University of Glasgow

Adam Smith
Business School

ECONOMICS DISSERTATION COVER SHEET

STUDENT ID: 2928256P

DATE: 14/08/2024

NAME OF SUPERVISOR: Dr. Marco Ercolani

DISSERTATION TITLE: The Impact of Political Events on Market Dynamics (2014-2024): Evidence from 14 European Countries

WORD COUNT: 11752

PROGRAMME OF STUDY: Data Analytics for Economics and Finance, MSc

Adam Smith Business School

West Quadrangle, Gilbert Scott Building, Glasgow, G12 8QQ, Scotland UK
Telephone: +44 (0)141 330 3993 Facsimile: +44 (0)141 330 4939
Email: business-school@glasgow.ac.uk

AACSB ACCREDITED ASSOCIATION OF MBAS ACCREDITED EFMD EQUIS ACCREDITED

The University of Glasgow, charity number SC004401

Table of Contents

Contents

1 Introduction ... 5
1.1 Study Objectives and Considerations ... 5
1.2 Main events ... 6
1.3 Dissertation outline ... 8
2 Literature Review ... 8
2.1 How stock prices are shaped ... 8
2.2 Stock Market Volatility: definition and modelling ... 9
2.3 How does political uncertainty affect investors? ... 10
2.4 ARMA and GARCH Models ... 11
2.5 Review of existing literature ... 12
3 Methodology ... 14
3.1 Data ... 14
3.2 Models Used ... 14
3.3 Process ... 17
4 Results ... 18
4.1 Asset returns ... 18
4.2 GARCH (1,1): Volatility Model Estimates ... 20
5 Event study ... 26
5.1 Crimea Annexation by Russia (March 18, 2014) ... 27
5.2 Announcement of Brexit Referendum Results (June 24, 2016) ... 28
5.3 US Presidential Election - Trump Elected (November 8, 2016) ... 30
5.4 Start of US-China Trade War (July 6, 2018) ... 31
5.5 French "Yellow Vest" Protests Begin (November 17, 2018) ... 33
5.6 First COVID-19 Lockdowns in Europe (March 2020) ... 34
5.7 US Presidential Election – Joe Biden elected (November 3, 2020) ... 36
5.8 Approval of First COVID-19 Vaccine by European Medicines Agency (December 21, 2020) ... 37
5.9 Russian Invasion of Ukraine (February 24, 2022) ... 39
6 Conclusion ... 40
7 Reference List ... 41

8 Appendices 44
8.1 Appendix 1: Indexes Used for the analysis per country. 44
8.2 Appendix 1: Asset Returns Graphs per Country 44
8.3 Appendix 2: Asset Returns Stationarity and Non-Normality Tests.......... 50
8.4 Appendix 3: Modelled (Fitted) Volatility Graph per country 52
8.5 Appendix 4: Modelled Volatility Stationarity and Non-Normality Tests 58
8.6 Appendix 5: ARX Model – Exogenous variable (EUI) estimates.......... 58

Abstract

The aim of this paper is to explore the impact of political uncertainty on European stock markets, focusing on the mechanisms through which political events influence investor behaviour and market performance. By utilizing a comprehensive dataset spanning across 14 European countries and tracing over the last decade (2014-2024), the study employs econometric models to analyse market reactions to political events such as elections, referendums, and policy changes. Findings revealed that political uncertainty leads to increased market volatility, causing more risk averse investors to change their investment decisions, resulting in short-term declines in stock prices. Additionally, the study demonstrated varying effects across different sectors and countries, suggesting that both the nature of political events and the economic context play crucial roles in shaping market responses. This research contributes to a deeper understanding of the intersection between political events and financial markets, offering valuable insights for policymakers, investors, and financial analysts.

1 Introduction

1.1 Study Objectives and Considerations

It has been observed that uncertainty arising from many political events causes stock prices to drop. As uncertainty rises more, stock prices fall further (Brogaard et al., 2019). This relationship is much more intricate than it seems, and the exploration of the above phenomenon can give valuable insight into the financial connections between countries.

Establishing cause and effect in event studies that analyse how political events trigger changes in the stock markets is very challenging due to the complexity of financial markets. Stock markets are influenced by a multitude of simultaneous factors, including economic data, corporate earnings, global market trends, and investor sentiment. Isolating the impact of a single political event from these myriad influences is inherently difficult. Furthermore, markets can react to political events before they occur, based on expectations and speculations, which can dilute the observable impact of the actual event. The market reaction may also occur over varying time frames, complicating the establishment of direct cause and effect (Baker and Wurgler, 2006).

Another significant challenge is the presence of confounding variables. During any political event, other significant developments might happen concurrently, such as economic reports, corporate announcements, or international news. These confounding variables can affect market behaviour, making it hard to attribute changes solely to the political event in question (Boyd, Hu and Jagannathan, 2005). Additionally, investor behaviour is influenced by psychological factors and biases, leading to irrational market movements that obscure the direct effects of political events. The heterogeneity of political events further complicates this analysis, as elections, policy announcements, geopolitical conflicts, and scandals can have different effects, and their impact may vary across sectors and regions.

Data limitations also pose significant challenges. The availability and granularity of data can hinder analysis, as high-frequency trading data may show immediate reactions, but longer-term effects require more extensive data analysis that may not always be available or precise. Statistical models used in event studies often rely on assumptions that might not hold in real-world scenarios. Model misspecification or incorrect assumptions about market efficiency and investor behaviour can lead to erroneous conclusions. Moreover, political events can influence market conditions, but market reactions can also feed back into the political landscape, creating a complex interplay that is difficult to disentangle. Because of these challenges, while correlations can often be observed between political events and market reactions, establishing a definitive causal relationship requires careful consideration and robust analytical approaches (Tetlock, 2007).

The exploration of how political occurrences influence the behaviour of European stock markets is of significant interest for multiple reasons. Firstly, it addresses a critical intersection between political science and financial economics, providing insights into how political events and instability influence different markets. This understanding is vital for investors, policymakers, and scholars, as it aids in developing risk management strategies and economic projections. Additionally, the study of European stock markets is optimal given the region's diverse political landscape, frequent political disruptions and frequent changes in governments, which substantially affect the market volatility and individual investment choices. This research enhances the understanding of how political uncertainty influences financial market reactions, contributing to the existing body of literature and offering practical insights for mitigating market volatility amidst political instability.

This paper explores how 9 of the most significant political events, both in Europe and in the Unites States of America, affected the 14 major European Stock Markets in the last decade. The approach is centred around modelling the volatility of stock markets using a GARCH model and then examining said volatility along the change in returns of the stock markets around the time of the political events. Various time windows are created to further explore into the long-term and short-term effects on the stock markets. The main aim is to investigate the negative relationship between political uncertainty and the stock market returns. Additionally, an attempt is made to explain the mechanisms of how the investors react to said shocks and how uncertainty that arises in the investors' minds is projected into the decline of stock prices. This dissertation aims to outline the trends in European stock markets over the past decade and serve as a reference for understanding market reactions to uncertainty

1.2 Main events

The political events this dissertation focuses on are presented below in chronological order. These were selected as they represent the biggest political events of the last decade.

- <u>Crimea Annexation by Russia (March 18, 2014):</u> Russia formally annexed Crimea following a disputed referendum, leading to international sanctions and heightened geopolitical tensions. This event impacted the European markets with significant trade relations with Russia.

- Announcement of Brexit Referendum Results (June 24, 2016): The United Kingdom voted to leave the European Union, a decision that shocked global markets and led to significant volatility, particularly in European stocks and the pound sterling.

- US Presidential Election - Donald Trump Elected (November 8, 2016): Donald Trump's election as US President led to initial market uncertainty, followed by significant rallies in various sectors due to his promises of deregulation and tax cuts.

- Start of US-China Trade War (July 6, 2018): The US imposed tariffs on $34 billion worth of Chinese goods, escalating into a trade war that affected global markets due to fears of reduced global trade volumes and economic growth.

- French "Yellow Vest" Protests Begin (November 17, 2018): These protests caused significant social unrest in France, impacting investor confidence and market performance in one of the Eurozone's largest economies.

- First COVID-19 Lockdowns in Europe (March 2020): As European countries started imposing lockdowns in response to the COVID-19 pandemic (starting around early March 2020), stock markets experienced sharp declines due to uncertainty about the economic impact.

- US Presidential Election (November 3, 2020): Joe Biden was elected President of the United States, influencing market expectations regarding future US policies on trade, regulation, and international cooperation (Investment Products and Capabilities).

- Approval of First COVID-19 Vaccine by European Medicines Agency (December 21, 2020): The approval of the Pfizer-BioNTech COVID-19 vaccine marked a turning point in pandemic management, leading to positive market reactions on hopes of an economic recovery.

- Russian Invasion of Ukraine (February 24, 2022): This event led to immediate negative impacts on European markets, driven by concerns over energy supplies and broader geopolitical stability.

1.3 Dissertation outline

This dissertation is structured to provide a comprehensive analysis regarding the effects of political instability on European stock markets in the last decade. Section 2 conducts a literature review, drawing insights from various academic papers that explore the connection between political uncertainty and asset prices. Key definitions and economic concepts necessary for the analysis are also presented in this section. Section 3 details the methodology, including the collection, preparation, and processing of data. This section also outlines the mathematical models and regression analysis used. In Section 4, the results are presented, visualized, and discussed, with a particular focus on the volatility of stock markets using GARCH models and the changes in returns around significant political events. Section 5 contains the event study with a discussion per event. Section 6 is the conclusion with the references and appendices following in Section 7 and 8 respectively.

2 Literature Review

2.1 How stock prices are shaped

There is a lot to gain from understanding stock market fundamentals and how stock prices are shaped. Multiple factors shape a stock price, and they vary from the nature to the company to the market conditions and to finally the investors themselves. The first factor is investor sentiment. Investor's sentiment refers to the general attitude of investors toward a specific stock or the broader market. When positive sentiment exists, typically prices increase and likewise, when negative sentiment exists typically prices decrease (Baker and Wurgler, 2004). This sentiment is also shaped by various factors, including media reports on company performance, industry trends, economic indicators, earning reports and geopolitical events. An example of this is the company NVIDIA and the excitement of the investors to buy its stock when it announced bigger than expected profits, solidifying them a place amongst the biggest companies of the world and gaining huge media attention.

The second factor that can shape stock prices is what is known as herd behaviour among investors. In times of uncertainty, investors frequently mimic the actions of others leading to trends and market bubbles. When a stock's price rises, regardless of the reason, it often attracts more investors who anticipate further growth, thereby driving the price even higher (called a trend). Conversely, herd behaviour can also lead to irrational exuberance, causing stock prices to inflate beyond their intrinsic value. This overvaluation eventually necessitates market corrections and even crashes. This is known as creating a bubble and the sudden market crash is termed as a bubble burst (Bikhchandani and Sharma, 2001).

The third factor is the emotions of each individual investor. Behavioural economics attempts to understand these personal emotions and their connection to economic events, thus playing a major role in Economics. Two primary emotions, greed and fear, significantly influence the stock market. Greed often drives investors to purchase stocks at elevated prices during bull markets (when prices are rising or expected to rise), in hope of further gains. On the other hand, fear can lead to panic-selling in periods of bear markets (declining stock prices and pessimistic sentiment), resulting in declining stock prices (Lo, Repin and Steenbarger, 2005). Additionally, psychological biases, such as overconfidence and anchoring, can further impact investor behaviour. Overconfident investors may take excessive risks, thereby increasing market volatility. Anchoring occurs when investors place unnecessary emphasis on initial information, such as a stock's initial price or a previous high, which can lead to mispricing the asset. Although all four of the aforementioned factors are individual level influences, all investors are motivated by one or more of them, meaning they can collectively move stock prices and even markets (Statman, Thorley and Vorkink, 2006).

Concluding, two additional phenomena that significantly influence investor behaviour and market dynamics are confirmation bias and loss aversion. Confirmation bias causes investors to favour information that supports their existing beliefs while ignoring evidence that contradicts them. This selective gathering of information can reinforce existing market trends and contribute to mispricing due to investors' bias (Park et al., 2010). Loss aversion on the other hand describes the tendency of investors to experience the pain of losses more acutely than the pleasure of gains. This heightened sensitivity to losses can result in irrational decision-making, such as holding onto underperforming stocks for too long in the hope of a rebound or prematurely selling successful stocks to secure gains (Kahneman and Tversky, 2013). Together these biases contribute to market inefficiencies and can exacerbate volatility as they influence both individual and collective investor behaviour.

2.2 Stock Market Volatility: definition and modelling

In financial markets, volatility and returns are two fundamental concepts that delineate different aspects of investment performance. Volatility refers to the extent of price fluctuations of a stock or market index over a specific period, typically quantified using statistical measures like standard deviation. This metric encapsulates the risk associated with the investment, as higher volatility indicates more pronounced price swings, thus presenting greater risk. On the other hand, returns measure the profitability of an investment, calculated as the percentage change in the asset's value over time. While returns show the financial gain or loss, volatility highlights the uncertainty or stability in achieving those returns. Investors must balance these elements; high volatility may offer the potential for high returns but at greater risk. Conversely, investments with lower volatility tend to provide more stable, albeit potentially lower, returns. Thus, understanding both volatility and returns is crucial for assessing both the risks and rewards in investment decisions, enabling investors to align their strategies with their risk tolerance and financial goals (French, Schwert and Stambaugh, 1987).

By understanding volatility, investors and financial analysts can better predict and manage potential losses in the markets. This modelling helps in constructing diversified portfolios that are equipped to withstand unexpected market movements, optimizing asset allocation to balance potential returns against risk exposure. Moreover, accurate volatility models are crucial for pricing options and other financial derivatives, since volatility influences the pricing of financial derivatives by affecting their risk and potential return. Overall, the ability to model and interpret market volatility supports more informed, strategic decision-making in finance, enhancing both individual and institutional investment outcomes (Kang, 2011).

2.3 How does political uncertainty affect investors?

Political uncertainty exerts a profound impact on stock market dynamics, predominantly through market volatility and its effect on risk premiums (the extra return expected from an investment due to its higher risk compared to a risk-free asset). Increased market volatility occurs as investors respond to expected or actual shifts in the political landscape, such as electoral outcomes, and to other significant events (wars , protests, pandemics, etc…). This heightened sensitivity to political developments prompts larger and more frequent stock market price swings as investors adjust their expectations based on the evolving political context and associated policy implications (Julio and Yook, 2012).

Moreover, in contexts of intensified political uncertainty, investors seek higher returns to offset the escalated risks, manifested in the expanded risk premiums associated with investment assets. As political uncertainty grows, it broadens the risk premium, thereby influencing the cost of capital and, consequently, investment decisions across various economic sectors. This alteration in risk premiums is particularly significant in economies or periods characterized by substantial political upheaval, where the uncertainty substantially changes the investors' risk evaluations and expected investment returns (Pástor and Veronesi, 2013).

Additionally, the impact of political decisions is directly observed in economic policies that influence crucial stock market sectors such as taxation, trade, and regulatory frameworks. These sectors directly affect the operational dynamics and profitability of companies. Uncertainty about these policy directions can stall corporate decision-making and investment, as businesses await clearer signals from government authorities (Baker, Bloom and Davis, 2021). Also, in times of political uncertainty, there is a noticeable decline in investor confidence which prompts a migration to safer asset classes. This shift reduces the liquidity and investment in equities, potentially leading to a generalized downturn in stock market activities. This flight to quality, characterized by an increase in demand for assets perceived as safer, such as government bonds or precious metals, can substantially depress equity markets (Çolak, Durnev and Qian, 2017). Concluding, international investment flows also react sensitively to perceptions of political stability. Foreign investors are likely to avoid or withdraw investments from markets they perceive as politically unstable, which can lead to significant capital outflows. This reduction in foreign investment can exacerbate the decline in stock prices and further destabilize the local market (Jensen and Schmith, 2005).

2.4 ARMA and GARCH Models

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model introduced by Bollerslev (1986) expands upon Engle's (1982) ARCH model, incorporating past conditional variances to better model financial time series. It evolves from the Autoregressive Moving Average (ARMA) model by specifically modelling the changing variance in the error terms. While the ARMA model provides a framework for understanding the autocorrelations within the mean of a time series (Box et al., 2015), GARCH models extend this to account for volatility (variance of errors) clustering, a prevalent feature in financial time series data. In practical terms, a GARCH model can be seen as an ARMA model applied to the variance of a time series, not just to the series itself. This is achieved by allowing past squared residuals (from the mean equation modelled by ARMA) and past variances to inform current period variances. This enhancement (evolution from ARCH to GARCH model), not only improves the estimation of financial time series data but also captures the 'volatility clustering' phenomenon often observed in stock market returns. Volatility clustering suggests that times of high volatility tend to be followed by more high volatility, while periods of low volatility are likely to be followed by continued low volatility. GARCH models are particularly valued for their ability to model and predict the changing variance (volatility) of stock returns, which is crucial for risk management, option pricing, and financial forecasting. Additionally, GARCH models account for the leverage effect, where negative returns lead to a greater increase in future volatility compared to positive returns of the same magnitude. The relationship between ARMA and GARCH models showcases the comprehensive approach to modelling both the mean and volatility dynamics in financial time series analysis, enhancing the predictive capabilities and robustness of econometric modelling.

2.5 Review of existing literature

This dissertation is inspired by and builds upon the following academic papers, which served as key sources of knowledge and ideas. The methodology presented in Section 3 is also heavily based on these papers as they share similar aims.

The paper "Global Political Uncertainty and Asset Prices" (Brogaard et al., 2019), examines the effect of global political uncertainty on asset prices, particularly focusing on U.S. federal elections as a proxy for such uncertainty. The study reveals that political uncertainty surrounding U.S. elections has a significant effect on global equity returns, volatility, and exchange rates. Non-U.S. equity returns tend to decline in the months preceding U.S. elections, while market volatility rises, and non-U.S. currencies weaken relative to the U.S. dollar. The researchers employ a panel regression analysis, utilizing data from 50 non-U.S. countries from 1990 to 2017. The methodology involves regressing stock market returns on election indicators while controlling for traditional risk factors and fixed effects. Data were sourced from DataStream for stock market information and Worldscope for firm-level financial data. The study used regression models to account for traditional risk factors and fixed effects, decomposing return innovations into cash flow and discount rate components. This analysis showed that the discount rate channel was the primary mechanism through which political uncertainty influenced asset prices. The study concludes that increased global risk aversion during periods of political uncertainty leads investors to shift from risky equities to safer assets like U.S. Treasuries, highlighting the significant influence of political uncertainty on asset prices.

The paper "Political Shocks and Asset Prices" (Carnahan and Saiegh, 2021), investigates the impact of political shocks on asset prices, using data from the Buenos Aires Stock Exchange in Argentina from 1967 to 2020. The study reveals that political shocks such as coups, wars, and national elections significantly increase stock market volatility, with irregular government turnovers causing the most substantial volatility increase. This study employed an event study approach combined with a GARCH (1,1) model to assess the impact of political shocks on stock price volatility in the Buenos Aires Stock Exchange from 1967 to 2020. The methodology isolated the effects of specific political events by comparing stock price volatility before and after these events within a three-day event window. The researchers controlled for confounding factors by ensuring no major political, macroeconomic, or market-related news coincided with the political events studied. The results show that while predictable events like planned successions do not significantly alter volatility, unexpected political changes lead to higher market risk. The study highlights the importance of political stability for maintaining investor confidence and market stability.

The paper “The Impacts of Political Uncertainty on Asset Prices: Evidence from the Bo Scandal in China” (Liu, Shu and Wei, 2016), investigates the impact of political uncertainty, specifically stemming from the Bo Xilai scandal in China, on asset prices. The study analyses daily stock returns of non-financial firms listed on the Shanghai and Shenzhen Stock Exchanges, employing an event study approach to assess cumulative abnormal returns (CARs) within a 3-day window from March 13-15, 2012, surrounding the scandal. To evaluate firms' sensitivity to policy changes, the study uses three proxies: sensitivity to monetary policy, sensitivity to fiscal policy, and political connections. Regression models controlled for firm characteristics to isolate the impact of policy sensitiveness on CARs, with robustness checks confirming the findings The analysis reveals that the is primarily driven by an increase in the discount rate due to heightened political uncertainty, rather than a decrease in expected future cash flows. Also, firms more sensitive to policy changes, such as those with high monetary or fiscal policy sensitivity and strong political connections, suffered from higher decline in stock prices.

The paper “Unanticipated Political Events and Stock Price Returns: An Event Study” (Dangol, 2008), investigates the impact of unanticipated political events on stock price returns in the Nepalese stock market. It was found that positive political news resulted in positive abnormal returns, whereas negative news led to negative returns, illustrating the significant influence of political events on investor behaviour and market returns. This research analysed the market’s response to events such as the Royal massacre, the dissolution of parliament, and ceasefire declarations from 2001 to 2006. It employed an event study methodology, incorporating daily stock prices, the NEPSE index, and dates of political announcements sourced from newspapers. The study utilized the market model from the capital asset pricing model (CAPM) to calculate abnormal returns within a 21-day window surrounding the event.

Normal returns were estimated using Ordinary Least Squares (OLS) regression over a 180-day period prior to each event. Prediction errors and cumulative average prediction errors (CPEs) were also analysed, revealing the profound impact of political uncertainty on market dynamics. The findings indicate that the Nepalese stock market is semi-strongly inefficient, needing 2 to 3 days to assimilate new political information, thus underlining the critical role of political stability in sustaining market confidence and equilibrium.

3 Methodology

3.1 Data

Daily closing price data from 01/01/2014 until 31/05/2024 were collected for stock prices of the 14 main European indexes. More details on the index used for each country can be found under Section 1.1 of the appendix. These were collected from Google Finance, Yahoo Finance and Investing.com. For markets using a different currency than the euro (United Kingdom, Sweden, Switzerland) the daily exchange rate was also sourced from the same websites as above and was used for the conversion. Missing data was handled by linear interpolation. Because the research is interested in stock market data only surrounding the main events of section 1.2, filling in missing data for other dates does not affect the event analysis.

3.2 Models Used

ARX (Autoregressive with Exogenous Inputs)-GARCH Model:

Combining the ARX and GARCH models, the returns can be modelled as follows:

Mean Equation:

$$r_t = \mu + \sum_{i=1}^{p} \varphi_i r_{t-i} + \sum_{j=0}^{q} \xi_j x_{t-j} + \varepsilon_t$$

Where:

- r_t are the returns at time *t*
- μ is the constant term (mean of returns)
- φ_i are the autoregressive coefficients
- r_{t-i} are the lagged returns
- ξ_j are the coefficients of the exogenous variables
- x_{t-j} are the exogenous variables

- e_t is the error term (residual) at time *t*

Variance Equation:

$$\sigma^2{}_t = \omega_0 + \sum_{i=1}^{p} a_i \varepsilon^2{}_{t-i} + \sum_{j=1}^{q} \beta_j \sigma^2_{t-j}$$

Where:

- σ_t^2 is the conditional variance at time *t*
- ω_0 is the constant term
- a_i are the coefficients for the lagged squared residual terms
- ε^2_{t-i} are the lagged squared residuals
- β_j are the coefficients for the lagged conditional variances
- σ^2_{t-j} are the lagged conditional variances

Let θ denote the combined parameter vector for the ARX-GARCH model:

$$\theta = (\mu, \varphi_1, \varphi_{2,} \ldots, \varphi_{p,} \xi_1, \xi_2, \ldots, \xi_q, \omega_0, \alpha_1, \alpha_2, \ldots, \alpha_p, \beta_1, \beta_2, \ldots \beta_q)$$

The parameters of the ARX-GARCH model are generally estimated using the Maximum Likelihood Estimation (MLE) method. The log-likelihood function for the GARCH model can be expressed as follows:

$$L(\theta; r) = -\frac{1}{2}\sum_{t=1}^{T}\left(\log(2\pi) + \log(\sigma_t^2) + \frac{\varepsilon_t^2}{\sigma_t^2}\right)$$

Where:

- $\varepsilon_t = r_t - \left(\mu + \sum_{i=1}^{p} \varphi_i r_{t-i} + \sum_{j=1}^{q} \beta_j x_{t-j}\right)$ is the residual
- T is the total number of observations

In the context of an ARX-GARCH model, the likelihood function is maximized with respect to all the parameters involved in both the ARX mean model and the GARCH variance model. This includes the parameters of the autoregressive component, the exogenous variables, and the conditional variance model. The objective of MLE is to find the parameter vector θ that maximizes the log-likelihood function:

$$\hat{\theta} = argmax_{\theta}\ L(\theta; r)$$

Due to the complexity of the log-likelihood function in the ARX-GARCH model, the maximization is typically performed using numerical optimization algorithms. These algorithms iteratively adjust the parameter values to find the maximum of the log-likelihood function. Commonly used optimization methods include, Newton-Raphson method, Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm and Expectation-Maximization (EM) algorithm.

The optimization process continues until convergence criteria are met. These criteria include the change in the log-likelihood value between iterations falls below a predefined threshold, the gradient (first derivative) of the log-likelihood function with respect to the parameters is close to zero and the parameter estimates change very little between iterations.

The Python library used for the purposes of this analysis is called arch, the parameters for ARX-GARCH models were estimated using the BFGS algorithm. This method is part of the scipy.optimize.minimize function, which effectively maximizes the likelihood function by leveraging gradient information. The BFGS algorithm is efficient as it typically requires fewer function evaluations and approximates the Hessian matrix, which contains the second-order partial derivatives of the likelihood function, making it suitable for large parameter spaces.

After conducting extensive research on the literature and experimenting with various parameter values for the GARCH model, it was determined that the GARCH(1,1) specification provided the best fit among the models that successfully converged. When fitting the GARCH model to the collected data, convergence was often unattainable for many of the models, particularly those with higher-order parameters. Several factors can influence the convergence of such models. For instance, if the initial parameter estimates are not close to the optimal values, the optimization algorithm may fail to converge or become trapped in a local minimum. Additionally, daily stock returns are characterized by high noise levels and significant volatility clustering, making it challenging for the model to accurately discern genuine underlying patterns from random fluctuations, which can hinder convergence. Furthermore, higher-order GARCH models impose additional constraints, such as non-negativity of parameters and the requirement that the sum of certain parameters remains below one. As the model complexity increases, meeting these constraints simultaneously becomes more difficult, leading to potential convergence problems. The GARCH(1,1) model, which includes one lag of both the autoregressive (ARCH) term and the moving average (GARCH) term, is well-regarded for its simplicity and effectiveness in capturing the volatility clustering commonly observed in financial time series data. Consequently, it has been widely adopted in empirical studies of stock market returns.

Additionally, the mean model was chosen to be an ARX that incorporates three autoregressive (AR) lags and a European uncertainty index as a control variable. This choice was justified due to the ability of this configuration effectively captures the dynamics of return series while accounting for external political uncertainty, providing a robust framework for modelling volatility in European stock markets.

3.3 Process

The rate of return of each market index can be formulated logarithm of ratios:

$$\text{Returns}_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$$

where $P_{i,t}$ is the price of country i at time t. These returns are then described statistically, plotted and discussed in Section 4.

An ARX model with three autoregressive lags is fitted on the returns, along with the EUI, a policy-related economic uncertainty index constructed monthly, as an exogenous variable without any lags. The data for this variable are from www.policyuncertainty.com. This index is constructed in the following way. For the European index, analysts utilize two newspapers from each country: The Times of London and Financial Times in the UK, Handelsblatt and Frankfurter Allgemeine Zeitung in Germany, Le Monde and Le Figaro in France, El Mundo and El Pais in Spain and Corriere Della Sera and La Stampa in Italy. They identify articles containing words like "uncertain" or "uncertainty," "economic" or "economy," along with at least one policy-related term. These searches are performed in the native languages of the respective newspapers. Next, they adjust the raw EPU counts by dividing them by the total number of articles published in the same newspaper during the same month. Before aggregating the data, the monthly series from each newspaper is standardized to have a unit standard deviation up to 2011. They then calculate the average across newspapers for each month to create country-level and Europe-wide EPU indexes, normalizing them to an average of 100 based on pre-2011 data. The country indexes are averaged from the results of two newspapers per country, while the Europe-wide index is averaged equally from all 10 newspapers. Additionally, the data from the last two months may be slightly revised with each monthly update, as some online newspaper archives might not immediately update their collections with all articles, leading to minor variations in totals for the previous 1-2 months.

An ARX-GARCH (1,1) model is fitted for each market. The GARCH models the conditional variance of the ARX model used for the returns. The GARCH (1,1) model was chosen primarily due to the successful convergence in contrast with other combinations of parameters as well as its frequent use by existing literature in modelling returns. The estimated volatilities for each country are saved and summarized in statistical tables presented in Section 4. These volatilities are then plotted and analysed. In Section 5, an event study is conducted that highlights the main findings for multiple time-windows around the events described in Section 1.2

4 Results

4.1 Asset returns

The key summary statistics of the daily returns per country are presented in Table 1. Daily returns time series, the stationarity (Augmented Dickey-Fuller) test or ADF and non-normality test (Jarque-Bera) can be found in Sections 2 and 3 of the Appendix. The mean returns across countries are generally low, near zero, indicating minimal average growth or change over the period studied. Volatility (which is indicated by the standard deviation or std), differs significantly among countries, reflecting varying levels of market risk and potential reward. Skewness and kurtosis metrics reveal that many countries' asset returns exhibit negative skewness, with more frequent extreme losses than gains, and high kurtosis, indicating a higher likelihood of extreme returns compared to a normal distribution. Collectively, the statistics in Table 1 provide a foundational understanding of the risk profiles and return characteristics in each country's market, which is essential for making informed investment decisions.

Austria's data shows a small positive mean close to zero, indicating minimal average growth or change. The distribution has a high degree of variability and exhibits significant negative skewness and high kurtosis, suggesting a prevalence of extreme negative outliers. The ADF test confirms stationarity, while the Jarque-Bera test indicates non-normality due to its tail behaviour and peak.

Belgium also has a slightly positive mean with moderate variability. It demonstrates extreme negative skewness and very high kurtosis, similar to Austria, indicating significant tail risks. The tests for stationarity and normality are analogous, with data confirmed to be stationary and significantly non-normal.

Finland's statistics show a somewhat higher mean compared to Austria and Belgium, with moderate variability. The distribution has less negative skew and lower kurtosis compared to the previous countries, yet still displays a tendency towards non-normality with significant negative outliers. Stationarity is confirmed through the ADF test.

France displays a slightly higher mean with a corresponding moderate variability. The skewness is negative, and the kurtosis is elevated, indicating a peak and potential for outliers. The statistical tests confirm the data's stationarity and reject the normality hypothesis.

Germany shows a marginally higher mean than France with similar variability. It has less negative skewness and elevated kurtosis. Both ADF and Jarque-Bera tests indicate stationarity and non-normality, pointing to a distribution with outlier effects.

Greece's mean is slightly negative, indicating an average decline, with very high variability suggesting a volatile dataset. The distribution is less skewed compared to others and has significant kurtosis. The data is stationary but highly non-normal.

Ireland presents a higher mean relative to most other countries with moderate variability. Skewness is negative, and kurtosis is high. The stationarity of the dataset is confirmed, but it fails the normality test, indicating potential outliers.

Italy shows a positive mean and high variability. It has the most negative skewness and one of the highest kurtosis values, indicating extreme tail risks and peak. The data is strongly stationary and highly non-normal.

The Netherlands exhibits a relatively high mean and lower variability than Italy. Skewness and kurtosis are less pronounced but still significant, confirming non-normality. Stationarity is strongly indicated by the ADF test.

Portugal’s mean is nearly zero, with moderate variability. It has negative skewness and relatively low kurtosis, suggesting some asymmetry but less peak compared to other countries. The data is stationary and non-normal.

Spain has a low positive mean and moderate variability. Its skewness is significantly negative, and kurtosis is high, indicating a non-normal distribution prone to outliers. Stationarity is confirmed.

Sweden's mean is positive, though low, with variability similar to Spain's. It has negative skewness and the lowest kurtosis among the countries, suggesting fewer extreme outliers but still some asymmetry. The data is stationary and non-normal.

Switzerland shows a positive mean and the lowest variability, indicating stable conditions. It has the least negative skewness and very high kurtosis, suggesting fewer but more extreme outliers. The data is stationary and highly non-normal.

The UK has a low positive mean and moderate variability. Skewness is notably negative, and kurtosis is high, indicating a likelihood of negative outliers and a peak. The data is stationary and non-normal.

	mean	std	min	5%	95%	max	skewness	kurtosis
Austria	8.8898E-05	0.0108	-0.1467	-0.0162	0.0158	0.1021	-1.3353	21.7760
Belgium	7.8738E-05	0.0093	-0.1533	-0.0137	0.0138	0.0736	-1.6141	28.3238
Finland	0.00013072	0.0095	-0.1068	-0.0148	0.0144	0.0666	-0.8273	11.0120
France	0.00016745	0.0099	-0.1310	-0.0153	0.0146	0.0806	-0.9859	17.1919
Germany	0.00017796	0.0101	-0.1305	-0.0160	0.0155	0.1041	-0.6776	15.9789
Greece	-0.0001205	0.0228	-0.2983	-0.0373	0.0364	0.1757	-0.3027	14.5851
Ireland	0.00020515	0.0103	-0.1046	-0.0155	0.0160	0.0671	-0.9862	12.7368
Italy	0.00015772	0.0119	-0.1855	-0.0182	0.0180	0.0855	-1.7648	26.2254
Netherlands	0.00021435	0.0091	-0.1138	-0.0143	0.0140	0.0859	-0.8161	14.0363
Portugal	9.7145E-06	0.0095	-0.1027	-0.0153	0.0151	0.0753	-0.8825	10.7469
Spain	3.9018E-05	0.0104	-0.1515	-0.0158	0.0157	0.0823	-1.5630	24.5562
Sweden	0.00011146	0.0108	-0.1265	-0.0173	0.0172	0.0828	-0.6544	10.0204
Switzerland	0.00015755	0.0082	-0.1004	-0.0122	0.0123	0.1162	-0.2277	23.4986
UK	4.7377E-05	0.0094	-0.1282	-0.0138	0.0136	0.1001	-1.2418	19.8899

Table 1: Summary statistics for asset returns

(Data bars help illustrate differences between countries)

4.2 GARCH (1,1): Volatility Model Estimates

Tables 2.a, 2.b, 2.c present the GARCH model results per estimated coefficient. Daily volatility time series plots, the stationarity (Augmented Dickey-Fuller) test or ADF and non-normality test (Jarque-Bera) can be found in Sections 4 and 5 of the Appendix The GARCH (1,1) estimates for the European stock market returns over the past decade reveal statistically significant variance parameters (ω, α, β) , suggesting variation in market volatility and reaction to new information. The parameter 'omega', which represents the long-run average variance, shows a considerable range among different countries: Austria (0.017, p=0.0042), Belgium (0.0168, p=0.0024), and particularly Switzerland (0.0323, p=0.0016), possess a higher baseline volatility. These values, along with their respective standard errors and t-statistics, underline the robustness of the model fit across various markets. The p-values associated with 'omega' across most countries are below the typical significance level of 0.05, affirming the relevance of the GARCH model in capturing volatility dynamics.

The α coefficients indicate short-run volatility reactions, and the β coefficients reveal significant volatility persistence. For example, France's alpha of 0.0782 (p=0.0049) indicates a relatively high immediate response to market changes, whereas its beta of 0.909 (p<0.0001) suggests strong volatility persistence, indicative of volatility clustering. As mentioned previously, this volatility clustering is a common phenomenon in financial time series where high-volatility events are likely to be followed by other high-volatility events. This general pattern is replicated across other countries such as UK and Italy, reinforcing the utility of the GARCH model in providing insights into market volatility, which is crucial for risk management and derivative pricing.

Daily estimated volatility graphs and the stationarity (ADF) and non-normality tests (Jarque-Bera) can be found in Sections 3 and 4 of the Appendix.

	ω			
	Coeff	std err	t	p-value
Austria	0.0170	0.0059	2.8640	0.0042
Belgium	0.0168	0.0055	3.0400	0.0024
Finland	0.0174	0.0053	3.3100	0.0009
France	0.0214	0.0076	2.8100	0.0050
Germany	0.0128	0.0063	2.0390	0.0414
Greece	0.0120	0.0064	1.8780	0.0604
Ireland	0.0240	0.0074	3.2460	0.0012
Italy	0.0170	0.0064	2.6470	0.0081
Netherlands	0.0180	0.0061	2.9490	0.0032
Portugal	0.0215	0.0069	3.1020	0.0019
Spain	0.0234	0.0069	3.3880	0.0007
Sweden	0.0115	0.0041	2.7750	0.0055
Switzerland	0.0323	0.0102	3.1620	0.0016
UK	0.0214	0.0078	2.7340	0.0062

Table 2.a: Estimated parameter ω

	α			
	Coeff	std err	t	p-value
Austria	0.0681	0.0138	4.9550	0.0000
Belgium	0.0652	0.0132	4.9600	0.0000
Finland	0.0621	0.0109	5.6870	0.0000
France	0.0782	0.0181	4.3150	0.0000
Germany	0.0533	0.0162	3.2850	0.0010
Greece	0.0417	0.0125	3.3300	0.0009
Ireland	0.0624	0.0116	5.3880	0.0000
Italy	0.0681	0.0152	4.4800	0.0000
Netherlands	0.0802	0.0180	4.4660	0.0000
Portugal	0.0724	0.0143	5.0490	0.0000
Spain	0.0748	0.0178	4.1960	0.0000
Sweden	0.0494	0.0114	4.3480	0.0000
Switzerland	0.0848	0.0195	4.3500	0.0000
UK	0.0663	0.0150	4.4230	0.0000

Table 2.b: Estimated parameter α

	β			
	Coeff	std err	t	p-value
Austria	0.9137	0.0167	54.7970	0.0000
Belgium	0.9168	0.0155	59.2730	0.0000
Finland	0.9206	0.0127	72.3660	0.0000
France	0.9007	0.0211	42.7770	0.0000
Germany	0.9334	0.0205	45.4960	0.0000
Greece	0.9462	0.0172	55.0080	0.0000
Ireland	0.9114	0.0154	59.0280	0.0000
Italy	0.9158	0.0176	51.9530	0.0000
Netherlands	0.9028	0.0206	43.7900	0.0000
Portugal	0.9060	0.0181	50.0410	0.0000
Spain	0.9017	0.0188	47.8480	0.0000
Sweden	0.9393	0.0129	72.9160	0.0000
Switzerland	0.8822	0.0240	36.7110	0.0000
UK	0.9093	0.0206	44.0730	0.0000

Table 2.c: Estimated parameter β

Table 3 exhibits the statistical summary for the estimated volatility per country obtained by the GARCH model. The results highlight significant variability (which is indicated by the standard deviation or std) in volatility levels, reflecting diverse market conditions. The differences in estimated volatility parameters suggest that some markets experience more pronounced fluctuations, indicating higher levels of risk. This variability underscores the heterogeneous nature of financial markets, where different countries exhibit distinct risk profiles.

Austria's mean daily volatility is moderate at approximately 0.90, with a standard deviation of 0.41. The volatility ranges from a low of 0.52 to a high of 4.94. The data exhibits significant skewness and kurtosis, suggesting a heavy tail and an asymmetric distribution, which is typical in financial data. The ADF test indicates stationarity with a p-value significantly lower than 0.05, confirming that the volatility series is stable over time. The extremely low p-value in the Jarque-Bera test underscores the non-normality of returns.

Belgium shows a similar pattern with a mean volatility of 0.91 and a standard deviation of 0.40. The minimum and maximum volatilities recorded are very close to Austria's, with a slightly higher peak at 4.97. Like Austria, Belgium also displays high skewness and kurtosis. The ADF test confirms the stationarity of volatility, and the Jarque-Bera test results firmly reject the normality of volatility distributions.

Finland has a higher mean daily volatility at 0.94 but a lower standard deviation of 0.34 compared to Austria and Belgium, indicating less variability. The volatility peaks at 3.57, which is lower than in the other mentioned countries. The distribution characteristics (skewness and kurtosis) are somewhat less extreme but still indicative of a non-normal distribution. Both the ADF and Jarque-Bera tests provide results consistent with the other countries, indicating stationarity and rejecting normality.

France's stock market volatility has a mean of approximately 0.92, with a standard deviation similar to Belgium's at 0.40. The volatility extends from about 0.49 to 4.53. The statistical tests show that the volatility series is stationary and highly non-normal, similar to the other countries, with notable skewness and high kurtosis.

Germany's mean volatility is slightly higher than France's at 0.93, with a comparatively lower standard deviation of 0.36, suggesting tighter volatility clustering. The maximum volatility reaches up to 3.82. Statistical analysis shows that the volatility series is stable over time and deviates significantly from a normal distribution, as evidenced by the results of the ADF and Jarque-Bera tests.

Greece exhibits a mean daily volatility of approximately 0.96, which is among the highest in the dataset, with a standard deviation of 0.45, indicating significant variability. The volatility spans from a low of around 0.50 to a high of 5.10, which is the highest observed maximum volatility among the countries discussed. This suggests that the Greek stock market experiences considerable fluctuations. The skewness and kurtosis values are markedly high, emphasizing a highly asymmetric distribution with pronounced tails. The ADF test results confirm the stationarity of the volatility series, and the Jarque-Bera test solidly rejects the normality of the volatility distribution, reflecting significant deviations from a normal behaviour.

Ireland has a mean daily volatility of approximately 0.91, with a standard deviation of 0.40, which is consistent with the moderate levels seen in other European countries like Belgium and the Netherlands. The range of volatility observed spans from a low of around 0.49 to a high of 4.80, which indicates potential for substantial swings in market conditions. The statistical measures of skewness and kurtosis are elevated, suggesting that the volatility distribution is heavily skewed with pronounced tails. The ADF test confirms the stationarity of the volatility series, indicating that it does not exhibit a trend over time but rather fluctuates around a stable mean. The Jarque-Bera test results strongly reject the normality of the distribution, highlighting its asymmetric and tail-heavy nature.

Italy shows a mean daily volatility of approximately 0.93, with a standard deviation of 0.38, which indicates moderate variability within the observed range. The volatility spans from a low of about 0.50 to a high of 4.57. The skewness and kurtosis values are high, suggesting a significant tail and an asymmetric distribution. The ADF test suggests that the volatility series is stable over time with a very low p-value, reinforcing stationarity. Additionally, the Jarque-Bera test rejects the normality of the return distribution with a p-value approaching zero.

Netherlands exhibits a mean volatility that is slightly lower, at 0.91, but the standard deviation is around 0.40, indicating a level of volatility similar to that of Belgium and France. The range of volatility is between approximately 0.49 and 4.85. The skewness and kurtosis are also elevated, indicating a skewed distribution with heavy tails. The stationarity of the volatility series is confirmed by the ADF test, and the Jarque-Bera test results decisively reject the hypothesis of a normal distribution.

Portugal presents a mean daily volatility of about 0.94, with a standard deviation of 0.43, which indicates a relatively high level of variability compared to some other European countries. This mean value is closer to the higher end observed in countries like Greece. The volatility ranges from a minimum of approximately 0.52 to a maximum of 4.89, indicating significant potential for large swings in market conditions on certain days. The data for Portugal shows substantial skewness and very high kurtosis, suggesting a distribution that is heavily skewed with pronounced fat tails, reflecting extreme market movements more frequently than would be expected in a normal distribution. The results of the ADF test affirm the stationarity of the volatility time series, implying that the series is stable over time without persistent trends. The Jarque-Bera test confirms the non-normality of the distribution, strongly rejecting the hypothesis of normal distribution with a probability effectively at zero, similar to other countries.

Spain's data shows a mean volatility of about 0.92, with a standard deviation of 0.42, showcasing somewhat higher variability compared to some other countries. The minimum and maximum recorded volatilities are 0.48 and 4.77, respectively. The results also indicate significant skewness and a high level of kurtosis. The ADF test for Spain confirms that the volatility time series does not have a unit root, affirming its stationarity. The Jarque-Bera test, like with other countries, highlights the non-normal distribution of volatilities.

Sweden presents a mean volatility of 0.90, with a standard deviation of 0.39. The range of volatility noted spans from about 0.50 to a maximum of 4.23, which is somewhat lower than in other countries discussed. The skewness and kurtosis levels are high but slightly less extreme compared to countries like Austria or Belgium. The statistical tests ADF and Jarque-Bera show similar results to other countries, with the volatility series being stationary and significantly deviating from normality.

Switzerland has a mean daily volatility of 0.89, the lowest among the discussed countries, with a standard deviation of 0.37. The volatility extends from a minimum of 0.47 to a maximum of 4.02, indicating a generally lower volatility environment compared to its European counterparts. Despite this, the skewness and kurtosis remain high, pointing to a skewed distribution with heavy tails. The ADF test confirms the stationarity of the volatility series, and the Jarque-Bera test strongly rejects the normal distribution assumption.

The UK's mean daily volatility is around 0.92, with a standard deviation of 0.41. This places its volatility characteristics somewhat in the middle range compared to other European countries. The minimum and maximum volatilities noted are approximately 0.48 and 4.50, respectively. Like other countries, the UK shows a high degree of skewness and kurtosis in its distribution of stock market volatilities. The ADF test indicates that the UK's volatility time series is stationary, providing confidence in the stability of this series over time. The Jarque-Bera test rejects the assumption of a normal distribution, underscoring the presence of outliers and heavy tails typical of financial data.

	mean	std	min	max	5%	95%	Skewness	Kurtosis
austria	0.90419813	0.40915967	0.51905945	4.93600838	0.59003187	1.61778289	4.15986314	25.8901659
belgium	0.90718265	0.40224049	0.49387726	4.9685196	0.58834924	1.58669571	4.1887377	26.7004636
finland	0.9406725	0.33984164	0.52901425	3.56955289	0.63434031	1.54426872	3.05989591	14.0134766
france	0.9198995	0.39567019	0.49467945	4.52594378	0.576146	1.58098102	3.47454626	19.5010875
germany	0.92680321	0.3633556	0.48975558	3.8156517	0.58791723	1.53429497	3.05471271	14.9164693
greece	2.17082462	0.71753593	1.29698528	7.78201947	1.4515032	3.49552746	2.07847804	7.05458364
ireland	0.9287056	0.33424217	0.57483438	3.58530296	0.65502115	1.47644214	3.55469486	17.915338
Italy	0.92628626	0.38174192	0.49222802	4.90207237	0.59310354	1.52364111	3.8290156	24.4335878
netherlands	0.92443414	0.39474102	0.49212724	4.41037706	0.5545876	1.59886293	3.0549961	15.8860149
portugal	0.9401858	0.3342574	0.53668453	3.8688313	0.62386322	1.50354551	3.03578603	16.1882199
spain	0.92516536	0.37793999	0.54061318	4.63759893	0.62915474	1.5229702	4.11580033	26.2392091
sweden	0.94618937	0.32445421	0.53775927	3.24348099	0.62759505	1.50246976	2.77048183	12.011704
switzerland	0.92678545	0.36365888	0.55087755	4.96108077	0.63136802	1.44626853	4.52465729	31.0173059
uk	0.90421006	0.38746312	0.5446777	4.40337703	0.60033557	1.54231686	4.00648796	24.165722

Table 3: Statistical summary for volatility

5 Event study

In this section the results from the 9 events of Section 1.2 are presented. Three, Seven and Fourteen-day windows (before and after) were created around the main date of each event and the Tables 5.1 – 5.9, show the average return and volatility change per country. While returns are almost self-explanatory, it is important to understand the concept of increasing or decreasing volatility to interpret them. Each column has been fitted with a colour scale to further highlight the magnitude of the values, red for the smallest values and green for the largest values.

An escalation in stock market volatility denotes an elevated level of uncertainty and risk within the financial markets. This heightened volatility frequently indicates increased unpredictability regarding future economic conditions, corporate performance, or geopolitical developments, resulting in more significant price fluctuations as investors re-evaluate their positions. Such conditions suggest shifts in investor behaviour, including panic-driven selling or strategic buying, which contribute to swift and substantial market movements. Furthermore, elevated volatility correlates with a higher perceived risk, prompting investors to seek a greater risk premium for holding equities and necessitating modifications in asset pricing and investment strategies. Market liquidity may also be impacted, as increased volatility can diminish the propensity of market participants to trade, thereby widening bid-ask spreads. Volatility acts as a barometer of underlying economic or financial instability, often precipitated by events such as economic crises, political unrest, or major policy changes. For portfolio managers, rising volatility demands adjustments in asset allocation and risk management approaches, emphasizing the importance of diversification, hedging, and other risk mitigation techniques. In summary, an increase in stock market volatility signifies a greater degree of market uncertainty and risk, driven by a variety of economic, political, and market-specific factors, necessitating more vigilant and proactive decision-making by investors and portfolio managers.

5.1 Crimea Annexation by Russia (March 18, 2014)

Table 5.1 illustrates the changes in returns and volatility of major European stock markets across three different time windows—3 days, 7 days, and 14 days—surrounding Russia's annexation of Crimea on March 18, 2014. The data reveal a general trend of negative return changes in most countries, particularly evident within the 3-day and 7-day windows, indicating an initial adverse reaction from investors to the geopolitical instability. For example, Austria, Finland, France, and Spain experienced significant negative return changes in the 3-day window (-1.39%, -0.37%, -0.34%, and -0.82% respectively), reflecting heightened uncertainty and risk aversion. Greece stands out as an anomaly, showing positive return changes, especially notable in the 3-day (2.67%) and 7-day (2.29%) windows, which could be attributed to country-specific factors or short-term speculative trading. Greece's stock market may have experienced positive returns due to a decoupling from broader geopolitical events and the potential undervaluation of stocks recovering from a prolonged financial crisis. Additionally, positive local economic reforms, sector-specific growth in areas like tourism, and speculative investment could have further insulated and boosted the Greek market amidst global uncertainties.

In terms of volatility, most countries saw increased volatility following the annexation, with Austria's volatility change peaking at 0.31% in the 7-day window, suggesting greater market instability and uncertainty. Conversely, Greece exhibited minimal volatility change (0% in the 7-day window), further underscoring its unique market behaviour during this period. These observations imply that the annexation led to significant investor concern and market turbulence across Europe, with the degree of impact varying by country. The heightened volatility likely reflects the market's struggle to price in the geopolitical risk and the anticipated economic consequences of the annexation and subsequent international sanctions on Russia.

Country	3 days		7 days		14 days	
	Return change (%)	Volatility change (%)	Return change (%)	Volatility change (%)	Return change (%)	Volatility change (%)
Austria	-1.390	0.142	-0.861	0.312	-0.771	0.293
Belgium	0.320	-0.005	0.014	0.178	-0.178	0.193
Finland	-0.367	-0.048	-0.413	0.144	-0.384	0.151
France	-0.337	-0.047	-0.334	0.214	-0.406	0.226
Germany	-0.203	0.015	-0.240	0.222	-0.608	0.257
Greece	2.673	0.041	2.286	0.000	1.628	0.039
Ireland	-0.037	0.030	-0.411	0.151	-0.474	0.151
Italy	-0.190	-0.035	-0.010	0.218	-0.158	0.210
Netherlands	-0.300	-0.043	-0.090	0.262	-0.334	0.294
Portugal	-0.190	-0.007	-0.291	0.186	-0.101	0.183
Spain	-0.823	-0.039	-0.269	0.160	-0.206	0.215
Sweden	-0.407	-0.043	-0.123	0.131	-0.184	0.157
Switzerland	-0.173	0.002	-0.241	0.239	-0.262	0.236
UK	-0.340	-0.043	-0.209	0.036	-0.587	0.031

Table 5.1: Stock returns and Volatility changes following the Crimea annexation by Russia

5.2 Announcement of Brexit Referendum Results (June 24, 2016)

Table 5.2 details the changes in returns and volatility for major European stock markets in the wake of the Brexit referendum results announcement on June 24, 2016. As expected, the returns in the UK did not stabilize as quickly as other countries with volatility increasing during the 3,7 and 14-days windows. The data indicate substantial negative return changes across most countries in the immediate aftermath, especially within the 3-day window. Notably, Sweden and Ireland experienced the most significant declines, with returns dropping by -4.287% and -4.040%, respectively. A reason that can explain why Sweden was affected so intensely by the Brexit is that it has significant trade relationships with the UK, especially in industries like automotive, machinery, and pharmaceuticals. These sharp declines reflect the market's reaction to the unexpected outcome, highlighting investor concerns over economic uncertainty and potential disruptions in trade and financial relationships.

Volatility changes also surged significantly post-referendum, with Finland and Ireland showing marked increases in the 3-day and 7-day windows (1.359% and 1.191%, respectively, in the 3-day window). This heightened volatility underscores the market's uncertainty and the challenges in assessing the long-term impacts of Brexit. Over the 14-day window, while some markets like Greece and Portugal showed signs of recovery with positive return changes (0.334% and 0.328%, respectively), the overall trend remained one of increased volatility, indicating persistent uncertainty.

The market's response can be attributed to several factors. The immediate shock of the referendum results likely triggered widespread risk aversion, prompting investors to sell off stocks in anticipation of economic instability. Additionally, the potential for renegotiated trade deals, changes in regulatory environments, and the overall uncertainty surrounding the UK's future relationship with the EU contributed to the volatility. This period exemplifies how significant political events can lead to abrupt shifts in market sentiment and increased financial market instability.

Country	3 days		7 days		14 days	
	Return change (%)	**Volatility change (%)**	**Return change (%)**	**Volatility change (%)**	**Return change (%)**	**Volatility change (%)**
Austria	-2.310	0.375	-0.860	0.578	-0.058	0.576
Belgium	-2.017	0.423	-0.481	0.693	0.141	0.705
Finland	-3.387	1.359	-0.871	1.233	-0.137	1.110
France	-1.573	0.131	-0.467	0.515	0.046	0.571
Germany	-1.997	0.214	-0.697	0.451	-0.066	0.505
Greece	-2.280	0.145	-0.444	0.303	0.334	0.311
Ireland	-4.040	1.191	-1.414	1.362	-0.387	1.336
Italy	-2.497	0.319	-0.834	0.844	0.073	0.867
Netherlands	-2.010	0.221	-0.547	0.497	0.099	0.542
Portugal	-0.963	0.145	-0.417	0.380	0.328	0.399
Spain	-1.517	0.283	-0.289	0.938	0.260	0.968
Sweden	-4.287	1.051	-1.446	0.960	-0.435	0.880
Switzerland	-1.097	0.220	-0.093	0.252	0.261	0.197
UK	-2.047	0.404	-0.529	0.712	0.016	0.741

Table 5.2: Stock returns and Volatility changes following the announcement of Brexit

5.3 US Presidential Election - Trump Elected (November 8, 2016)

Table 5.3 summarizes the return and volatility changes in major European stock markets around the time of the U.S. Presidential Election of Donald Trump on November 8, 2016. The data show mixed market reactions over the 3-day, 7-day, and 14-day windows. In the 3-day window, several countries such as Portugal (-1.94%) and Spain (-1.61%) experienced significant negative return changes, indicating initial market concern. Conversely, some markets like Austria (0.12%) and Ireland (0.08%) saw slight positive returns, suggesting varied investor sentiment. Switzerland saw the most increase in returns with 0.2%. The increase in can be attributed to expectations of his pro-business policies, like tax cuts and deregulation, which were anticipated to boost the U.S. economy. This growth would benefit Swiss multinational companies with U.S. exposure and a weaker Swiss franc, enhancing export competitiveness and driving up Swiss stock prices.

Over the 7-day window, most markets showed modest positive return changes, with Germany (0.62%) and Austria (0.56%) leading the gains. Volatility changes were relatively mild, with some markets like Finland (1.23%) and Ireland (1.36%) experiencing increased volatility, reflecting ongoing uncertainty about the election's implications.

By the 14-day window, return changes generally stabilized, with Greece (0.60%) and Finland (0.38%) showing notable positive returns. Volatility changes remained low across most markets, indicating a return to relative stability. The varied responses can be attributed to differing economic exposures and investor perceptions of the election's impact on global trade and economic policies. The initial negative reactions likely reflect uncertainty and risk aversion, while the subsequent recovery indicates market adaptation to the new political landscape.

Country	3 days		7 days		14 days	
	Return change (%)	Volatility change (%)	Return change (%)	Volatility change (%)	Return change (%)	Volatility change (%)
Austria	0.117	-0.064	0.563	-0.111	0.354	-0.028
Belgium	-0.350	0.057	0.241	0.040	0.204	0.051
Finland	-0.043	0.129	0.351	0.182	0.382	0.166
France	-0.540	-0.013	0.343	0.030	0.259	0.045
Germany	-0.050	-0.036	0.624	-0.021	0.361	-0.018
Greece	-0.083	-0.025	0.190	-0.046	0.597	-0.020
Ireland	0.083	0.022	0.121	0.108	0.224	0.098
Italy	-0.853	-0.116	0.213	-0.108	0.112	-0.034
Netherlands	-0.937	0.028	0.239	0.053	0.278	0.038
Portugal	-1.943	0.072	0.149	0.073	0.094	0.060
Spain	-1.610	0.069	-0.201	0.018	0.002	0.009
Sweden	-0.340	-0.006	-0.050	0.017	0.606	0.003
Switzerland	0.277	0.027	0.524	0.051	0.229	0.057
UK	-0.027	0.034	0.574	0.059	0.451	0.070

Table 5.3: Stock returns and Volatility changes following the US Presidential Election 2016

5.4 Start of US-China Trade War (July 6, 2018)

Table 5.4 presents percentage changes in returns and volatility for major European stock markets around the start of the US-China Trade War on July 6, 2018. The data indicate varied market reactions over the 3-day, 7-day, and 14-day windows. In the 3-day window, Austria and Greece showed notable positive return changes of 1.38% and 0.87%, respectively, while countries like Portugal (-0.39%) and Spain (-0.34%) experienced negative returns, reflecting mixed investor sentiment. Volatility changes were relatively mild across most markets during this period.

In the 7-day window, return changes remained modest, with Austria (0.52%) and Switzerland (0.45%) showing positive returns, indicating some market resilience. Greece experienced a significant negative return change of -0.76%, suggesting heightened investor concern. Volatility changes continued to be minimal, indicating that the market had begun to stabilize after the initial reaction.

Over the 14-day window, markets generally showed small positive return changes, with Italy (0.57%) and Switzerland (0.30%) leading the gains. Volatility changes remained low, signifying a return to relative stability. The initial mixed reactions and subsequent stabilization can be attributed to the uncertainty and risk associated with the trade war's impact on global trade and economic policies. The varying responses across countries reflect differences in economic exposure to US-China trade relations and investor perceptions of the trade war's long-term implications.

Country	3 days		7 days		14 days	
	Return change (%)	**Volatility change (%)**	**Return change (%)**	**Volatility change (%)**	**Return change (%)**	**Volatility change (%)**
Austria	1.38	-0.04	0.52	0.00	0.41	0.01
Belgium	-0.09	-0.05	-0.06	-0.06	0.14	-0.02
Finland	-0.22	-0.06	-0.39	-0.09	-0.06	-0.07
France	-0.02	-0.06	-0.07	-0.07	0.12	0.00
Germany	-0.33	-0.05	-0.07	-0.07	0.14	-0.02
Greece	0.87	-0.03	-0.76	-0.04	-0.38	0.02
Ireland	-0.14	-0.02	-0.17	-0.03	-0.04	-0.03
Italy	-0.15	0.05	0.00	0.05	0.57	0.02
Netherlands	-0.35	-0.04	-0.16	-0.07	0.02	-0.02
Portugal	-0.39	-0.12	-0.39	-0.19	0.15	-0.14
Spain	-0.34	-0.06	-0.09	-0.10	0.32	-0.09
Sweden	0.09	-0.04	0.27	-0.03	0.37	0.02
Switzerland	0.33	-0.07	0.45	-0.09	0.30	0.07
UK	-0.05	-0.02	-0.12	0.03	0.07	0.11

Table 5.4: Stock returns and Volatility changes following the start of US-China Trade War

5.5 French "Yellow Vest" Protests Begin (November 17, 2018)

Table 5.5 displays the percentage changes in returns and volatility of major European stock markets around the onset of the French "Yellow Vest" protests on November 17, 2018. The data show predominantly negative return changes in the immediate 3-day window, with Austria (-1.04%), Belgium (-0.77%), and Finland (-0.59%) experiencing notable declines, indicating an initial market reaction to the protests. Switzerland (0.37%) and the UK (0.67%) were exceptions, showing positive returns, potentially reflecting different regional economic impacts or investor sentiments.

Over the 7-day window, most markets continued to experience slight negative returns, with Greece (-0.99%) showing a significant decline. However, Ireland (0.31%) and the UK (0.40%) posted positive returns, suggesting a degree of market resilience or differing investor perceptions of the protest's impact.

In the 14-day window, the markets began to stabilize, with Italy (0.36%) and Switzerland (0.24%) leading in positive return changes. Volatility changes were generally low across all periods, indicating that while the protests had an immediate negative impact on returns, the overall market volatility did not significantly increase. This stabilization might be attributed to the market's ability to absorb the shock of the protests and investors' recalibration of their risk assessments.

The initial negative returns likely reflect investor concerns about the protests' potential impact on the French economy and broader European stability. However, the relatively low volatility changes suggest that investors did not perceive the protests as a long-term threat, allowing markets to recover and stabilize over the two-week period.

Country	3 days		7 days		14 days	
	Return change (%)	Volatility change (%)	Return change (%)	Volatility change (%)	Return change (%)	Volatility change (%)
Austria	-1.040	0.169	-0.241	0.101	-0.008	-0.001
Belgium	-0.770	0.196	-0.254	0.133	-0.101	0.029
Finland	-0.587	0.115	-0.264	0.077	-0.127	-0.012
France	-0.163	0.066	0.009	0.009	0.079	-0.065
Germany	-0.433	0.094	0.047	0.055	0.059	0.048
Greece	-0.527	0.004	-0.989	-0.019	-0.174	-0.002
Ireland	-0.083	-0.025	0.313	0.054	0.083	0.044
Italy	-0.117	0.075	0.160	0.049	0.361	0.050
Netherlands	-0.317	0.195	-0.044	0.144	-0.051	0.067
Portugal	-0.293	0.103	-0.026	0.084	0.096	0.028
Spain	-0.383	0.100	-0.100	0.060	-0.034	0.079
Sweden	-0.503	0.149	0.027	0.129	0.274	-0.022
Switzerland	0.367	-0.001	0.350	0.013	0.241	-0.022
UK	0.673	-0.031	0.396	-0.029	0.163	-0.070

Table 5.5: Stock returns and Volatility changes following the French "Yellow Vest" Protests

5.6 First COVID-19 Lockdowns in Europe (March 2020)

Table 5.6 illustrates the percentage changes in returns and volatility for major European stock markets around the initial COVID-19 lockdowns in Europe. The timeframe for lockdown implementation varied across countries, which means that the impact of these events on stock markets also differed. To capture a comprehensive view of this influence, the analysis was centred around March 23, 2020, as this date allows for the inclusion of data from multiple countries' lockdown periods. Consequently, the accuracy of the results may have been affected by these variations in lockdown timing. In the 3-day window, Ireland (0.49%), Portugal (0.28%), and Italy (0.27%) exhibited positive return changes, while the Netherlands (-0.76%) and Greece (-0.58%) experienced significant negative returns This immediate reaction likely reflects differing initial investor responses to the lockdown measures.

Over the 7-day window, several markets showed recovery with notable positive returns in Finland (1.30%), Greece (1.83%), and Ireland (1.91%), suggesting a short-term rebound or optimism about the lockdowns' effectiveness. Conversely, Austria (-0.93%) and Italy (-0.44%) continued to show declines, reflecting ongoing uncertainty in these regions.

In the 14-day window, markets generally stabilized, with Austria (0.64%), Italy (0.35%), and Switzerland (0.24%) showing positive returns. Volatility changes remained significant, with Austria (-0.49%) and Ireland (-0.45%) indicating substantial decreases in volatility, suggesting markets were adjusting to the new reality of lockdowns.

The initial negative returns can be attributed to the sudden economic halt caused by the lockdowns, while the subsequent recoveries may reflect investor optimism about government interventions and potential pandemic containment. The volatility changes indicate initial panic and subsequent stabilization as markets began to adapt to the unprecedented situation.

Country	3 days		7 days		14 days	
	Return change (%)	**Volatility change (%)**	**Return change (%)**	**Volatility change (%)**	**Return change (%)**	**Volatility change (%)**
Austria	0.267	-0.294	-0.930	-0.947	0.639	-0.489
Belgium	-0.107	-0.096	-0.539	-0.434	0.332	-0.135
Finland	-0.183	-0.221	1.304	-0.015	0.264	-0.229
France	0.220	-0.215	0.407	-0.430	0.131	-0.304
Germany	0.100	-0.164	0.343	-0.101	0.108	-0.385
Greece	-0.583	-0.082	1.826	-0.096	-0.074	-0.318
Ireland	0.490	-0.252	1.910	-0.108	0.046	-0.452
Italy	0.273	-0.140	-0.438	-0.661	0.354	-0.321
Netherlands	-0.760	-0.267	0.421	-0.289	-0.074	-0.249
Portugal	0.283	-0.179	0.953	-0.495	0.072	-0.315
Spain	0.103	-0.163	-0.141	-0.660	0.226	-0.280
Sweden	-0.270	-0.157	1.607	0.013	-0.014	-0.335
Switzerland	-0.130	-0.230	1.000	-0.452	-0.200	-0.185
UK	-0.180	-0.244	1.746	-0.147	-0.007	-0.226

Table 5.6: Stock returns and Volatility changes following the first COVID-19 Lockdowns in Europe

5.7 US Presidential Election – Joe Biden elected (November 3, 2020)

Table 5.7 presents percentage changes in returns and volatility for major European stock markets around the U.S. Presidential Election of Joe Biden on November 3, 2020. The data indicate overall positive market reactions, especially in the 7-day and 14-day windows. In the 3-day window, notable positive return changes were observed in Germany (0.40%), France (0.36%), and the Netherlands (0.47%), indicating initial investor optimism. Conversely, Portugal experienced a significant negative return change of -0.69%.

Over the 7-day window, substantial positive return changes were recorded in Austria (2.32%), Belgium (2.19%), and France (2.09%), reflecting growing market confidence in the election outcome. The volatility changes were mostly mild, with notable decreases in Ireland (-0.12%) and Italy (-0.20%), suggesting reduced market uncertainty.

In the 14-day window, the trend of positive returns continued, with Greece (1.62%), Austria (1.46%), and Spain (1.45%) showing significant gains. Volatility changes remained stable, with Austria (0.64%) and Spain (0.83%) showing increases, while other markets experienced moderate fluctuations.

The patterns followed by European stock markets after the elections of Joe Biden and Donald Trump were similar in that both events led to significant market reactions, but for different reasons. After Trump's election in 2016, European markets experienced a brief period of volatility due to uncertainty over his unpredictable policies, particularly regarding trade and international relations. However, markets soon rebounded as investors anticipated pro-business policies like tax cuts and deregulation. Similarly, after Biden's election in 2020, European markets initially reacted with caution due to uncertainties about regulatory changes and tax policies. However, they quickly stabilized as investors welcomed the prospect of more predictable and stable global trade policies, along with expectations of economic stimulus. In both cases, the markets responded positively to the reduction in uncertainty and the anticipation of policies that could stimulate economic growth.

Country	3 days		7 days		14 days	
	Return change (%)	Volatility change (%)	Return change (%)	Volatility change (%)	Return change (%)	Volatility change (%)
Austria	-0.330	-0.060	2.321	0.443	1.456	0.635
Belgium	0.017	-0.081	2.194	0.430	1.345	0.548
Finland	0.140	-0.069	1.610	0.096	0.994	0.210
France	0.363	-0.055	2.091	0.525	1.314	0.637
Germany	0.400	-0.030	1.681	0.113	1.211	0.196
Greece	-0.207	0.031	2.009	0.295	1.616	0.450
Ireland	0.090	-0.119	0.714	-0.069	0.504	0.085
Italy	0.360	-0.030	1.754	-0.200	1.234	0.280
Netherlands	0.473	-0.024	0.987	0.250	0.851	0.251
Portugal	-0.693	-0.063	0.853	0.174	0.874	0.258
Spain	-0.100	-0.023	2.351	0.694	1.446	0.835
Sweden	0.660	-0.016	1.380	0.132	1.009	0.199
Switzerland	0.377	-0.008	0.603	0.063	0.589	0.077
UK	-0.047	-0.041	1.530	0.403	0.914	0.503

Table 5.7: Stock returns and Volatility changes following the US Presidential Election 2020

5.8 Approval of First COVID-19 Vaccine by European Medicines Agency (December 21, 2020)

Table 5.8 displays percentage changes in returns and volatility for major European stock markets around the approval of the first COVID-19 vaccine by the European Medicines Agency on December 21, 2020. The data indicate a generally positive market reaction across the 3-day, 7-day, and 14-day windows. In the 3-day window, most countries experienced significant positive return changes, with Spain (1.83%), Portugal (1.81%), and Greece (1.49%) leading the gains. This immediate positive response likely reflects investor optimism about the vaccine's potential to curb the pandemic and support economic recovery.

Over the 7-day window, the trend of positive returns continued, with Italy (1.75%), Portugal (0.75%), and Spain (0.70%) maintaining notable gains. Volatility changes remained minimal, with a slight increase in stability, as reflected by the mild changes in volatility.

In the 14-day window, the markets continued to show positive returns, with Spain (0.53%), Italy (0.36%), and France (0.36%) leading the way. Volatility changes remained stable or decreased in most countries, indicating that the initial optimism about the vaccine approval had been absorbed by the markets, leading to a period of stabilization.

The positive returns can be attributed to the vaccine approval signalling a significant step toward ending the pandemic, thus boosting investor confidence in economic recovery. The low and stable volatility changes suggest that markets viewed the vaccine approval as a stabilizing factor, reducing uncertainty about future economic conditions.

Country	3 days		7 days		14 days	
	Return change (%)	**Volatility change (%)**	**Return change (%)**	**Volatility change (%)**	**Return change (%)**	**Volatility change (%)**
Austria	1.120	0.014	0.119	-0.012	0.205	-0.101
Belgium	1.003	0.028	0.140	0.015	0.321	-0.040
Finland	0.480	0.007	0.277	0.063	0.179	0.026
France	0.913	0.062	0.454	0.127	0.359	0.065
Germany	0.937	0.039	0.023	0.072	0.078	0.055
Greece	1.490	-0.027	0.431	-0.062	-0.249	-0.168
Ireland	0.693	0.042	0.087	0.013	0.271	0.051
Italy	1.153	0.081	0.394	0.110	0.361	0.047
Netherlands	0.887	0.079	0.170	0.145	0.138	0.117
Portugal	1.810	0.120	0.747	0.146	0.269	0.101
Spain	1.827	0.087	0.701	0.121	0.529	0.048
Sweden	0.427	0.006	0.176	0.020	0.203	-0.023
Switzerland	0.240	0.022	0.249	0.207	0.216	0.238
UK	1.233	0.032	0.266	0.040	0.310	0.019

Table 5.8: Stock returns and Volatility changes following the approval of First COVID-19 Vaccine by European Medicines Agency

5.9 Russian Invasion of Ukraine (February 24, 2022)

Table 5.9 presents the percentage changes in returns and volatility for major European stock markets around the Russian invasion of Ukraine on February 24, 2022. The data indicate an initial negative reaction across most markets in the 3-day window, with significant negative return changes in Portugal (-1.03%), Austria (-0.52%), and France (-0.55%), reflecting heightened investor concern and uncertainty. Greece was an outlier, showing a positive return change of 1.98%, possibly due to specific local factors or short-term speculative trading. Greece's positive stock market returns can be attributed to its strategic role as an energy transit hub, gaining importance as Europe sought alternatives to Russian energy. This increased investor confidence, particularly in sectors like shipping and energy, boosting the Greek market.

In the 7-day window, most markets showed slight recoveries or continued declines. Austria (-0.48%) and Greece (-0.70%) saw notable declines, while Belgium (0.18%) and Switzerland (0.19%) experienced positive returns, suggesting a varied regional impact of the invasion.

Over the 14-day window, most markets remained negative, with Austria (-1.50%), Greece (-0.18%), and Ireland (-1.33%) showing significant declines. Volatility changes were pronounced, with Austria (1.17%), France (0.72%), and Finland (0.64%) experiencing substantial increases, indicating sustained market instability.

The initial negative returns across most markets can be attributed to the immediate shock and uncertainty caused by the invasion, leading to risk aversion and sell-offs. The increased volatility reflects ongoing market adjustments and the difficulty in assessing the long-term economic impacts of the conflict, including potential sanctions, disruptions in trade, and changes in energy prices. The varied responses across different countries highlight the differential economic exposures and sensitivities to the geopolitical event.

Country	3 days		7 days		14 days	
	Return change (%)	Volatility change (%)	Return change (%)	Volatility change (%)	Return change (%)	Volatility change (%)
Austria	-0.517	0.700	-0.476	0.924	-1.504	1.172
Belgium	-0.097	0.203	0.183	0.304	-0.581	0.420
Finland	-0.227	0.310	-0.040	0.414	-0.960	0.642
France	-0.553	0.373	-0.201	0.459	-0.934	0.718
Germany	-0.147	0.259	-0.099	0.352	-0.963	0.531
Greece	1.980	0.030	-0.701	0.138	-0.179	0.283
Ireland	-0.287	0.336	-0.170	0.413	-1.327	0.630
Italy	-0.123	0.246	-0.156	0.307	-1.154	0.549
Netherlands	-0.147	0.239	-0.017	0.266	-0.716	0.463
Portugal	-1.027	0.152	-0.454	0.158	-0.424	0.255
Spain	-0.020	0.191	0.169	0.242	-0.762	0.507
Sweden	0.437	0.108	0.226	0.136	-0.519	0.221
Switzerland	0.300	0.223	0.190	0.207	-0.176	0.107
UK	0.080	0.434	0.104	0.519	-0.548	0.587

Table 5.9: Stock returns and Volatility changes following the Russian Invasion of Ukraine

6 Conclusion

Through a comprehensive econometric analysis of the volatility of markets significant insights of how political events shape investor sentiment and market volatility have been uncovered.

The findings reveal a consistent pattern where political uncertainty, stemming from events like elections, referendums, and geopolitical tensions, leads to increased market volatility forcing investors, and specifically those who are more risk averse, to change their investment strategies. This response is evident across various time windows, with markets typically experiencing immediate negative returns and increased volatility following major political events. However, the extent and duration of these impacts vary across countries, reflecting differences in economic exposure and investor perceptions.

Key events analysed in this study, such as the Brexit referendum and the US-China trade war, demonstrated profound and immediate effects on market stability, with heightened volatility persisting for extended periods. Conversely, events like the annexation of Crimea and the French "Yellow Vest" protests, while impactful, exhibited more short-lived market reactions. These variations highlight the importance of context and the specific nature of political events in determining market responses.

The application of the GARCH model provided a robust framework for capturing and forecasting market volatility, emphasizing the necessity for advanced econometric tools in understanding financial market dynamics.

Overall, this research underscores the critical intersection between political events and financial markets, offering valuable insights for investors, policymakers, and financial analysts. For investors, understanding the mechanisms through which political uncertainty affects market behaviour can aid in developing more resilient investment strategies. For policymakers, the findings highlight the importance of maintaining political stability to foster a conducive environment for financial markets. Future research could expand on this study by incorporating more diverse political events and exploring the role of investor sentiment and media influence in shaping market reactions. Additionally, examining the long-term effects of sustained political uncertainty on market performance and economic growth would provide a deeper understanding of the broader implications.

In conclusion, political uncertainty remains a significant determinant of market behaviour, with its effects reverberating through investor decisions and market dynamics. By deepening our understanding of these relationships, we can better navigate the complex interplay between politics and finance, ultimately contributing to more stable and predictable financial markets.

7 Reference List

Baker, M. and Wurgler, J. (2006). Investor Sentiment and the Cross-Section of Stock Returns. *The Journal of Finance*, 61(4), pp.1645–1680. doi:https://doi.org/10.1111/j.1540-6261.2006.00885.x.

Baker, S.R., Bloom, N. and Davis, S.J. (2021). Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics*, 131(4), pp.1593–1636.

Bikhchandani, S. and Sharma, S. (2001). Herd Behaviour in Financial Markets: A Review. *SSRN Electronic Journal*, [online] 47(3). doi:https://doi.org/10.2139/ssrn.228343.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3), pp.307–327.

Box, G.E.P. and Al, E. (2015). *Time series analysis: forecasting and control*. Hoboken, New Jersey: John Wiley & Sons.

Boyd, J.H., Hu, J. and Jagannathan, R. (2005). The Stock Market's Reaction to Unemployment News: Why Bad News Is Usually Good for Stocks. *The Journal of Finance*, 60(2), pp.649–672. doi:https://doi.org/10.1111/j.1540-6261.2005.00742.x.

Brogaard, J., Dai, L., Ngo, P.T.H. and Zhang, B. (2019). Global Political Uncertainty and Asset Prices. *The Review of Financial Studies*, 33(4). doi:https://doi.org/10.1093/rfs/hhz087.

Carnahan, D. and Saiegh, S. (2021). Political shocks and asset prices. *Political Science Research and Methods*, pp.1–18. doi:https://doi.org/10.1017/psrm.2021.58.

Çolak, G., Durnev, A. and Qian, Y. (2017). Political Uncertainty and IPO Activity: Evidence from U.S. Gubernatorial Elections. *Journal of Financial and Quantitative Analysis*, [online] 52(6), pp.2523–2564. doi:https://doi.org/10.1017/s0022109017000862.

Dangol, J. (2008). Unanticipated Political Events and Stock Returns: An Event Study. *NRB Economic Review*, [online] pp.86–110. doi:https://doi.org/10.3126/nrber.v20i1.52973.

Engle, R.F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, 50(4), pp.987–1007. doi:https://doi.org/10.2307/1912773.

French, K.R., Schwert, G.W. and Stambaugh, R.F. (1987). Expected Stock Returns and Volatility. *Journal of Financial Economics*, [online] 19(363), pp.3–29. Available at: https://repository.upenn.edu/entities/publication/bc7a54aa-e25f-4cd6-929f-7141970635cf [Accessed 29 Jul. 2024].

Jensen, N.M. and Schmith, S. (2005). Market Responses to Politics. *Comparative Political Studies*, 38(10), pp.1245–1270. doi:https://doi.org/10.1177/0010414005279790.

Julio, B. and Yook, Y. (2012). Political Uncertainty and Corporate Investment Cycles. *The Journal of Finance*, 67(1), pp.45–83. doi:https://doi.org/10.1111/j.1540-6261.2011.01707.x.

Kahneman, D. and Tversky, A. (2013). Prospect Theory: An Analysis of Decision Under Risk. *Handbook of the Fundamentals of Financial Decision Making*, [online] 47(2), pp.99–127. doi:https://doi.org/10.1142/9789814417358_0006.

Kang, L. (2011). Volatility and time series econometrics: essays in honour of Robert Engle. *Journal of Applied Statistics*, 38(10), pp.2371–2372. doi:https://doi.org/10.1080/02664763.2010.530388.

Liu, L.X., Shu, H. and Wei, K.C.J. (2016). *The Impacts of Political Uncertainty on Asset Prices: Evidence from the Bo Scandal in China*. [online] Ssrn.com. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2902559 [Accessed 2 Aug. 2024].

Lo, A.W., Repin, D.V. and Steenbarger, B.N. (2005). Fear and Greed in Financial Markets: A Clinical Study of Day-Traders. *American Economic Review*, 95(2), pp.352–359. doi:https://doi.org/10.1257/000282805774670095.

Park, J., Konana, P., Gu, B., Kumar, A. and Raghunathan, R. (2010). *Confirmation Bias, Overconfidence, and Investment Performance: Evidence from Stock Message Boards*. [online] papers.ssrn.com. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1639470.

Pástor, Ľ. and Veronesi, P. (2013). Political uncertainty and risk premia. *Journal of Financial Economics*, [online] 110(3), pp.520–545. doi:https://doi.org/10.1016/j.jfineco.2013.08.007.

Sims, C.A. (1980). Macroeconomics and reality. *Econometrica*, 48(1), p.1. doi:https://doi.org/10.2307/1912017.

Statman, M., Thorley, S. and Vorkink, K. (2006). Investor Overconfidence and Trading Volume. *Review of Financial Studies*, 19(4), pp.1531–1565. doi:https://doi.org/10.1093/rfs/hhj032.

Tetlock, P. (2007). Giving Content to Investor Sentiment: The Role of Media in the Stock Market. *The Journal of Finance*, 62(3), pp.1139–1168. doi:https://doi.org/10.1111/j.1540-6261.2007.01232.x.

8 Appendices

8.1 Appendix 1: Indexes Used for the analysis per country

Austria: ATX

Belgium: BEL 20

Finland: OMX Helsinki 25

France: CAC 40

Germany: DAX

Greece: ATHEX

Ireland: ISEQ

Italy: FTSE MIB

Netherlands: AEX

Portugal: PSI 20

Spain: IBEX 35

Sweden: OMX Stockholm 30

Switzerland: SMI

United Kingdom: FTSE 100

8.2 Appendix 1: Asset Returns Graphs per Country

The graphs below illustrate daily returns of the stock markets during 2014-2024 with the y-axis representing daily returns and the x-axis representing the timeline.

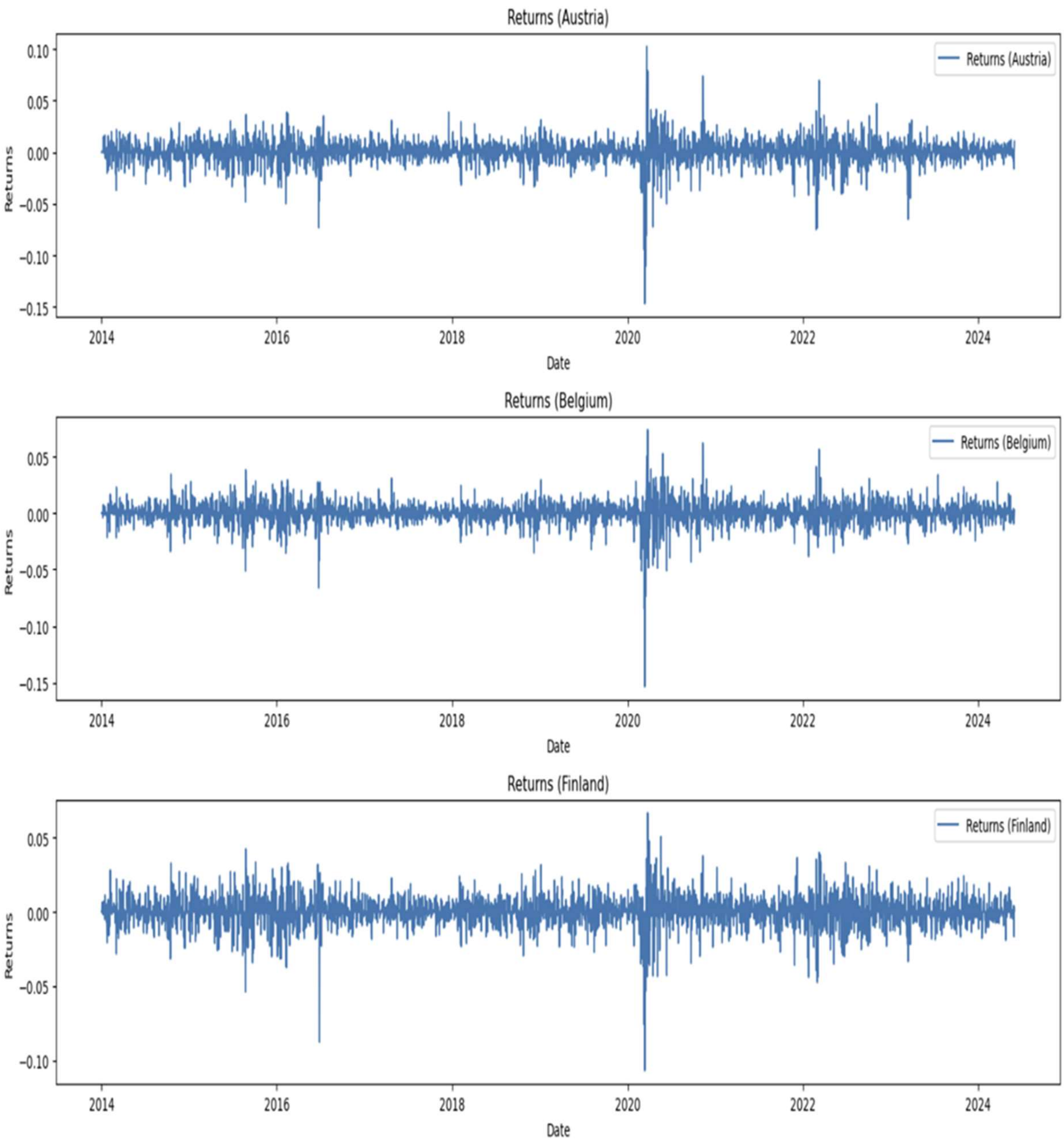


Figure A.1: Returns of Austria, Belgium and Finland

The Austrian market exhibits relatively stable fluctuations with occasional spikes, particularly marked around early 2020, likely due to the global impact of the COVID-19 pandemic, which resulted in significant market disruptions. Following this period, the market demonstrates a trend towards stabilization, albeit with moderate fluctuations. Similarly, the Belgian market displays stable daily returns with occasional sharp spikes, and a notable increase in volatility in early 2020, reflecting global economic conditions. Post-2020, the returns stabilize with less pronounced spikes, indicating a recovery phase. The Finnish market shows consistent daily return fluctuations with fewer pronounced spikes compared to Austria and Belgium, yet also exhibits increased volatility around early 2020. Post-pandemic, the returns exhibit greater stability with smaller fluctuations. These observations underscore the impact of the COVID-19 pandemic, highlighting a significant increase in market volatility during early 2020, followed by a trend towards stabilization and recovery in subsequent years. The consistent fluctuations in daily returns across all three markets signify the inherent volatility of stock markets, influenced by economic policies, global events, and market sentiments, while also demonstrating resilience and recovery post-crisis.

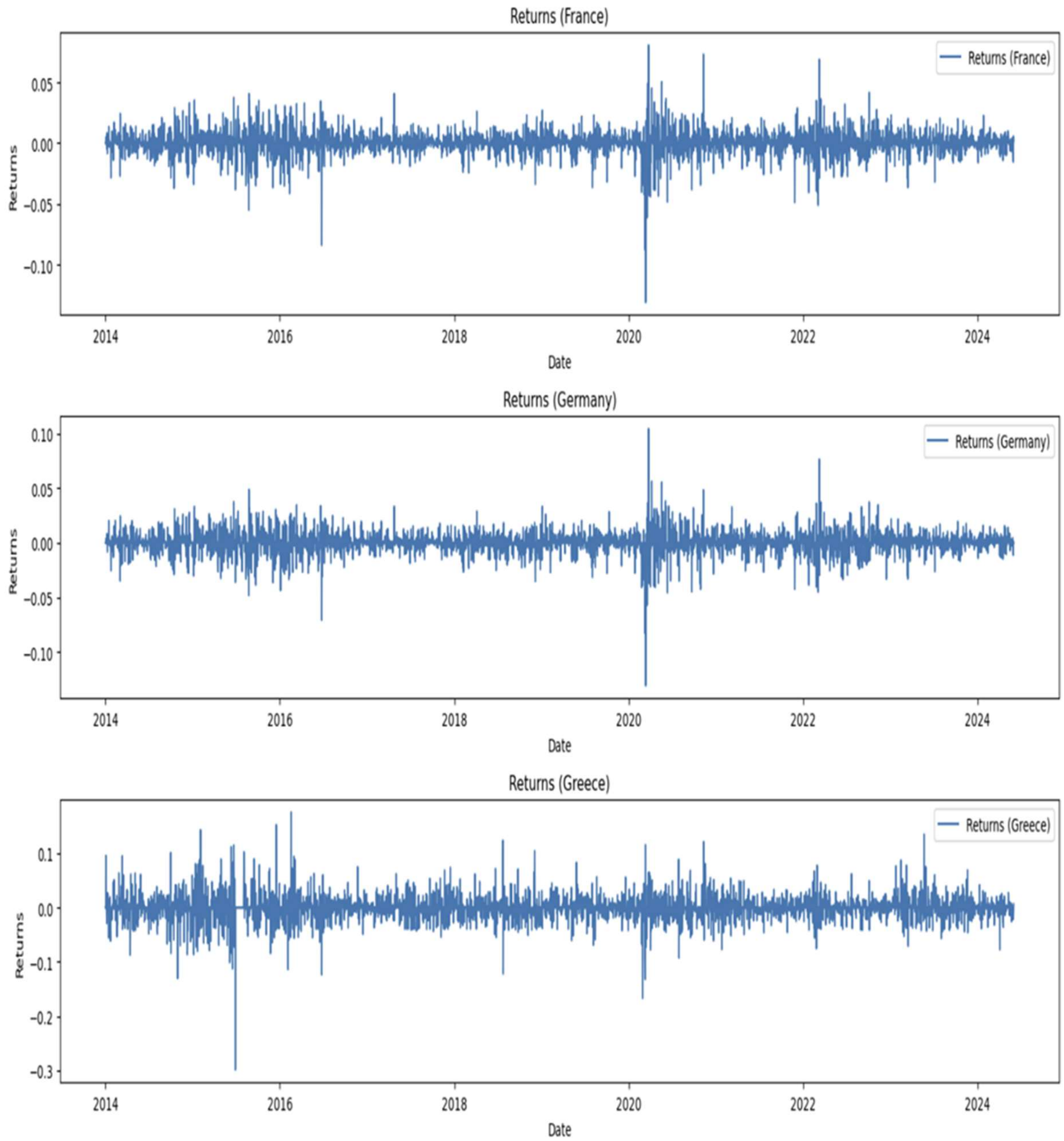


Figure A.2: Returns of France, Germany and Greece

The French market exhibits relatively stable fluctuations with occasional sharp spikes, particularly around early 2020, reflecting the significant impact of the COVID-19 pandemic on market stability. Post-2020, the French market shows signs of stabilization with less pronounced fluctuations. The German market displays similar characteristics, with stable daily returns disrupted by increased volatility in early 2020, followed by a trend towards recovery and stability. The Greek market, however, exhibits higher volatility throughout the observed period, with pronounced spikes and dips, especially around early 2020. The more significant fluctuations in the Greek market suggest a higher susceptibility to economic and political uncertainties.

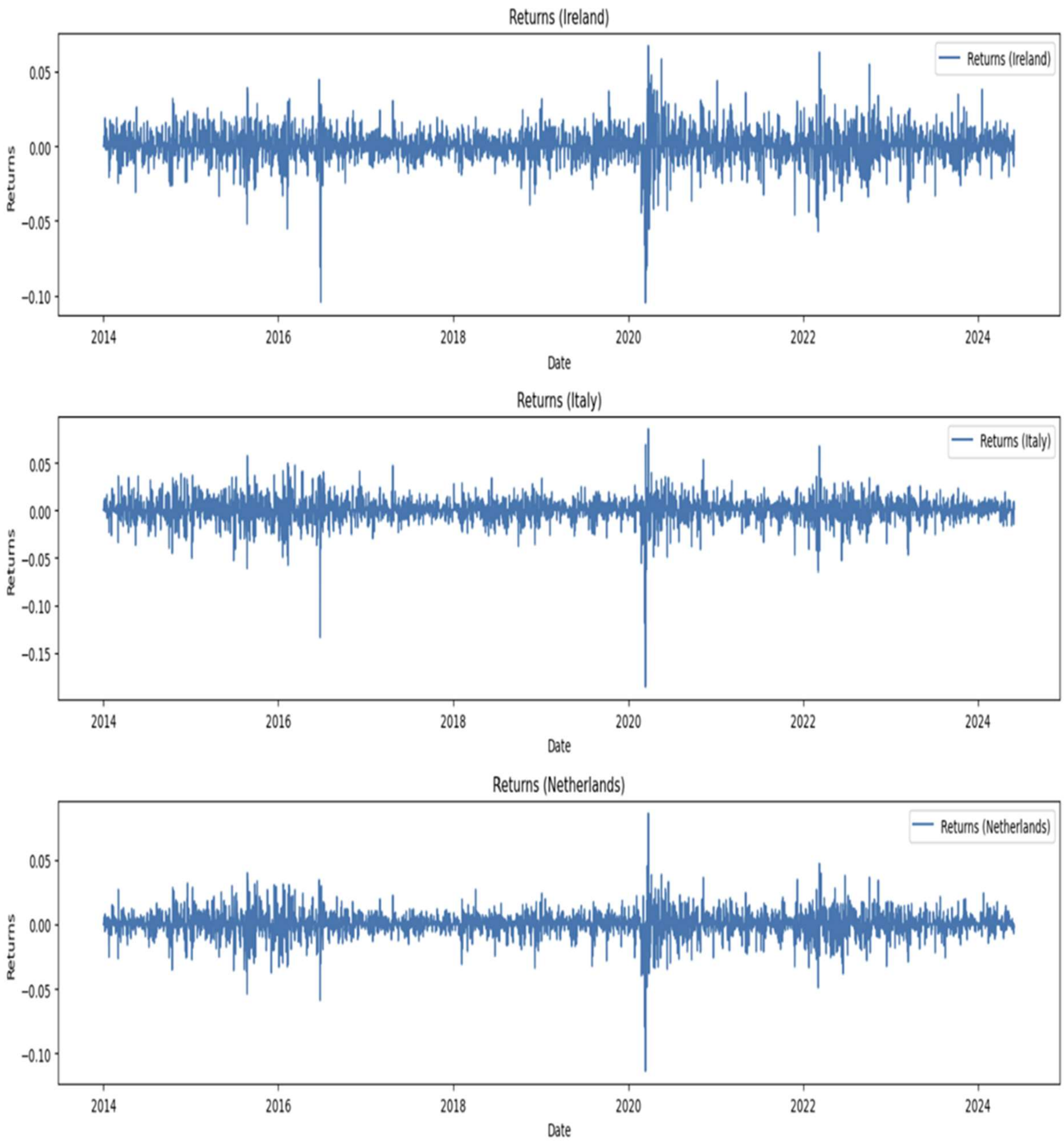


Figure A.3: Returns of Ireland, Italy and Netherlands

The Irish market shows stable fluctuations with occasional sharp spikes, particularly around early 2020, indicating the substantial impact of the COVID-19 pandemic. Post-2020, the market appears to stabilize, though with ongoing moderate fluctuations. The Italian market exhibits similar stability with pronounced volatility during early 2020, followed by a recovery phase characterized by reduced volatility. The Dutch market also demonstrates stable daily returns, disrupted by significant spikes in early 2020, reflecting the global economic turmoil of the pandemic. Post-2020, the Dutch market shows a trend towards stabilization with occasional fluctuations. These patterns highlight the significant impact of the COVID-19 pandemic on market stability across these European countries, followed by a recovery phase indicating resilience.

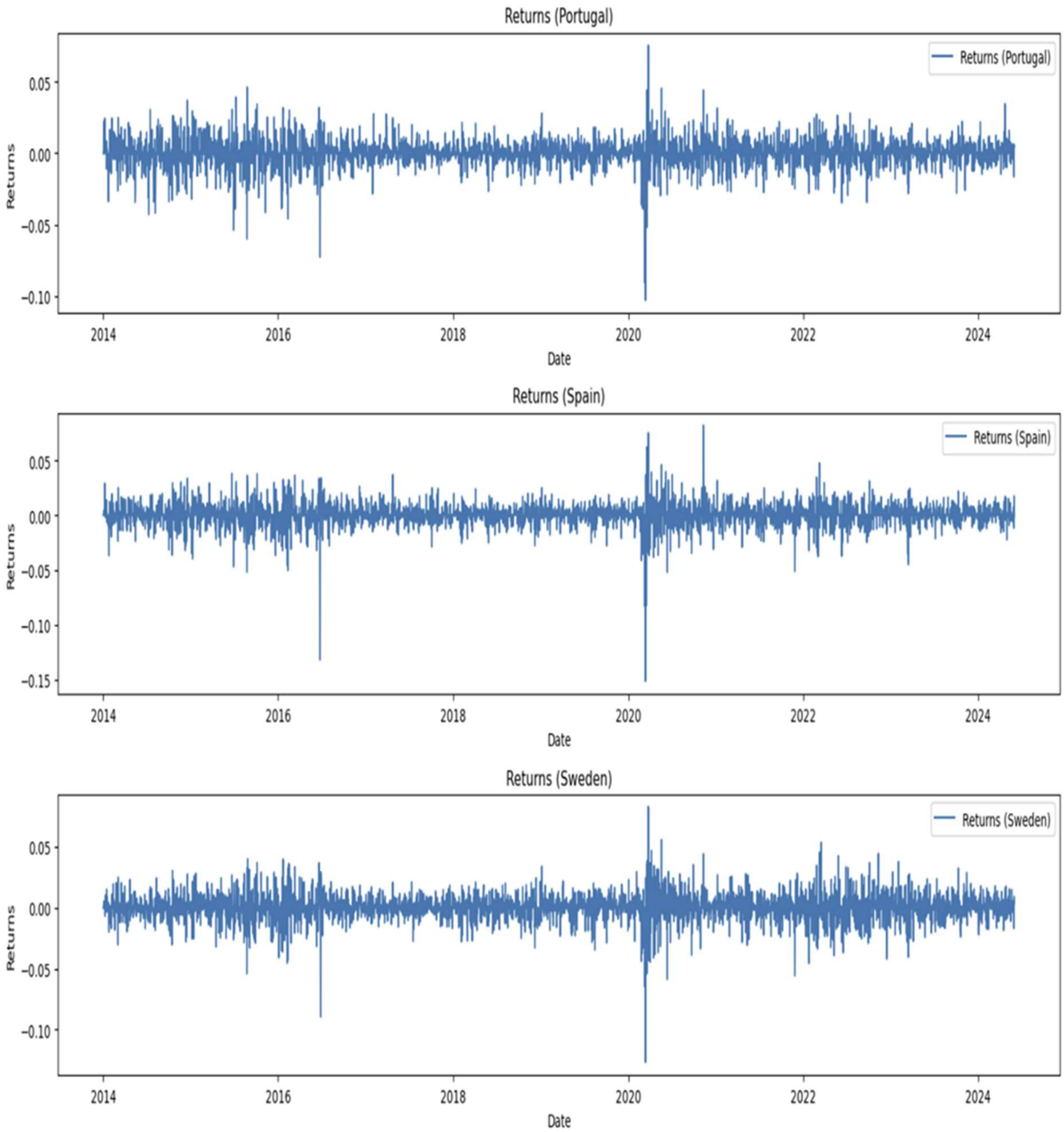


Figure A.4: Returns of Portugal, Spain and Sweden

The Portuguese market demonstrates relatively stable fluctuations with occasional sharp spikes, particularly around early 2020, reflecting the significant impact of the COVID-19 pandemic on market stability. Following this period, the market shows signs of stabilization with reduced volatility. Similarly, the Spanish market exhibits stable daily returns with marked volatility in early 2020, followed by a trend towards recovery and reduced fluctuations post-pandemic. The Swedish market also displays consistent daily returns with significant spikes around early 2020, indicative of the global economic disruption caused by the pandemic. Post-2020, the Swedish market trends towards stabilization with occasional fluctuations.

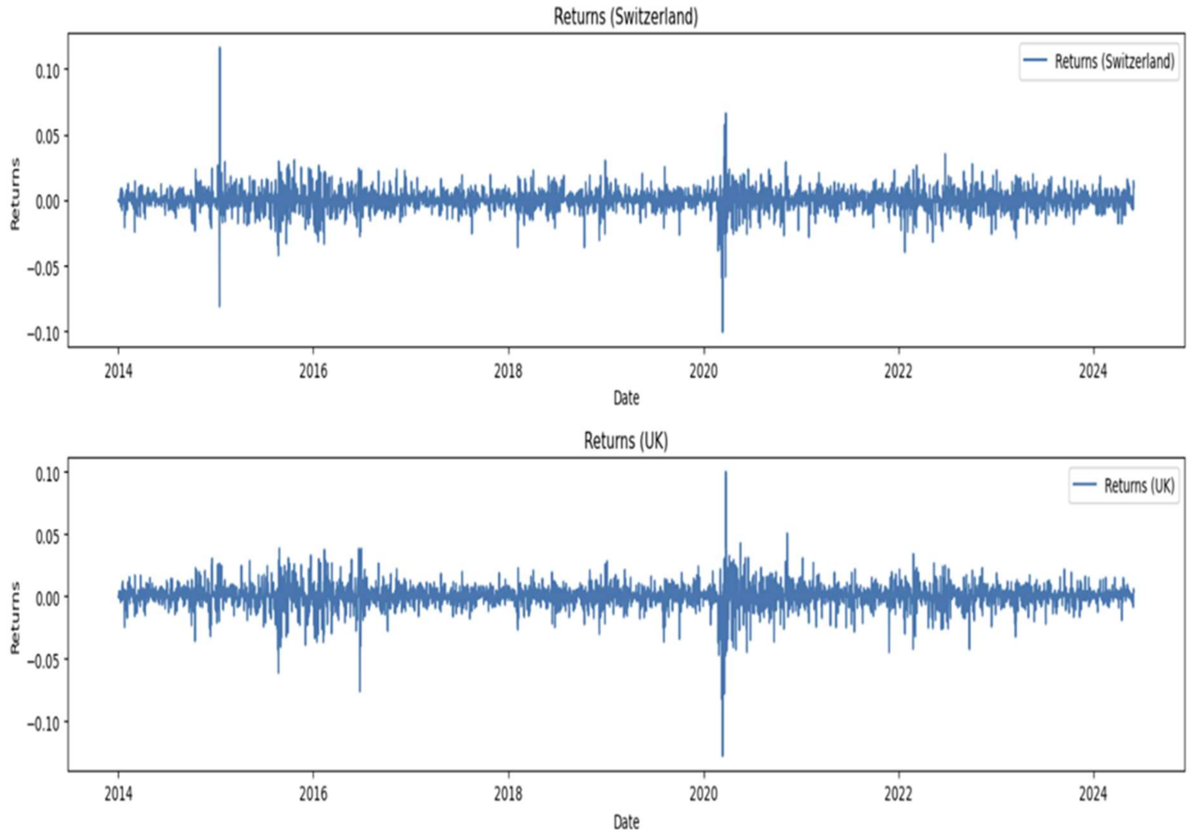


Figure A.5: Returns of Switzerland and United Kingdom

The Swiss market demonstrates relatively stable fluctuations with occasional sharp spikes, particularly noticeable around early 2020, corresponding to the onset of the COVID-19 pandemic, which caused significant market instability. Following this period, the Swiss market shows a trend towards stabilization with reduced volatility. Similarly, the UK market exhibits stable daily returns disrupted by increased volatility during early 2020, reflecting the global economic turmoil caused by the pandemic. Post-2020, the UK market also trends towards recovery and stabilization with occasional fluctuations.

8.3 Appendix 2: Asset Returns Stationarity and Non-Normality Tests

Table A.1 presents non-stationarity tests and normality tests on the asset return variables. The Augmented Dickey-Fuller (ADF) test is a statistical procedure utilized primarily to test for the presence of a unit root in a time series sample. This test is crucial for determining whether a time series is stationary, an essential characteristic for many econometric analyses. The ADF test extends the basic Dickey-Fuller test by including lagged differences of the series in its regression model to account for higher-order serial correlation. This regression model typically comprises a constant, a time trend, and up to p lagged differences of the dependent variable. The null hypothesis of the test asserts that the time series has a unit root, indicative of non-stationarity. Rejecting the null hypothesis suggests that the time series is stationary, enabling more reliable statistical inferences derived from subsequent analyses.

The Jarque-Bera (JB) test is another statistical test used to assess whether sample data have the skewness and kurtosis matching a normal distribution. Primarily, this test is used in the fields of finance and economics to validate the assumption of normality, a common requirement in many financial models. The Jarque-Bera test is based on the sample size, and the estimates of skewness and kurtosis of the series. The test statistic is computed under the null hypothesis that the data is normally distributed, and large values of the statistic provide evidence against the null hypothesis. This is particularly important when employing statistical techniques that assume normality, as deviations from this can lead to significant errors in hypothesis testing and model-based predictions.

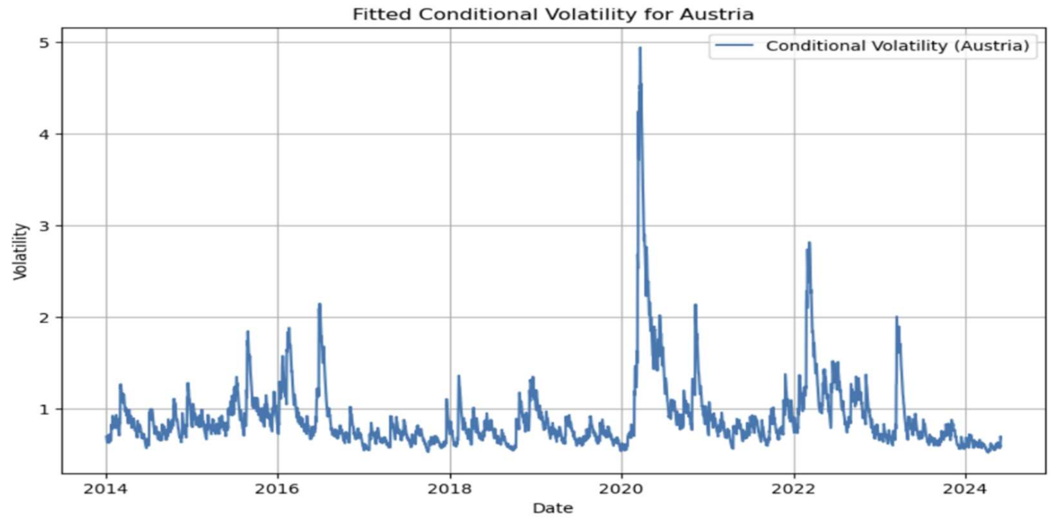
	ADF Statistic	ADF p-value	Jarque-Bera Statistic	Jarque-Bera p-value
Austria	-15.687	1.44987E-28	76290.0	0
Belgium	-17.990	2.75562E-30	128806.9	0
Finland	-16.718	1.41745E-29	19654.3	0
France	-16.648	1.61335E-29	47462.8	0
Germany	-16.141	4.67354E-29	40760.0	0
Greece	-17.719	3.47674E-30	33775.0	0
Ireland	-17.959	2.82044E-30	26329.4	0
Italy	-34.133	0	110986.3	0
Netherlands	-33.758	0	31649.6	0
Portugal	-16.490	2.19671E-29	18799.9	0
Spain	-17.446	4.67901E-30	97125.3	0
Sweden	-16.453	2.36742E-29	16186.1	0
Switzerland	-18.469	2.14139E-30	87554.4	0
UK	-15.747	1.23503E-28	63681.8	0

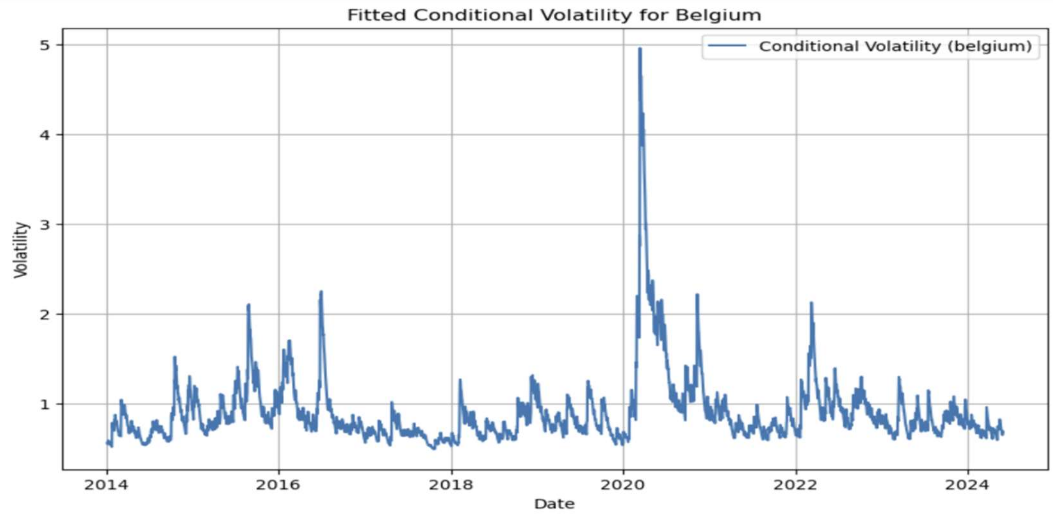
Table A.1: non-stationarity and normality tests for asset returns

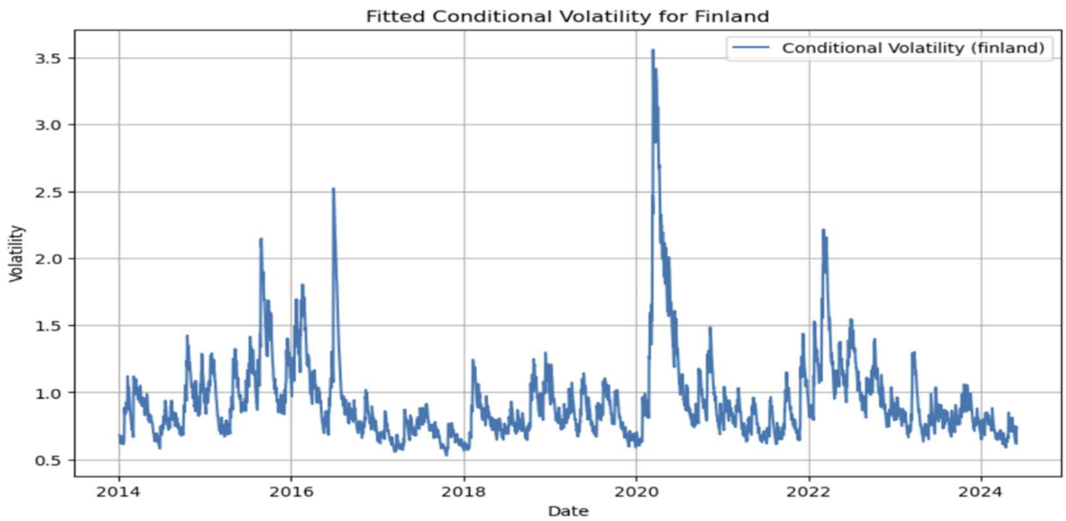
8.4 Appendix 3: Modelled (Fitted) Volatility Graph per country

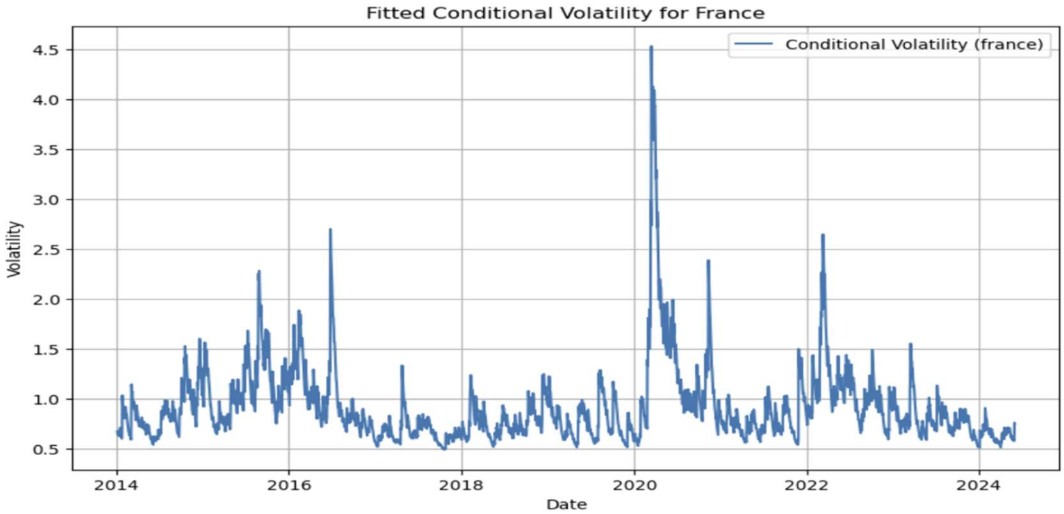
The graphs show pronounced spikes in volatility during periods of market turmoil, reflecting the impact of significant economic events and global financial crises. Notable peaks are occurring around three major global events: the Brexit referendum in 2016, the onset of the COVID-19 pandemic in early 2020, and the Russia-Ukraine conflict in 2022. Each country exhibits peaks of varying significance, reflecting their unique economic conditions and market sensitivities. The Brexit referendum induced widespread market uncertainty across Europe, while the COVID-19 pandemic caused unprecedented global market disruptions, leading to the highest volatility spikes. The Russia-Ukraine conflict in 2022 also contributed to increased volatility, albeit to different extents in each country. These patterns underscore the impact of significant geopolitical and economic events on market stability across Europe. Countries such as Greece exhibit high and erratic volatility, indicating a highly unstable market environment. This is contrasted by countries like Switzerland and Germany, where the volatility levels are relatively lower and more stable, suggesting more predictable and less risky financial conditions.

Additionally, the volatility patterns in the graphs demonstrate clustering effects, where periods of high volatility tend to be followed by further high volatility, and periods of low volatility tend to follow low volatility. This phenomenon, known as volatility clustering, is evident across all countries and is a well-documented characteristic of financial time series. The persistence of volatility over time underscores the importance of using advanced econometric models, such as GARCH models, to capture and forecast future volatility accurately.

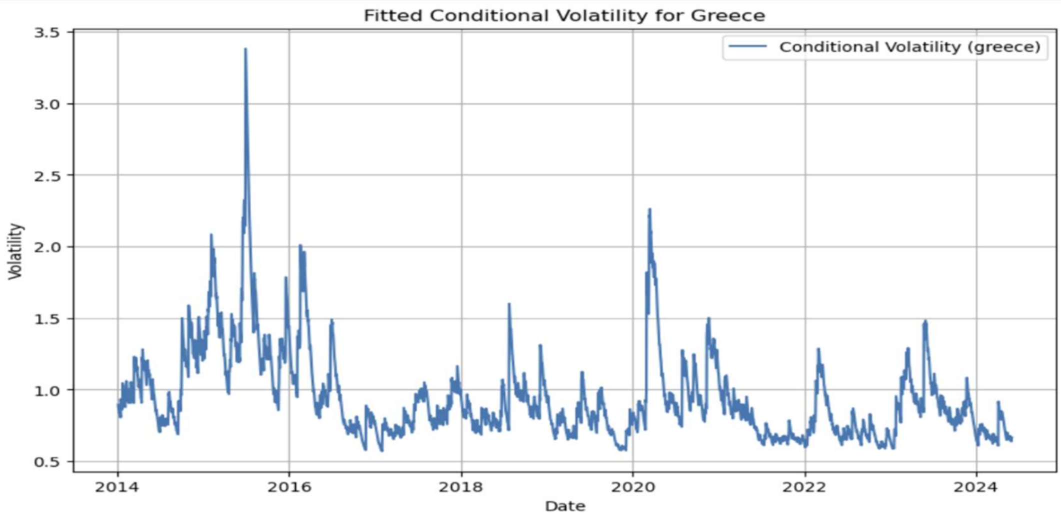

Fitted Conditional Volatility for Austria
Conditional Volatility (Austria)
Volatility
Date
1
2
3
4
5
2014
2016
2018
2020
2022
2024

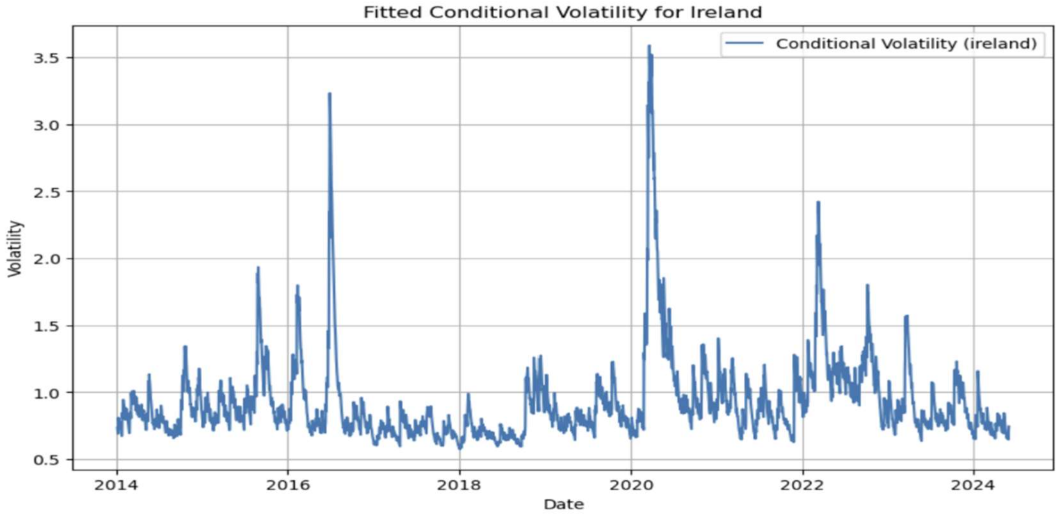

Fitted Conditional Volatility for Belgium
Conditional Volatility (belgium)
Volatility
Date
1
2
3
4
5
2014
2016
2018
2020
2022
2024

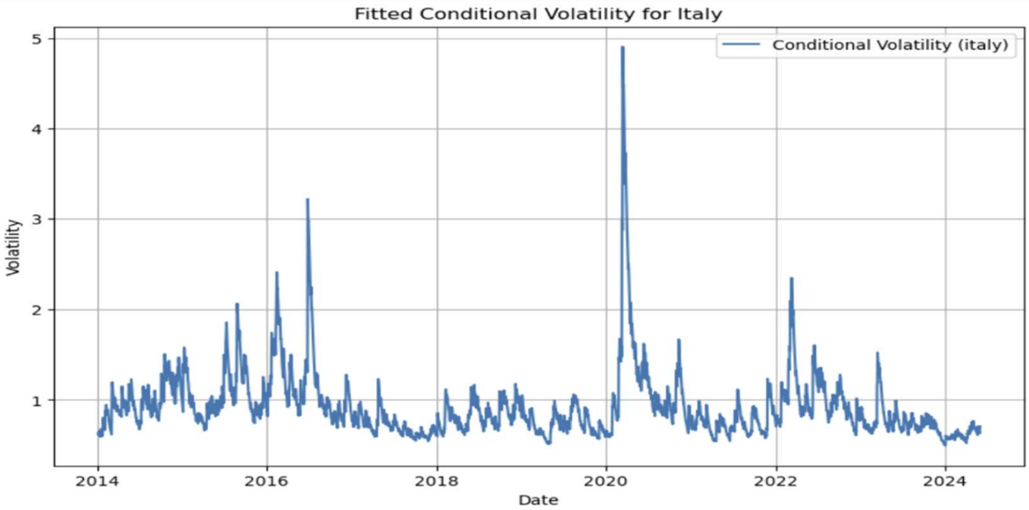

Fitted Conditional Volatility for Finland
Conditional Volatility (finland)
Volatility
Date
0.5
1.0
1.5
2.0
2.5
3.0
3.5
2014
2016
2018
2020
2022
2024

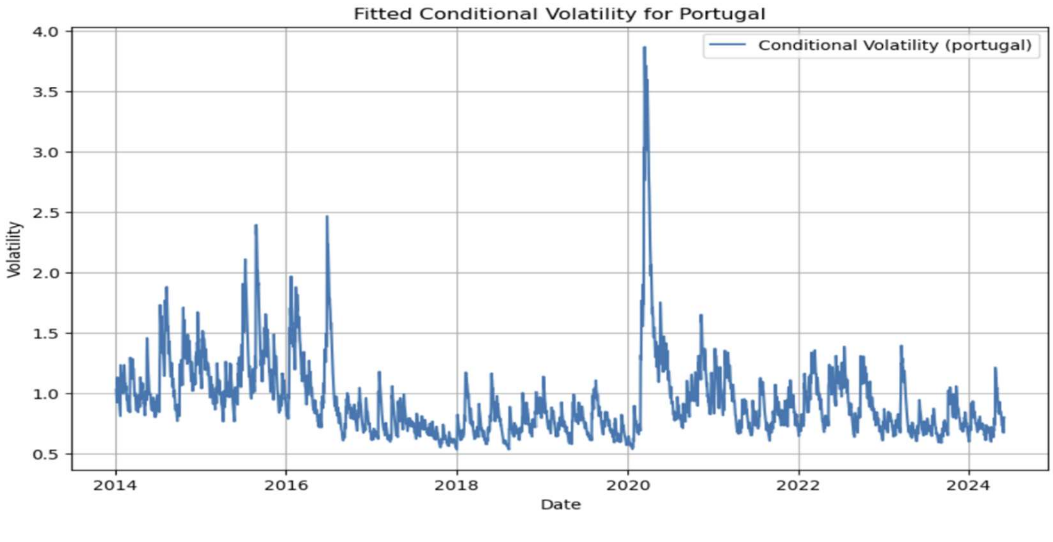

Fitted Conditional Volatility for France
Conditional Volatility (france)
Volatility
Date
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
2014
2016
2018
2020
2022
2024

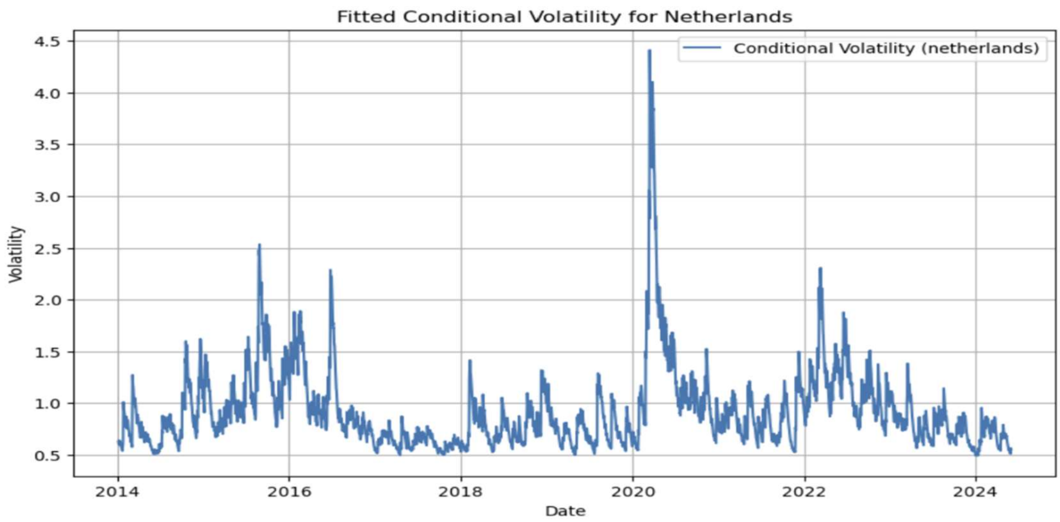

Fitted Conditional Volatility for Germany
Conditional Volatility (germany)
Volatility
Date
3.5
3.0
2.5
2.0
1.5
1.0
0.5
2014
2016
2018
2020
2022
2024

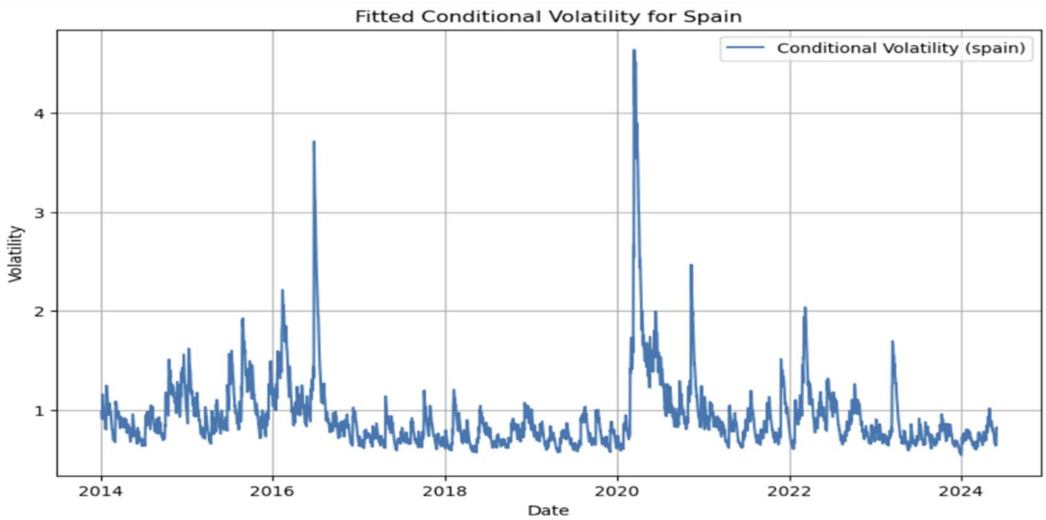

Fitted Conditional Volatility for Greece
Conditional Volatility (greece)
Volatility
Date
3.5
3.0
2.5
2.0
1.5
1.0
0.5
2014
2016
2018
2020
2022
2024

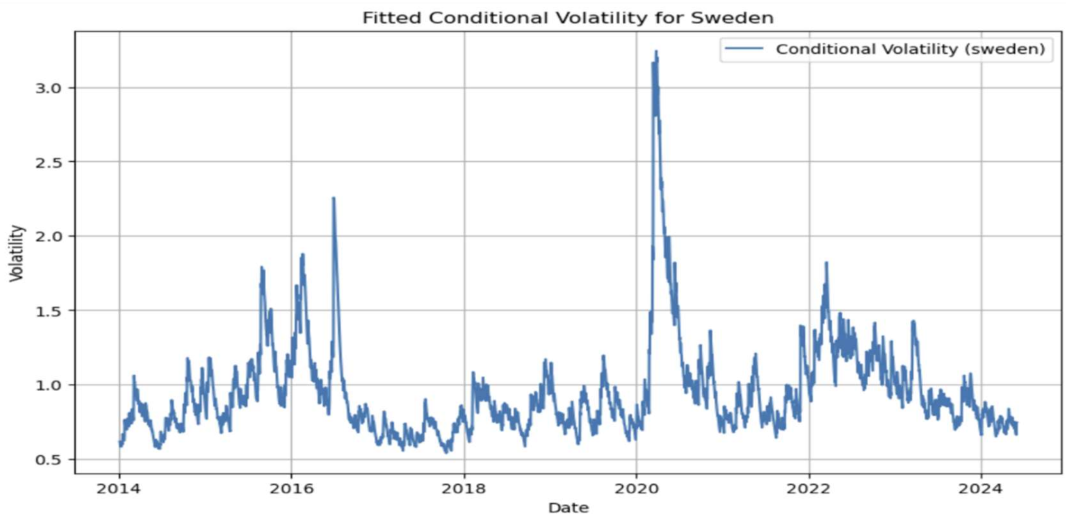

Fitted Conditional Volatility for Ireland
Conditional Volatility (ireland)
Volatility
Date
0.5
1.0
1.5
2.0
2.5
3.0
3.5
2014
2016
2018
2020
2022
2024

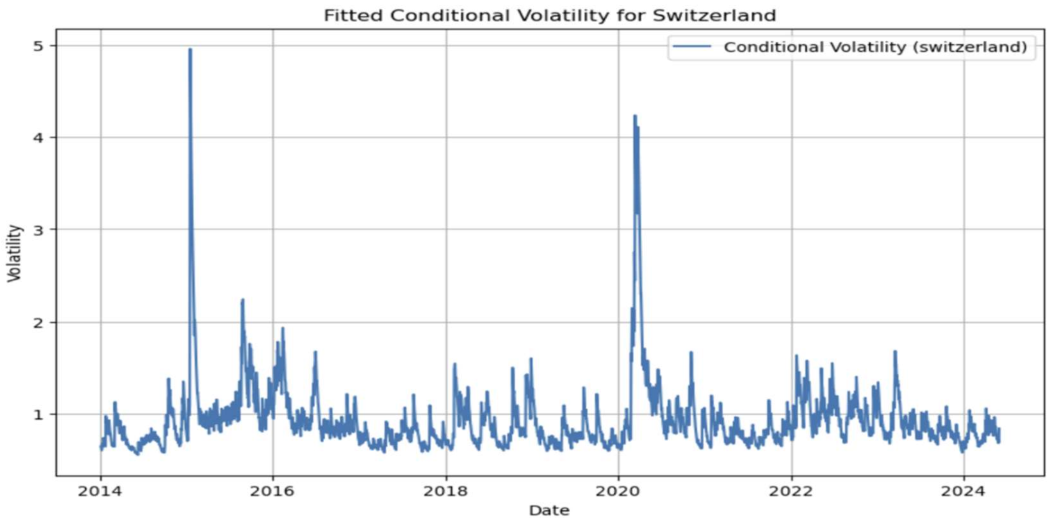

Fitted Conditional Volatility for Italy
Conditional Volatility (italy)
Volatility
Date
1
2
3
4
5
2014
2016
2018
2020
2022
2024

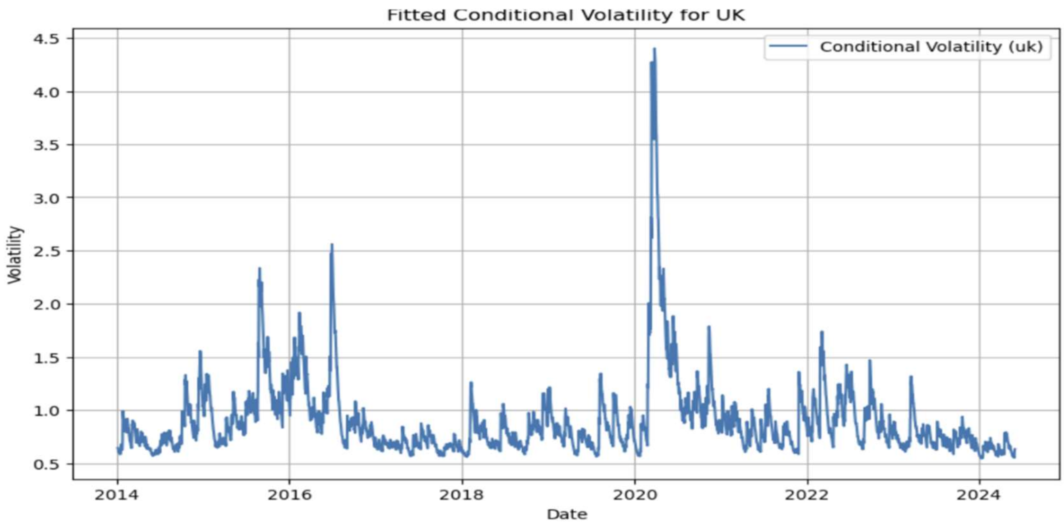

Fitted Conditional Volatility for Portugal
Conditional Volatility (portugal)
Volatility
Date
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
2014
2016
2018
2020
2022
2024


Fitted Conditional Volatility for Netherlands
Conditional Volatility (netherlands)
Volatility
Date
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
2014
2016
2018
2020
2022
2024


Fitted Conditional Volatility for Spain
Conditional Volatility (spain)
Volatility
Date
4
3
2
1
2014
2016
2018
2020
2022
2024


Fitted Conditional Volatility for Sweden
Conditional Volatility (sweden)
Volatility
Date
3.0
2.5
2.0
1.5
1.0
0.5
2014
2016
2018
2020
2022
2024


Fitted Conditional Volatility for Switzerland
Conditional Volatility (switzerland)
Volatility
Date
1
2
3
4
5
2014
2016
2018
2020
2022
2024


Fitted Conditional Volatility for UK
Conditional Volatility (uk)
Volatility
Date
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
2014
2016
2018
2020
2022
2024

8.5 Appendix 4: Modelled Volatility Stationarity and Non-Normality Tests

	ADF Statistic	ADF p-value	Jarque-Bera Statistic	Jarque-Bera p-value
Austria	5.795	4.76621E-07	117121.25	0
Belgium	5.299	5.50705E-06	124022.96	0
Finland	5.310	5.21851E-06	37032.73	0
France	5.930	2.39295E-07	67876.72	0
Germany	5.070	1.62116E-05	41149.96	0
Greece	5.014	2.08534E-05	10627.019	0
Ireland	6.270	3.96864E-08	58836.749	0
Italy	6.150	7.72505E-08	103837.880	0
Netherlands	5.380	3.81653E-06	45880.84	0
Portugal	6.460	1.42997E-08	47341.84	0
Spain	6.420	1.81649E-08	119771.94	0
Sweden	5.050	1.72946E-05	27712.99	0
Switzerland	6.880	1.46478E-09	165337.70	0
UK	5.831	3.9805E-07	102657.10	0

Table A.2: stationarity and non-normality tests for asset returns

8.6 Appendix 5: ARX Model – Exogenous variable (EUI) estimates

Table A.3 presents the ARX Model (mean model) estimates for the variable EUI which was used as exogenous without any lags in the estimation . The motivation for incorporating the European Uncertainty Index (EUI) as an exogenous variable in the ARX-GARCH model for daily returns of European markets stems from the significant impact that economic and political uncertainty has on financial market volatility. The EUI captures fluctuations in uncertainty across Europe, reflecting investor sentiment and expectations about the future. By including the EUI in the ARX model, the aim was to explore if this analyst-made variable that was capable to account for these external shocks, thereby improving the accuracy of volatility forecasting and gaining deeper insights into how uncertainty influences market behaviour. The regression results indicate that the European Uncertainty Index (EUI) is not statistically significant in explaining the daily returns of the European markets across the countries analysed. This is evidenced by the p-values for all countries, which are all well above the conventional significance levels of 0.01, 0.05, and even 0.10. The coefficients associated with EUI are also relatively small and fluctuate between positive and negative values, further suggesting that the EUI does not have a consistent or substantial impact on the daily returns within these specific European markets. Consequently, the results imply that the EUI variable has no explanatory power over the returns, as specified in the context of this paper, and may not be a strong predictor of daily market returns or that other factors might overshadow the effect of uncertainty in these markets. This lack of statistical significance could also indicate that the relationship between market returns and uncertainty is more complex or nonlinear, requiring more sophisticated modelling approaches to capture it adequately.

	EUI			
	Coeff	std err.	t	p-Value
Austria	0.007	0.017	0.412	0.680
Belgium	-0.014	0.016	-0.883	0.377
Finland	-0.012	0.020	-0.605	0.545
France	0.004	1.616	0.225	0.822
Germany	0.011	0.016	0.705	0.481
Greece	0.001	0.014	-0.054	0.957
Ireland	0.004	0.018	0.231	0.817
Italy	0.005	0.017	0.318	0.750
Netherlands	0.002	0.016	0.117	0.906
Portugal	-0.001	0.017	-0.060	0.952
Spain	0.002	0.018	0.127	0.899
Sweden	0.015	0.016	0.944	0.345
Switzerland	0.002	0.015	0.136	0.892
UK	-0.005	0.014	-0.369	0.712

Table A.3: ARX model estimates of EUI