21/02/2022 - 14/10/2022 and 17/10/2022 - 06/10/2023

Let's conduct an individual analysis of the results obtained using the EGARCH model for the period from 21/02/2022 to 14/10/2022 and for the period from 17/10/2022 to 06/10/2023.

In the estimation of the EGARCH model for these two periods, the student's t-distribution was not used, as the sample size, being less than 250 observations, does not provide statistical evidence to justify using this type of distribution.

Table 4.3 Results of the EGARCH model estimation for the period 21/02/2022 - 14/10/2022

	VIX	VSTOXX	JNIV	RVI
ω	-0,9657 *	-0,0771 *	-10,8657 ***	-3,4443 ***
β	0,8483 ***	0,9722 ***	0,8911 ***	0,3367 *
γ	-0,1956 **	-0,1186 ***	-0,1301 **	-0,3774 *
α	0,1681 *	0,0959 **	0,0079	0,5458 **

Note: Statistically significant at the confidence level * P < 0,1 ** P < 0,05 *** P < 0,01

The quality of the results presented in Table 4.3 is not the best due to the sample size being only 150 observations.

The result of the parameter α from the JNIV cannot be analyzed as it is not statistically significant. The value of α for the RVI is significantly higher than the value of the VIX and VSTOXX, suggesting that a shock in variance has a much greater impact on the future volatility of RVI returns than on those of VIX and VSTOXX.

The RVI has a much lower β value compared to the other indices. This means that the results for VSTOXX, JNIV, and VIX show greater persistence of past volatility, whereas in the case of RVI, past volatility has a smaller contribution to the prediction of future volatility.

The most negative γ parameter value is found in the RVI. Although the VIX has a less negative value than the RVI, its γ value is more negative than the value of the VSTOXX and JNIV. This indicates that in the RVI, bad news increases volatility more than good news does, compared to the increase observed in the other indices.

Table 4.4 Results of the EGARCH model estimation for the period 17/10/2022 - 06/10/2023

	VIX	VSTOXX	JNIV	RVI
ω	-1,1089 ***	-1,7562 ***	-1,9404 ***	-2,2703 **
β	0,8263 ***	0,7388 ***	0,7476 ***	0,5112 ***
γ	-0,0977 ***	-0,2106 ***	-0,2117 ***	-0,0902
α	0,0866 **	0,2701 ***	0,3813 ***	0,5113 ***

Note: Statistically significant at the confidence level * P < 0,1 ** P < 0,05 *** P < 0,01

The parameter results presented in Table 4.4 of the EGARCH model are statistically significant at the 1% confidence level for all four implied volatility indices, except for the α parameter of the VIX, which is statistically significant at the 5% confidence level, and the γ parameter of the RVI, which is not statistically significant.

The α parameter value for the RVI is significantly higher than the value of the other indices. The JNIV and VSTOXX have a much higher α value than the VIX. This suggests that a shock in variance has a much greater impact on the future volatility of RVI returns than on the other indices.

The VIX has the highest β value. The VSTOXX and JNIV have similar values that are significantly higher than the β of the RVI. This indicates that the VIX results show greater persistence of past volatility, whereas in the RVI, past volatility has a smaller contribution to the prediction of future volatility.

The result of the γ parameter for the RVI cannot be analyzed as it is not statistically significant. The JNIV and VSTOXX have very similar γ values, which are higher than those of the VIX. This indicates that in the JNIV and VSTOXX, bad news increases volatility more than good news does, compared to the increase observed in the VIX.

Having analyzed the results, we will now draw the appropriate conclusions from this investigation.

5. Conclusion

In this research work, the objective was to conduct a study on the volatility of the returns of four implied volatility indices during the period of the war in Ukraine, using the EGARCH model.

Starting by analyzing the period of the war in Ukraine, we observed a significant increase in the α parameter across the four implied volatility indices. In relative terms, the VIX and VSTOXX were the indices that experienced the largest increases, while in absolute terms, the JNIV and RVI showed the greatest increases.

These results reveal that the magnitude of the shock caused by the war in Ukraine significantly impacted the future volatility of returns across all the indices analyzed.

Regarding the β parameter, we observed a decrease across all four implied volatility indices during the period of the war in Ukraine. The RVI was the index that showed the largest decrease in both relative and absolute terms.

The results suggest that the war in Ukraine contributed to increase uncertainty, making it more difficult to predict future volatility across all four implied volatility indices, with the most significant impact observed on the RVI.

For the γ parameter, we identified a distinct reaction compared to the other two parameters. The γ of the VSTOXX and RVI became more negative, while the γ of the VIX and JNIV became less negative.

This analysis of the γ parameter suggests that during the period of the war in Ukraine, in the VSTOXX and RVI indices, bad news would increase volatility even more compared to good news of the same magnitude. In contrast, for the VIX and JNIV indices, bad news would still increase volatility, but on a smaller scale compared to the 2017-2019 period, relative to good news.

In summary, during the period of the war in Ukraine:

- The shock to variance significantly affected the future volatility of returns across all the indices analyzed.

- There was an increase in uncertainty, which made it more challenging to predict future volatility across all four implied volatility indices, with the most significant impact on the RVI.

- Bad news will increase volatility even more compared to good news of the same magnitude in the VSTOXX and RVI indices, while in the VIX and JNIV indices, bad news will still increase volatility, but to a lesser extent compared to the 2017-2019 period, relative to good news.

During the period of the war in Ukraine, when the market was declining, we can conclude that:

- The shock to variance affected future volatility of returns much more in the RVI than in the VIX and VSTOXX.

- Past volatility contributed less to predicting future volatility in the RVI.

- In the RVI, bad news increases volatility more than good news, compared to the increase observed in the other indices.

During the period of the war in Ukraine when the market was rising, we can conclude that:

- The shock to variance affects future volatility of returns much more in the RVI than in the other indices.

- Past volatility contributed less to predicting future volatility in the RVI.

- In the JNIV and VSTOXX, bad news increases volatility more than good news, compared to the increase observed in the VIX.

In future research, other types of assets, such as cryptocurrencies or commodities, could be analyzed. Additionally, using different volatility models for result analysis could be considered.

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Attachments

Attachment 1 - ADF test of VIX returns

Augmented Dickey-Fuller Unit Root Test on VIX_PROFITABILITY

Null Hypothesis: VIX_PROFITABILITY has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-36.43805	0.0000
Test critical values:	1% level	-3.965869	
	5% level	-3.413638	
	10% level	-3.128877	

Attachment 2 - ADF test of VSTOXX returns

Augmented Dickey-Fuller Unit Root Test on VSTOXX_PROFITABILITY

Null Hypothesis: VSTOXX_PROFITABILITY has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-36.03187	0.0000
Test critical values:	1% level	-3.965836	
	5% level	-3.413621	
	10% level	-3.128868	

Attachment 3 - ADF test of JNIV returns

Augmented Dickey-Fuller Unit Root Test on JNIV_PROFITABILITY

Null Hypothesis: JNIV_PROFITABILITY has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-36.08761	0.0000
Test critical values:	1% level	-3.966174	
	5% level	-3.413787	
	10% level	-3.128966	

Attachment 4 - ADF test of RVI returns

Augmented Dickey-Fuller Unit Root Test on RVI_PROFITABILITY

Null Hypothesis: RVI_PROFITABILITY has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-41.55821	0.0000
Test critical values:	1% level	-3.966005	
	5% level	-3.413704	
	10% level	-3.128917	

Attachment 5 - Phillips-Perron test of VIX returns

Phillips-Perron Unit Root Test on VIX_PROFITABILITY

Null Hypothesis: VIX_PROFITABILITY has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 16 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-37.89747	0.0000
Test critical values:	1% level	-3.965869	
	5% level	-3.413638	
	10% level	-3.128877	

Attachment 6 - Phillips-Perron test of VSTOXX returns

Phillips-Perron Unit Root Test on VSTOXX_PROFITABILITY

Null Hypothesis: VSTOXX_PROFITABILITY has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 16 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-37.02193	0.0000
Test critical values:	1% level	-3.965836	
	5% level	-3.413621	
	10% level	-3.128868	

Attachment 7 - Phillips-Perron test of JNIV returns

Phillips-Perron Unit Root Test on JNIV_PROFITABILITY

Null Hypothesis: JNIV_PROFITABILITY has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 18 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-37.13957	0.0000
Test critical values:	1% level	-3.966174	
	5% level	-3.413787	
	10% level	-3.128966	

Attachment 8 - Phillips-Perron test of RVI returns

Phillips-Perron Unit Root Test on RVI_PROFITABILITY

Null Hypothesis: RVI_PROFITABILITY has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 4 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-41.76386	0.0000
Test critical values:	1% level	-3.966005	
	5% level	-3.413704	
	10% level	-3.128917	

Attachment 9 - ARCH-LM test of VIX returns

Heteroskedasticity Test: ARCH

F-statistic	11.88014	Prob. F(1,1173)	0.0006
Obs*R-squared	11.78108	Prob. Chi-Square(1)	0.0006

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/20/24 Time: 11:29
Sample (adjusted): 3 1177
Included observations: 1175 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.005417	0.000767	7.062652	0.0000
RESID^2(-1)	0.100130	0.029050	3.446758	0.0006

R-squared	0.010026	Mean dependent var	0.006019
Adjusted R-squared	0.009182	S.D. dependent var	0.025719
S.E. of regression	0.025600	Akaike info criterion	-4.490713
Sum squared resid	0.768764	Schwarz criterion	-4.482085
Log likelihood	2640.294	Hannan-Quinn criter.	-4.487459
F-statistic	11.88014	Durbin-Watson stat	2.004485
Prob(F-statistic)	0.000587		

Attachment 10 - ARCH-LM test of VSTOXX returns

Heteroskedasticity Test: ARCH

F-statistic	7.179281	Prob. F(1,1178)	0.0075
Obs*R-squared	7.147908	Prob. Chi-Square(1)	0.0075

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/20/24 Time: 11:35
Sample (adjusted): 3 1182
Included observations: 1180 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.005254	0.000864	6.080713	0.0000
RESID^2(-1)	0.077830	0.029047	2.679418	0.0075

R-squared	0.006058	Mean dependent var	0.005698
Adjusted R-squared	0.005214	S.D. dependent var	0.029208
S.E. of regression	0.029132	Akaike info criterion	-4.232255
Sum squared resid	0.999748	Schwarz criterion	-4.223656
Log likelihood	2499.031	Hannan-Quinn criter.	-4.229013
F-statistic	7.179281	Durbin-Watson stat	2.006158
Prob(F-statistic)	0.007478		

Attachment 11 - ARCH-LM test of JNIV returns

Heteroskedasticity Test: ARCH

F-statistic	6.414277	Prob. F(1,1129)	0.0115
Obs*R-squared	6.389339	Prob. Chi-Square(1)	0.0115

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/20/24 Time: 11:38
Sample (adjusted): 3 1133
Included observations: 1131 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003502	0.000408	8.579267	0.0000
RESID^2(-1)	0.075160	0.029677	2.532642	0.0115

R-squared	0.005649	Mean dependent var	0.003787
Adjusted R-squared	0.004769	S.D. dependent var	0.013227
S.E. of regression	0.013196	Akaike info criterion	-5.816113
Sum squared resid	0.196583	Schwarz criterion	-5.807217
Log likelihood	3291.012	Hannan-Quinn criter.	-5.812752
F-statistic	6.414277	Durbin-Watson stat	2.000519
Prob(F-statistic)	0.011455		

Attachment 12 - ARCH-LM test of RVI returns

Heteroskedasticity Test: ARCH

F-statistic	8.952240	Prob. F(1,1153)	0.0028
Obs*R-squared	8.898677	Prob. Chi-Square(1)	0.0029

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/20/24 Time: 11:40
Sample (adjusted): 3 1157
Included observations: 1155 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.006463	0.001761	3.670223	0.0003
RESID^2(-1)	0.087775	0.029336	2.992029	0.0028

R-squared	0.007704	Mean dependent var	0.007085
Adjusted R-squared	0.006844	S.D. dependent var	0.059632
S.E. of regression	0.059427	Akaike info criterion	-2.806391
Sum squared resid	4.071961	Schwarz criterion	-2.797643
Log likelihood	1622.691	Hannan-Quinn criter.	-2.803089
F-statistic	8.952240	Durbin-Watson stat	2.005213
Prob(F-statistic)	0.002830		

Attachment 13 - White test of VIX returns

Heteroskedasticity Test: White
Null hypothesis: Homoskedasticity

F-statistic	8.562880	Prob. F(2,1173)	0.0002
Obs*R-squared	16.92249	Prob. Chi-Square(2)	0.0002
Scaled explained SS	1939914.	Prob. Chi-Square(2)	0.0000

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 04/06/25 Time: 00:16
Sample: 2 1177
Included observations: 1176
Collinear test regressors dropped from specification

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.959804	0.082980	11.56672	0.0000
VIX_PROFITABILITY(-1...	10.58271	3.560324	2.972402	0.0030
VIX_PROFITABILITY(-1)	1.205437	1.191373	1.011805	0.3118

R-squared	0.014390	Mean dependent var	1.024065
Adjusted R-squared	0.012709	S.D. dependent var	2.767978
S.E. of regression	2.750332	Akaike info criterion	4.863868
Sum squared resid	8872.953	Schwarz criterion	4.876801
Log likelihood	-2856.954	Hannan-Quinn criter.	4.868745
F-statistic	8.562880	Durbin-Watson stat	1.861655
Prob(F-statistic)	0.000203		

Attachment 14 - White test of VSTOXX returns

Heteroskedasticity Test: White
Null hypothesis: Homoskedasticity

F-statistic	7.523067	Prob. F(2,1178)	0.0006
Obs*R-squared	14.89421	Prob. Chi-Square(2)	0.0006
Scaled explained SS	5532908.	Prob. Chi-Square(2)	0.0000

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 04/06/25 Time: 00:22
Sample: 2 1182
Included observations: 1181
Collinear test regressors dropped from specification

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.893531	0.145589	6.137353	0.0000
VSTOXX_PROFITABILITY(-1...	19.19543	5.281232	3.634650	0.0003
VSTOXX_PROFITABILITY(-1)	-5.606037	2.063871	-2.716274	0.0067

R-squared	0.012612	Mean dependent var	1.002759
Adjusted R-squared	0.010935	S.D. dependent var	4.922190
S.E. of regression	4.895204	Akaike info criterion	6.016926
Sum squared resid	28228.44	Schwarz criterion	6.029815
Log likelihood	-3549.995	Hannan-Quinn criter.	6.021785
F-statistic	7.523067	Durbin-Watson stat	2.008035
Prob(F-statistic)	0.000567		

Attachment 15 - White test of JNIV returns

Heteroskedasticity Test: White
Null hypothesis: Homoskedasticity

F-statistic	7.492578	Prob. F(2,1129)	0.0006
Obs*R-squared	14.82816	Prob. Chi-Square(2)	0.0006
Scaled explained SS	3078753.	Prob. Chi-Square(2)	0.0000

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 04/06/25 Time: 00:28
Sample: 2 1133
Included observations: 1132
Collinear test regressors dropped from specification

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.858439	0.073822	11.62851	0.0000
JNIV_PROFITABILITY(-1)^2	22.96635	5.992893	3.832264	0.0001
JNIV_PROFITABILITY(-1)	-2.871057	1.279871	-2.243239	0.0251

R-squared	0.013099	Mean dependent var	0.945921
Adjusted R-squared	0.011351	S.D. dependent var	2.375528
S.E. of regression	2.362008	Akaike info criterion	4.559548
Sum squared resid	6298.782	Schwarz criterion	4.572883
Log likelihood	-2577.704	Hannan-Quinn criter.	4.564585
F-statistic	7.492578	Durbin-Watson stat	1.881971
Prob(F-statistic)	0.000585		

Attachment 16 - White test of RVI returns

Heteroskedasticity Test: White
Null hypothesis: Homoskedasticity

F-statistic	8.223526	Prob. F(2,1153)	0.0003
Obs*R-squared	16.25793	Prob. Chi-Square(2)	0.0003
Scaled explained SS	11217197	Prob. Chi-Square(2)	0.0000

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 04/06/25 Time: 00:37
Sample: 2 1157
Included observations: 1156
Collinear test regressors dropped from specification

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.866462	0.245990	3.522347	0.0004
RVI_PROFITABILITY(-1)^2	17.97420	4.471007	4.020169	0.0001
RVI_PROFITABILITY(-1)	-8.284161	3.300732	-2.509795	0.0122

R-squared	0.014064	Mean dependent var	0.998380
Adjusted R-squared	0.012354	S.D. dependent var	8.340454
S.E. of regression	8.288776	Akaike info criterion	7.070274
Sum squared resid	79215.50	Schwarz criterion	7.083386
Log likelihood	-4083.618	Hannan-Quinn criter.	7.075222
F-statistic	8.223526	Durbin-Watson stat	2.001288
Prob(F-statistic)	0.000284		

Attachment 17 – Ljung-Box test of VIX returns

Sample (adjusted): 2 1177
Q-statistic probabilities adjusted for 1 dynamic regressor

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.004	-0.004	0.0215	0.884
		2	-0.070	-0.070	5.8628	0.053
		3	-0.037	-0.037	7.4431	0.059
		4	-0.004	-0.009	7.4602	0.113
		5	0.037	0.032	9.0519	0.107
		6	-0.080	-0.082	16.597	0.011
		7	-0.045	-0.042	18.994	0.008
		8	-0.041	-0.051	20.956	0.007
		9	0.022	0.010	21.537	0.010
		10	-0.001	-0.013	21.538	0.018
		11	-0.022	-0.019	22.096	0.024
		12	-0.026	-0.032	22.924	0.028
		13	-0.006	-0.014	22.966	0.042
		14	-0.018	-0.035	23.335	0.055
		15	-0.008	-0.014	23.420	0.076
		16	0.012	0.005	23.589	0.099
		17	0.005	-0.000	23.615	0.130
		18	-0.003	-0.010	23.625	0.168
		19	-0.018	-0.023	24.014	0.196
		20	-0.022	-0.031	24.595	0.217

Attachment 18 – Ljung-Box test of VSTOXX returns

Sample (adjusted): 2 1182
Q-statistic probabilities adjusted for 1 dynamic regressor

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.001	-0.001	0.0015	0.969
		2	-0.018	-0.018	0.3823	0.826
		3	0.000	0.000	0.3823	0.944
		4	-0.108	-0.109	14.301	0.006
		5	0.023	0.023	14.954	0.011
		6	-0.034	-0.039	16.333	0.012
		7	0.017	0.019	16.695	0.019
		8	-0.034	-0.048	18.044	0.021
		9	0.019	0.026	18.496	0.030
		10	-0.042	-0.054	20.590	0.024
		11	-0.074	-0.068	27.154	0.004
		12	-0.011	-0.025	27.293	0.007
		13	-0.003	0.002	27.304	0.011
		14	-0.049	-0.067	30.232	0.007
		15	0.015	0.005	30.503	0.010
		16	-0.021	-0.032	31.029	0.013
		17	0.001	-0.000	31.029	0.020
		18	0.039	0.021	32.844	0.017
		19	-0.053	-0.053	36.165	0.010
		20	-0.013	-0.024	36.365	0.014

Attachment 19 – Ljung-Box test of JNIV returns

Sample (adjusted): 2 1133
Q-statistic probabilities adjusted for 1 dynamic regressor

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.001	0.001	0.0013	0.971
		2	0.016	0.016	0.2841	0.868
		3	-0.070	-0.070	5.8701	0.118
		4	-0.013	-0.013	6.0512	0.195
		5	-0.046	-0.044	8.4388	0.134
		6	-0.035	-0.040	9.8588	0.131
		7	0.001	0.001	9.8605	0.197
		8	-0.013	-0.019	10.053	0.261
		9	0.005	-0.001	10.086	0.344
		10	-0.033	-0.035	11.295	0.335
		11	-0.044	-0.050	13.515	0.261
		12	-0.037	-0.039	15.109	0.236
		13	-0.017	-0.022	15.428	0.281
		14	0.012	0.004	15.605	0.338
		15	0.050	0.041	18.506	0.237
		16	-0.010	-0.021	18.623	0.289
		17	0.052	0.045	21.681	0.197
		18	-0.014	-0.013	21.916	0.236
		19	-0.019	-0.024	22.331	0.268
		20	-0.051	-0.042	25.326	0.189

Attachment 20 – Ljung-Box test of RVI returns

Sample (adjusted): 2 1157
Q-statistic probabilities adjusted for 1 dynamic regressor

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.016	-0.016	0.2999	0.584
		2	-0.064	-0.064	4.9841	0.083
		3	0.081	0.079	12.616	0.006
		4	-0.022	-0.024	13.187	0.010
		5	-0.009	0.001	13.282	0.021
		6	-0.015	-0.024	13.533	0.035
		7	-0.051	-0.049	16.587	0.020
		8	0.035	0.032	17.978	0.021
		9	0.016	0.013	18.264	0.032
		10	0.002	0.014	18.269	0.051
		11	-0.010	-0.017	18.398	0.073
		12	-0.046	-0.048	20.917	0.052
		13	-0.076	-0.082	27.642	0.010
		14	-0.060	-0.068	31.827	0.004
		15	-0.002	-0.003	31.832	0.007
		16	0.028	0.032	32.753	0.008
		17	0.007	0.014	32.804	0.012
		18	0.007	0.004	32.866	0.017
		19	0.014	0.002	33.101	0.023
		20	0.014	0.007	33.322	0.031