INSTITUTO
UNIVERSITÁRIO
DE LISBOA

The Russia–Ukraine War and Its Impact on Sectorial Indexes Volatility: Evidence from S&P 500 and STOXX 600

Diogo André Daniel Abrantes

Master in Monetary and Financial Economics

Supervisor:
Prof. Doctor Luís Filipe Martins, Associate Professor, ISCTE-IUL
Department of Economics

September, 2025

CIÊNCIAS SOCIAIS
E HUMANAS

Department of Political Economy

The Russia–Ukraine War and Its Impact on Sectorial Indexes Volatility: Evidence from S&P 500 and STOXX 600

Diogo André Daniel Abrantes

Master in Monetary and Financial Economics

Supervisor:
Prof. Doctor Luís Filipe Martins, Associate Professor, ISCTE-IUL
Department of Economics

September, 2025

Acknowledgments

To all my family, that accompanied me through all this academic period, especially two people, my mother Paula and my brother Ruben. They are my inspiration, my role models, my everything. What I am today and all that I have accomplished is thanks to them. I cannot put in words what my family means to me and the support they always gave to me, all I can say is thank you.

To all professors of the Financial and Monetary Economic masters, but especially to professor Luís Filipe Martins, since day one he was always available to help me improve this thesis, his contribute was essential for me to finish this thesis.

To my friends, my deepest gratitude. For your constant friendship, for the conversations that distracted me at just the right moments, and for the words of support during the difficult times. Thank you for making me laugh when I needed it most, for believing in me even when I had doubts, and for always being there, but above all, thank you for accepting me for who I am, for not giving up on me and for making me a better person. Your presence made this journey unforgettable and my life much happier.

Finally, to all those who unfortunately won't be able to be with me and see what I conquered and what I became, my grandmother, my grandfather and my father. I hope all of you are proud of me.

To all of you,

Muito obrigado

Abstract

The objective of this dissertation is to analyze the impact of the war between Russia and Ukraine on financial market volatility, focusing primarily on sectoral indices from Europe and the United States. To identify which sectors were most affected, two different GARCH models are applied: a GARCH (1,1) with a war dummy and a GJR-GARCH (1,1) model with a war dummy.

The American indices analyzed in this thesis are the S&P 500, S&P 500 Financials, S&P 500 Industrials, S&P 500 Materials, S&P 500 Energy, and S&P 500 Consumer Staples. For the European indices, the selected ones are the STOXX 600, STOXX 600 Banks, STOXX 600 Insurance, STOXX 600 Industrials, STOXX 600 Oil & Gas, and STOXX 600 Food & Beverage. The time period spans from 24 February 2021 to 24 February 2023.

The results show that persistent volatility and shocks led to a permanent change in conditional variance. For most indices, the war had a significant impact on stock market volatility. The exceptions are the European financial sector and the Oil & Gas sector. The findings also indicate the presence of asymmetric effects, with negative shocks having a stronger impact on conditional variance than positive shocks, and these impacts vary across sectors. The only exceptions are the European financial sector and the European Oil & Gas sector. Overall, the results suggest that the most affected sectors were Industrials, in both the United States and Europe, and the Energy sector in the United States.

JEL Classification: C22, G14, G15

Key words: GARCH, GJR-GARCH, Russia, Ukraine, Volatility, Sectorial Index, Financial Markets

Resumo

O objetivo desta dissertação passa por perceber qual foi o impacto da guerra entre a Rússia e a Ucrânia na volatilidade dos mercados financeiros, em especial nos índices setoriais da Europa e dos Estados Unidos da América. Para perceber quais foram os setores mais afetados pela guerra aplicaram-se dois modelos GARCH diferentes: um GARCH (1,1) com uma variável binária da guerra e um GJR-GARCH (1,1) com uma variável da guerra. Os índices americanos que vão ser estudados nesta tese serão o S&P 500, S&P 500 Financials, S&P 500 Industrials, S&P 500 Materials, S&P 500 Energy e o S&P 500 Consumer Staples. Quanto aos índices Europeus, os escolhidos foram o STOXX 600, STOXX 600 Banks, STOXX 600 Insurance, STOXX 600 Industrials, STOXX 600 Oil & Gas e o STOXX 600 Food & Beverage. O período temporal começa a 24 de Fevereiro de 2021 e termina a 24 de Fevereiro de 2023.

Os resultados mostram que os choques levaram a uma mudança permanente na volatilidade condicional. Para a maioria dos índices guerra teve um grande impacto na volatilidade dos mercados de ações. Os resultados mostram também que existem efeitos assimétricos, sendo que as notícias negativas apresentam um impacto maior na volatilidade condicional quando comparados com os impactos das boas noticias. Os impactos são diferentes em cada setor sendo que o setor financeiro e de petróleo e gás europeus não apresentam esta assimetria. Os setores que tiveram a volatilidade mais afetada foram os setores industriais, tanto americanos como europeus, e o setor energético americano.

Classificação JEL: C22, G14, G15

Palavras-chave: GARCH, GJR-GARCH, Rússia, Ucrânia, Volatilidade, Índices Setoriais, Mercados Financeiros

Contents

List of Annexes

List of figures

List of Tables

List of Abbreviations

ADF – Augmented Dickey–Fuller

AIC - Akaike information criterion

AR – Autoregressive

ARCH – Autoregressive Conditional Heteroskedasticity

ARMA – Autoregression Moving Average

BRIC – Brazil Russia India and China

CAC - Cotation Assistée en Continu

DAX - Deutscher Aktienindex

EU – European Union

FED – **Federal** Reserve Board

FTSE 100 - Financial Times Stock Exchange 100

GARCH – Generalized Autoregressive Conditional Heteroskedasticity

GFC - Global Financial Crisis

GJR-GARCH – Glosten, Jagannathan, and Runkle Generalized Autoregressive Conditional Heteroskedasticity

EGARCH – Exponential Generalized Autoregressive Heteroskedasticity

EGX 30 – Egyptian Exchange 30

GDP - Gross Domestic Product

GFC – Global Financial Crisis

HAR - Heterogeneous Autoregressive

JSEALSI - Johannesburg Stock Exchange All Share Index

KPSS – Kwiatkowski–Phillips–Schmidt–Shin

MA – Moving Average

MOVE – Merrill Lynch Option Volatility Estimate

MSCI - Morgan Stanley Capital International

NATO– North Atlantic Treaty Organization

NiGEM - National Institute Global Econometric Model

OECD – Organisation for Economic Co-operation and Development

UK – United Kingdom

PP - Phillips-Perron

PSI - Portuguese Stock Index

S&P – Standard & Poor's

S&P/ASX 200 - Standard & Poor/Australian Securities Exchange 200

S&P BSE - Standard & Poor Bombay Stock Exchange

S&P/TSX - Standard & Poor/Toronto Stock Exchange

S&P/NZX - Standard & Poor/New Zealand Stock Exchange

SSE - Shanghai Stock Exchange

TGARCH – Threshold Generalised Autoregressive Conditional Heteroscedasticity

TTF - Title Transfer Facility

TVP-VAR - Time-Varying Parameter Vector Autoregressive

USA – United States of America

VAR - Vector Autoregressive

VIX – Volatility Index

WTI - West Texas Intermediate

1. Introduction

The day 24 February 2022 will be marked on the history of the world, as it was the day that Russia invaded the sovereign nation of Ukraine apparently without any other reason besides feeding the Imperial desires of a small group of people. Since that day thousands of people have died, an entire country has been shredded to pieces, both economically and in its infrastructures, and the lives of millions of people have been affected. This conflict affected not only the two participants of the war but the economies of almost every country in Europe and America. The financial markets tend to be the image of what the world is experiencing economically, and even though it is almost impossible to predict how they will react to any kind of event, it is important to understand the impact of such geopolitical events like wars, pandemics and crisis (both political and economic) on the financial markets. This way an investor will be more prepared for any kind of difficult situation that may appear.

The literature is mostly consensual of the impact that war and other crises like the Covid and the 2008 Global Financial Crisis have on the financial markets volatility. Wu et al. (2023) concluded that the Russia-Ukraine conflict has reduced stock market volatility at lower conflict levels, but it turns out to increase stock volatility after the conflict escalates. Moreover, there is more sensitivity on the stock market participants in NATO (North Atlantic Treaty Organization) countries about the changes in the war situation in Russia and Ukraine, while in contrast the non-NATO stock market participants are more concerned with the potential derivative effects of the Russia-Ukraine conflict. Yousaf et al., (2023) state that all financial markets and alternative assets experienced high volatility, except for bitcoin, during the observation periods. Chowdhury & Khan (2024) found that the war had a clear impact on the volatility of all selected stock markets and it is expected that the USA will experience recession. In the case of the Covid impact, for example, Khan et al. (2023) states that the COVID-19 pandemic led to a significant increase in the different stock market volatility. However the magnitude of the impact varied across sample markets, which can be explained with the different stages of the pandemic outbreaks.

To understand how the volatility changes in this kind of situation will give investors a better understanding on how to act during these periods of crisis, and knowing which sectors are more affected by these issues will help the investors decide where to make a move. That is the main contribution of this work: using GACH-type models to understand how the different sectors react, in terms of volatility, to war.

This thesis is divided as follows; chapter 2 is a small introduction to how the war began and what volatility is. Chapter 3 includes the literature review divided into three sections, starting with the literature about the impact of the war on the global economy, secondly a section about the impact of the conflict on the financial markets volatility and finishing with the impact of other crises on the volatility. Chapter 4 presents the econometric framework and statistical metrics applied in the analysis and the different data and temporal windows that will be applied. Chapter 5 is composed of the results of the two different models and its analysis Finally, chapter 6 concludes the work with a summary of the findings.

2. Context

2.1. Historical Context

This conflict has its roots in November 2013, when the Ukrainian government, led at the time by the pro-Russian president Viktor Yanukovych, decided not to sign a planned Association Agreement with the European Union. This decision sparked protests across Ukraine, especially in Kyiv, which became known as the Euromaidan or the Revolution of Dignity.

On 21 November, following signals from the Party of Regions that the Association Agreement might not be signed, a group of approximately 1,500 people gathered on Kyiv's Maidan, including citizens from across Ukraine. In the days that followed, the Euromaidan movement spread throughout the country. On 30 November, Ukrainian police attacked the peaceful protesters, injuring at least 79 people. The next day, the rally in Kyiv's Independence Square grew into a demonstration of up to half a million citizens demanding Yanukovych's resignation. This marked a turning point in the movement: it was no longer only about the Association Agreement, but also about ending the system responsible for the violence of 30 November.[1]

On 16 January 2014, the regime introduced the so-called "dictatorship laws," which severely restricted freedom of speech and assembly. These policy changes reinvigorated the revolution and escalated the violence, resulting in the first deaths. On 28 January, Yanukovych revoked the "dictatorship laws" and accepted the resignation of Prime Minister Mykola Azarov, who subsequently fled the country. On 19 February, Yanukovych ordered the use of live ammunition against protesters, resulting in the deaths of more than eighty people. Following a final ultimatum from the protesters, Yanukovych and most of his government fled the country, allowing the protesters to peacefully take control of Kyiv.[2]

By the end of February 2014, unidentified military personnel surrounded airports in Crimea, and pro-Russian forces seized the Crimean autonomous assembly. In March 2014, the assembly issued a declaration of independence and held a referendum on union with Russia.

[1] https://www.theguardian.com/world/2013/nov/30/ukraine-bloody-backlash-sanctions-eu
[2] https://www.tandfonline.com/doi/epdf/10.1080/00085006.2023.2293420?needAccess=true

According to Russian sources, nearly 95% of voters supported joining Russia, but the results were not internationally recognized. Since then, Russia has maintained control over Crimea and supported pro-Russian forces who took control of parts of Donetsk and Luhansk. This was Russia's response to the Euromaidan.[3]

From May 2015 to October 2021, the conflict in the Donbas region continued to escalate, with Russia denying any involvement. During this period, the Ukrainian government approved a series of reforms aimed at reducing systemic corruption. On 21 April 2019, former actor and comedian Volodymyr Zelenskyy won the presidential election.

In November 2021, Russia began a buildup of troops and military equipment along its border with Ukraine. Over the following months, Russia deployed additional forces to Belarus, Transdniestria, and Crimea. Allied intelligence estimated that nearly 190,000 Russian troops were mobilized and positioned around Ukraine. Putin demanded limits on NATO expansion that would effectively remove the NATO security umbrella from Eastern and Southern Europe as well as the Baltic states—demands that were rejected by Western allies. In response to this rejection, Putin recognized the independence of the self-proclaimed people's republics of Donetsk and Luhansk. Shortly thereafter, the Russian army entered Ukrainian territory under the pretext of acting as "peacekeepers." Most Western leaders pledged solidarity with Ukraine and responded by imposing a series of sanctions on Russian financial institutions. With the full-scale invasion on 24 February 2022, Europe found itself at war for the first time since World War II.[4]

2.2. Financial Context

In 2020, the coronavirus lockdowns caused spikes in market volatility similar to those observed during the 2008 global financial crisis, a period in which U.S. equity markets experienced their largest single-day drop since the Black Monday crash of 1987. Volatility is a measure of price fluctuations and is fundamental to the functioning of financial markets, as it reflects an asset's potential to rise or fall relative to its current price.

Assets with higher volatility are generally considered riskier, as greater uncertainty about an asset's value leads to larger price fluctuations. Periods of heightened market volatility

[3] https://researchbriefings.files.parliament.uk/documents/CBP-9476/CBP-9476.pdf
[4] https://www.britannica.com/place/Ukraine/The-Russian-invasion-of-Ukraine

are typically driven by two key factors. The first is macroeconomic uncertainty, which makes it difficult for the market to accurately value assets; examples include the COVID-19 pandemic or natural disasters. The second factor is a lack of liquidity. Liquidity refers to how easily an asset can be bought or sold without significantly affecting its market price. When there are insufficient buyers, assets must be sold at lower prices, and conversely, prices can rise when there is excess demand.

There are two types of volatility: realized volatility and implied volatility. Realized volatility refers to past price movements, measuring how an asset's price has fluctuated over time. Implied volatility, on the other hand, reflects the market's expectation of how much an asset's price is likely to move in the future. It is typically associated with options, which give holders the right to buy or sell an asset at a predetermined price at a future date.

There are two types of volatility: realized volatility and implied volatility. Realized volatility measures past price movements, showing how an asset's price has fluctuated over time. Implied volatility, by contrast, reflects the market's expectations of future price movements. It is typically associated with options, which grant holders the right to buy or sell an asset at a predetermined price on a specified future date.

For investors, it is important to understand how financial markets react to geopolitical events. After providing a brief introduction to volatility and the origins of this conflict, it is now essential to review what the scientific literature reveals on this topic and to clarify how this thesis will contribute to a better understanding of the consequences of the conflict on financial markets.

3. Literature Review

The Russia-Ukraine war is among the most significant historical events of recent decades. Simultaneously, research has examined how major historical events influence market volatility. It's crucial to understand not only how this specific conflict affects the financial market's volatility but also how other geopolitical events and crises impact it. To gain a clear understanding of this conflict's effects on volatility, it is also essential to consider its impact on the global economy, especially the financial markets.

3.1. The economic impact of the Ukrainian war

Ozili, (2022) explored the impact of the war on the global economy by analyzing a period from December 2021 to March 2022 and concluded that the war had an impact on global supply chain disruption, which manifested through rising prices, and consequently led to a rise in inflation. The empirical results also showed that the Ukrainian war led to an increase in food and crude oil prices, and that the rise in prices of food was driven by an increase in the price of dairy and oils. Regarding inflation, Ozili, (2022) explains that it increased in Ukraine and Russia first, and after that in other countries. Finally, the author also states that sanctions weren't the best solution because they produced economic spillovers to countries that weren't part of the conflict.

Liadze et al., (2023) researched to quantify the impact of the war on the global economy by applying a National Institute Global Econometric Model (NiGEM). The authors project that the war had a cost of close to 1% of the global gross domestic product (GDP) in 2022 when compared with a GDP forecast performed at the beginning of 2022. The authors also refer that the European region was the most affected by the war because of the proximity of Ukraine and Russia, which resulted in a cost bigger than 1% of the European GDP, and as for the most affected countries, the authors believe it was Germany, France, and Italy.

Food Security Information Network, (2023) performed a report that addresses the impact of the Ukrainian war on food crises around the world. It states that the war had a big impact on the global food systems since both Ukraine and Russia produce and trade fuel, fertilizer, and essential food commodities. The authors also state that the prices increased in all countries with food shortages, and inflation was over 10% in 38 of these countries.

As soon as Russia invaded Ukraine, many countries decided to impose sanctions on Russia. The European Parliament, (2024) elaborated a report about the economic consequences of the war, in that report it is referred that the European Union (EU) adopted twelve sanction packages on Russia which contributed to a 2,1% shrank of the Russian GDP, however, after Russia adjusted to the sanctions, in 2023 the country had a growth of 2,6%, thanks to a development of new markets such as China and India. The same report also mentions that before the war, Europe was heavily dependent on Russian energy, which meant that with the sanctions in place, the EU had to find a quick alternative, which involved, for example, an investment in renewable energies. However, the rise in energy prices, which resulted from the war, led to record-level energy prices. The high energy prices also led to a rise in food and other goods prices, leading to record inflation in 2022, and even though the inflation has fallen since 2022, the slow growth and recessions in the euro zone have prevented economic prospects. It is also important to note that the spike of inflation that happened had to be fought with ten consecutive interest rate increases.

3.2. The impact of the Ukrainian war on the financial markets volatility

A study conducted by the OCDE, (2022) about the impact of the Russian-Ukrainian war stated that “the combination of geopolitical uncertainty, higher commodity prices, sanctions and regional business disruptions has contributed to elevated volatility and risk aversion” (OCDE, 2022: p. 7), and that volatility has risen substantially in the United States (US) markets. It is also stated that oil prices have become more volatile. Through the analysis of the Merrill Lynch Option Volatility Estimate (MOVE) index, which is an index that reflects the level of volatility in the U.S. treasury futures, they saw that it had peaked at 60% of its previous high in 2020, oscillating over subsequent weeks but remaining elevated. Yet, at the time of the study, the implied volatility on equity and oil markets had declined to below pre-invasion levels. The authors also stated that the MOVE index rose amid more range-bound implied volatility in equity and oil indices following the Russian invasion of Ukraine, yet implied volatility of European equity markets rose more significantly than in the US and Japanese equity markets.

Fang & Shao, (2022) conducted a study to understand the impact of the war on the volatility risk of the commodity market. For that, the authors constructed a new index to measure the intensity of the bilateral geopolitical risk and use it to reflect the intensity of the Russia-Ukraine conflict. Secondly, the authors examine how the conflict affects the volatility risk of commodity markets. They found that the conflict increases the volatility risk in the commodity markets, with agricultural products, metals, and energy among the most affected markets. The authors also found that the volatility risk is higher on commodities with greater dependence on Russia exports, the impact is bigger because of the investors' panic and the FED's interest rate spikes.

Alam et al., (2022) investigated the impacts of the war on the dynamic connectedness among five commodities (Gold, Silver, Platinum, WTI Crude Oil and Natural Gas) and the G7 and BRIC markets (Canada, France, Germany, Italy, Japan, United Kingdom, United States, Brazil, Russia, India and China), both with a sample from 1 September 2021 to 24 March 2022, by applying a TVP-VAR method. The effects can be observed from the results of the invasion on the returns connectedness in the sample. The authors found that due to the invasion, there is a very strong connection between all commodities and markets. The findings also showed gold and silver as the receivers from the rest of the commodities and all the sample markets, while platinum, natural gas, silver, and crude oil are transmitters of shocks.

Beraich et al., (2022) investigated the volatility spillover effects in the financial markets before and during the Russia and Ukrainian war. To understand this, the author chose three indices to analyze: Dow Jones Europe, MSCI-USA, and MSCI China. The sample used runs from 1 January 2019 to 1 June 2022 and splits the data into two sub-periods: from 1 January 2019 to 24 February 2022 and from 24 February 2022 to 1 June 2022. To perform the evaluation and analysis of the volatility spillovers between the main international markets, the authors applied generalized vector autoregressive (VAR) models of order p. The results of this study showed that the connectivity varied over time and increased during the conflict. Also, the U.S. market showed the highest volatility spread, which means that the MSCI-USA is the most connected to other indices. The authors also state that the spillover increased during the war, but remains low compared to that during COVID-19.

Boungou & Yatié, (2022) analyzed the impact of the Ukraine-Russia war on world stock returns using samples from 94 countries with daily data, which ranged from 22 January to 24 March 2022. The authors used panel data, which is estimated using the log of stock market indexes and the log of Wikipedia Trends search data, which can be used as a metric for expressing public interest in a topic. The authors concluded that the tensions between the two involved countries had a negative impact on the selected stock markets. Also, they state that the negative impact is significantly greater after 24 February 2022 than it was in the time period before that date. Finally, the authors also state that the geographically closer the countries are to the conflict, the bigger the impact of the war on the stock markets.

Izzeldin et al., (2023) performed a study to analyze the impact of the Russian-Ukrainian war on the Financial Markets, as well as a comparison with the impact of the 2008 Global Financial Crisis (GFC) and the COVID-19 using stock markets from 25 countries and 20 commodities. For this research, the authors employed a Markov-Switching Heterogeneous Autoregressive (HAR) model on daily volatility proxies around each of the three crises, with a total period of 6 months (3 months before each event and 3 months after the beginning of each event), which allows identify regime shifts and computation of metrics for the synchronization, duration and intensity of each crisis. The analysis of the stock market suggests that the volatility response to the Russian Ukrainian war crisis was instantaneous, unlike the GFC or COVID-19, where a certain lag was observed. They believed that the reaction of stock markets shows that the invasion was interpreted as real news by investors.

Wu et al., (2023) also performed a study to analyze the impact of the Russia-Ukraine conflict on the stock volatility. The authors selected the major stock indexes from eight countries, divided into two groups: North Atlantic Treaty Organization (NATO), which includes the S&P 500, the DAX, FTSE-100, and CAC-40, and non-NATO countries, constituted by the Hang Seng (Hong Kong), Nikkei 225, Singapore Straits, and the Zurich Market. The data period is from January 2014 to September 2022. The authors establish two-phase models for the samples to understand the impact of the conflict on the volatility. In the first part, which starts in January 2014 and ends in December 2021, they construct a panel regression model to explore the impact before the beginning of the conflict. In the second part, they build another panel regression model to understand the impact after the war begins (samples from January to November 2022). In a third phase, they analyze the risk transmission mechanism among the different samples using a volatility spillover method. Finally, the authors use a time-frequency decomposition method to compare the impacts of the war on the two groups of countries. the first conclusion was that the Russia-Ukraine conflict reduces stock market volatility at lower conflict levels, but it turns out to increase stock volatility after the conflict escalates. The authors also concluded that there is more sensitivity among the stock market participants in NATO countries about the changes in the war situation in Russia and Ukraine, while, in contrast, the non-NATO stock market participants are more concerned with the potential derivative effects of the Russia-Ukraine conflict.

McKinsey & Company, (2023) analyzed the first sixteen months of the invasion in terms of the impact of the war on financial markets, and they concluded that the stock prices' volatility rose after the invasion, but not as sharply as in previous crises. As for the volatility, the mixed economic signals contributed to higher volatility, which hit the companies through margin compression and slower growth.

Yousaf et al., (2023) conducted a study with a variety of financial assets, such as stock indexes, cryptocurrency, and commodities, to understand the impact of the COVID-19 pandemic and the Russia-Ukraine war on these financial assets' volatility. To do that Yousaf et al., (2023) used GARCH (1,1), GJR-GARCH, and EGARCH specifications, with the log-likelihood values indicating that GARCH (1,1) is the most appropriate model for the study. The research concluded that all financial markets and alternative assets experienced high volatility, except for bitcoin, during the observation periods. The study also found that all assets become more volatile during the pandemic.

Manelli et al., (2024) also conducted a study about the impact of the Russian-Ukrainian war on the volatility. The authors used the Eurostoxx 50, the price of wheat futures, and TTF natural gas, from 25 February 2019 to 28 September 2023, and applied and quantile VAR analysis. They concluded that the conflict affected the commodity market through both economic and financial channels and increased the volatility risk. Moreover, the impact of the conflict and the risk of volatility on commodity markets is further amplified for countries, such as the EU, that are neighbors and show a great trade dependence with one or both countries involved.

Chowdhury & Khan, (2024) also studied the impact of the war on the financial markets by collecting and analyzing daily data of stock markets and macroeconomic variables. To understand this the authors applied an Exponential Generalized Autoregressive Heteroskedasticity (EGARCH) on daily stock indexes from the S&P 500, S&P/TSX (Canada), SMIM (Switzerland), FTSE, S&P BSE (India), SSE (China), S&P/ASX 200 (Australia), S&P/NZX (New Zeland), JSEALSI (South Africa), EGX 30 (Egypt), PSI, COLCAP (Colombia). The authors found that the war had a clear impact on the volatility of all selected stock markets, and it is expected that the USA will experience a recession. As for the European stocks, those were very close to touching technical correction territory.

In research done by Reuters, (2024) it was shown that the prices of oil, natural gas, wheat, and corn spiked in the first 6 months of the war, and natural gas is still spiking during the analyzed period. As for the volatility of the stocks and oil, it spiked right after the invasion.

U et al., (2024) employed a Baruník and Křehlík's frequency-dependent variance decomposition to investigate the effects of the conflict on volatility spillovers in financial markets and found that "the long-term component of volatility spillover between the stock markets, currency markets, commodity market and energy market increases, while short- and medium-term components decrease" (U et al., 2024: p.16). This indicates that the investors believe that the shock may last for a long time. The authors also concluded that "the relationship between the strength of the conflict and the volatility spillovers is strong at the onset of war and becomes weaker after investors recognize that the conflict will persist as an enduring war" (U et al., 2024: p.16).

3.3. The impact of other geopolitical events on the financial markets volatility

Choudhry, (1997) conducted an empirical work using monthly stock indexes from Canada, Denmark, Sweden, Switzerland, the United Kingdom and the United States from January 1926 to December 1944, which refers to the time period between the great depression and the second World War, to investigate the stock returns volatility and the effects of the short-run deviations between stock indices on stock returns volatility on these markets. Choudhry, (1997) applied two different models, a GARCH (1,1) and a GARCH (1,1)-X, on the six different series. Both tests also included dummy variables to account for the possible structural shifts of the unconditional variance during the depression years and the leverage effect, which implies that positive and negative innovations of the same magnitude have different effects on the conditional variance. The results from the GARCH (1,1)-X model indicate a significant effect imposed by the deviations on the volatility in some of the stock markets under study. These results suggest that more precise forecasts of changes in stock prices may be obtained. Results from both models also imply an ARCH effect, but these effects were not found to be very explosive, and there was also strong evidence of permanent shocks to volatility. Some evidence of the structural shift in the unconditional variance due to the depression is also found, while very little support is found for the leverage effect.

Choudhry, (2010) investigates the impacts of the Second World War on the Dow Jones Industrial Index. To do that, he applied a structural shift test provided by Zivot and Andrews (1992) on the daily average index movement and returns volatility from 1 January 1939 until 31 December 1945. Choudhry, (2010) main conclusions were that the events from the war affected the index stock prices and returns volatility. Also, every time there was news that the war would prolong, there was a drop in the prices and a rise in volatility, but news seen as good for the investors, like the Allies forces victories, tended to increase the price and lower the volatility.

Schwert, (2011) studied the impact of the 2008 crisis, which was a major disruption to the financial sector. One of the most visible indicators of the crisis that captured the attention of the public was the high level of stock return volatility. Schwert, (2011) study showed that the spike of volatility in many countries was highest among stocks in the financial sector, but high market-wide. It also concluded that the volatility returned to normal levels within months.

Chaudhary et al. (2020) analyzed the impact of the Covid-19 pandemic on the returns and volatility of the stock market indices of ten countries: the US, China, Japan, Germany, India, the UK, France, Italy, Brazil, and Canada. To understand this particular impact, the authors applied a GARCH (1,1) model on daily returns of each of the market indices from January 2019 to June 2020. The results of the econometric model showed that COVID-19 increased the volatility of the indices. The results also showed daily negative mean returns for all indices, from January 2020 to June 2020, also. During the second quarter of the COVID period, the markets bounced back, but the volatility remains higher than in normal periods.

Khan et al. (2023) examined the market volatility and asymmetric behavior from six different markets: Bitcoin, EUR, S&P 500, Gold, Crude Oil, and Sugar. For this study, the authors applied 3 different econometric models, GARCH (1,1), EGARCH (1,1), and GJR-GARCH (1,1), on daily time series that range from 27 November 2018 to 15 June 2021. The authors found that the volatility persistence was high in all the samples during the pandemic; also, gold had an insignificant asymmetric effect on the volatility, while crude oil and the S&P 500 had a positive asymmetric effect during COVID.

Khan et al., (2024) carried out a study where they examined the impact of the COVID-19 pandemic on the stock market volatility, examining data from 1st of January 2016 to 31st of December 2021. The results of the GARCH (1,1) model indicated that the ARCH and GARCH term coefficients were positive and significant in all markets, suggesting that both more recent and older news have a similar impact on the conditional variances of the markets, which means that the shocks of conditional variance take a long time to die away. The results for the GARCH (1,1) with COVID-19 as an exogenous dummy variable in the mean and variance equations indicated that the corresponding coefficient was both positive and highly significant for most of the sample markets. This indicates that the COVID-19 pandemic led to a significant increase in the stock market volatility; however, the magnitude of the impact varied across sample markets, which can be explained by the different stages of the pandemic outbreaks. Another model that was used by Khan et al. (2024) was a TGARCH (1,1), with COVID-19 as a dummy variable, that confirmed the results of the GARCH (1,1). Besides that, it also revealed that the coefficient for COVID-19 in the variance equation had a significant positive impact on the conditional variance for the markets, which implies that the pandemic resulted in an overall increase in stock market volatility.

Notably, there have been a lot of studies and work done about the impact of the Russian and Ukrainian war, and other geopolitical events, on the financial markets volatility. However, the research done so far about this topic does not address the impact of the war on sectorial indexes. With the understanding of the impact on the sectorial indexes, one will be able to understand which sectors experienced the most volatility caused by the war, and with that, which ones should be the best ones to invest in during these times of crisis. This thesis will help us understand what the impact of the war on the sectorial index's volatility was, but also help confirm or contradict the research already done by the scientific community on the impact of the war on the stock and commodities markets. Besides that, from a government point of view, it will be possible to understand which sectors might need more support.

4. Data and Methodology

The main variables for this study will be divided into two groups: the main stock indexes and the sectoral indexes. The stock index variables that will be used in this study will be the S&P 500 and the STOXX 600. The S&P 500 represents the five hundred biggest companies of the US, while the STOXX 600 represents the six hundred biggest companies of Europe, both European Union and non-European Union countries, like the United Kingdom. Inside the S&P 500, there are companies like NVIDIA, Tesla, and Amazon, while in the STOXX 600, there are companies like Telecom, BP, and Santander.

The variables chosen to understand the impact of the Russian-Ukrainian war on the volatility of stocks in different sectors are the following indexes: S&P500 Energy, S&P500 Industrials, S&P500 Materials, S&P500 Consumer Staples, and S&P500 Financials, the EURO STOXX Banks, EURO STOXX Insurance, EURO STOXX Industrials, EURO STOXX Oil & Gas, and EURO STOXX Food & Beverage. With these indices, it will be possible to understand which sectors were the most affected, both in the US and Europe.

The periodicity of the data will be daily closing prices and the period spans from 24 February 2021 to 23 February 2023, where the comparison will be made between the period between 24 of February of 2021 and 24 of February of 2022 and the period between the 24 of February 2022 and 24 of February 2023, which will make a comparison of the volatility one year before the war started and one year after the beginning of the war. All the data will be taken from Investing.com[5].

The methodology used is very similar to the one in Khan et al., (2024), but now applied to the Russian-Ukrainian war.

The daily returns of the market's indexes will be calculated using the logarithmic returns formula:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \qquad (1)$$

where R_t is the return of the index at the end of day t, P_t is the closing price of the index on day t, P_{t-1} represents the closing price of the index on the previous day, and *ln* represents the natural logarithm.

[5] https://www.investing.com/

The stationarity of the prices and returns will be studied first to understand if it is necessary to apply the first differences. The stationarity tests that will be used include the ADF test presented by Dickey & Fuller, (1979), the PP test proposed by Phillips & Perron, (1988)and the KPSS test suggested by Kwiatkowski et al., (1992). The values in **Table 1** represent the values of the test statistics, which. At a 10%, -2,57 is the critical value for the ADF tests, -2,569977 for the PP test, and 0,119 for the KPSS test.

Table 1 - Stationarity Tests

	Stationarity Tests					
	Closing Values			Returns Values		
	ADF	PP	KPSS	ADF	PP	KPSS
S&P 500	-2,10005	-2,0128	1,2605	-16,736	-22,5731	0,0568
S&P 500 Financials	-2,3599	-2,2463	1,0063	-16,6783	-22,0126	0,0701
S&P 500 Industrials	-2,6115	-2,4802	0,6279	-16,5972	-21,8939	0,0728
S&P 500 Materials	-2,7967	-2,6955	0,6842	-15,8901	-21,5522	0,0529
S&P 500 Energy	-1,1835	-1,1318	0,4365	-16,1341	-22,0735	0,0508
S&P 500 Consumer Staples	-3,3294	-3,0137	0,9703	-16,5451	-21,577	0,0294
STOXX 600	-2,3817	-2,2394	0,9345	-16,387	-22,4677	0,0991
STOXX 600 Banks	-1,7155	-1,797	0,6559	-16,4194	-22,7668	0,0905
STOXX 600 Insurance	-2,397	-2,355	0,5369	-16,941	-22,7211	0,0586
STOXX 600 Industrial	-1,7372	-1,6459	0,8996	-16,4127	-22,1826	0,1168
STOXX 600 Oil & Gas	-1,3423	-1,1325	0,2989	-17,9881	-23,5134	0,0244
STOXX 600 Food & Beverage	-3,1521	-2,8537	1,2254	-16,4416	-23,1363	0,0584

Source: Author.

The daily closing prices don't show a stationary property, something that is possible to understand when looking at the graphics in Chapter 5.1. Since the logarithmic returns values follow from applying the first differences method, the results show that these seem to be stationary, something that was also possible to see in the graphics present in chapter 5.2. From **Annex 13** to **Annex 24** it is possible to find the ACF and PACF graphics of the closing prices, and from **Annex 25** to **Annex 36** the logarithmic returns.

To understand the volatility and the impact the war had on it, a GARCH (1,1) and GJR-GARCH (1,1) specifications will be considered. Since this research will apply GARCH models, it's also important to conduct the ARCH-LM test, with ten lags in this case, to understand if the ARCH effect is present. The results in **Table 2** point to the presence of ARCH effects, with the only exception being the S&P 500 Consumer Staples. Even though the ARCH-LM test doesn't point to the existence of the ARCH effect, the GARCH models will still be used since it will be important to use the same models for all the data to get a consistent comparison.

Table 2 - ARCH-LM Tests

ARCH-LM Tests (ten lags)	
Index	***p-value***
S&P 500	2,81E-05
S&P 500 Financials	4,15E-02
S&P 500 Industrials	1,01E-02
S&P 500 Materials	6,20E-04
S&P 500 Energy	5,35E-02
S&P 500 Consumer Staples	2,15E-01
STOXX 600	1,55E-07
STOXX 600 Banks	9,40E-15
STOXX 600 Insurance	1,12E-08
STOXX 600 Industrial	6,19E-07
STOXX 600 Oil & Gas	1,99E-02
STOXX 600 Food & Beverage	1,16E-12

Source: Author.

The GARCH model, introduced by Bollerslev, (1986), is a parsimonious specification that generalizes the original ARCH model of Engle, (1982). This extension is similar to the transition from an AR model to an Autoregressive ARMA model in traditional time series analysis for the mean. A low-order GARCH model exhibits the same properties as a higher-order ARCH model while avoiding the challenges of estimating numerous parameters subject to non-negativity constraints.

A linear regression model with GARCH effects of order p and q, GARCH (p,q), can be represented by:

$$y_t = \mu + bx_t + u_t \tag{2}$$

$$h_t = c + \sum_{i=1}^{p} \alpha_i u_{t-i}^2 + \sum_{j=1}^{q} \beta j h_{t-j} \tag{3}$$

The conditional variance effect of GARCH is described by the second equation. In this study, it was assumed that the u_t errors follow a normal distribution.

As for the GARCH (1,1), which will be the model used in this study, the conditional variance equation is given by:

$$h_t = c + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1} \tag{4}$$

where *ht* represents the conditional variance at time *t*, α_1 denotes the ARCH term coefficient, and β the GARCH term. The time-varying volatility is influenced by its own lagged conditional variance h_{t-1}, and the lagged squared errors u^2_{t-1}. The ARCH term α measures how the market reacts to shocks in returns, while the GARCH term β reflects the persistence of these shocks and the time required for their effects to dissipate.

A dummy variable, *War,* will be added to the equation to analyze the impact of the war on the markets, which assumes a value of 0 for the pre-war period (24 February 2021 to 23 February 2022) and a value of 1 for the war period (24 February 2022 to 24 February 2023). The modified GARCH model equation is thereby given by:

$$y_t = \mu + \rho War_t + u_t \tag{5}$$

$$h_t = c + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1} + \xi_1 War_t \tag{6}$$

The GJR-GARCH model was proposed by Glosten et al., (1993) and it's an extension of the GARCH model. The GJR-GARCH (1,1) model is given as:

$$h_t = c + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1} + \gamma_1 u_{t-1}^2 \lambda_{t-1} \tag{7}$$

To capture the impact of the war on the volatility, the equation is modified as follows:

$$h_t = c + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1} + \gamma_1 u_{t-1}^2 \lambda_{t-1} + \xi_1 War_t \tag{8}$$

where λ_t takes the value of 1 for $u_t < 0$ (bad news) and 0 when $u_t > 0$ (good news). Good news has an impact of α_1, and the bad news has an impact of $(\alpha_1 + \gamma_1)$. γ_1 is the asymmetry or leverage term. If the coefficient is different than 0, there is an asymmetry in how returns respond to the news; if the value is equal to 0, that would suggest that the return volatility is characterized by symmetry. The models are estimated by maximum likelihood, as is the inference. The information criteria tests from the model are the Akaike information criterion (AIC), Bayes, Shibata, and Hannan-Quinn.

By using the selected indices, it is possible to understand the impact of the war in most regions in the world, and that will give us a good perspective on the impact of the war on the financial markets.

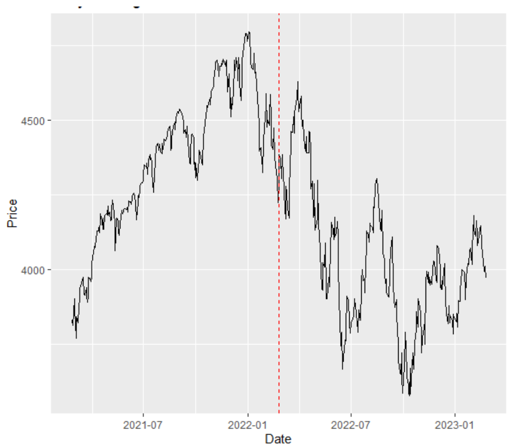
The GARCH model will help understand how big the persistence was in the volatility, the bigger the α and β the greater the persistence. However, this model treats the good news and the bad news the same way. That's why the model GJR-GARCH is incorporated into this study to understand the impact of the good news and the bad news on the volatility.

5. Empirical Analysis

5.1. Graphical Analysis

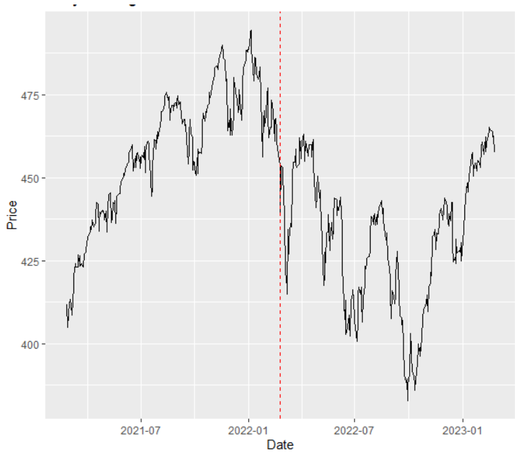
Two types of graphics will be analyzed in this chapter, firstly, the closing prices (**Figure 1** to **Figure 12**) and secondly, the logarithmic first returns graphics (**Figure** *13* to **Figure** *24*).

Figure 1 - Daily closing price of S&P 500



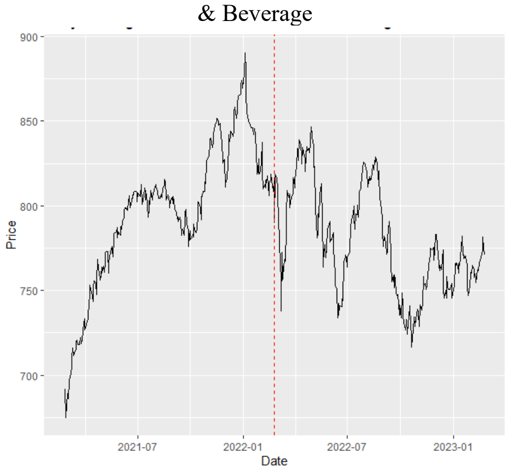
Source: Author.

Figure 2 - Daily closing price of STOXX 600



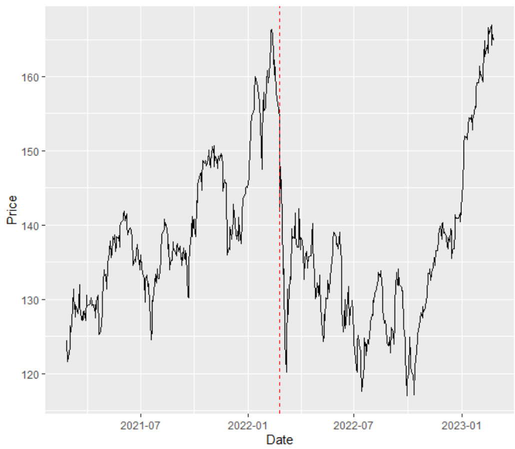
Source: Author.

Figure 3 - Daily closing price of STOXX 600 Food & Beverage



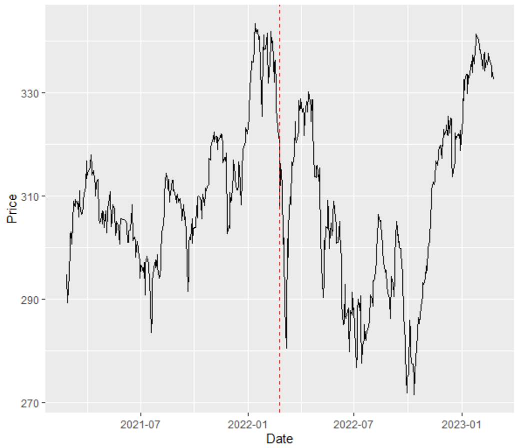
Source: Author.

Figure 4 - Daily closing price of STOXX 600 Banks



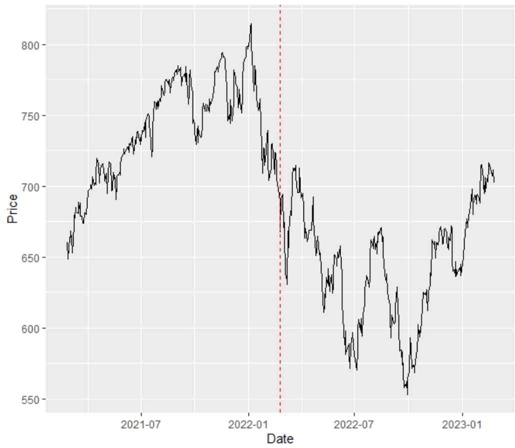
Source: Author.

Figure 5 - Daily closing price of STOXX 600 Insurance



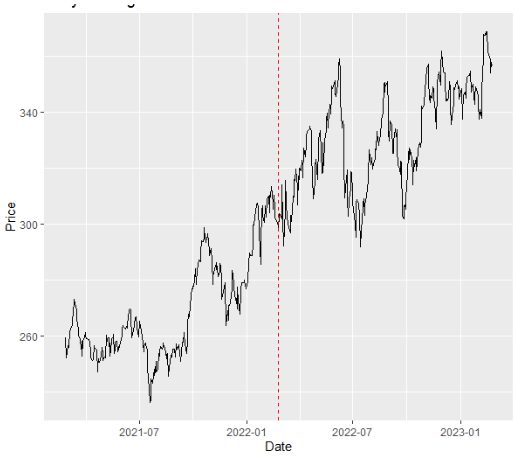
Source: Author.

Figure 6 - Daily closing price of STOXX 600 Industrial



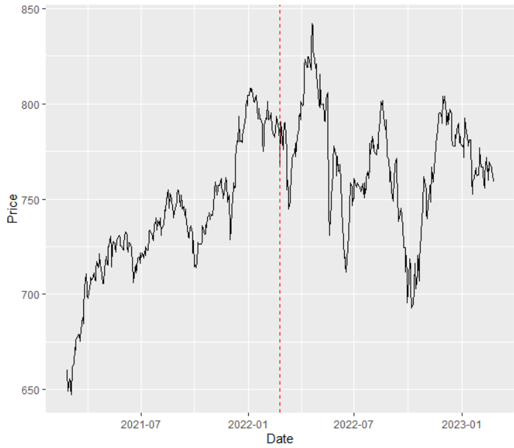
Source: Author.

Figure 7 - Daily closing price of STOXX 600 Oil & Gas



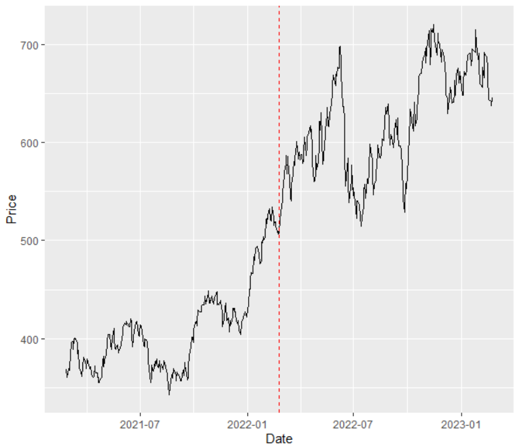
Source: Author.

Figure 8 - Daily closing price of STOXX 600 Consumer Staples



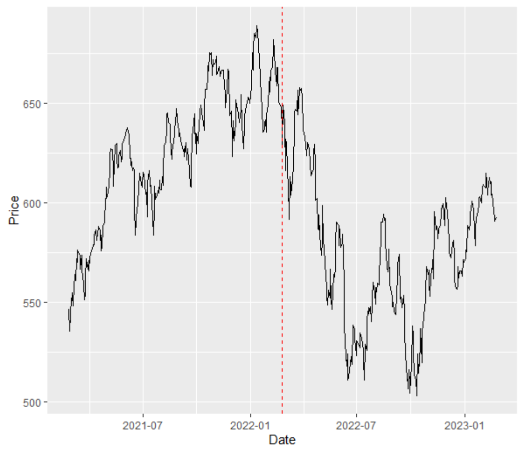
Source: Author.

Figure 9 - Daily closing price of S&P 500 Energy



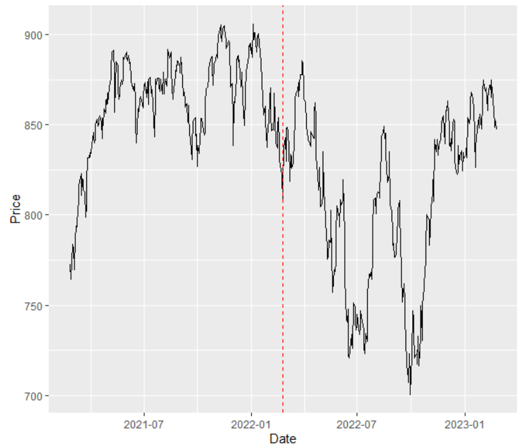
Source: Author.

Figure 10 - Daily closing price of S&P 500 Financials



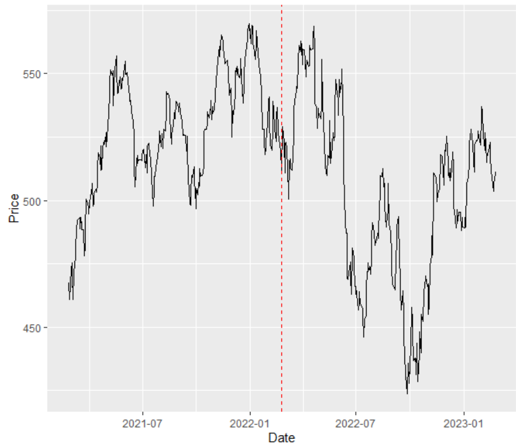
Source: Author.

Figure 11 - Daily closing price of S&P 500 Industrial



Source: Author.

Figure 12 - Daily closing price of S&P 500 Materials

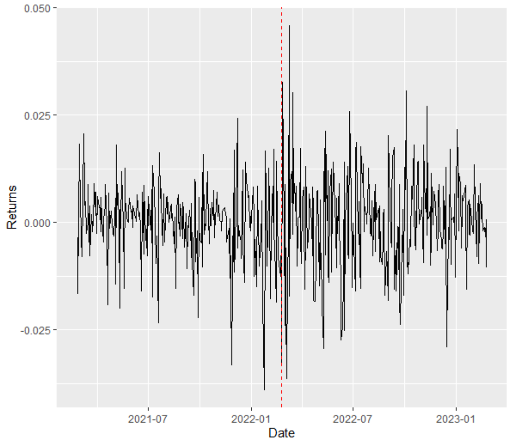


Source: Author.

Regarding the closing prices, it is noticeable that almost all the indexes were following a growing trend before the beginning of the war, with the STOXX 600 Industrials being the only exception, which started a declining trend some months before the war. After the beginning of the conflict, most of the indices started to show a declining trend with a big effect on almost all of the STOXX 600 indexes, which can be explained by the proximity to the conflict. The exceptions to this fall in stock prices were the STOXX 600 Oil & Gas and the S&P 500 Energy, which can be explained by the fact that Russia was one of the biggest players on the energy market. Because of the sanctions, most countries decided to look for other options for energy supply, with some of those options being in Europe and the USA, raising the sales of the companies present in that index and consequently their value on the stock market.

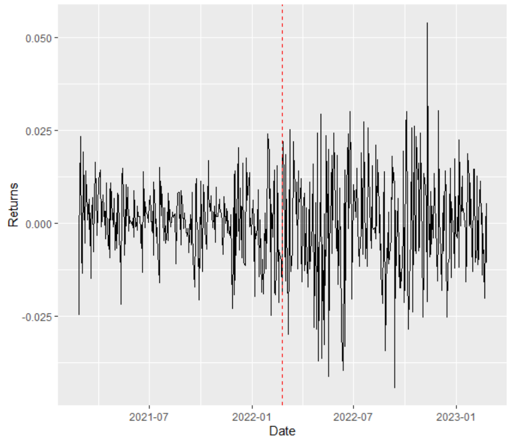
It is also noticeable that the S&P 500 Consumer Staples and STOXX 600 Food & Beverage recovered and adapted more quickly than the other indexes and sectors. This is because the companies in this index are part of a defensive sector, which means that people still buy this product even during a crisis. At first glance, it is also notable that the daily closing prices are a non-stationary series.

Figure 13 - STOXX 600 Returns



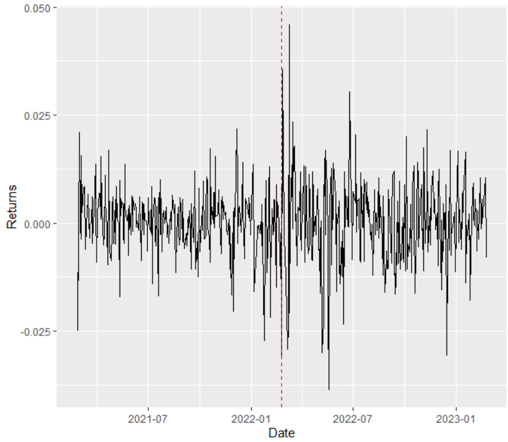
Source: Author.

Figure 14 - S&P 500 Returns



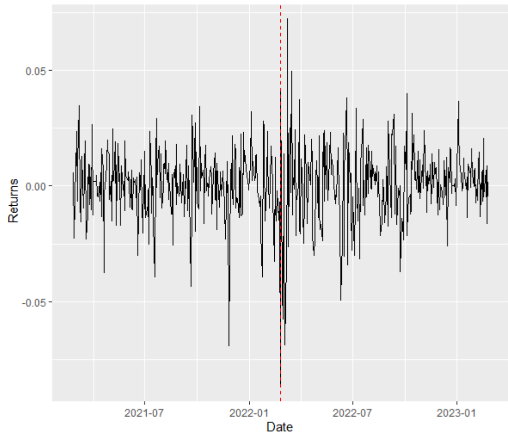
Source: Author.

Figure 15 - STOXX 600 Food & Beverage



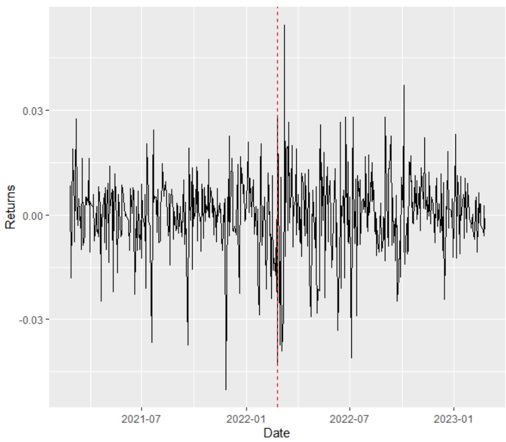
Source: Author.

Figure 16 - STOXX 600 Banks Returns



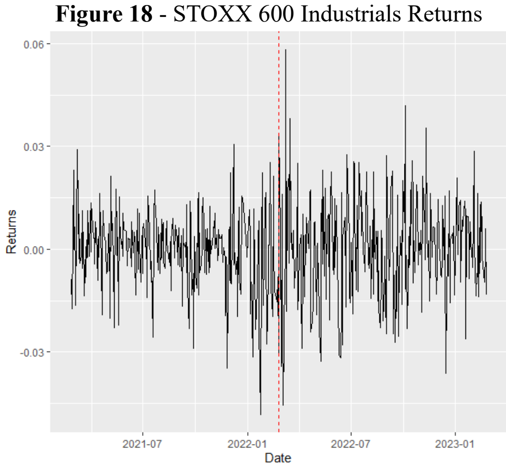
Source: Author.

Figure 17 - STOXX 600 Insurance Returns



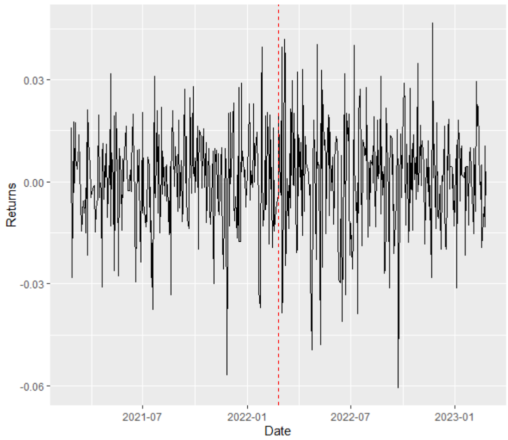
Source: Author.

Figure 18 - STOXX 600 Industrials Returns



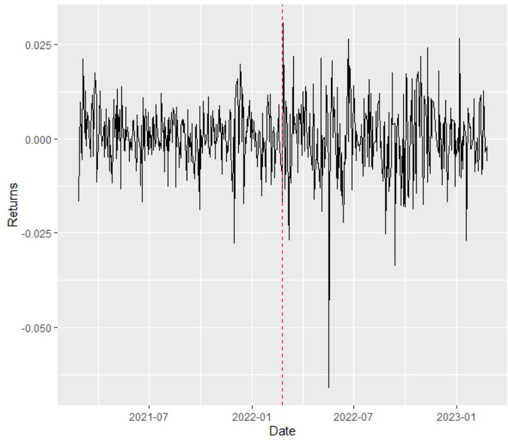
Source: Author.

Figure 19 - STOXX 600 Oil & Gas



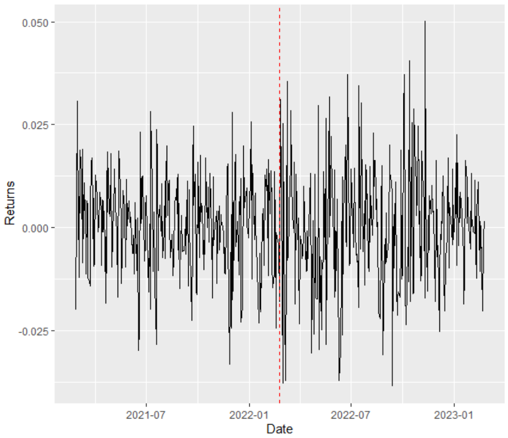
Source: Author.

Figure 20 - S&P 500 CS Returns



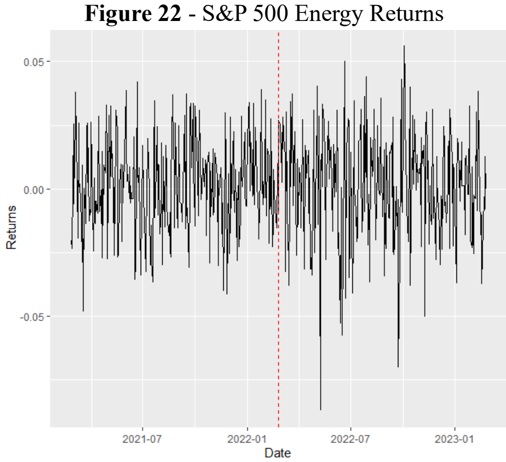
Source: Author.

Figure 21 - S&P 500 Financials Returns



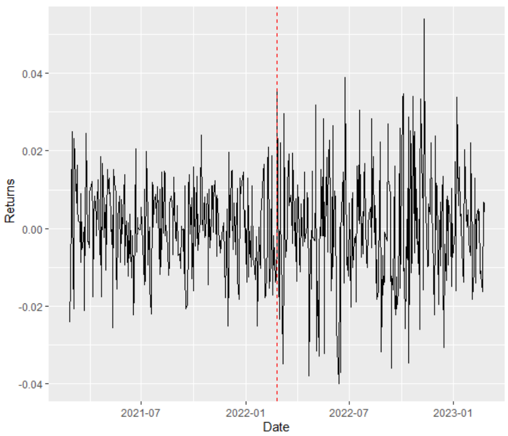
Source: Author.

Figure 22 - S&P 500 Energy Returns



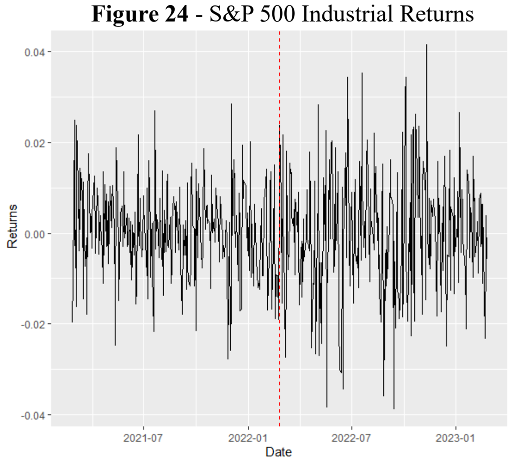
Source: Author.

Figure 23 - S&P 500 Materials Returns



Source: Author.

Figure 24 - S&P 500 Industrial Returns



Source: Author.

When analyzing the logarithmic returns, it is possible to have an understanding of the impact on the volatility; for this, it is important to see the amplitude of the series. For the S&P

500, there is a noticeable increase in the amplitude; the same can be observed for the S&P 500 Materials and S&P 500 Industrials, and as for the other series, we can see that the amplitude is bigger but didn't have the same impact. For example, the STOXX 600 Food & Beverage and the S&P 500 Consumer Staples have some spikes after the beginning of the conflict, but maintain a very similar amplitude. This confirms that for defense sectors, the impacts are not as big as in other sectors, and therefore, the volatility won't escalate as much.

In terms of the main indexes, the S&P 500 and the STOXX 600, it looks like the one that suffered a bigger impact on the volatility was the S&P 500, which can indicate that the American companies suffered the most with the conflict in terms of uncertainty. A final remark is biggest winners in terms of stock values with the war, S&P 500 Energy, and STOXX 600 Oil & Gas, although these sectors seemed to have a big value increase, their volatility also seems to have increased. Contrary to the daily closing prices, the logarithmic returns seem to be a stationary series.

5.2. Descriptive Statistics

By analyzing the tables from **Annex 1** to **Annex 12**, which have the results regarding the descriptive statistics, it is possible to understand that there was a fall in the sample averages of almost all the indexes, which can imply that there was a general decrease in the returns of the assets. Other values that should be taken into consideration are the Maximum and Minimum. In almost every index, there is an increase in the maximum values and a fall in the minimum values, which can mean that the conflict generated big falls and increases in the assets and a bigger amplitude, which can indicate an increase in the volatility.

As for the Skewness, it is noticeable that its value increased in all the indexes from one period to another. In some of them, the values turned from negative to positive, which means that the larger returns are more likely than the smaller ones after the invasion. It is also clear that the distribution is more pronounced to its right. As for the Kurtosis, the bigger it is, the bigger the probability of shocks in the markets, which can indicate that the volatility might be affected because of the war. The results show that the Kurtosis increased for every American stock, while for the European stocks, it declined in all except for the STOXX 600 Banks. This can mean the probability of shocks fell from one period to the other, which can be explained by a more cautious approach from investors since the war is happening on European soil.

The Standard Deviation increased in all the indexes, which means that the values were more scattered from the mean and can imply that there was more fluctuation from the values, and therefore, the volatility probably increased from one period to another. As for the JB-tests, in most of the analyzed variables, the results point to a non-normal distribution.

In **Table 3** it’s possible to find the correlations between all the indices. A first look into the S&P 500 correlations with its sectorial indexes, it is possible to see that the financial, industrial, and materials sectors are the ones with the largest correlations with the main index. This can be explained by the composition of the S&P 500; the financial sector comprises around 13% of the S&P 500, while the industrial sector comprises close to 9% of the S&P 500. This means that the companies from these sectors contribute a lot to this index, for example, in the financial index, it’s possible to find companies like VISA or JPMorgan, and in the Industrial index, we find, for example the UPS.

Something that can explain the big correlation between the S&P 500 Financials and the S&P 500 is the fact that most of the companies that compose the Financials index are banks. When economic activity is booming, the companies will be able to get more loans and investments, which will benefit the banking sector, since they will get more gains with interest. The opposite is also true.

As for the Energy and Consumer Staples sectors, they represent a very small percentage of the S&P 500, which explains the small correlation. Also, the Consumer Staples is a more defensive sector; it won’t have a similar behavior to the economic cycle as other companies in the Index.

As for the STOXX 600, the correlation is similar to what happens in the American indexes, a big correlation with the financial and industrial sectors, and a weak one with the energy sector.

Table 3 - Correlation

	S&P 500	S&P 500 Financials	S&P 500 Industrials	S&P 500 Materials	S&P 500 Energy	S&P 500 Consumer Staples	STOXX 600	STOXX 600 Banks	STOXX 600 Insurance	STOXX 600 Industrials	STOXX 600 Oil & Gas	STOXX 600 Food & Beverage
S&P 500	1	0,8245771	0,8749528	0,830865	0,43269	0,6649615	0,5249291	0,350323	0,363093	0,53141	0,2201307	0,3418022
S&P 500 Financials	0,824577	1	0,8732454	0,838681	0,51199	0,6004342	0,5754049	0,585088	0,546631	0,5526854	0,3386384	0,37817858
S&P 500 Industrials	0,874953	0,8732454	1	0,882359	0,50852	0,6778608	0,5149367	0,410506	0,433032	0,5276098	0,2821656	0,33086813
S&P 500 Materials	0,830865	0,8386814	0,8823588	1	0,52026	0,6207942	0,5730654	0,449025	0,471235	0,5647487	0,3126907	0,35894552
S&P 500 Energy	0,432692	0,5119899	0,5085173	0,520262	1	0,2496875	0,2946899	0,318091	0,292458	0,2327531	0,6533742	0,06117048
S&P 500 Consumer Staples	0,664962	0,6004342	0,6778608	0,620794	0,24969	1	0,3351985	0,231193	0,233987	0,2991073	0,0607806	0,39123638
STOXX 600	0,524929	0,5754049	0,5149367	0,573065	0,29469	0,33519845	1	0,766458	0,831324	0,9482049	0,5174545	0,73944479
STOXX 600 Banks	0,350323	0,585088	0,4105064	0,449025	0,31809	0,23119275	0,7664581	1	0,852164	0,6836892	0,499779	0,46552167
STOXX 600 Insurance	0,363093	0,5466307	0,4330317	0,471235	0,29246	0,23398697	0,8313238	0,852164	1	0,7501571	0,5012764	0,56670508
STOXX 600 Industrials	0,53141	0,5526854	0,5276098	0,564749	0,23275	0,29910728	0,9482049	0,683689	0,750157	1	0,4070165	0,65201522
STOXX 600 Oil & Gas	0,220131	0,3386384	0,2821656	0,312691	0,65337	0,06078061	0,5174545	0,499779	0,501276	0,4070165	1	0,18604806
STOXX 600 Food & Beverage	0,341802	0,3781786	0,3308681	0,358946	0,06117	0,39123638	0,7394448	0,465522	0,566705	0,6520152	0,1860481	1

Source: Author.

5.3. GARCH (1,1) with dummy results and analysis

In the conditional mean equation (**μ**), the null hypothesis states that there is no statistically significant average return, whereas under the alternative hypothesis, the average return is significantly different from zero. Regarding the coefficient associated with the event dummy in the mean equation (**ρ**), the null hypothesis posits that the event does not affect mean returns, while the alternative hypothesis asserts that the war significantly affects the conditional mean. In the constant term of the variance equation (**c**), the null hypothesis assumes the absence of a constant component in the conditional variance, whereas the alternative hypothesis indicates the presence of such a component. For the ARCH (**α**) and GARCH (**β**) parameters, the null hypothesis specifies that no ARCH or GARCH effects are present; under the alternative hypothesis, these effects are statistically significant, implying volatility clustering. Finally, for the dummy variable in the variance equation (**ξ**), the null hypothesis states that the war has no impact on the conditional variance, while the alternative hypothesis suggests that the war induces a significant change in volatility.

The constant variance term, the ARCH, and GARCH terms are all positive for all the indexes, confirming the existence of the ARCH and GARCH effect. The positive ARCH term means that the recent news had a significant impact on the market's volatility, and the GARCH term represents the distant news, and the positive value means that the distant news had a significant impact on the stock market's volatility. The GARCH term has a big value in most of the indexes, which means that the volatility was persistent and the shocks on the conditional variance took time to fade away. The results of the European indexes indicate that they were more affected and have a more persistent volatility, which can be explained by the sanctions imposed on Russia, which affected the energy market, mainly the oil and gas market, and mostly the European countries. Looking into the sum of the GARCH and ARCH terms (**α + β**), it is noticeable that most of the results are very close to 1, apart from the S&P 500 Industrials and the S&P 500 Materials, which means that a shock at a specific time will remain for a long time, this can indicate that the persistence of volatility and shocks led to a permanent change on the conditional variance.

Table 4 - GARCH (1,1) with war variable results

	S&P 500	S&P 500 Financials	S&P 500 Industrials	S&P 500 Materials	S&P 500 Energy	S&P 500 Consumer Staples	STOXX 600	STOXX 600 Banks	STOXX 600 Insurance	STOXX 600 Industrial	STOXX 600 Oil & Gas	STOXX 600 Food & Beverage
μ	0,000681 (1,44089)	0,00061 (0,94869)	0,000321 (0,59615)	0,000377 (0,582327)	0,001302 (1,2156)	0,000599 (1,55023)	0,000742 (1,55539)	0,001084 (1,263379)	0,000212 (0,34725)	0,000795 (1,591)	0,000526 (0,741303)	0,000669 (1,54719)
ρ	-0,000542 (-0,50877)	-0,000205 (-0,16932)	0,000123 (0,11537)	0,000106 (0,088081)	-0,000196 (-0,1167)	-0,000577 (-0,72155)	-0,000132 (-0,15562)	0,000304 (0,225451)	0,000588 (0,60299)	-0,000227 (-0,43298)	0,000147 (0,132003)	-0,000525 (-0,83555)
c	0,000006 (6,86417)	0,000038 (1,41573)	0,00004 (2,21823)	0,000041 (1,509993)	0,000057 (3,5731)	0,000014 (7,86089)	0,000009 (5,90902)	0,000023 (5,024284)	0,000016 (3,16338)	0,000011 (6,38556)	0,000003 (0,129657)	0,000008 (13,47597)
α	0,105215 (10,71098)	0,150484 (2,57397)	0,156143 (2,1762)	0,100421 (1,931468)	0,038775 (1,2832)	0,065787 (1,65669)	0,202488 (13,85114)	0,085011 (3,475283)	0,110281 (4,23301)	0,147885 (5,71635)	0,018225 (45,303148)	0,112298 (11,61251)
β	0,812098 (34,89681)	0,56426 (2,29856)	0,41536 (1,71598)	0,5278 (1,941423)	0,784255 (13,2856)	0,630553 (6,14606)	0,699317 (29,81535)	0,817177 (19,164155)	0,767614 (7,97423)	0,764559 (24,3943)	0,970716 (26,534477)	0,751763 (37,23621)
(α + β)	0,917313	0,714744	0,571503	0,628221	0,82303	0,69634	0,901805	0,902188	0,877895	0,912444	0,988941	0,864061
ξ	0,000015 (8,71002)	0,000028 (1,05012)	0,000045 (1,84267)	0,000053 (1,293923)	0,000028 (2,0568)	0,000024 (2,01507)	0,000005 (93,64942)	4,72E-13 (0,1E-5)	0,12E-13 (0,1E-5)	0,000013 (9,85237)	1,116E-13 (1,222E-4)	0,000006 (129,52455)
AIC	-6,1241	-5,8142	-6,0701	-5,8393	-4,9722	-6,6081	-6,464	-5,53	-6,1403	-5,8839	-5,491	-6,6507
Bayes	-6,0738	-5,7639	-6,0198	-5,7891	-4,922	-6,5578	-6,4137	-5,4797	-6,09	-5,8337	-5,4408	-6,6004
Shibata	-6,1244	-5,8145	-6,0704	-5,8396	-4,9725	-6,6084	-6,4643	-5,5303	-6,1405	-5,884	-5,4913	-6,651
Hannan-Quinn	-6,1044	-5,7945	-6,0504	-5,8196	-4,9525	-6,5884	-6,4443	-5,5103	-6,1205	-5,8642	-5,4713	-6,631

Source: Author.

For most indexes, the Dummy variable's coefficient (ξ) seems to indicate that most of them are statistically significant and positive, which means that the war had a big impact on the stock market volatility. With the exception being the European financial sector and the Oil & Gas sector, such a small result of the point estimates seems to indicate that the war had no impact on the volatility of these sectors.

By analyzing the results of the Ljung-Box tests, standardized (**Annex 37** and **Annex 38**) and standardized squared (**Annex 39** and **Annex 40**), all the results point to the absence of correlation at least until lag 9. Regarding the ARCH-LM (**Annex 41** and **Annex 42**), it didn't show evidence of a deterioration of the model in most of the indexes. Finally, regarding the results of the Sign Bias Test (**Annex 43** and **Annex 44**), where the H_0 represents the inexistence of sign bias in the conditional variance and H_1 represents that at least one form of sign bias is present and the model fails to capture the asymmetric impact, show that for most of the indexes the GARCH with dummy can capture the volatility since the p-values of the Joint Effect, which are between parentheses, are above 0,05 and therefore not significant, with the only exception being the S&P 500 Financials.

5.4. GJR-GARCH (1,1) with dummy results and analysis

The final model to consider is a GJR-GARCH (1,1) model with a war variable, which has its results presented on **Table *5***, also with the estimated point values, and between parentheses the t-value. Regarding the asymmetric term (γ), the null hypothesis states that there is no asymmetry in the volatility response to positive and negative shocks. Conversely, the alternative hypothesis posits the presence of an asymmetric effect, implying that negative shocks have a different impact on conditional volatility than positive shocks of the same magnitude.

The ARCH and GARCH terms are all positive for all the indexes and statistically significant, indicating the presence of ARCH and GARCH effects. The positive values for the ARCH models and GARCH models also suggest that the recent and distant news had a significant impact on the market's volatility. The sum of the GARCH and ARCH models also shows that the persistence of volatility and shocks leads to a permanent change in the conditional variance. The GJR-GARCH model confirms the GARCH model results regarding the distant and recent news.

The asymmetric term is significant in most of the markets, which indicates that there are asymmetric effects for news in these markets, with the bigger values on the American energy and the European industrial sector. These results also show that the negative shocks had a bigger impact on the conditional variance as compared to good news, and that the impacts are different in each sector. The only sectors where there is evidence of an asymmetrical effect are the S&P500 main Index, the American energy sector and the European industrial sector, which means that the good and bad news had similar impacts. When analyzing the coefficient that represents the war (ξ), it is possible to see that it is statistically significant for almost all the samples, which confirms that the war had a (positive) impact on the volatility of the selected markets. In the case of the main S&P 500 index and the Industrial sector in Europe, it is possible to say that even though there wasn't an asymmetric effect, there was a structural change in volatility. These results confirm the ones from the previous GARCH model.

Finally, regarding the model quality, and just like the other model, the results of the Ljung-Box tests (**Annex 37**, **Annex 38**, **Annex 39** and **Annex 40**) point to the absence of correlation at least until lag 9. The ARCH-LM (**Annex 41** and **Annex 42**) indicates the inexistence of conditional heteroscedasticity.

As for the information criteria, when comparing with the other models, the GJR-GARCH (1,1) with a war variable fits the data in the analysis better. Finally, regarding the results of the Sign Bias Test (**Annex 43** and **Annex 44**), the values have improved when compared with the ones from the GARCH model, which means that this particular model is better at capturing the volatility.

Table 5 – GJR-GARCH (1,1) with war variable results

	S&P 500	S&P 500 Financials	S&P 500 Industrials	S&P 500 Materials	S&P 500 Energy	S&P 500 Consumer Staples	STOXX 600	STOXX 600 Banks	STOXX 600 Insurance	STOXX 600 Industrial	STOXX 600 Oil & Gas	STOXX 600 Food & Beverage
μ	0,00028 (0,59853)	0,000292 (0,45596)	-0,000198 (-0,39411)	0,000075 (0,115696)	0,001137 (1,050095)	0,000361 (1,04239)	0,000342 (0,98478)	0,001326 (1,67694)	0,000178 (0,34397)	0,00023 (1,3652)	0,001028 (1,12709)	0,0005 (2,2242)
ρ	-0,000783 (-0,84013)	-0,000701 (-0,66321)	0,000134 (0,13302)	0,000015 (0,012479)	-0,000061 (-0,036137)	-0,000483 (-0,64325)	-0,000179 (-0,26832)	-0,000463 (-0,36791)	0,000106 (0,11338)	-0,000308 (-0,37557)	-0,001344 (-0,71574)	-0,000844 (-1,3116)
c	0,000568 (2,88122)	0,001065 (0,91712)	0,000976 (1,6803)	0,000987 (0,629018)	0,002964 (2,86732)	0,00075 (2,34706)	0,000998 (4,35457)	0,001409 (4,85614)	0,001093 (3,48163)	0,001134 (3,50043)	0,000035 (0,30909)	0,000625 (1,8262)
α	0,092623 (5,9082)	0,080849 (1,63844)	0,077346 (3,29856)	0,055926 (1,809577)	0,038787 (2,330002)	0,061081 (2,00808)	0,132561 (7,31764)	0,112162 (5,04596)	0,099369 (5,46654)	0,110251 (5,55779)	0,027966 (3,43509)	0,080428 (3,1848)
β	0,859513 (29,53467)	0,845132 (6,0465)	0,836938 (11,36814)	0,862507 (5,018385)	0,804236 (13,556838)	0,850345 (14,23435)	0,781891 (25,0817)	0,81825 (23,91581)	0,825893 (24,44623)	0,803797 (20,84293)	0,977 (298,3906)	0,857792 (14,4178)
(α + β)	0,952136	0,925981	0,914284	0,918433	0,843023	0,911426	0,914452	0,930412	0,925262	0,914048	1,004966	0,93822
ξ	1 (4,41499)	1 (2,38915)	1 (3,48158)	1 (2,629916)	1 (1,430052)	0,999998 (1,92519)	1 (5,50747)	0,999991 (4,77632)	0,999994 (4,24754)	1 (4,40771)	0,999745 (1,66137)	1 (2,9571)
γ	0,000497 (2,38011)	0,000266 (0,6752)	0,000465 (1,60205)	0,000472 (0,594762)	0,000677 (2,042701)	0,000393 (1,68433)	0,000217 (1,16915)	1,875E-12 (8,883E-7)	1,498E-12 (1,028E-7)	0,000555 (2,35764)	0 (7,446E-11)	0,000171 (1,0423)
AIC	-6,1717	-5,8458	-6,0987	-5,8536	-4,976	-6,6162	-6,5545	-5,6194	-6,2189	-5,9391	-5,502	-6,6792
Bayes	-6,1131	-5,7871	-6,04	-5,795	-4,9174	-6,5576	-6,4959	-5,5607	-6,1602	-5,8804	-5,4434	-6,6205
Shibata	-6,1721	-5,8462	-6,099	-5,854	-4,9764	-6,6166	-6,5549	-5,6198	-6,2192	-5,9394	-5,5024	-6,6795
Hannan-Quinn	-6,1487	-5,8228	-6,0757	-5,8306	-4,953	-6,5932	-6,5315	-5,5964	-6,1959	-5,9161	-5,479	-6,6562

Source: Author.

5.5. Conditional volatility graphic analysis

From **Annex 47** to **Annex 58** it is possible to see the conditional volatility graphics for the GARCH (1,1) with a war dummy model. They show that the conditional volatility from the American indexes seems to be more affected by the war than the volatility from Europe.

By analyzing the conditional volatility graphics present from **Figure *25*** to **Figure *36***, which were obtained using the GJR-GARCH (1,1) model, it is possible to see that in all the indexes the conditional volatility increased from the period before the war to the period after the start of the war. The date of the beginning of the war is shown in the red line in all the graphics.

The amplitude in all the indices increased from one period to another, and the maximum and minimum values it reached after the beginning of the war are all higher than the ones reached before the beginning of the conflict. There is an evident sign of asymmetry.

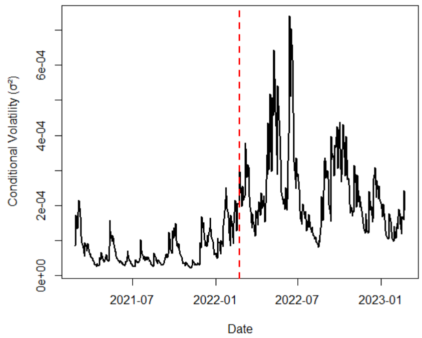
In the previous chapters, it was possible to see that the sum of the ARCH and GARCH being too close to one means that a shock at a specific time will remain for a long time, which indicates the persistence of volatility and shocks leads to a permanent change in the conditional variance. In almost every index, the results were very close to 1, which can be confirmed by the conditional volatility graphics. As it is possible to see in the graphics, volatility only tends to calm down for most of the indexes at the end of 2022 or the beginning of 2023.

It is also interesting to note that between April and May 2022, there is a new spike of volatility in most of the indexes, especially on the American indexes; most of them experience the highest peak of conditional volatility during that time. This can be explained by the increasing prices in many sectors, like the Energy and Food sectors, which led to a peak in inflation.

Lastly, in all of the indexes, it is possible to see that the conditional volatility tends to diminish, which indicates that the markets slowly adapted to the conditions. For the American stocks and the STOXX 600 Oil & Gas index, it was after the period between

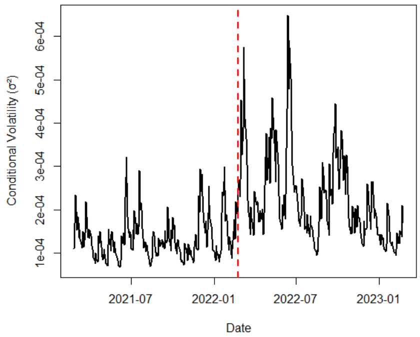
April and June, and for the other European indexes, after the peak of volatility shown in the period, which corresponds to a period between March and the beginning of April.

Figure 25 - S&P 500 Conditional Volatility (GJR)



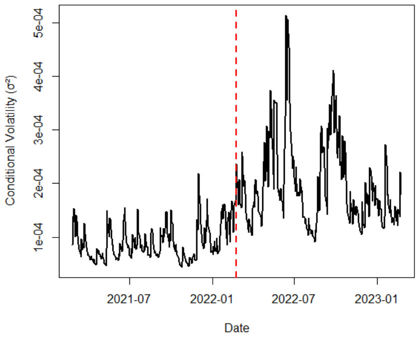
Source: Author.

Figure 26 - S&P 500 Financials Conditional Volatility (GJR)



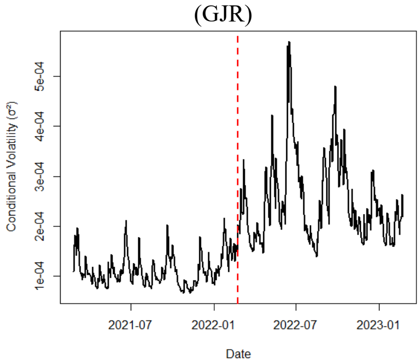
Source: Author.

Figure 27 - S&P 500 Industrials Conditional Volatility (GJR)



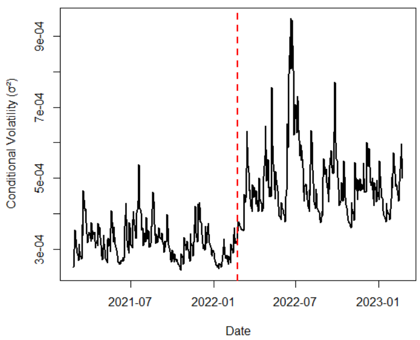
Source: Author.

Figure 28 - S&P 500 Materials Conditional Volatility (GJR)



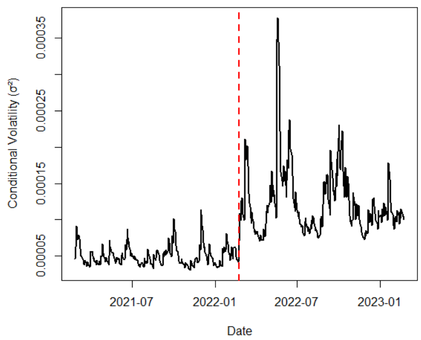
Source: Author.

Figure 29 - S&P 500 Energy Conditional Volatility (GJR)



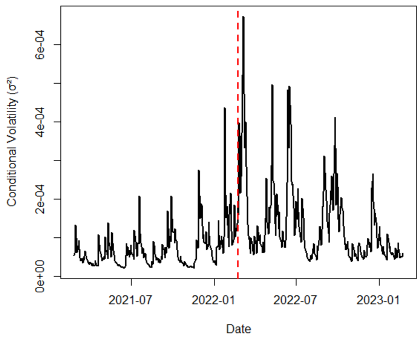
Source: Author.

Figure 30 - S&P 500 CS Conditional Volatility (GJR)



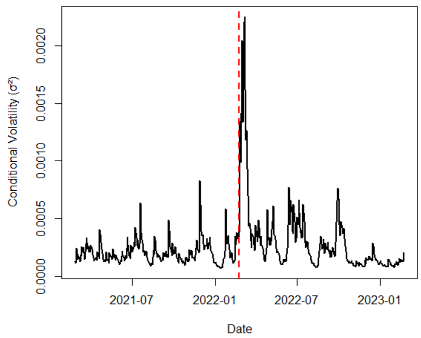
Source: Author.

Figure 31 - STOXX 600 Conditional Volatility (GJR)



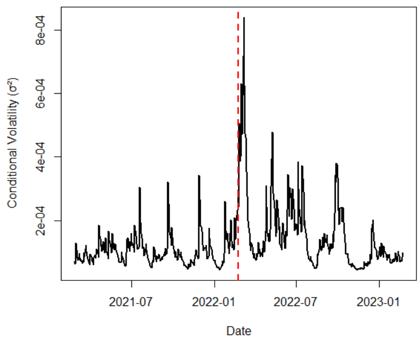
Source: Author.

Figure 32 - STOXX 600 Banks Conditional Volatility (GJR)



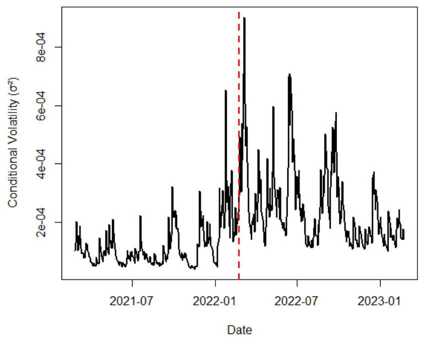
Source: Author.

Figure 33 - STOXX 600 Insurance Conditional Volatility (GJR)



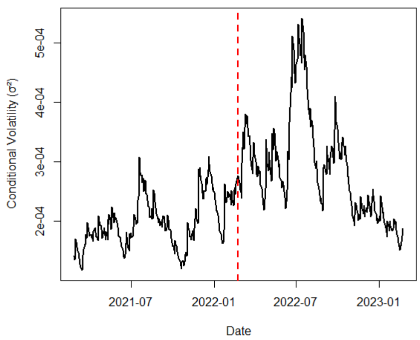
Source: Author.

Figure 34 - STOXX 600 Industrial Conditional Volatility (GJR)



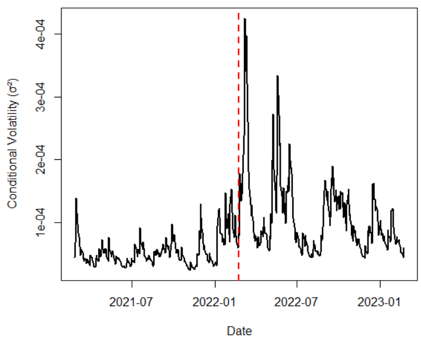
Source: Author.

Figure 35 - STOXX 600 Oil and Gas Conditional Volatility (GJR)



Source: Author.

Figure 36 - STOXX 600 Food & Beverage Conditional Volatility (GJR)



Source: Author.

5.6. Robustness Tests

To ensure that the results obtained aren't specific to this particular scenario or a statistical coincidence, some robustness tests will be performed. These tests will be done by applying the same models as before, GARCH (1,1) with dummy and GJRGARCH (1,1) with dummy, on a different period and with different variables. The period that will be utilized is from 24 October 2021 to 24 June 2022, four months before the start of the war and four months after the beginning of the war. The new variables are the S&P 100, the Dow Jones, and the STOXX 50. Once again, all the data is taken from Investing.com[6]

The results for the GARCH (1,1) with a war variable in **Annex 45** and for the GJRGARCH (1,1) with the war variable in **Annex 46**. The GARCH (1,1) and GJRGARCH (1,1) with dummy are almost all validated since the conclusions are the same. Some exceptions can be seen on some GARCH terms and the dummy variables for the financial sectors from Europe and the Oil & Gas sector from Europe, which can probably be explained by the smaller data period when comparing with the other results.

5.7. Final discussion about the results

At first glance, observing the graph of the daily closing prices, it is possible to see that the war did not prevent prices from continuing their increasing trend. On the negative side, the most affected sectors are the financial ones, with a very big impact on the European ones, the industrial sector, especially in Europe, which shows a decline after the beginning of the war. Regarding indexes such as Consumer Staples and Food & Beverage, the war seems to have an impact, but both indexes seem to recover better than other indexes. Such can be because both S&P 500 Consumer Staples and STOXX 600 Food & Beverage represent companies more related to the defensive sector of the economy, which doesn't get hit during moments of crisis like other sectors.

When it comes to the logarithmic returns, these show that the amplitude in almost all indexes increased from one period to the other. This can indicate an increase in volatility, where once again the defensive sector's indexes seem to have less impact.

The results of the GARCH and ARCH terms show that both recent and distant news have an impact on volatility. The big value of the GARCH term also seems to indicate that the volatility was persistent and the shocks on the conditional variance took time to fade away. The sum of the GARCH and ARCH terms is very close to 1 in most of the indexes. This means that a shock at a specific time will remain for a long time; this can indicate that the persistence of volatility and shocks led to a permanent change in the conditional variance. The indices that showed a bigger value are the main American

[6] https://www.investing.com/

index, S&P 500, the S&P 500 Materials, and the STOXX 600 Oil & Gas. As for the war dummy, they show that the war had an impact on almost all sectoral indexes, with the exception being the European financial sectors and the European Oil & Gas index. The biggest values are for the American industrial and materials indexes.

Finally, the GJR-GARCH (1,1) with a war dummy confirms the conclusion regarding the ARCH and GARCH terms from the previous models. As for the dummy result, they also confirm the findings from the GARCH (1,1) model, and also show that the European financial sectors and the European Oil & Gas index volatility were not impacted by the war. These results also show that the industrials sectors from both the USA and Europe, the energy sector from the USA, the Oil & Gas index from Europe, and the main indexes seem to be the most affected indexes. As for symmetry, the results show the inexistence of asymmetric volatility in the European financial sector and the Oil & Gas index, and, allied with the results from the dummy, show that even though there wasn't an asymmetric effect, there was a structural change in volatility. For most indexes, the negative shocks had a bigger impact on the conditional variance as compared to good news, and these impacts are different in each sector.

Putting all together, it is possible to understand that the most affected sectors by the war were the industrial and financial sectors from both the USA and Europe, and also the main indexes. It is interesting to see that the indexes that seem to be the most affected ones are also the ones that have a bigger correlation, for example, the S&P 500, S&P 500 Financials, and the S&P 500 Industrials.

6. Conclusion

The main objective of this work was to understand the impact of the conflict between Russia and Ukraine on the financial markets, mainly on the European and American sectorial indexes, through the application of two different GARCH models.

It was possible to find a gap in the literature regarding the impact on the sectoral indexes and understand which ones were the most affected by the war. Regarding the main indices representing the European and American markets, the conclusion is the same as in other studies, such as Wu et al., (2023), Yousaf et al., (2023) and Chowdhury & Khan, (2024), the conflict had a big impact on the volatility of the markets. It is also interesting to see that it matches the conclusion of the literature whose main objective was to study the impacts of other crises on the volatility, such as Choudhry, (1997), Chaudhary et al., (2020) and Khan et al., (2023), which found that different crises like the Second World War or the COVID pandemic had a structural impact on the volatility.

To meet the objective of this thesis, two GARCH models were applied, starting with the GARCH (1,1) model with a war dummy, and the GJR-GARCH (1,1) model with a war dummy variable that made it possible to understand the existence of asymmetry in the volatility. The data used was indexes from Europe and America from different sectors to try to understand which one was the most affected, and the period span from 24 February 2021 to 24 February 2023, divided into two periods, 24 February 2021 to 24 February 2022 (one year before the start of the war) and from 24 February 2022 to 24 February 2023 (one year after the beginning of the war).

Most of the results seem to indicate that the war had a big impact on the financial markets, that both close and distant news have an impact on the volatility, and that the negative news seems to have a bigger impact on the volatility than de good ones. Finally, the most affected indices seem to be the financial and industrial ones, together with the main indices, which are also the ones with the largest correlations.

These results can be used by investors to find out which of the sectors are safer to invest in and which ones should be avoided during crises. Also, it will help governments understand which sectors might become more unstable and might need more help. The biggest limitation of this study was the lack of sectoral indices, as more sectors could be important to have a wider understanding of the impact of the war on different sectors.

Future studies can have as their main objective the understanding of why the financial and industrial sectors seem to be the most affected indices, and also whether other indices in the world were affected by the war. It would also be interesting to know which commodities were most affected by the war. To deepen the understanding of the impact of crises on the sectoral indexes, and to study the impact of other crises, like the COVID pandemic or the GFC, on sectoral indexes.

Bibliography

Alam, M. K., Tabash, M. I., Billah, M., Kumar, S., & Anagreh, S. (2022). The Impacts of the Russia–Ukraine Invasion on Global Markets and Commodities: A Dynamic Connectedness among G7 and BRIC Markets. *Journal of Risk and Financial Management*, *15*(8). https://doi.org/10.3390/jrfm15080352

Beraich, M., Amzile, K., Laamire, J., Zirari, O., & Fadali, M. A. (2022). Volatility Spillover Effects of the US, European and Chinese Financial Markets in the Context of the Russia–Ukraine Conflict. *International Journal of Financial Studies*, *10*(4). https://doi.org/10.3390/ijfs10040095

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *31*(3). https://doi.org/10.1016/0304-4076(86)90063-1

Boungou, W., & Yatié, A. (2022). The impact of the Ukraine–Russia war on world stock market returns. *Economics Letters*, *215*. https://doi.org/10.1016/j.econlet.2022.110516

Chaudhary, R., Bakhshi, P., & Gupta, H. (2020). Volatility in International Stock Markets: An Empirical Study during COVID-19. *Journal of Risk and Financial Management*, *13*(9). https://doi.org/10.3390/jrfm13090208

Choudhry, T. (1997). Stock return volatility and World War II: Evidence from Garch and Garch-X models. *International Journal of Finance and Economics*, *2*(1). https://doi.org/10.1002/(SICI)1099-1158(199701)2:1<17::AID-IJFE36>3.0.CO;2-S

Choudhry, T. (2010). World War II events and the Dow Jones industrial index. *Journal of Banking and Finance*, *34*(5). https://doi.org/10.1016/j.jbankfin.2009.11.004

Chowdhury, E. K., & Khan, I. I. (2024). Reactions of Global Stock Markets to the Russia–Ukraine War: An Empirical Evidence. *Asia-Pacific Financial Markets*, *31*(3). https://doi.org/10.1007/s10690-023-09429-4

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the Estimators for Autoregressive Time Series With a Unit Root. *Journal of the American Statistical Association*, *74*(366). https://doi.org/10.1080/01621459.1979.10482531

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, *50*(4). https://doi.org/10.2307/1912773

European Parliament. (2024). *Economic impact of Russia's war on Ukraine: European Council response*. https://www.europarl.europa.eu/thinktank/en/document/EPRS_BRI(2024)757783

Fang, Y., & Shao, Z. (2022). The Russia-Ukraine conflict and volatility risk of commodity markets. *Finance Research Letters*, *50*. https://doi.org/10.1016/j.frl.2022.103264

Food Security Information Network. (2023). *The Global Report on Food Crises 2023*. https://www.fsinplatform.org/global-report-food-crises-2023

GLOSTEN, L. R., JAGANNATHAN, R., & RUNKLE, D. E. (1993). On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *The Journal of Finance*, *48*(5). https://doi.org/10.1111/j.1540-6261.1993.tb05128.x

Izzeldin, M., Muradoğlu, Y. G., Pappas, V., Petropoulou, A., & Sivaprasad, S. (2023). The impact of the Russian-Ukrainian war on global financial markets. *International Review of Financial Analysis*, *87*. https://doi.org/10.1016/j.irfa.2023.102598

Khan, M., Fifeld, S., & Power, D. (2024). The impact of the COVID 19 pandemic on stock market volatility: evidence from a selection of developed and emerging stock markets. *SN Business & Economics*, *4*, 63–89.

Khan, M., Kayani, U. N., Khan, M., Mughal, K. S., & Haseeb, M. (2023). COVID-19 Pandemic & Financial Market Volatility; Evidence from GARCH Models. *Journal of Risk and Financial Management*, *16*(1). https://doi.org/10.3390/jrfm16010050

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. How sure are we that economic time series have a unit root? *Journal of Econometrics*, *54*(1–3). https://doi.org/10.1016/0304-4076(92)90104-Y

Liadze, I., Macchiarelli, C., Mortimer-Lee, P., & Sanchez Juanino, P. (2023). Economic costs of the Russia-Ukraine war. *World Economy*, *46*(4). https://doi.org/10.1111/twec.13336

Manelli, A., Pace, R., & Leone, M. (2024). Russia–Ukraine Conflict, Commodities and Stock Market: A Quantile VAR Analysis. *Journal of Risk and Financial Management*, *17*(1). https://doi.org/10.3390/jrfm17010029

McKinsey & Company. (2023, July 28). *War in Ukraine: Twelve disruptions changing the world—update*.

OCDE. (2022). *Impacts of the Russian Invasion of Ukraine on Financial Market Conditions and Resilience*. https://www.oecd.org/en/publications/impacts-of-the-russian-invasion-of-ukraine-on-financial-market-conditions-and-resilience_879c9322-en.html

Ozili, P. K. (2022). Global Economic Consequence of Russian Invasion of Ukraine. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4064770

Phillips, P. C. B., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, *75*(2). https://doi.org/10.1093/biomet/75.2.335

Reuters. (2024, August 24). *How the Ukraine-Russia war rattled global financial markets*. https://www.reuters.com/markets/europe/how-ukraine-russia-war-rattled-global-financial-markets-2022-08-24/

Schwert, G. W. (2011). Stock Volatility during the Recent Financial Crisis. *European Financial Management*, *17*(5). https://doi.org/10.1111/j.1468-036X.2011.00620.x

U, T. S. C., Lin, Y., & Wang, Y. (2024). The impact of the Russia–Ukraine war on volatility spillovers. *International Review of Financial Analysis*, *93*. https://doi.org/10.1016/j.irfa.2024.103194

Wu, F. lin, Zhan, X. dong, Zhou, J. qi, & Wang, M. hui. (2023). Stock market volatility and Russia–Ukraine conflict. *Finance Research Letters*, *55*. https://doi.org/10.1016/j.frl.2023.103919

Yousaf, I., Hunjra, A. I., Alshater, M. M., Bouri, E., & Li, Y. (2023). Multidimensional connectedness among the volatility of global financial markets around the Russian-Ukrainian conflict. *Pacific Basin Finance Journal*, *82*. https://doi.org/10.1016/j.pacfin.2023.102163

Annexes

Annex 1 - Descriptive Statistic S&P 500

Descriptive Statistic (S&P 500)					
Pre-War Period		**War Period**		**Total Period**	
Mean	2,92E-04	**Mean**	-2,47E-04	**Mean**	2,24E-05
Mode	-5,40E-03	**Mode**	-7,50E-03	**Mode**	-8,00E-04
Median	1,00E-03	**Median**	-1,22E-03	**Median**	-2,05E-04
Maximum	2,41E-02	**Maximum**	5,40E-02	**Maximum**	5,40E-02
Minimum	-2,48E-02	**Minimum**	-4,42E-02	**Minimum**	-4,42E-02
Skewness	-2,97E-01	**Skewness**	-7,19E-02	**Skewness**	-1,52E-01
Std. Dev	8,95E-03	**Std. Dev**	1,50E-02	**Std. Dev**	1,23E-02
Kurtosis	3,354068	**Kurtosis**	3,473326	**Kurtosis**	4,238744
JB-Test	5,017106	**JB-Test**	2,569347	**JB-Test**	34,16344
N	252	**N**	252	**N**	504

Annex 2 - Descriptive Statistic S&P 500 Financials

Descriptive Statistic (S&P 500 Financials)					
Pre-War Period		**War Period**		**Total Period**	
Mean	5,35E-04	**Mean**	-2,87E-04	**Mean**	1,24E-04
Mode	-1,12E-02	**Mode**	-4,80E-03	**Mode**	-9,30E-03
Median	9,80E-04	**Median**	-1,90E-03	**Median**	1,84E-04
Maximum	3,08E-02	**Maximum**	5,01E-02	**Maximum**	5,01E-02
Minimum	-3,33E-02	**Minimum**	-3,84E-02	**Minimum**	-3,84E-02
Skewness	-1,46E-01	**Skewness**	2,32E-01	**Skewness**	9,32E-02
Std. Dev	1,16E-02	**Std. Dev**	1,51E-02	**Std. Dev**	1,35E-02
Kurtosis	2,864947	**Kurtosis**	3,38061	**Kurtosis**	3,436611
JB-Test	1,086068	**JB-Test**	3,780637	**JB-Test**	4,732502
N	252	**N**	252	**N**	504

Annex 3 - Descriptive Statistic S&P 500 Industrials

Descriptive Statistics (S&P 500 Industrials)					
Pre-War Period		**War Period**		**Total Period**	
Mean	9,66E-05	**Mean**	1,91E-04	**Mean**	1,44E-04
Mode	-2,70E-03	**Mode**	-1,10E-02	**Mode**	-5,30E-03
Median	8,69E-04	**Median**	2,16E-04	**Median**	7,88E-04
Maximum	2,85E-02	**Maximum**	4,14E-02	**Maximum**	4,14E-02
Minimum	-2,77E-02	**Minimum**	-3,86E-02	**Minimum**	-3,86E-02
Skewness	-2,67E-02	**Skewness**	-5,03E-02	**Skewness**	-4,18E-02
Std. Dev	9,89E-03	**Std. Dev**	1,37E-02	**Std. Dev**	1,19E-02
Kurtosis	3,085623	**Kurtosis**	3,323385	**Kurtosis**	3,598923
JB-Test	0,107009	**JB-Test**	1,204483	**JB-Test**	7,679737
N	252	N	252	N	504

Annex 4 - Descriptive Statistic S&P 500 Materials

Descriptive Statistics (S&P 500 Materials)					
Pre-War Period		**War Period**		**Total Period**	
Mean	2,69E-04	**Mean**	-8,99E-06	**Mean**	1,30E-04
Mode	-1,90E-03	**Mode**	3,00E-04	**Mode**	-1,90E-03
Median	5,25E-04	**Median**	-6,65E-04	**Median**	3,08E-04
Maximum	2,51E-02	**Maximum**	5,40E-02	**Maximum**	5,40E-02
Minimum	-2,57E-02	**Minimum**	-4,00E-02	**Minimum**	-4,00E-02
Skewness	-1,61E-01	**Skewness**	1,50E-01	**Skewness**	6,81E-02
Std. Dev	1,07E-02	**Std. Dev**	1,58E-02	**Std. Dev**	1,35E-02
Kurtosis	2,543901	**Kurtosis**	3,326414	**Kurtosis**	3,617093
JB-Test	3,271129	**JB-Test**	2,058976	**JB-Test**	8,386179
N	252	**N**	252	**N**	504

Annex 5 - Descriptive Statistic S&P 500 Energy

Descriptive Statistics (S&P 500 Energy)					
Pre-War Period		**War Period**		**Total Period**	
Mean	1,22E-03	**Mean**	9,18E-04	**Mean**	1,07E-03
Mode	9,30E-03	**Mode**	-1,40E-02	**Mode**	9,30E-03
Median	7,47E-04	**Median**	1,26E-03	**Median**	9,75E-04
Maximum	4,20E-02	**Maximum**	5,61E-02	**Maximum**	5,61E-02
Minimum	-4,79E-02	**Minimum**	-8,67E-02	**Minimum**	-8,67E-02
Skewness	1,93E-02	**Skewness**	-4,81E-01	**Skewness**	-3,20E-01
Std. Dev	1,80E-02	**Std. Dev**	2,23E-02	**Std. Dev**	2,02E-02
Kurtosis	2,689591	**Kurtosis**	3,601802	**Kurtosis**	3,493093
JB-Test	1,027356	**JB-Test**	13,52303	**JB-Test**	13,68172
N	252	**N**	252	**N**	504

Annex 6 - Descriptive Statistic S&P 500 Consumer Staples

Descriptive Statistics (S&P 500 Consumer Staples)

Pre-War Period		War Period		Total Period	
Mean	6,18E-04	**Mean**	-1,11E-04	**Mean**	2,54E-04
Mode	4,00E-04	**Mode**	-4,70E-03	**Mode**	4,00E-04
Median	4,50E-04	**Median**	-1,09E-04	**Median**	3,44E-04
Maximum	2,13E-02	**Maximum**	3,07E-02	**Maximum**	3,07E-02
Minimum	-2,77E-02	**Minimum**	-6,59E-02	**Minimum**	-6,59E-02
Skewness	-3,43E-01	**Skewness**	-7,78E-01	**Skewness**	-7,92E-01
Std. Dev	6,99E-03	**Std. Dev**	1,12E-02	**Std. Dev**	9,31E-03
Kurtosis	4,071701	**Kurtosis**	7,30998	**Kurtosis**	8,269314
JB-Test	16,9892	**JB-Test**	220,4591	**JB-Test**	635,7488
N	252	**N**	252	**N**	504

Annex 7 - Descriptive Statistic STOXX 600

Descriptive Statistics (STOXX 600)

Pre-War Period		War Period		Total Period	
Mean	3,72E-04	**Mean**	3,34E-05	**Mean**	2,03E-04
Mode	7,00E-04	**Mode**	-1,30E-03	**Mode**	2,60E-03
Median	1,08E-03	**Median**	5,25E-04	**Median**	9,18E-04
Maximum	2,42E-02	**Maximum**	4,58E-02	**Maximum**	4,58E-02
Minimum	-3,89E-02	**Minimum**	-3,63E-02	**Minimum**	-3,89E-02
Skewness	-8,54E-01	**Skewness**	5,69E-02	**Skewness**	-2,25E-01
Std. Dev	8,48E-03	**Std. Dev**	1,15E-02	**Std. Dev**	1,01E-02
Kurtosis	5,563969	**Kurtosis**	4,269339	**Kurtosis**	4,943009
JB-Test	99,68618	**JB-Test**	17,05367	**JB-Test**	83,54576
N	252	**N**	252	**N**	504

Annex 8 - Descriptive Statistic STOXX 600 Banks

Descriptive Statistics (STOXX 600 Banks)

Pre-War Period		War Period		Total Period	
Mean	8,81E-04	**Mean**	2,59E-04	**Mean**	5,70E-04
Mode	2,30E-03	**Mode**	-4,00E-04	**Mode**	1,90E-03
Median	1,80E-03	**Median**	4,67E-04	**Median**	1,08E-03
Maximum	3,49E-02	**Maximum**	7,22E-02	**Maximum**	7,22E-02
Minimum	-6,89E-02	**Minimum**	-8,54E-02	**Minimum**	-8,54E-02
Skewness	-6,86E-01	**Skewness**	-4,91E-01	**Skewness**	-5,80E-01
Std. Dev	1,38E-02	**Std. Dev**	1,78E-02	**Std. Dev**	1,59E-02
Kurtosis	5,699189	**Kurtosis**	6,641155	**Kurtosis**	6,793326
JB-Test	96,28521	**JB-Test**	149,3234	**JB-Test**	330,4458
N	252	**N**	252	**N**	504

Annex 9 - Descriptive Statistic STOXX 600 Insurance

Descriptive Statistics (STOXX 600 Insurance)					
Pre-War Period		**War Period**		**Total Period**	
Mean	3,72E-04	**Mean**	1,41E-04	**Mean**	2,57E-04
Mode	1,60E-03	**Mode**	-4,40E-03	**Mode**	2,40E-03
Median	1,09E-03	**Median**	1,46E-04	**Median**	6,58E-04
Maximum	2,74E-02	**Maximum**	5,42E-02	**Maximum**	5,42E-02
Minimum	-5,00E-02	**Minimum**	-4,27E-02	**Minimum**	-5,00E-02
Skewness	-9,71E-01	**Skewness**	-8,47E-02	**Skewness**	-3,87E-01
Std. Dev	1,01E-02	**Std. Dev**	1,29E-02	**Std. Dev**	1,16E-02
Kurtosis	6,322806	**Kurtosis**	4,906532	**Kurtosis**	5,586831
JB-Test	155,5324	**JB-Test**	38,4672	**JB-Test**	153,1319
N	252	**N**	252	**N**	504

Annex 10 - Descriptive Statistic STOXX 600 Industrial

Descriptive Statistics (STOXX 600 Industrial)					
Pre-War Period		**War Period**		**Total Period**	
Mean	1,33E-04	**Mean**	7,55E-05	**Mean**	1,04E-04
Mode	-2,30E-03	**Mode**	1,90E-03	**Mode**	-2,10E-03
Median	1,24E-03	**Median**	9,71E-05	**Median**	9,35E-04
Maximum	3,05E-02	**Maximum**	5,81E-02	**Maximum**	5,81E-02
Minimum	-4,82E-02	**Minimum**	-4,56E-02	**Minimum**	-4,82E-02
Skewness	-5,87E-01	**Skewness**	1,28E-01	**Skewness**	-8,19E-02
Std. Dev	1,12E-02	**Std. Dev**	1,52E-02	**Std. Dev**	1,33E-02
Kurtosis	4,443515	**Kurtosis**	3,530286	**Kurtosis**	4,060531
JB-Test	36,35735	**JB-Test**	3,641323	**JB-Test**	24,18208
N	252	**N**	252	**N**	504

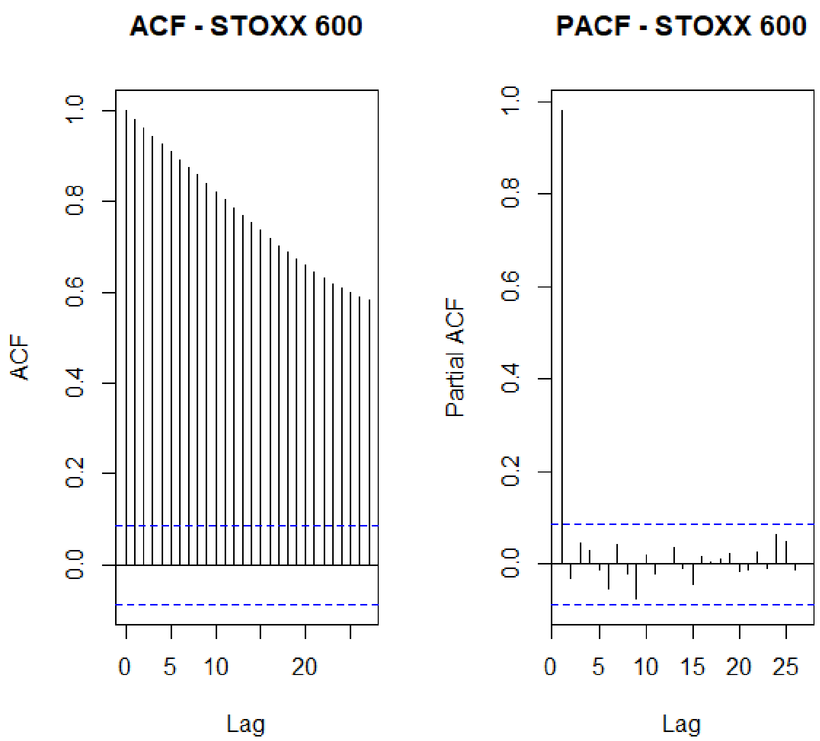
Annex 11 - Descriptive Statistic STOXX 600 Oil & Gas

Descriptive Statistics (STOXX 600 Oil & Gas)					
Pre-War Period		**War Period**		**Total Period**	
Mean	6,25E-04	**Mean**	6,98E-04	**Mean**	6,61E-04
Mode	6,90E-03	**Mode**	-1,00E-03	**Mode**	-1,00E-03
Median	5,81E-04	**Median**	1,73E-03	**Median**	1,36E-03
Maximum	3,96E-02	**Maximum**	4,67E-02	**Maximum**	4,67E-02
Minimum	-5,68E-02	**Minimum**	-6,05E-02	**Minimum**	-6,05E-02
Skewness	-4,06E-01	**Skewness**	-2,75E-01	**Skewness**	-3,24E-01
Std. Dev	1,38E-02	**Std. Dev**	1,71E-02	**Std. Dev**	1,55E-02
Kurtosis	4,070012	**Kurtosis**	3,692406	**Kurtosis**	3,976125
JB-Test	18,9489	**JB-Test**	8,211752	**JB-Test**	28,8281
N	252	**N**	252	**N**	504

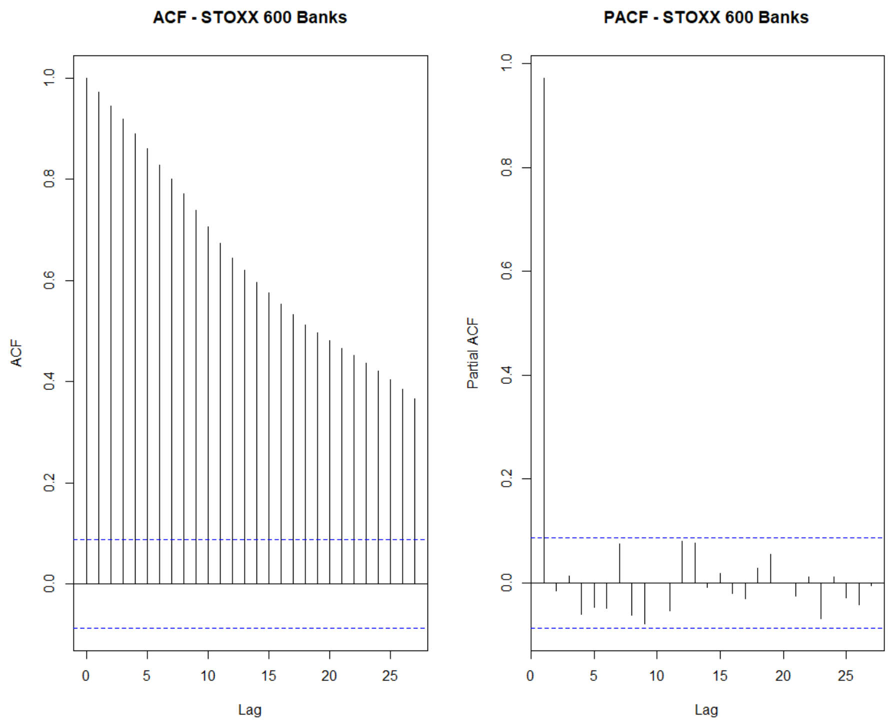
Annex 12 - Descriptive Statistic STOXX 600 Food & Beverage

Descriptive Statistics (STOXX 600 Food & Beverage)					
Pre-War Period		**War Period**		**Total Period**	
Mean	6,05E-04	**Mean**	-2,20E-04	**Mean**	1,93E-04
Mode	5,90E-03	**Mode**	1,18E-02	**Mode**	-2,70E-03
Median	9,13E-04	**Median**	-2,11E-04	**Median**	6,36E-04
Maximum	2,18E-02	**Maximum**	4,59E-02	**Maximum**	4,59E-02
Minimum	-2,72E-02	**Minimum**	-3,85E-02	**Minimum**	-3,85E-02
Skewness	-5,04E-01	**Skewness**	1,95E-02	**Skewness**	-1,60E-01
Std. Dev	7,28E-03	**Std. Dev**	1,07E-02	**Std. Dev**	9,17E-03
Kurtosis	4,582264	**Kurtosis**	5,069043	**Kurtosis**	5,632805
JB-Test	36,9608	**JB-Test**	44,96577	**JB-Test**	147,7123
N	252	**N**	252	**N**	504

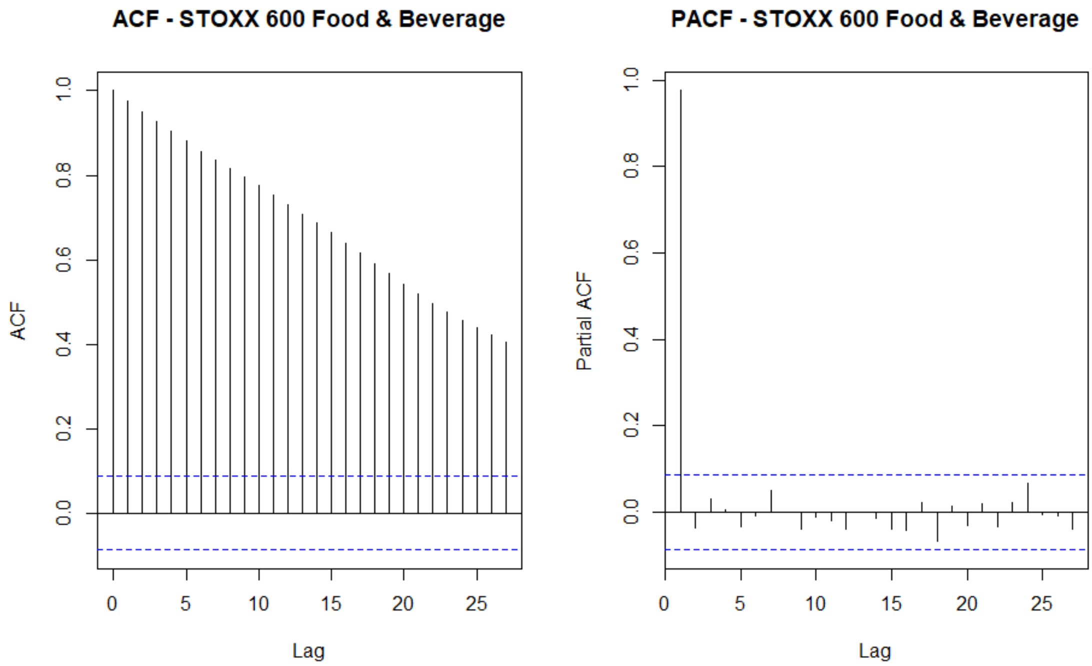
Annex 13 - ACF and PACF from STOXX 600 Closing prices



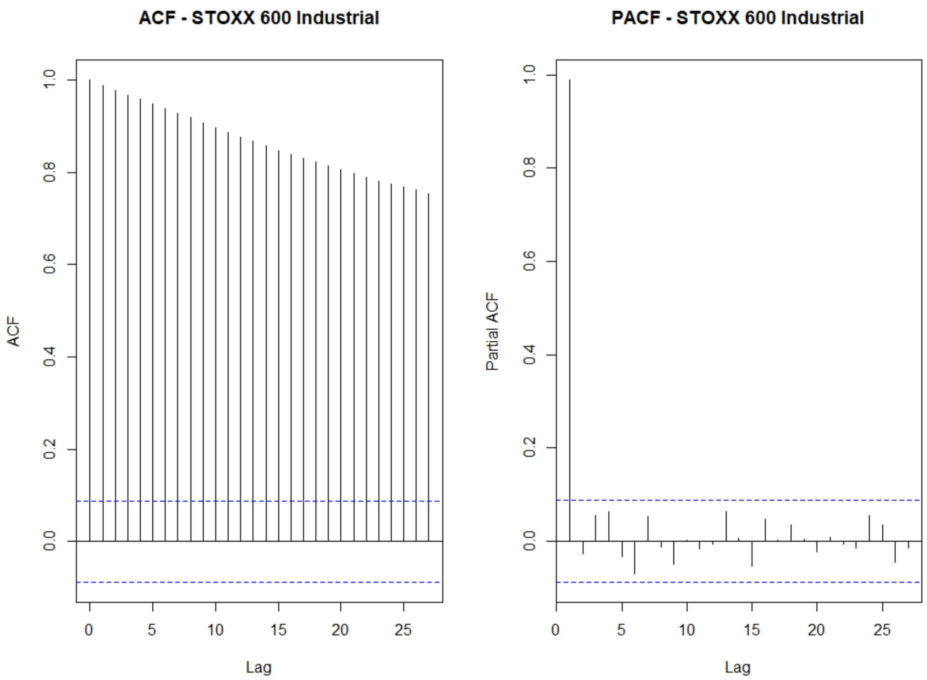
Annex 14 - ACF and PACF from STOXX 600 Banks Closing prices



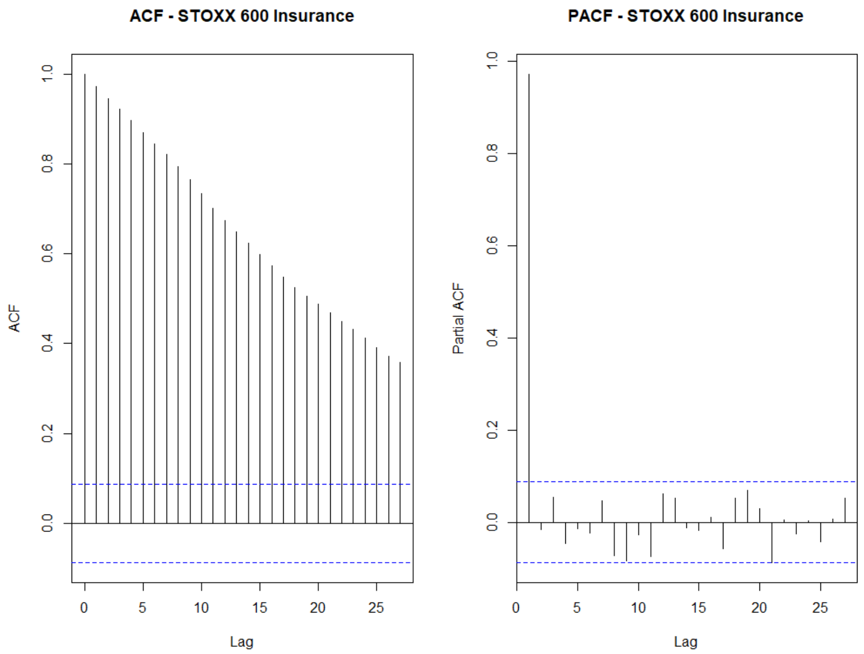
Annex 15 - ACF and PACF from STOXX 600 Food & Beverage Closing prices



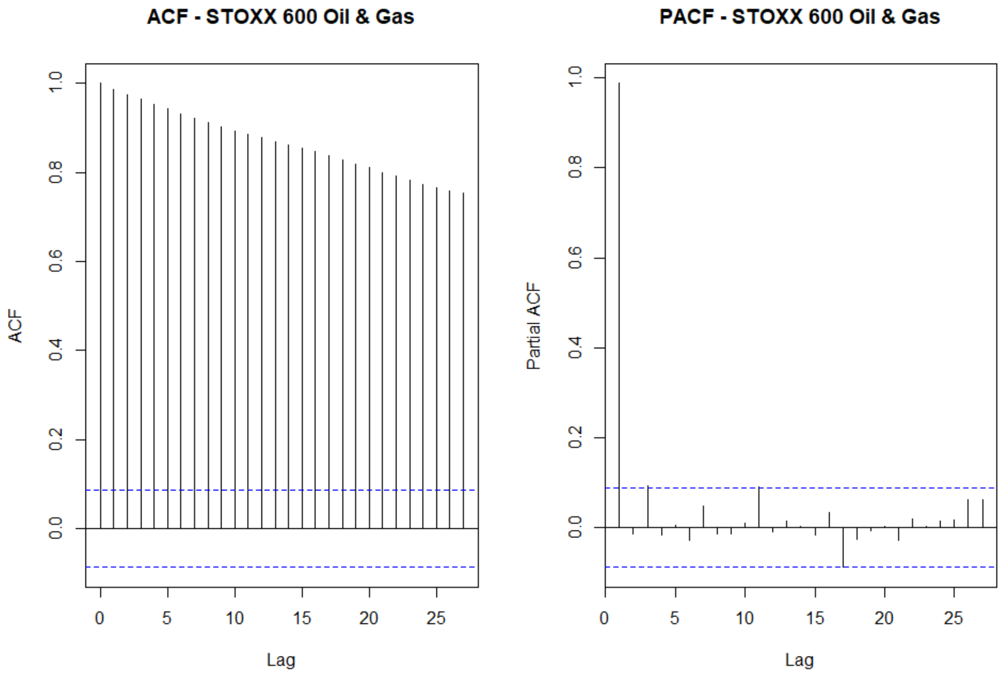
Annex 16 - ACF and PACF from STOXX 600 Industrial Closing prices



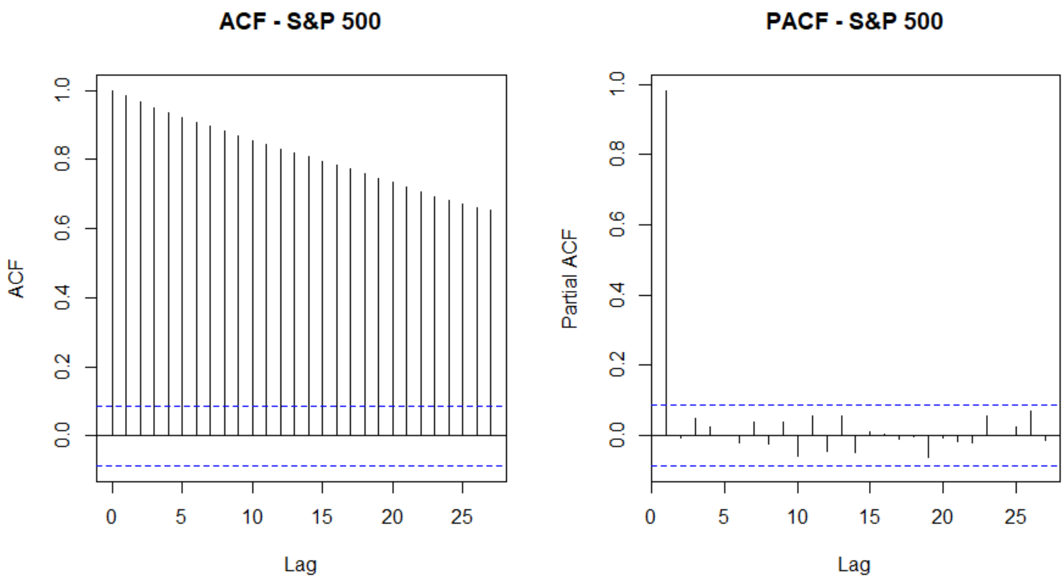
Annex 17 - ACF and PACF from STOXX 600 Insurance Closing prices



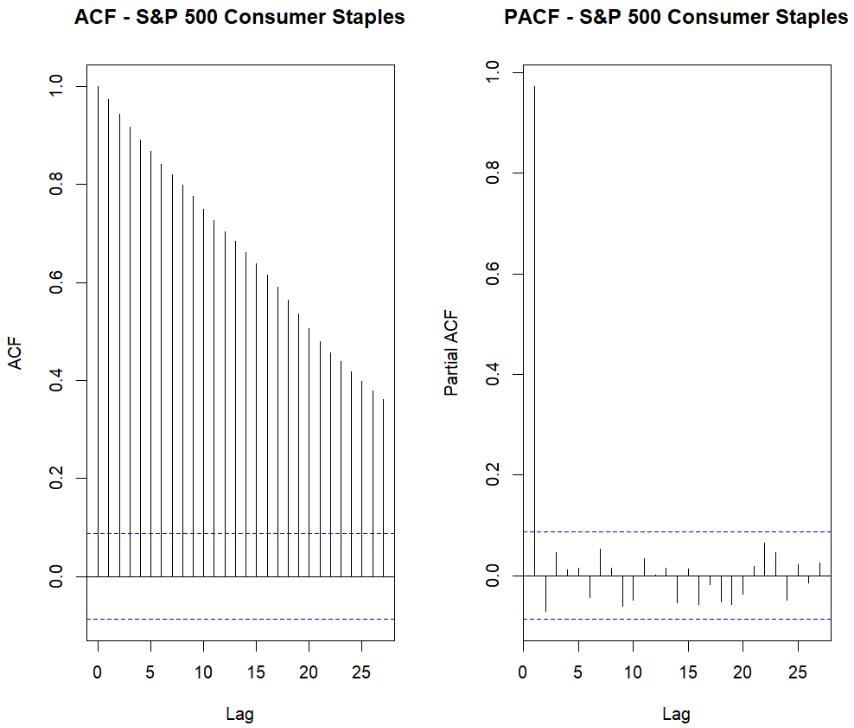
Annex 18 - ACF and PACF from STOXX 600 Oil & Gas Closing prices



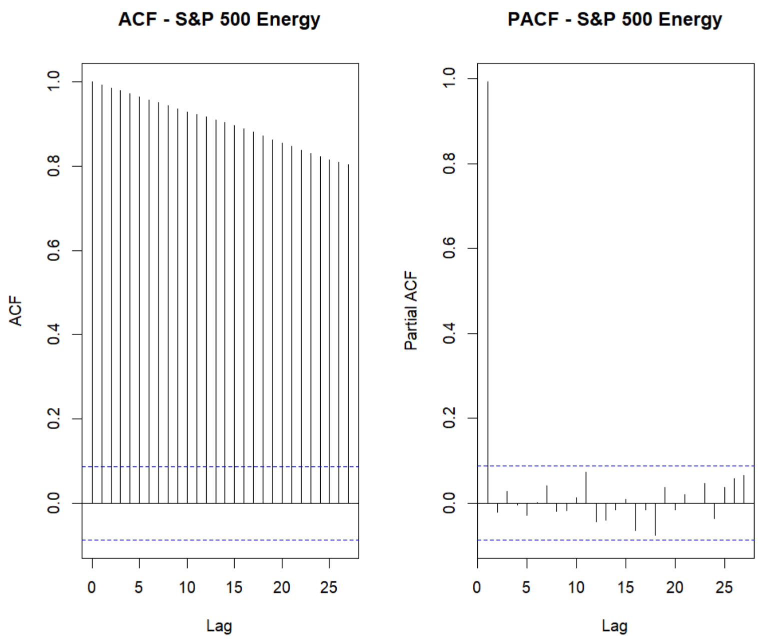
Annex 19 - ACF and PACF from S&P 500 Closing prices



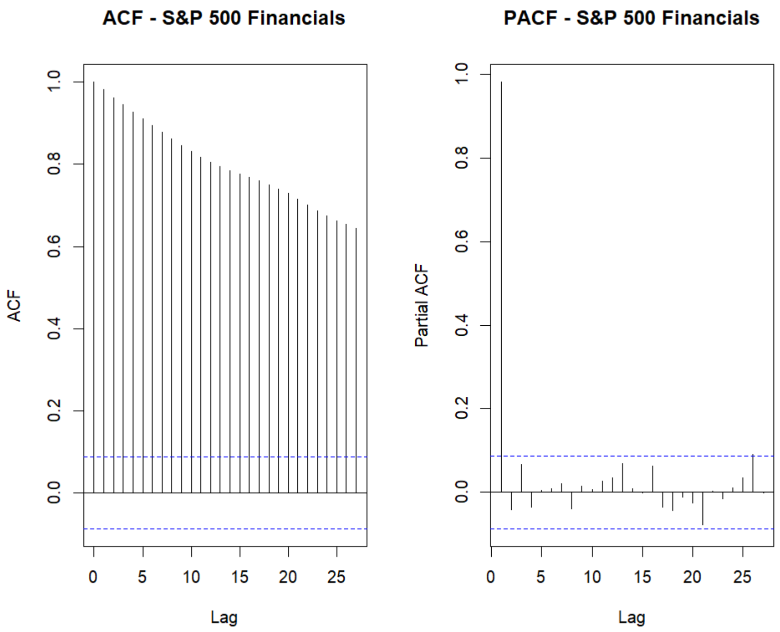
Annex 20 - ACF and PACF from S&P 500 Consumer Staples Closing prices



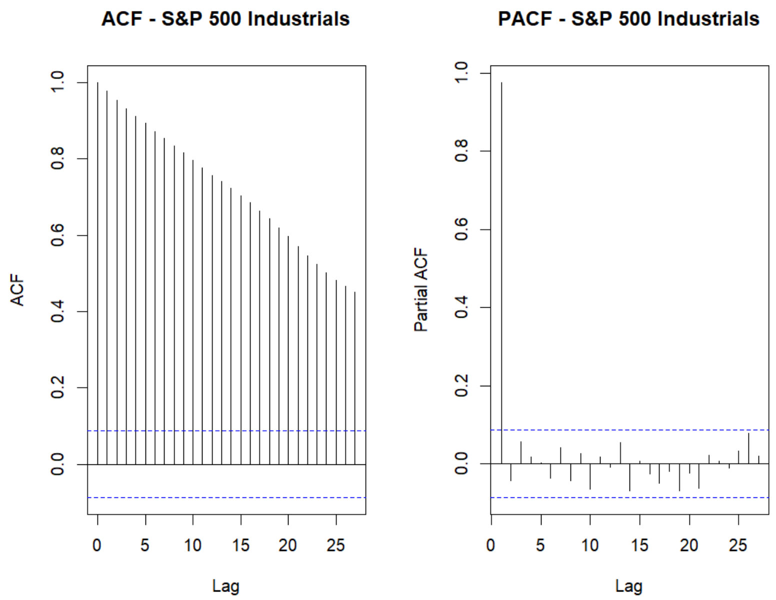
Annex 21 - ACF and PACF from S&P 500 Energy Closing prices



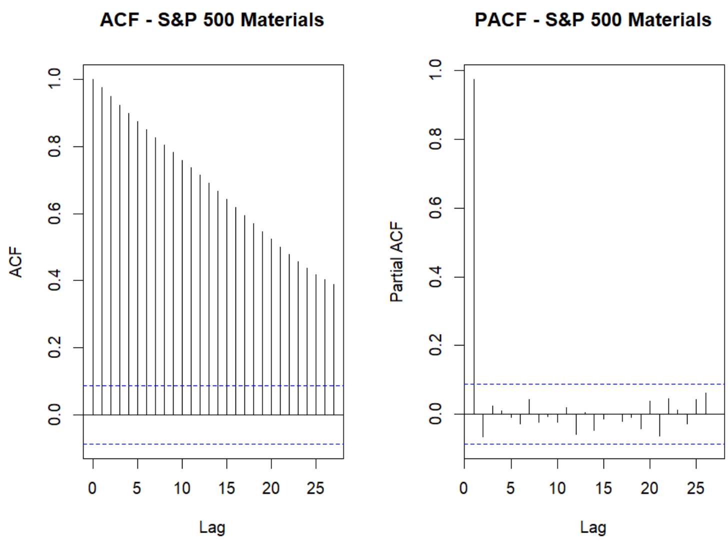
Annex 22 - ACF and PACF from S&P 500 Financials Closing prices



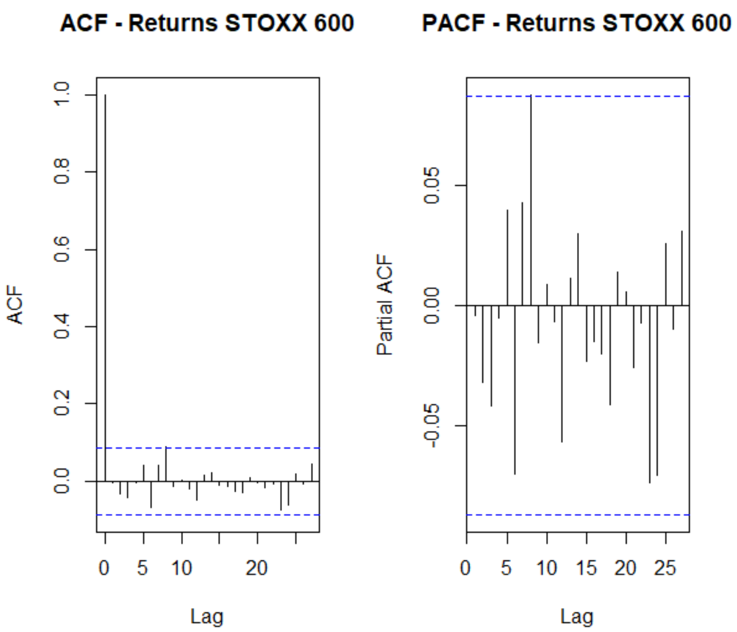
Annex 23 - ACF and PACF from S&P 500 Industrials Closing prices



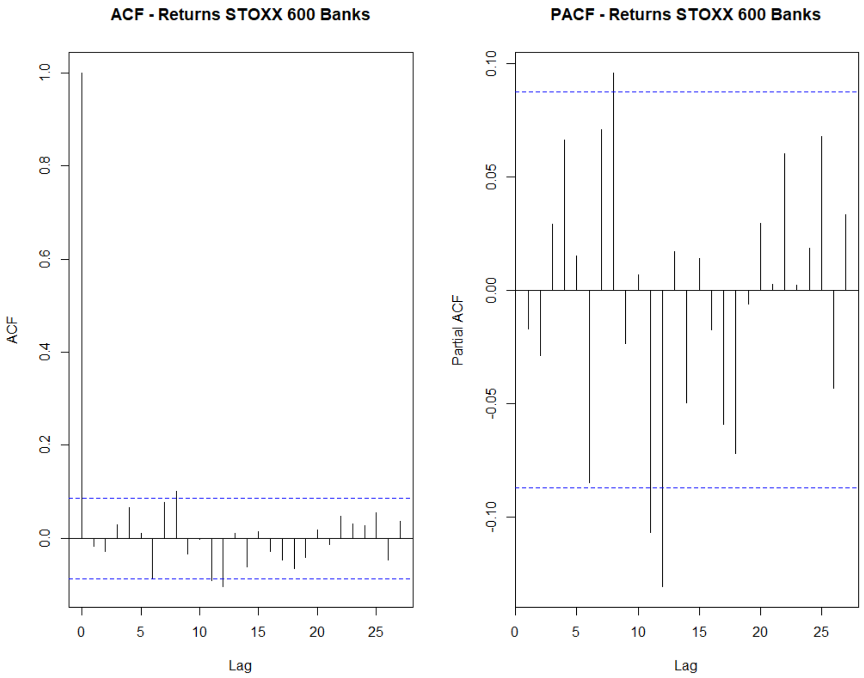
Annex 24 - ACF and PACF from S&P 500 Materials Closing prices



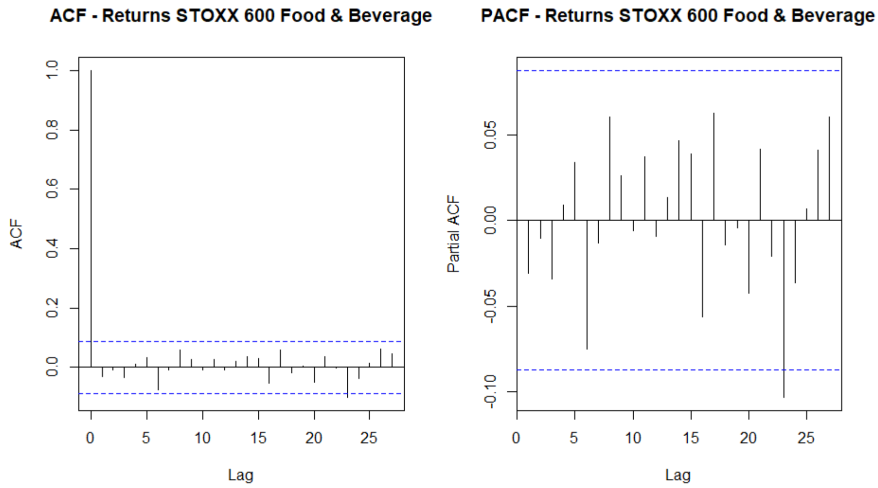
Annex 25 - ACF and PACF from STOXX 600 Returns



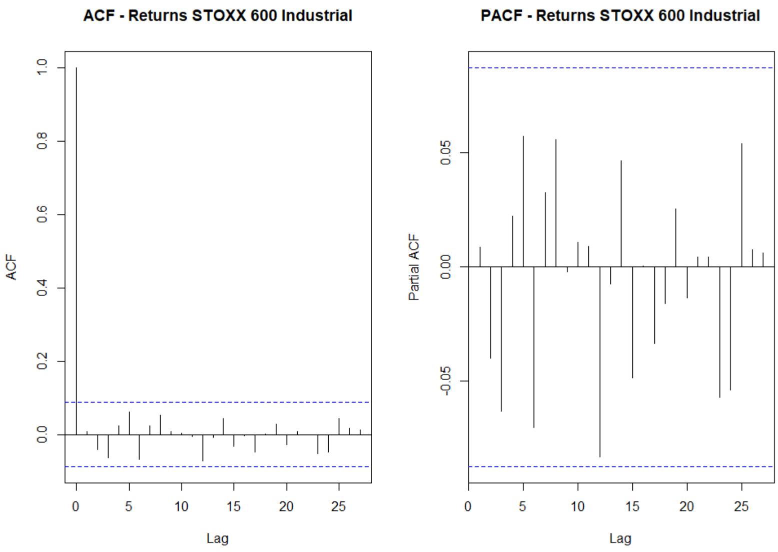
Annex 26 - ACF and PACF from STOXX 600 Banks Returns



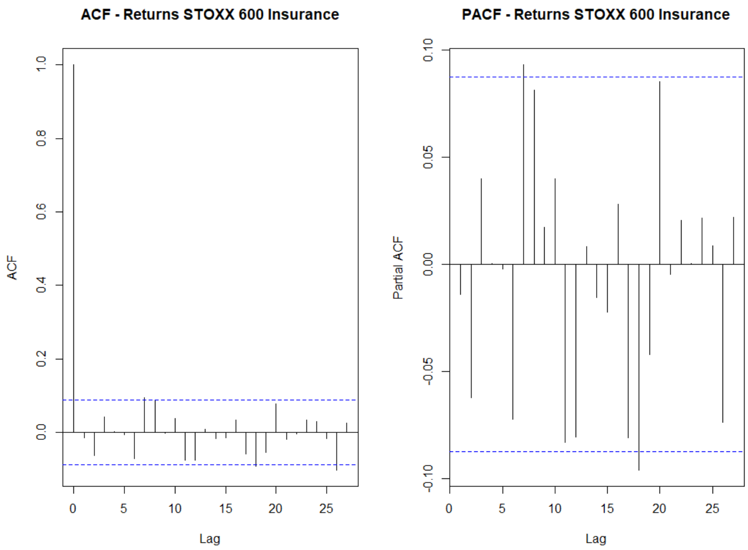
Annex 27 - ACF and PACF from STOXX 600 Food & Beverage Returns



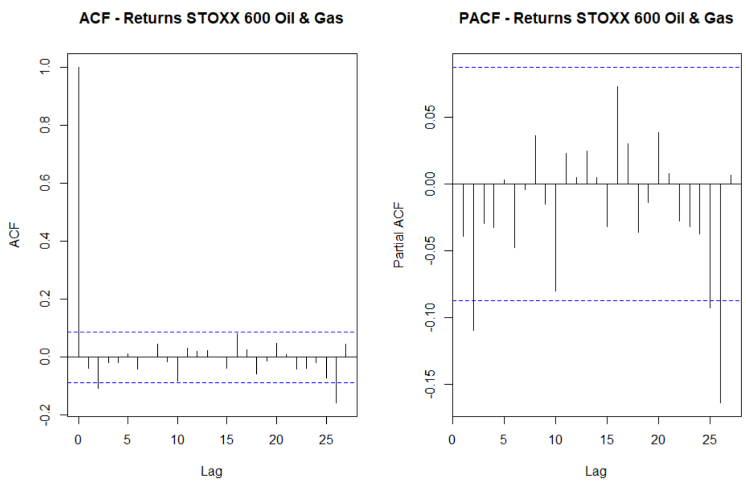
Annex 28 - ACF and PACF from STOXX 600 Industrials Returns



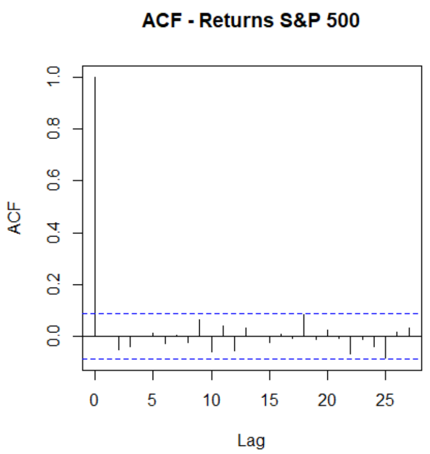
Annex 29 - ACF and PACF from STOXX 600 Insurance Returns

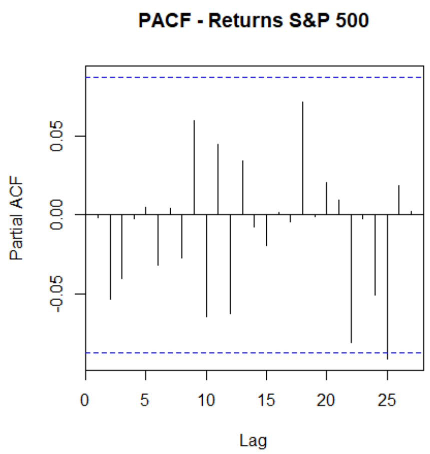


Annex 30 - ACF and PACF from STOXX 600 Oil & Gas Returns

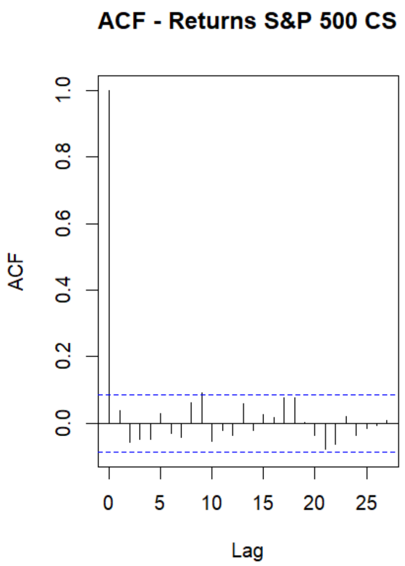


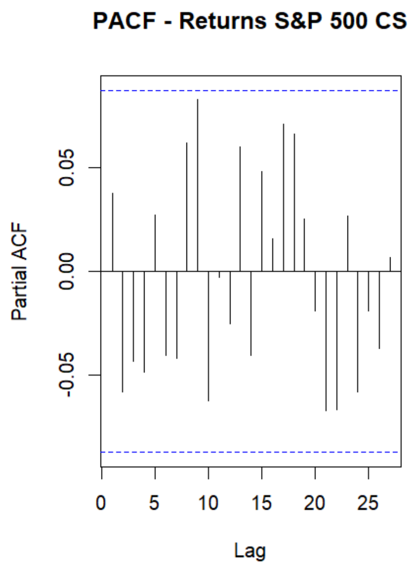
Annex 31 - ACF and PACF from S&P 500 Returns



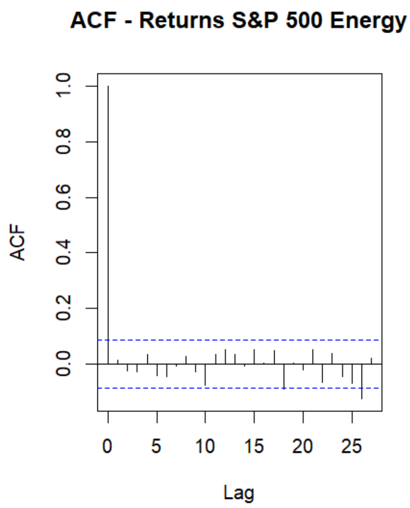


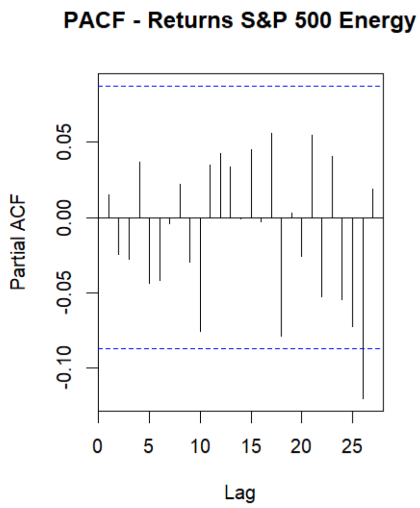
Annex 32 - ACF and PACF from S&P 500 Consumer Staples Returns



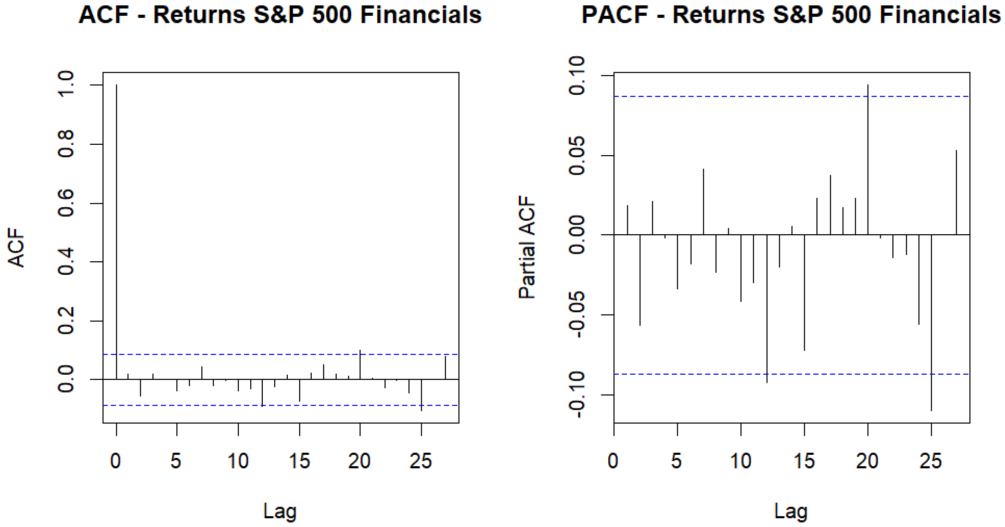


Annex 33 - ACF and PACF from S&P 500 Energy Returns

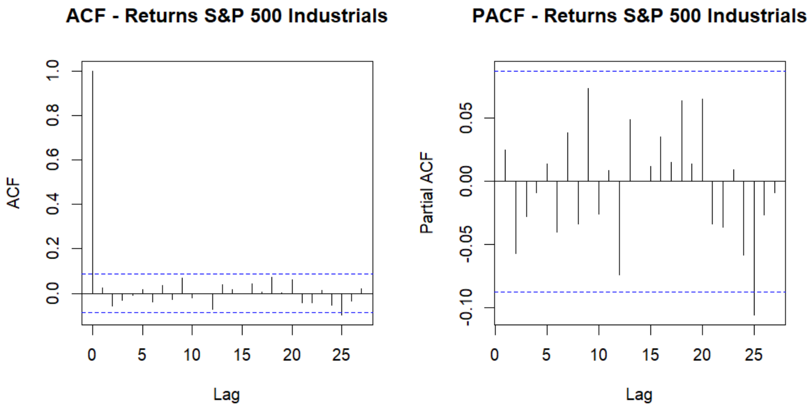




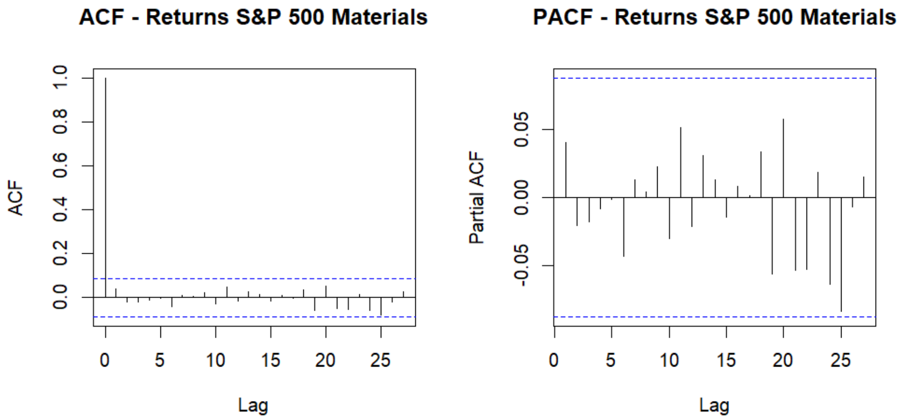
Annex 34 - ACF and PACF from S&P 500 Financials Returns



Annex 35 - ACF and PACF from S&P 500 Industrials Returns



Annex 36 - ACF and PACF from S&P 500 Materials Returns



Annex 37 - Weighted Ljung-Box Test on Standardized Residuals for American indexes

	Weighted Ljung-Box Test on Standardized Residuals											
	S&P 500		**S&P 500 Financials**		**S&P 500 Industrials**		**S&P 500 Materials**		**S&P 500 Energy**		**S&P 500 Consumer Staples**	
	GARCH (1,1) w/ dummy	**GJR (1,1) w/ dummy**	**GARCH (1,1) w/ dummy**	**GJR (1,1) w/ dummy**	**GARCH (1,1) w/ dummy**	**GJR (1,1) w/ dummy**	**GARCH (1,1) w/ dummy**	**GJR (1,1) w/ dummy**	**GARCH (1,1) w/ dummy**	**GJR (1,1) w/ dummy**	**GARCH (1,1) w/ dummy**	**GJR (1,1) w/ dummy**
Lag[1]	0,0005585 (0,9811)	0,005266 (0,9422)	0,1557 (0,6932)	0,1528 (0,6959)	0,02916 (0,8644)	0,08294 (0,7733)	0,8929 (0,3447)	0,6917 (0,4056)	0,08799 (0,7667)	0,03203 (0,858)	0,02324 (0,8788)	0,02227 (0,8814)
Lag[2*(p+q)+(p+q)-1][2]	0,4758206 (0,705)	0,37519 (0,7552)	0,6112 (0,6436)	0,3653 (0,7604)	0,7663 (0,5807)	0,5805 (0,657)	1,0856 (0,4713)	0,8637 (0,5446)	0,2375 (0,8316)	0,10861 (0,9137)	0,49561 (0,6957)	0,56153 (0,6654)
Lag[4*(p+q)+(p+q)-1][5]	1,7721679 (0,6731)	1,593382 (0,7169)	1,0179 (0,8556)	0,6513 (0,932)	2,22666 (0,5659)	2,11414 (0,5917)	1,6461 (0,704)	1,5473 (0,7283)	0,93646 (0,8739)	0,81912 (0,8991)	2,00872 (0,6164)	2,06058 (0,6042)

Annex 38 - Weighted Ljung-Box Test on Standardized Residuals for European Indexes

	Weighted Ljung-Box Test on Standardized Residuals											
	STOXX 600		**STOXX 600 Banks**		**STOXX 600 Insurance**		**STOXX 600 Industrial**		**STOXX 600 Oil & Gas**		**STOXX 600 Food & Beverage**	
	GARCH (1,1) w/ dummy	**GJR (1,1) w/ dummy**	**GARCH (1,1) w/ dummy**	**GJR (1,1) w/ dummy**	**GARCH (1,1) w/ dummy**	**GJR (1,1) w/ dummy**	**GARCH (1,1) w/ dummy**	**GJR (1,1) w/ dummy**	**GARCH (1,1) w/ dummy**	**GJR (1,1) w/ dummy**	**GARCH (1,1) w/ dummy**	**GJR (1,1) w/ dummy**
Lag[1]	0,0416 (0,8384)	0,04428 (0,8333)	0,1383 (0,71)	0,3312 (0,565)	0,3377 (0,5611)	0,7174 (0,397)	0,0006887 (0,9791)	0,03785 (0,8457)	0,6665 (0,4143)	0,3792 (0,5381)	0.4506 (0.5021)	0,1594 (0,6897)
Lag[2*(p+q)+(p+q)-1][2]	0,1056 (0,9157)	0,37855 (0,7535)	0,1645 (0,8765)	0,5739 (0,6599)	0,5714 (0,661)	0,7634 (0,5818)	0,2029298 (0,8524)	0,43248 (0,7262)	3,1143 (0,1307)	2,2289 (0,2274)	0.5813 (0.6567)	0,5572 (0,6674)
Lag[4*(p+q)+(p+q)-1][5]	1,1894 (0,8155)	1,64449 (0,7044)	0,4236 (0,9688)	0,9148 (0,8787)	1,1746 (0,819)	1,7162 (0,6868)	3,1239822 (0,3849)	3,86972 (0,2708)	4,9284 (0,1589)	3,7397 (0,2884)	2.1993 (0.5721)	2,6928 (0,466)

Annex 39 - Weighted Ljung-Box Test on Standardized Squared Residuals for American Indexes

	Weighted Ljung-Box Test on Standardized Squared Residuals											
	S&P 500		**S&P 500 Financials**		**S&P 500 Industrials**		**S&P 500 Materials**		**S&P 500 Energy**		**S&P 500 Consumer Staples**	
	GARCH (1,1) w/ dummy	GJR (1,1) w/ dummy	GARCH (1,1) w/ dummy	GJR (1,1) w/ dummy	GARCH (1,1) w/ dummy	GJR (1,1) w/ dummy	GARCH (1,1) w/ dummy	GJR (1,1) w/ dummy	GARCH (1,1) w/ dummy	GJR (1,1) w/ dummy	GARCH (1,1) w/ dummy	GJR (1,1) w/ dummy
Lag[1]	0,3238 (0,5693)	1,408 (0,2355)	0,0412 (0,8391)	0,04717 (0,8281)	0,09441 (0,7586)	0,00627 (0,9369)	0,1842 (0,6678)	0,01024 (0,9194)	1,094 (0,2957)	2,128 (0,1446)	0,08004 (0,7772)	0,000151 (0,9902)
Lag[2*(p+q)+(p+q)-1][5]	0,5556 (0,9488)	2,213 (0,569)	0,1937 (0,993)	1,10329 (0,8359)	0,25566 (0,988)	1,3558 (0,7753)	0,3826 (0,9742)	0,89511 (0,8829)	2,182 (0,5761)	2,726 (0,4593)	0,25192 (0,9884)	0,134018 (0,9966)
Lag[4*(p+q)+(p+q)-1][9]	1,2555 (0,9731)	2,949 (0,7673)	0,3516 (0,9995)	2,12698 (0,8893)	0,5603 (0,9978)	2,78227 (0,7943)	1,3837 (0,9645)	2,26601 (0,871)	2,852 (0,7831)	3,282 (0,7116)	0,59809 (0,9972)	0,553438 (0,9979)

Annex 40 - Weighted Ljung-Box Test on Standardized Squared Residuals for European Indexes

	Weighted Ljung-Box Test on Standardized Squared Residuals											
	STOXX 600		**STOXX 600 Banks**		**STOXX 600 Insurance**		**STOXX 600 Industrial**		**STOXX 600 Oil & Gas**		**STOXX 600 Food & Beverage**	
	GARCH (1,1) w/ dummy	GJR (1,1) w/ dummy	GARCH (1,1) w/ dummy	GJR (1,1) w/ dummy	GARCH (1,1) w/ dummy	GJR (1,1) w/ dummy	GARCH (1,1) w/ dummy	GJR (1,1) w/ dummy	GARCH (1,1) w/ dummy	GJR (1,1) w/ dummy	GARCH (1,1) w/ dummy	GJR (1,1) w/ dummy
Lag[1]	0,01027 (0,9193)	1,189 (0,2754)	0,1344 (0,7139)	1,045 (0,3067)	0,1568 (0,6922)	1,037 (0,3085)	0,5031 (0,4781)	2,368 (0,12388)	2,091 (0,1482)	1,903 (0,1677)	0,3204 (0,5714)	0,8153 (0,36657)
Lag[2*(p+q)+(p+q)-1][5]	1,03175 (0,8524)	3,656 (0,3001)	0,3793 (0,9746)	2,344 (0,5397)	0,4828 (0,9603)	2,209 (0,57)	2,1428 (0,5851)	6,344 (0,07457)	3,378 (0,3423)	2,433 (0,5202)	2,3534 (0,5376)	3,9741 (0,25732)
Lag[4*(p+q)+(p+q)-1][9]	1,64675 (0,9427)	4,594 (0,4914)	1,9647 (0,9092)	3,508 (0,6729)	1,6163 (0,9455)	3,035 (0,7531)	3,3662 (0,6973)	7,794 (0,14127)	4,833 (0,4543)	4,113 (0,5698)	7,6313 (0,1518)	8,6725 (0,09478)

Annex 41 - ARCH-LM tests for American Indexes

	ARCH LM Tests											
	S&P 500		S&P 500 Financials		S&P 500 Industrials		S&P 500 Materials		S&P 500 Energy		S&P 500 Consumer Staples	
	GARCH (1,1) w/ dummy	GJR (1,1) w/ dummy	GARCH (1,1) w/ dummy	GJR (1,1) w/ dummy	GARCH (1,1) w/ dummy	GJR (1,1) w/ dummy	GARCH (1,1) w/ dummy	GJR (1,1) w/ dummy	GARCH (1,1) w/ dummy	GJR (1,1) w/ dummy	GARCH (1,1) w/ dummy	GJR (1,1) w/ dummy
ARCH Lag[3]	0,03897 (0,8435)	0,9598 (0,3272)	0,07999 (0,7773)	0,5613 (0,4537)	0,05166 (0,8202)	1,526 (0,2167)	0,02336 (0,8785)	0,5591 (0,4546)	1,72 (0,1897)	0,8584 (0,3542)	0,236 (0,6271)	0,02683 (0,8699)
ARCH Lag[5]	0,24015 (0,9557)	1,4424 (0,6076)	0,18137 (0,9698)	1,8897 (0,4961)	0,31565 (0,9361)	2,711 (0,3345)	0,44746 (0,899)	1,8452 (0,5065)	1,774 (0,5234)	0,9705 (0,7417)	0,3041 (0,9392)	0,1591 (0,9748)
ARCH Lag[7]	0,96743 (0,9188)	1,872 (0,7444)	0,20102 (0,997)	2,4512 (0,6225)	0,47915 (0,9802)	3,482 (0,4274)	0,54288 (0,9743)	2,2682 (0,6606)	2,189 (0,6774)	1,3843 (0,8443)	0,5075 (0,9777)	0,5588 (0,9728)

Annex 42 - ARCH-LM tests for European Indexes

	ARCH LM Tests											
	STOXX 600		STOXX 600 Banks		STOXX 600 Insurance		STOXX 600 Industrial		STOXX 600 Oil & Gas		STOXX 600 Food & Beverage	
	GARCH (1,1) w/ dummy	GJR (1,1) w/ dummy	GARCH (1,1) w/ dummy	GJR (1,1) w/ dummy	GARCH (1,1) w/ dummy	GJR (1,1) w/ dummy	GARCH (1,1) w/ dummy	GJR (1,1) w/ dummy	GARCH (1,1) w/ dummy	GJR (1,1) w/ dummy	GARCH (1,1) w/ dummy	GJR (1,1) w/ dummy
ARCH Lag[3]	1,544 (0,214)	3,703 (0,05432)	0,2605 (0,6098)	0,1264 (0,7222)	0,1038 (0,7473)	0,1347 (0,7136)	1,344 (0,2464)	3,54 (0,05991)	0,001411 (0,97)	0,03013 (0,8622)	2,734 (0,09824)	4,581 (0,03233)
ARCH Lag[5]	1,719 (0,5366)	4,127 (0,1628)	0,4818 (0,889)	0,6031 (0,8528)	0,4958 (0,8849)	0,803 (0,7922)	1,609 (0,564)	4,351 (0,1448)	0,4725 (0,8917)	0,94072 (0,7506)	3,595 (0,21435)	5,544 (0,0768)
ARCH Lag[7]	1,864 (0,7461)	4,237 (0,31363)	2,0992 (0,6963)	1,4511 (0,8311)	1,6638 (0,788)	1,2196 (0,8754)	1,954 (0,7272)	4,73 (0,25329)	0,706251 (0,9561)	1,28571 (0,8631)	7,462 (0,06894)	8,913 (0,03272)

Annex 43 - Sign Bias Test for America Indexes

Sign Bias Test

	S&P 500		**S&P 500 Financials**		**S&P 500 Industrials**		**S&P 500 Materials**		**S&P 500 Energy**		**S&P 500 Consumer Staples**	
Group	**GARCH (1,1) w/ dummy**	**GJR (1,1) w/ dummy**	**GARCH (1,1) w/ dummy**	**GJR (1,1) w/ dummy**	**GARCH (1,1) w/ dummy**	**GJR (1,1) w/ dummy**	**GARCH (1,1) w/ dummy**	**GJR (1,1) w/ dummy**	**GARCH (1,1) w/ dummy**	**GJR (1,1) w/ dummy**	**GARCH (1,1) w/ dummy**	**GJR (1,1) w/ dummy**
Sign Bias	1,158 (0,2474)	0.83150 (0.4061)	1,229 (0,21972)	0,709 (0,4786)	0,8999 (0,3686)	1,055 (0,2919)	0,7356 (0,46234)	0,1231 (0,9021)	0,33 (0,7415)	0,1668 (0,8676)	0,3034 (0,7617)	0,06125 (0,9512)
Negative Sign Bias	0,1258 (0,9)	1.30470 (0.1926)	1,012 (0,31208)	0,1398 (0,8889)	1,1565 (0,248)	0,2254 (0,8217)	1,1499 (0,25072)	0,3628 (0,7169)	0,6992 (0,4848)	1,1987 (0,2312)	0,713 (0,4762)	0,31314 (0,7543)
Positive Sign Bias	0,2161 (0,829)	0.08544 (0.9319)	0,31 (0,75668)	0,2955 (0,7677)	0,4138 (0,6792)	0,2701 (0,7872)	0,178 (0,85878)	0,3057 (0,76)	0,9958 (0,3198)	0,8303 (0,4067)	0,4762 (0,6341)	0,38319 (0,7017)
Joint Effect	2,2349 (0,5251)	1.82729 (0.6090)	11,098 (0,01121)	2,439 (0,4864)	5,9952 (0,1118)	1,6721 (0,6432)	6,9648 (0,07303)	0,8378 (0,8404)	2,4018 (0,4933)	2,1415 (0,5436)	2,5374 (0,4686)	0,6412 (0,8869)

Annex 44 - Sign Bias Test for European Indexes

Sign Bias Test

	STOXX 600		**STOXX 600 Banks**		**STOXX 600 Insurance**		**STOXX 600 Industrial**		**STOXX 600 Oil & Gas**		**STOXX 600 Food & Beverage**	
Group	**GARCH (1,1) w/ dummy**	**GJR (1,1) w/ dummy**	**GARCH (1,1) w/ dummy**	**GJR (1,1) w/ dummy**	**GARCH (1,1) w/ dummy**	**GJR (1,1) w/ dummy**	**GARCH (1,1) w/ dummy**	**GJR (1,1) w/ dummy**	**GARCH (1,1) w/ dummy**	**GJR (1,1) w/ dummy**	**GARCH (1,1) w/ dummy**	**GJR (1,1) w/ dummy**
Sign Bias	0,6691 (0,50377)	0,9012 (0,3679)	2,0547 (0,04042)	1,502 (0,13373)	0,5386 (0,5904)	1,4664 (0,14317)	1,8457 (0,06553)	1,9664 (0,04981)	0,4468 (0,65519)	0,2495 (0,8031)	0,6727 (0,50142)	0,4888 (0,6252)
Negative Sign Bias	0,2443 (0,80707)	1,2288 (0,2197)	0,7928 (0,42825)	1,8127 (0,07048)	0,8011 (0,4234)	0,1566 (0,87566)	0,2377 (0,8122)	1,9388 (0,05308)	1,8933 (0,05889)	0,3804 (0,7038)	2,0522 (0,04067)	1,611 (0,1078)
Positive Sign Bias	1,8215 (0,06912)	1,5568 (0,1202)	0,192 (0,8478)	0,3107 (0,75618)	1,4142 (0,1579)	1,8552 (0,06415)	0,6781 (0,49799)	0,4752 (0,63485)	0,331 (0,74079)	0,8592 (0,3906)	1,057 (0,29101)	0,7544 (0,451)
Joint Effect	9,7145 (0,02116)	6,0942 (0,1071)	7,1743 (0,06654)	4,7208 (0,19342)	3,4077 (0,3329)	3,8354 (0,2798)	10,7133 (0,01338)	7,1155 (0,06831)	9,936 (0,01912)	1,5691 (0,6664)	7,2329 (0,06483)	4,3417 (0,2268)

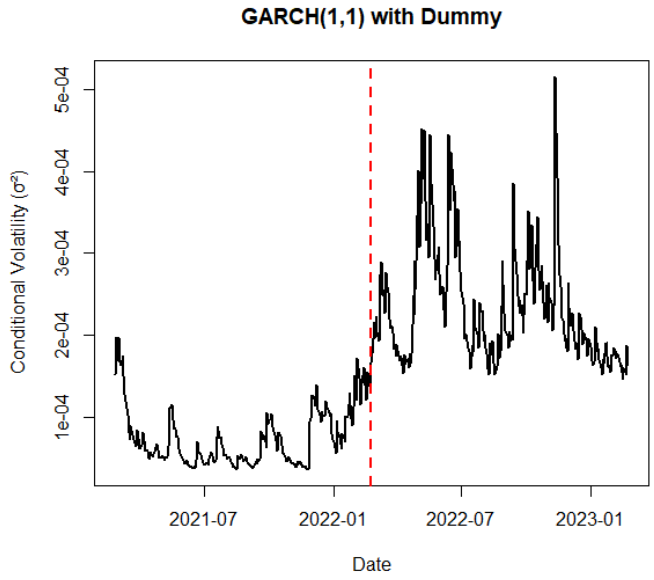
Annex 45 - GARCH (1,1) with war variable (Robustness Test)

	S&P 100	S&P 500 Financials	Dow Jones	S&P 500 Materials	S&P 500 Energy	S&P 500 Consumer Staples	STOXX 50	STOXX 600 Banks	STOXX 600 Insurance	STOXX 600 Industrial	STOXX 600 Oil & Gas	STOXX 600 Food & Beverage
μ	-0,000969 (-0,907869)	-0,000630 (-0,67443)	-0,001044 (-1,05477)	-0,000800 (-1,48650)	0.001582 (9.3222e-01)	0,000692 (0,84114)	0,000377 (0,28001)	0,002140 (1,12758)	0,000778 (0,71916)	-0,000287 (-0,22741)	-0,000132 (-9,7326e-02)	0,000679 (0,67238)
ρ	-0,000207 (-0,092976)	-0,001474 (-1,58966)	0,000191 (0,11224)	0,000372 (0,90383)	0.000801 (2.4832e-01)	-0,000818 (-0,50444)	-0,002739 (-1,25965)	-0,003552 (-1,06448)	-0,002028 (-1,17823)	-0,002318 (-1,85135)	0,000748 (3,4497e-01)	-0,001311 (-0,58329)
c	0,000534 (1,818935)	0,001888 (0,16382)	0,000663 (1,72422)	0,000571 (1,51360)	0.000011 (1.5132)	0,000011 (1,37578)	0,001205 (1,48897)	0,001738 (2,92604)	0,001362 (2,92234)	0,001472 (2,48366)	0,000047 (3,0022)	0,001406 (0,87835)
α	0,062823 (2,811170)	0,066455 (0,25054)	0,066316 (2,77809)	0,075459 (4,93921)	0 (7.4289e-01)	0,001460 (1,44747)	0,160599 (3,60904)	0,126450 (3,43814)	0,111633 (3,55631)	0,119081 (3,30013)	0,000003 (1,2749)	0,110691 (1,73427)
β	0,911333 (29,474625)	0,801713 (0,68284)	0,882767 (21,15283)	0,892255 (26,04062)	1 (3.2266e+03)	1 (2040,04529)	0,783595 (24,02269)	0,799805 (12,12390)	0,817246 (21,35500)	0,806968 (19,21413)	0,999996 (4,0579e+04)	0,771558 (3,77451)
(α + β)	0,974156	0,868168	0,949083	0,967714	1	1,00146	0,944194	0,926255	0,928879	0,926049	0,999999	0,882249
ξ	0.999999 (2.483933)	1 (0,18860)	1 (1,57379)	1 (2,70133)	0.999976 (3.8384e-02)	0,999997 (0,39273)	1 (3,41577)	1 (3,59772)	1 (3,31425)	1 (3,13796)	0,225336 (1,6343e-01)	1 (0,90846)
γ	0.000152 (0.676684)	0,000644 (0,11129)	0,000297 (0,96961)	0,000349 (1,30877)	0.000165 (2.1180)	0,000069 (4,23236)	0,000587 (1,07164)	0,000808 (0,76226)	0	0,000312 (0,69972)	0	0,000431 (0,70377)
AIC	-5,6747	-5,5382	-6,0892	-5,7149	-4,8664	-6,2323	-5,5895	-4,9602	-5,792	-5,4717	-5,1312	-6,15
Bayes	-5,5461	-5,407	-5,9585	-5,5842	-4,7363	-6,1011	-5,4614	-4,8321	-5,6634	-5,3436	-5,0031	-6,0219
Shibata	-5,6779	-5,5416	-6,0925	-5,7182	-4,8697	-6,2356	-5,5927	-4,9633	-5,7952	-5,4749	-5,1343	-6,1531
Hannan-Quinn	-5,6225	-5,485	-6,0362	-5,6618	-4,8136	-6,179	-5,5375	-4,9082	-5,7398	-5,4198	-5,0792	-6,098

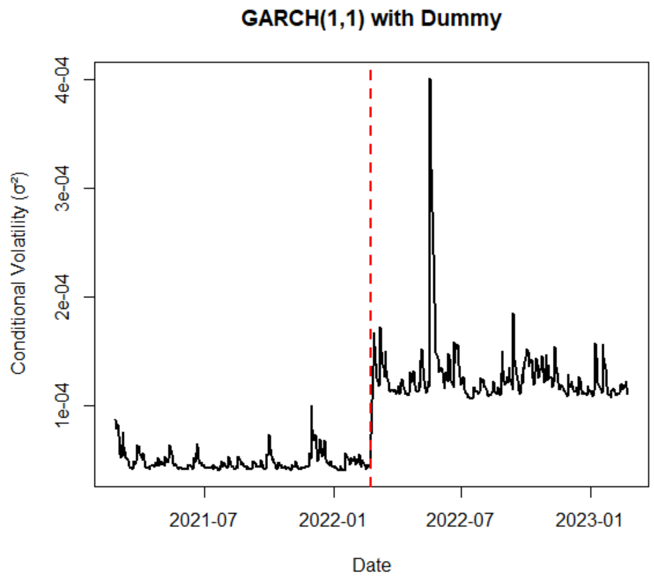
Annex 46 – GJR-GARCH (1,1) with war variable (Robustness Tests)

	S&P 100	S&P 500 Financials	Dow Jones	S&P 500 Materials	S&P 500 Energy	S&P 500 Consumer Staples	STOXX 50	STOXX 600 Banks	STOXX 600 Insurance	STOXX 600 Industrial	STOXX 600 Oil & Gas	STOXX 600 Food & Beverage
μ	-0,000631 (-0,510657)	-0,000624 (-0,46428)	-0,000895 (-0,80749)	-0,000442 (-0,33974)	0,001981 (1,1670)	0,000586 (0,70479)	-0,000172 (-0,10954)	0.000209 (0.10645)	0,000341 (0,332894)	-0,000272 (-0,12073)	0,000099 (7,9762e-02)	0,000126 (0,13443)
ρ	0,000077 (0,033969)	-0,000806 (-0,33631)	0,000633 (0,35067)	0,001424 (0,46272)	0,000506 (1,5560e-01)	-0,000879 (-0,44628)	-0,000361 (-0,17237)	-0.002179 (-0.59987)	-0,001231 (-0,573145)	-0,001257 (-0,48115)	0,000463 (2,3025e-01)	0,000288 (0,15843)
c	0.000014 (6.123864)	0,000048 (1,38729)	0,000018 (1,34338)	0,000035 (0,74754)	0 (8,6600e-04)	0,000057 (4,21720)	0,000037 (1,62832)	0.000221 (0.74872)	0,000001 (0,031917)	0,000033 (1,02595)	0	0,000054 (2,68701)
α	0,122870 (2.082940)	0,134909 (1,09485)	0,130304 (2,05599)	0,168341 (0,89470)	0,000001 (1,4139e-02)	0,004810 (0,20233)	0,160315 (1,39550)	0.027696 (0.22343)	0,000428 (0,271309)	0,152804 (0,87017)	0,000022 (5,6735)	0,272163 (1,89191)
β	0,782529 (12.933288)	0,543580 (3,28868)	0,654526 (4,58778)	0,547542 (1,88630)	0,991762 (1,6270e+03)	0	0,663029 (7,33899)	0	0,997159 (45,285148)	0,708544 (8,61123)	0,999927 (8,2387e+02)	0,070600 (0,46681)
(α + β)	0,905399	0,678489	0,78483	0,715883	0,991763	0,00481	0,823344	0.027696	0,997587	0,999949	0,999949	0,342763
ξ	0.000019 (1.819552)	0.000060 (1.04593)	0,000028 (1,01084)	0,000057 (0,69719)	0,000014 (3,0961e+03)	0,000133 (2,39889)	0,000023 (0,86233)	0.000554 (0.66070)	0	0,000001 (3,3882e+03)	0,000001 (3,3882e+03)	0,000076 (1,95677)
AIC	-5,6471	-5,539	-6,0762	-5,6828	-4,8653	-6,2674	-5,4729	-4,8656	-5,6219	-5,1292	-5,1292	-6,154
Bayes	-5,5369	-5,4266	-5,9642	-5,5708	-4,7538	-6,155	-5,3631	-4,7558	-5,5117	-5,0194	-5,0194	-6,0442
Shibata	-5,6494	-5,5415	-6,0787	-5,6853	-4,8678	-6,2699	-5,4752	-4,8679	-5,6242	-5,1316	-5,1316	-6,1563
Hannan-Quinn	-5,6024	-5,4934	-6,0308	-5,6373	-4,82	-6,2218	-5,4283	-4,8211	-5,5772	-5,0847	-5,0847	-6,1094

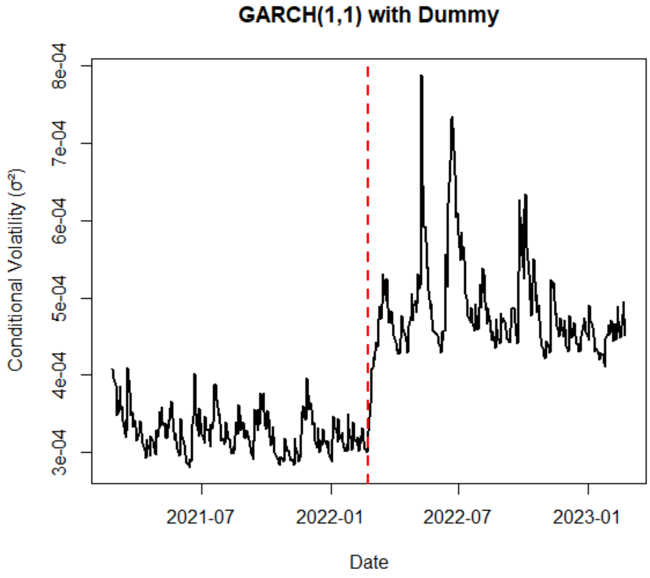
Annex 47 - S&P 500 Conditional Volatility (GARCH)



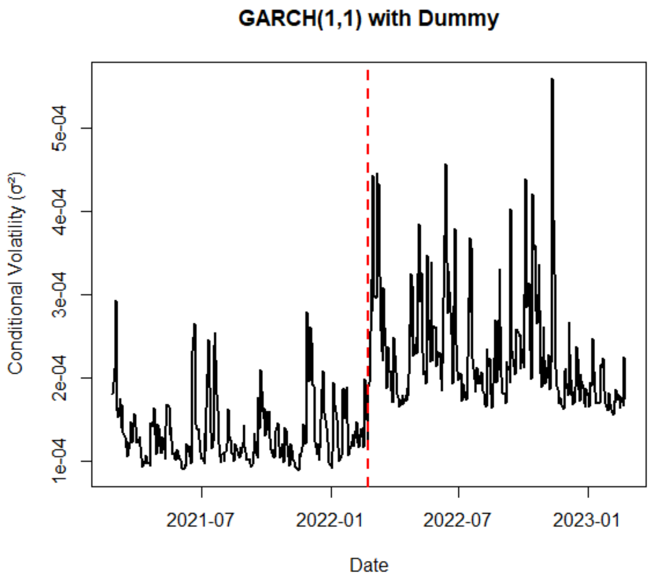
Annex 48 - S&P 500 CS Conditional Volatility (GARCH)



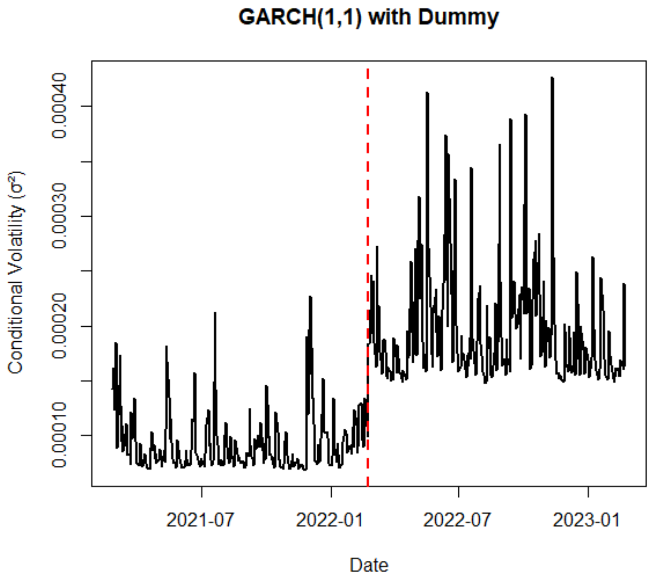
Annex 49 - S&P 500 Energy Conditional Volatility (GARCH)



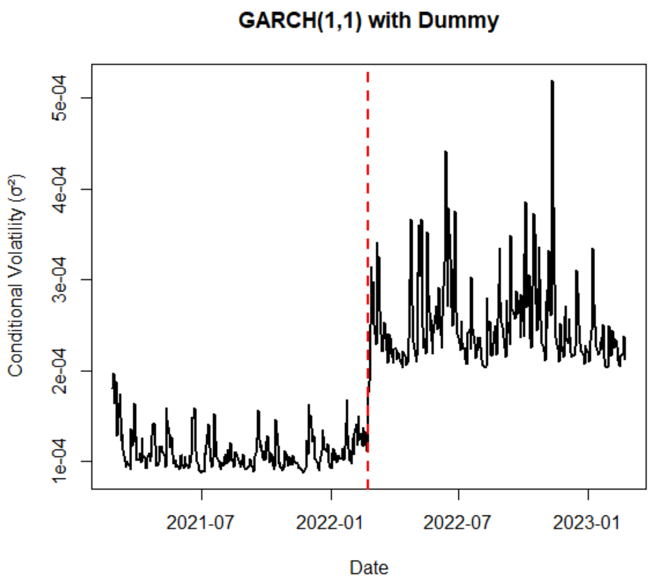
Annex 50 - S&P 500 Financials Conditional Volatility (GARCH)



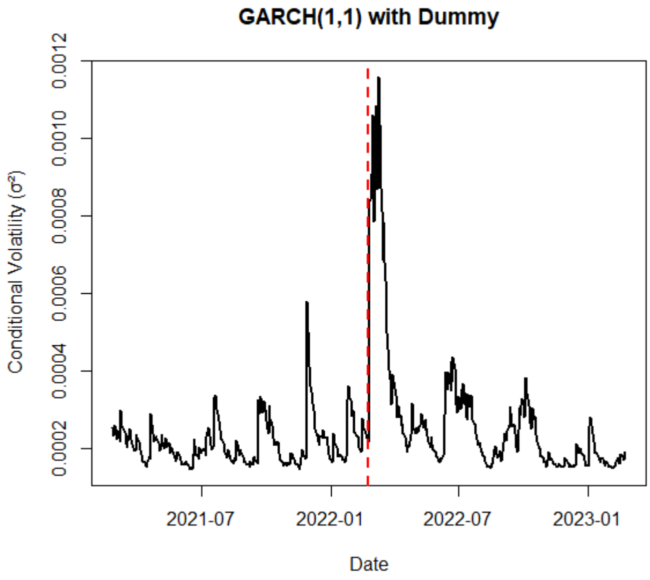
Annex 51 - S&P 500 Industrial Conditional Volatility (GARCH)



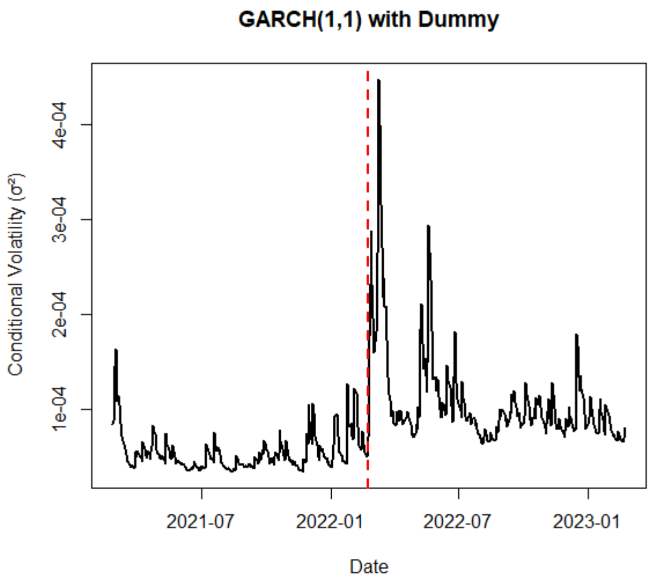
Annex 52 - S&P 500 Materials Conditional Volatility (GARCH)



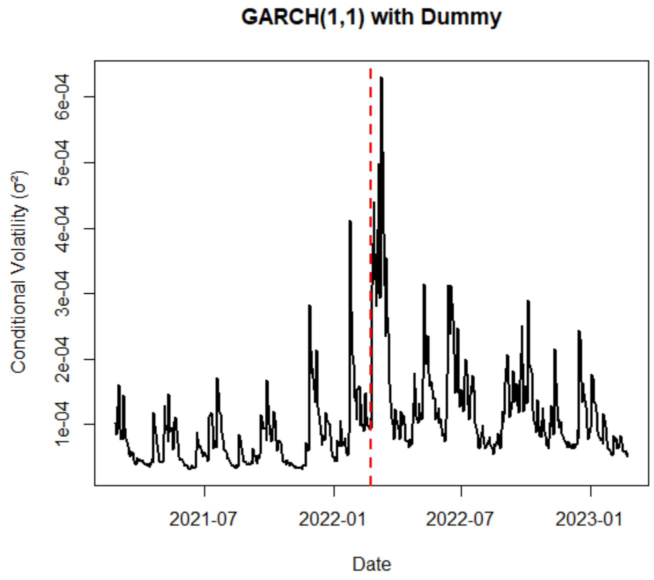
Annex 53- STOXX 600 Banks Conditional Volatility (GARCH)



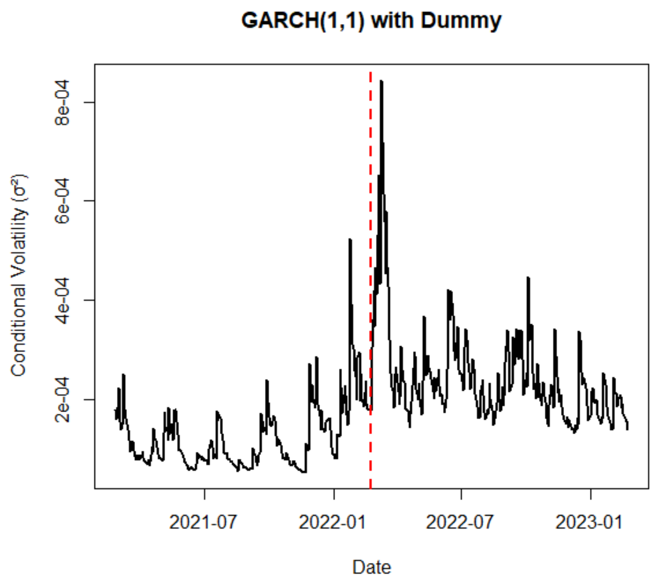
Annex 54 – STOXX 600 FB Conditional Volatility (GARCH)



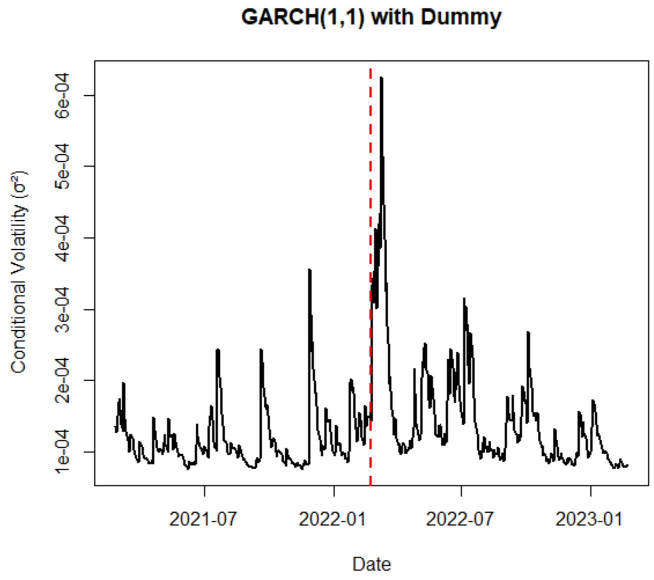
Annex 55 – STOXX 600 Conditional Volatility (GARCH)



Annex 56 – STOXX 600 Industrial Conditional Volatility (GARCH)



Annex 57 – STOXX 600 Insurance Conditional Volatility (GARCH)



Annex 58 – STOXX 600 Oil & Gas Conditional Volatility (GARCH)