

Did the Russian war against Ukraine increase global stock market sector volatility in 2022?

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Geopolitical shocks cause uncertainty to investors' future expectations. We analyzed the effects of the Russian attack on Ukraine in February 2022 on the volatility of global stock market sectors. By using an event study approach, we examined abnormal volatility by comparing out-of-sample GARCH-model forecasts around the Russian attack with observed volatility in MSCI World sector indices. We have evidence that volatility increased in the short term for almost all stock market sectors after 24 February 2022. In addition, we show that the effect was different for the sectors considered. The largest volatility increased in the financials, consumer staples and utilities sector. Furthermore, we investigated the persistence of abnormal volatility after the Russian attack. We found that abnormal volatility persisted for up to ten trading days, on average, across all sectors. This is an indication that investor uncertainty continued after the event.

Keywords: Russia-Ukraine conflict, volatility, stock market, event study, GARCH.

JEL codes: C58, G15.

Introduction

Time and again, the world is strongly influenced by geopolitical shocks. In contrast to regional shocks, these geopolitical shocks are characterized by the fact that they have a worldwide impact and can affect financial markets around the world almost immediately (Engle–Campos-Martins 2023). These shocks are usually coincident with an increase in general uncertainty, which in turn affects the behavior of market participants worldwide (Baker et al. 2016; Baur–Smales 2020; Caldara–Iacoviello 2022).

Uncertainty in the financial markets is reflected here by the fact that opinions on the valuation of assets are more unclear and, therefore, result in stronger selling as well as more buying. This is reflected in increased volatility (Salisu et

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al. 2022). Bouras et al. (2019) showed that geopolitical risks influenced volatility significantly, while the impact of country-specific risks on stock market volatility was rather weak. In terms of geopolitical shocks, the Russian attack on Ukraine is the most significant in recent history, alongside the international financial crisis and COVID-19 (Izzeldin et al. 2021; Izzeldin et al. 2023). In this article, we analyze the impact of this shock on the uncertainty dynamics of global stock market sectors.

Volatility is a key factor in investors' financial market decisions and is also fundamental to asset pricing, regulation, and risk management. Volatility is an important measure of risk in the financial markets, and understanding the extent of price fluctuations in stocks or indices helps investors and financial institutions to manage their risk more effectively. For example, higher volatility is more likely to deter conservative investors or lead to adjustments in portfolio allocation. Volatility can be used as a measure for hedging strategies required by investors. It can also play a role as a decision-making criterion for determining the holding period of an investment. The pricing of derivatives is another application, as volatility is a key component in this process. Regarding options, higher volatility increases the option premium, as the option is more likely to end up in the money. In the context of economic indicators, volatility is used as an indicator of economic uncertainty or instability. A sudden increase in volatility can reflect investor nervousness about economic policies, geopolitical events, or financial crises. Analysts and policymakers monitor such fluctuations to assess economic health and plan appropriate actions. In this context, regulators and policymakers analyze volatility and market dynamics to ensure market stability and develop regulations to protect investors and maintain fair, orderly, and efficient markets.

There are different ways to measure the volatility of asset prices and it makes sense to briefly summarize them here. One famous approach is to use the standard deviation, which can be estimated by the square root of the sample variance (Garman–Klass 1980; Granger–Poon 2001). For normally distributed data, in particular, the standard deviation is the appropriate measure of dispersion (Fisher 1920). Other methods, especially for reducing extreme value bias, are proposed by Andrade (2020), Ball–Torous (1984), Berry (1987), and Jensen et al. (2006).

For market participants, volatility is closely linked to the assessment of risk. In the financial markets, downside risks are typically rated higher than upside risks, so semi-variance is a risk measurement metric that focuses on the downside

volatility of an investment portfolio or asset. Unlike standard deviation, which considers all deviations from the mean, semi-variance only considers the negative deviations or losses below a specified threshold (Barndorff-Nielsen et al. 2008; Choobineh–Branting, 1986). This metric provides investors with a more focused and conservative view of the risk, emphasizing the potential for losses rather than considering all deviations equally. An indirect but market-related way of measuring volatility is by using option prices since the implied volatility contained in these prices can be regarded as a forecast for the expected volatility (e.g., Day–Lewis 1992). Higher implied volatility corresponds to a higher expected level of future price fluctuations (Black–Scholes 1973; Beckers 1981; Canina–Figlewski 1993).

When modeling and forecasting the development of financial markets, stochastic processes (Doob 1942; Pavliotis 2014) are frequently used, such as the ARIMA models (Box–Jenkins 1970; Box et al. 2015; De Gooijer–Hyndman 2006). These models lead to good forecasts of the time-varying expected value. A common assumption of these models is that the variance of the stochastic error term is constant over time, which is referred to as homoscedasticity. Therefore, the ARIMA models are only suitable to a limited extent for modeling and predicting strong market fluctuations. However, two phenomena are often observed with financial market data. The first is that volatility is not constant over time, a phenomenon known as heteroscedasticity (Engle 1982). Secondly, high volatility occurs in clusters, i.e., there is a serial correlation (Cont 2001; Engle 1982; Taylor 2008). To describe the time-varying volatility, Engle (1982) designed the model of autoregressive conditional heteroscedasticity (ARCH). Later, Bollerslev (1986) introduced the generalized autoregressive conditional heteroscedasticity model (GARCH) to better describe volatility persistence, which often occurs in financial time series. The most common extensions are the EGARCH (Exponential GARCH), IGARCH (Integrated GARCH) and TGARCH (Threshold GARCH) (Engle–Bollerslev 1986; Nelson 1991; Glosten et al. 1993; Palm 1996). These models are now frequently used to predict volatility on the financial markets. As with the ARIMA models, a test-based specification of the model is also important for the GARCH models to achieve adequate forecast results (Lundbergh–Teräsvirta 2002). They are also combined with the ARMA models to simultaneously model and forecast the conditional mean and the conditional variance. A question that is often investigated is which type of model predicts volatility better. Brailsford–Faff (1996) found evidence that more complex prediction models, like ARCH class

models, outperform simpler volatility models, like the class of moving average models. Savickas (2003) analyzed statistical tests in event-induced variance and compared them according to their performance. He found that the GARCH-based approach performed best due to the highest test power.

In contrast to other studies, our analysis of volatility dynamics associated with a geopolitical shock focuses on a sector-specific view. This detailed analysis allows us to gain more insight compared to the analysis of sector-aggregated indices, such as a better understanding of sector dynamics. Every industry – like technology, healthcare, finance, or energy – has unique characteristics and influencing factors (Elyasiani et al. 2020). A sector-specific analysis helps to understand these nuances. It also enables better investment decisions as investors can differentiate between sectors that they believe will perform better in the current market phase. Certain sectors tend to outperform others at different stages of the economic cycle (He et al. 2020). Cyclical sectors, such as the consumer discretionary sector, are more sensitive to economic changes, while non-cyclical sectors, such as healthcare, are less sensitive (Long–Plosser 1987). Investors can, therefore, increase their returns by rotating their investments between sectors (Sasseti–Tani 2006). It is also easier to distinguish between the expected returns and the risk taken. By understanding the specifics of a sector, investors can better assess the risks associated with investing in that sector and thus better hedge against risk. Sector analysis can also point to emerging trends, such as the increasing importance of renewable energy in the utilities sector or the impact of e-commerce on the retail sector. In addition, a sector-specific view enables better benchmarking of individual stocks and, thus, a better classification of performance. We used the sector indices of the MSCI World Index (Morgan Stanley Capital International Index) to include the most relevant companies in the respective sectors in our analysis. The MSCI World Index, established in 1986, is widely recognized and measures the performance of large and mid-capitalization stocks from 23 equity markets in developed countries (MSCI 2024a). MSCI’s sector indices are aimed at systematically monitoring market segments and capturing the various characteristics and returns of global sectors (MSCI 2024b). This index captures approximately 85% of the free float-adjusted market capitalization in each country and provides a global broad equity benchmark to evaluate the performance of stocks in developed markets (McKinnon 2019). Furthermore, institutional investors widely use it for

index funds and as a benchmark for global equity portfolios. Its components are weighted by market capitalization, and the index is reviewed quarterly to include or exclude stocks based on market capitalization and other criteria. It includes companies from North America, Europe, and the Asia-Pacific region, making it a diversified option for investors seeking exposure to global equity markets. There are advantages and disadvantages to using the MSCI World Sector Indices. The advantage is that they include the largest companies from 23 industrialized countries with many different business models. In addition, the methodology of the index is very transparent, and it is frequently adjusted. It is widely accepted by investors and analysts and is often used as a benchmark. Disadvantages include the focus on industrialized countries, the weighting by market capitalization (small but important companies for an industry can be underrepresented) and a certain risk of currency fluctuations for companies that are not listed in U.S. dollars. In addition, the weighting process results in a high proportion of U.S. companies, which is associated with an increased country risk.

Our analysis aims to shed light on the impact of the Russian attack on Ukraine on the world's largest companies and how the major geopolitical shifts have caused uncertainty. We want to understand volatility here as a measure of risk or as an indicator of the strength of changes since large price fluctuations, especially if they occur frequently, are a sign of investor dissent. They disagree on expectations and the fair pricing of assets, which results in strong upward and downward movements in the markets. However, strong volatility is also caused by large price movements in one direction. Here, investors adjust their valuation based on new information on the markets. We want to determine the excessive volatility that the Russian attack has caused in the biggest companies and most important business models worldwide and whether this volatility is persistent. Moreover, we want to analyze if there are statistically significant differences in this volatility between different sectors. By conducting an event study, we used the concept of abnormal volatility (Beaver 1968; Brown–Warner 1985) and cumulative abnormal volatility, and we analyzed the behavior of the eleven different MSCI World sector indices around the time of the Russian attack, on 24 February 2022. Our specific research questions are as follows:

Research question 1: Will we find significant abnormal volatility (± 5 days) in the MSCI market sectors around the time of the Russian attack on Ukraine on 24 February 2022?

Research question 2: Will we find persistent abnormal volatility in the MSCI market sectors after 24 February 2022?

Research question 3: Are there any significant differences between the MSCI market sectors in terms of abnormal volatility?

We contribute to the rapidly growing literature by examining the impact of the Russian attack on volatility at the global sector level. A lot of research showed the effect of this attack on the world's largest stock indices. At this point, we want to further differentiate with our work by examining the views of market participants regarding the risk associated with various sectors. The MSCI market sectors broadly represent the various business models and the largest companies that use them worldwide. In contrast to the analysis of the largest stock indices reflecting the largest companies in a country, we want to analyze and compare market participants' assessments of the risk associated with a business model. This can then indicate the risk of investing in such a business model. In addition, we present an approach to sector hedging in a portfolio, which can be more efficient than broader index hedging as it identifies sector-specific risks. The paper is organized as follows. The literature review gives an overview of the research so far. After that, we introduce the methods used in our article. The dataset section describes the analyzed data and provides summary statistics. We discuss our findings in detail in the results section. The conclusion summarizes the article and provides suggestions for further research.

Literature review

Concerning the Russian attack on Ukraine, there is already a body of literature available.

The general effects of the Russian war in Ukraine, such as sanctions, reductions in international trade, and inflationary pressures, were examined by several research studies (e.g., Astrov et al. 2022; Khudaykulova et al. 2022; Liadze 2022; Mbah–Wasum 2022; Orhan 2022; Ozili 2024).

Of course, in addition to the real economy, the financial markets were also affected. Several publications cover the effects on the financial markets. Ahmed et al. (2022) found evidence of negative abnormal returns in various STOXX Europe 600 sectors due to the Russian attack. Chowdhury–Khan (2024) also found negative abnormal returns in the global stock markets. By contrast, the energy industry reached a negligible positive average abnormal return (Ahmed et

al. 2022; Robus et al. 2024). Boubaker et al. (2022) found cumulative abnormal returns for various stock market indices around the day of the Russian attack, on the 24th of February. They also showed that there is a negative relationship between a country's degree of international integration and its sensitivity to geopolitical shocks. By analyzing global stock markets around the time of the Russian attack, Bounboua–Yati (2022) found empirical evidence of a significant negative impact on stock indices in 94 countries. Sun et al. (2022) analyzed the responses of various countries, regions, and sectors to the Russia-Ukraine conflict. Their findings revealed diverse market reactions, with the intensity of the response being linked to the level of a country's involvement in the conflict. European stock markets exhibited a strong negative reaction, whereas U.S. stock markets showed a mild decline. A similar trend was observed across individual sectors. Notably, the financial services sector experienced a stronger negative reaction than the manufacturing industry. In contrast, energy companies, particularly those in gas and crude oil, benefited from the developments (Robus et al. 2024). Yudaruddin et al. (2023) investigated the reaction of over 2,000 consumer staples companies to the Russian attack. They found negative abnormal returns almost everywhere around the time of the Russian attack. They also found that the reaction of firms from NATO member countries was significantly smaller than that of the other firms considered.

In this paper, we focus on the reaction of volatility. There are also a lot of studies on this topic. A large field of research deals with volatility spillovers. They refer to the transmission of volatility from one financial market to another and are characteristics of the interconnectedness of these markets. Spillovers can occur across asset classes, markets, regions, or periods. Babar (2023) analyzed the connectedness between agricultural commodities and emerging stock markets. They found that most commodities are net transmitters, and equity indices are net receivers of volatility spillovers. Moreover, they found evidence of increasing spillovers during the COVID-19 pandemic and the Russia-Ukraine war. Beraich et al. (2022) investigated the volatility spillover of the Chinese, European and American financial markets during the Russia-Ukraine war. They found that spillovers were significantly lower before the crisis than during the crisis. This can be interpreted as an increase in the crisis-related interconnectedness of international financial markets after the Russian attack. However, this effect was smaller than during the COVID-19 pandemic. Kumar et al. (2023) analyzed the relationship

between crypto assets, commodities, and G20 capital markets in terms of risk and return during geopolitical crises. Using a TVP VAR model, they estimated volatility spillovers between asset classes and regional markets. For instance, they identified a significant level of interconnectedness among these assets during the COVID-19 pandemic. Specifically, the EU, Canada, France, Germany, and the UK were key sources of volatility spillovers, influencing other commodities, Bitcoin, and various markets (Robus et al. 2024). Smales (2021) investigated volatility spillovers between stock and oil markets. Umar et al. (2022) examined the link between Russian and European financial and commodity markets. By analyzing volatility spillovers during the Russian-Ukrainian war, they found evidence that Russian bonds and European equities were net transmitters of volatility shocks. Yousaf et al. (2023) analyzed the link between geopolitical events and uncertainty across global stock and commodity markets. They found that, during the Russian-Ukrainian war, uncertainty rose significantly, especially in the short term. However, other studies have also shown that volatility spillovers were much stronger during the COVID-19 pandemic and were observed in the short, medium, and long term. Another field of research deals with event-induced volatility. This volatility can be interpreted as uncertainty related to the occurrence of (geopolitical) shocks. Agyei (2023) found evidence of a strong correlation between geopolitical risks and stock market volatility. Batten et al. (2023) investigated the correlation between geopolitical event-induced volatility and negative returns in the banking sector. Comparing the effects of different events, they found that the most significant volatility shock affected bank returns during the global financial crisis, which followed the COVID-19 pandemic. The smallest effect was observed during the current war in Ukraine. Fiszeder–Malecka (2022) investigated the accuracy of volatility forecasting models during geopolitical events in stock, currency, cryptocurrency, and commodity markets. Specifically, in the case of the Russian War, they were able to show that the quality of prediction behaved differently. For crypto markets, no differences in forecasting quality were found before and during the war. There were significant differences in the stock market. Izzeldin et al. (2023) investigated the response of global stock and commodity markets to the Russian attack on Ukraine. They found evidence of event-driven volatility in the observed markets and showed that the speed of the volatility response was faster than during COVID-19 and the global financial crisis. Lo et al. (2022) examined how the Russian attack influenced financial market volatility in terms of a country's dependency on Russian commodities. Their analysis revealed

that regional stock market volatility increased significantly if a country was more dependent on Russian commodities. This can be interpreted as an increased risk of delivery disruption or as meaning that this connection to Russia has a negative impact on the respective companies. Ngwakwe (2022) examined the war-induced volatility of the EU, UK, and US stock markets. They found evidence that the Russian attack on Ukraine caused significant volatility. The effect was strongest in the EU, followed by the UK stock market. The US stock market was the least affected. Rice et al. (2023) found evidence of increasing volatility in major food-related commodity markets in late 2021. Despite the already high volatility, the Russian attack caused prices to spike in February 2022. Analyzing Russian attack-induced volatility for different asset classes, Taera et al. (2023) found that, except for Bitcoin, the volatility of all financial instruments studied increased. Gheorghe–Panazan (2023) found evidence of a correlation between the proximity of a country to the conflict zone and the volatility of the respective stock market during the Russia-Ukraine war. Countries that were closer to the Russian attack expected it earlier and experienced a more volatile market.

Methodology

We used the event study approach developed by Campbell–Lo (1996), Fama et al. (1969), and MacKinley (1997) to analyze the reaction of the global stock market sector to the Russian attack. For the evaluation of abnormal volatility, we use the approach of Ahmed et al. (2020), Beaver (1968), Brown–Warner (1985), Landsman–Maydew (2002), and Prasad et al. (2021). In terms of formal notation, we follow Robus et al. (2024).

First, we calculated daily MSCI sector index returns by:

$$R_{s,t} = \ln \left(\frac{P_{s,t}}{P_{s,t-1}} \right) \quad (1)$$

where the closing price of the sector index s at day t is denoted by $P_{s,t}$.

Further, we constructed the OLS market model for every sector s :

$$R_{s,t} = \alpha_s + \beta_s R_{m,t} + \varepsilon_{s,t} \quad (2)$$

where $\varepsilon_{s,t} \sim (0, \sigma_{s,t}^2)$ is white noise process, $R_{s,t}$ is the daily return of sector s at day t , and $R_{m,t}$ is the daily market return at day t . α_s, β_s are the sector individual parameters of the market model. We used the MSCI World Index as a benchmark for market returns $R_{m,t}$. The OLS market model assumes that the conditional expectation of $R_{s,t}$ is given by:

$$E(R_{s,t} | I_{t-1}) = \alpha_s + \beta_s R_{m,t} \quad (3)$$

where I_{t-1} is the information which was obtained up to day $t-1$.

We calculated abnormal returns by:

$$AR_{s,t} = R_{s,t} - E(R_{s,t}) = R_{s,t} - (\hat{\alpha}_s + \hat{\beta}_s R_{m,t}) \quad (4)$$

where the estimated OLS market model parameters are denoted by $\hat{\alpha}_s$ and $\hat{\beta}_s$ for each sector s within the period from $t-250$ to $t-6$.

We used a GARCH(1,1) approach to model the sector volatility $\sigma_{s,t}^2$

$$\hat{\sigma}_{s,t}^2 = \hat{\omega}_s + \hat{\theta}_s \varepsilon_{s,t-1}^2 + \hat{\phi}_s \sigma_{s,t-1}^2 \quad (5)$$

where $\hat{\omega}_s$, $\hat{\theta}_s$ and $\hat{\phi}_s$ are the model parameters to be estimated within the period from $t-250$ to $t-6$.

We computed abnormal volatility for sector s at time t ($AVOLA_{s,t}$) by:

$$AVOLA_{s,t} = AR_{s,t}^2 / \hat{\sigma}_{s,t}^2 \quad (6)$$

The procedure for an event study using abnormal volatility is based on estimating the model parameters in the pre-event phase and then using this model to make predictions for the event and post-event phases. Bialkowski et al. (2008) noted that a one-step forecast does not produce an event-independent forecast. This problem can be solved by making the volatility forecast depend only on the information available before the event. For this reason, a h -th step ahead forecast must be used instead of a h separate one-step ahead forecast. We define $T = t-6$ and compute h -step out-of-sample abnormal volatility forecasts for $h=1 \dots 31$ by:

$$AVOLA_{s,T+h} = AR_{s,T+h}^2 / \hat{\sigma}_{s,T+h}^2 \quad (7)$$

$$AR_{s,T+h}^2 = (R_{s,T+h} - (\hat{\alpha}_s + \hat{\beta}_s R_{m,T+h}))^2 \quad (8)$$

$$\hat{\sigma}_{s,T+h}^2 = \hat{\omega}_s \sum_{i=1}^{h-1} (\hat{\theta}_s + \hat{\phi}_s)^i + (\hat{\theta}_s + \hat{\phi}_s)^{i-1} + (\hat{\theta}_s \hat{\varepsilon}_{s,T}^2 + \hat{\phi}_s \hat{\sigma}_{s,T}^2) \quad (9)$$

For our analysis of whether volatility increases around the event day are persistent or not, we use the cumulative abnormal volatility ($CAVOLA_{s,t}$) with:

$$CAVOLA_{s,t+h} = \sum_{i=t}^{t+h} AR_{s,i}^2 / \sum_{j=t}^{t+h} \hat{\sigma}_{s,j}^2 \quad (10)$$

Dataset and summary statistics

The following section briefly discusses the dataset and presents some statistical analysis. In our analysis, we used the dataset and the description of Robus et al. (2024). The dataset contains 11 MSCI sector index time series (Appendix 1), with

closing prices (USD) from 4 March 2021 to 31 March 2022. Each series provides a total of 281 business days. The data was collected via MSCI (2024b).

We followed the example of Federle et al. (2022), Izzeldin et al. (2023), and Yousaf et al. (2023) by defining the event date as the 24th of February 2022 and denoting it as t . For our event study, we split the dataset for each sector time series into three parts. First, the pre-event phase contains 250 observations from 4 March 2021 to 16 February 2022. We used this data ($t-255$ to $t-6$) to estimate the parameters for the OLS market model and the GARCH(1,1) process.

The event phase from 17 February 2022 to 3 March 2022 ($t-5$ to $t+5$) contains market development observations around the time of the Russian attack. In accordance with Robus et al. (2024) and Yousaf et al. (2023), we used this period to analyze the market reaction. The post-event phase contains observations from 4 March 2022 to 31 March 2022. It was used to examine whether abnormal volatility was persistent and how long it remained at an above-average level compared to the pre-event phase. To achieve this, we combined the event and post-event phases ($t-5$ to $t+25$). We want to provide some summary statistics for MSCI sector indices. Details are described by Robus et al. (2024). As expected, we observed close-to-zero average and median daily returns for the MSCI World Index in the pre-event phase (Appendix 2), strong negative returns during the event phase (Appendix 3), and positive post-event returns (Appendix 4). Overall, this shows that the Russian attack initially led to sell-offs. However, we then see a strong recovery in the post-event phase, which is very different for the individual sectors, indicating a reallocation across sectors. This is understandable, as market participants' expectations regarding the development of business models within the sectors have changed, and they are reacting accordingly. The highest daily losses during the event phase were recorded by the following sectors: financials (-3.41%), consumer staples (-2.82%), materials (-2.64%), telecommunications (-2.63%), consumer discretionary (-2.51%), utilities (-1.97%), IT (-1.69%), real estate (-1.68%), industrials (-1.63%), energy (-1.46%) and health care (-1.25%).

To compare sample variances between pre-event and event phases, we applied Levene's test statistic (Appendix 5). The test is robust to deviations from the assumption that the samples to be compared must be normally distributed. Furthermore, the size of the two samples can be different. We found that almost all sector variances are significantly different from zero, which means that variances are significantly higher during the event phase. Data variability can also be seen

when we look at the range of the data (the difference between the minimum and the maximum) for the individual sectors. We found that it widens for the event and post-event phases, compared to the pre-event phase. These are all signs of an increase in stock price fluctuations due to the Russian attack.

Results

Abnormal Volatility

We start with an aggregated approach to abnormal volatility by looking at the sector-wide mean abnormal volatility for time points close to the event day (t-5 to t+5). For this, we calculated the truncated mean (TMean) by discarding the lowest and highest values from the calculation (Table 1).

Table 1. Abnormal volatility (AVOLA) for MSCI sector indices from 02/17/22 to 03/03/22. Statistical significance is indicated by *, using an F-Test at a 95% level

	CD	CS	EN	FN	HC	IN
t-5	2.53	2.76	0.09	45.77*	3.19*	2.42
t-4	0.46	0.15	0.48	0.65	1.78	2.03
t-3	0.11	0.34	0.01	0.29	0.02	0.67
t-2	4.44*	3.80*	0.32	7.05*	0.02	1.34
t-1	3.48*	0.70	0.10	24.13*	0.37	3.30*
t	0.11	56.46*	1.04	57.46*	0.51	1.67
t+1	2.74	19.59*	3.60	8.15*	26.72*	15.39*
t+2	0.11	0.53	0.85	1.60	0.11	0.44
t+3	2.10	0.80	0.06	18.60*	0.20	3.10**
t+4	0.41	0.01	3.83*	1.24	1.04	1.27
t+5	3.00*	0.00	0.29	0.23	0.02	0.04
	IT	MT	RE	TC	UT	TMean
t-5	0.31	0.29	0.26	4.18*	0.22	1.99
t-4	4.85*	0.26	0.78	0.40	0.77	0.86
t-3	1.51	0.08	0.31	0.00	0.62	0.23
t-2	0.41	0.68	0.15	0.52	0.05	1.46
t-1	0.49	0.18	2.56	1.69	4.91*	1.60
t	1.83	6.28*	1.45	2.70	0.47	8.99*
t+1	9.50*	5.95*	3.12*	2.06	48.90*	8.50*
t+2	0.11	0.08	0.88	0.00	1.13	0.39
t+3	0.63	1.03	0.10	1.34	4.82	1.16
t+4	0.17	1.34	2.91	0.22	0.00	1.07
t+5	0.17	0.27	0.31	0.94	0.04	0.28

Source: Authors' own calculations, Matlab

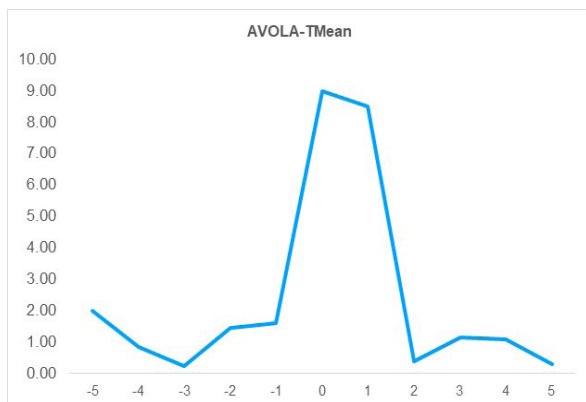
We have used the truncated mean here to avoid very high abnormal volatility values in a sector that excessively influences the average mean value. The values are to be interpreted as volatility forecasting factors using the GARCH(1,1) model (e.g., $AVOLA = 1.99$ means that the observed volatility was 1.99 times or 199% higher than the GARCH(1,1) forecasted volatility). We also conducted an F-test to determine the significance of the AVOLA values.

First, we can see that, around the event day, most of the AVOLA-TMean values for abnormal volatility are above one. This indicated that the observed volatility was greater than the GARCH(1,1) forecasts based on the pre-event data. Before the event day, we can see AVOLA-TMean values > 1 in $t-5$, $t-2$, and $t-1$, which indicates the uncertainty of market participants as to whether there will be a war between Russia and Ukraine. In particular, the increase in AVOLA at $t-2$ and $t-1$, after lower values at $t-4$ and $t-3$, can be explained by the fact that, on the 21st of February 2022, Russia recognized the independence of the territories in Donetsk Oblast and Luhansk Oblast controlled by pro-Russian separatists in eastern Ukraine and proclaimed the Donetsk and Luhansk “People’s Republics” (Bocquillon et al. 2024). Shortly after, Russian troops were deployed to protect the pro-Russian separatists (NZZ 2024).

With AVOLA-TMean values of 8.99 on the event day and 8.50 on the following day, we found that the actual volatility was 8.99 times (in t) and 8.50 times (in $t+1$) higher than the GARCH(1,1) forecasted volatility. Both values were statistically significant. This means there were large price fluctuations in the individual sectors, which must be understood as a reaction to the Russian attack. In general, these price fluctuations do not necessarily have to be accompanied by sharp price losses but should initially be understood as the strength of a price change. Robus et al. (2024) showed abnormally negative returns for most sectors on the event day. The next day, however, we can see that there are many positive abnormal returns. Here, we see the corresponding fluctuations. These price fluctuations show market participants’ reactions to the change in geopolitical conditions and their expectations regarding their sector investments. This results in the liquidation of stock portfolios and the shifting of stocks from one sector to another, considering the individual expectations of the respective business model. For example, in times of crisis, we often see stocks in the IT sector being sold off and stocks in the consumer staples sector being bought up (e.g., Prasad et al. 2021). After the event day, at $t+2$ up to $t+5$, we see AVOLA-TMean values are

less than or close to one, which means that the observed volatility is smaller or matches the forecast volatility and that the market moves less than predicted, with values less than one ($t+2$; $t+5$).

Figure 1 shows the apparent spike in AVOLA-TMean at t and, again, at $t+1$. With this finding, we have already shown the presence of abnormal volatility around 24 February 2022 from an average perspective.



Source: Authors' own illustration

Figure 1. Trimmed mean for abnormal volatility (%) of MSCI sector indices from 02/17/22 to 03/03/22

We will now discuss the findings for the individual sectors. Abnormal volatility with $AVOLA > 1$ on the event day t was seen in 8 out of 11 cases: financials (57.46), consumer staples (56.46), materials (6.28), utilities (4.91), telecommunication (2.70), IT (1.83), industrials (1.67) and real estate (1.45). Financials, consumer staples, and materials have statistically significant values. The reaction of market participants on the following day is even clearer. Here, all sectors have an $AVOLA > 1$. These are statistically significant for 8 sectors: utilities (48.90), health care (26.72), consumer staples (19.59), industrials (15.39), IT (9.50), financials (8.15), materials (5.95) and real estate (3.12). Here are some possible explanations for the behavior of individual sectors around the event day t . The consumer discretionary sector (Appendix 6), which includes companies related to, for example, cars, household appliances, specialty goods, luxury goods, and leisure goods, would be affected, as consumers tend to postpone major purchases in times of war, which has a negative impact on companies' sales.

Uncertainty in the consumer staples sector (Appendix 7) arose because of the sanctions imposed on Russia, where the loss of the Russian market is now expected to result in a major decline in sales, particularly for mass-market consumer goods (e.g., Coca-Cola, Nestlé and Unilever).

The energy sector (Appendix 8) showed relatively small abnormal volatility over the analyzed period, especially at t and $t+1$, indicating a low uncertainty level overall. This is because investments in energy companies are less speculative and more long-term. Another possible explanation is that market participants feel little uncertainty about companies' business model in the energy sector and that no significant changes are expected due to the war. Also, it could be that this uncertainty already existed before our observation at $t-5$, and any changes were already reflected in the stock price. Regarding the behavior of the energy sector, we found comparable results to the analysis of abnormal returns in Robus et al. (2024).

The financial sector (Appendix 9) includes to a large extent global operating banks and insurance companies. In times of war, economic losses are expected, often resulting in loan defaults and increased claims for insurance payouts. Additionally, the heightened uncertainty typically causes a decline in investment activity, adversely affecting banks' commission-based revenue streams. Declining investment also leads to a fall in demand for capital goods, negatively impacting the industrial sector.

The healthcare sector (Appendix 10) comprises companies that deliver medical services, manufacture medical equipment or pharmaceuticals, offer medical insurance, or support healthcare provision to patients in various capacities. In particular, the expected increase in demand for products and services from companies in the healthcare sector during an actual conflict is a plausible explanation for the reaction of the sector index.

The industrial sector (Appendix 11) covers various business models, including aerospace & defense, electronic equipment, infrastructure building, machinery, and transportation. The abnormal volatility around the event day could be attributed to the relatively lower country weighting of U.S. companies in the industrials sector compared to other sectors. Potential declines in the stock prices of companies based outside the U.S., such as those in France and the UK, may also have contributed to this volatility (Robus et al. 2024).

Companies in the IT sector (Appendix 12) are classically more speculative than companies in other sectors, as they are often young companies with high potential. Still, the return on sales is small in comparison to other sectors. In

addition, they often have a high debt ratio, which makes them susceptible to interest rate increases. The Russian attack increases the cost risk and profitability for these companies. As a result, investors often adjust their portfolios towards more conservative business models in times of crisis.

The materials sector (Appendix 13) comprises companies involved in the production of chemicals, metal processing, industrial gases, and the mining of gold and other metals. Potential opportunities may emerge from the exclusion of Russian companies, leading to supply shortages that could enhance the market position and profitability of the companies included in the index.

Real estate (Appendix 14) is a very conservative investment, but it is also affected by the interest rate risk. Inflation in the U.S., which began in 2021 after the COVID-19 pandemic had started to subside, combined with the Russian attack, increased uncertainty in this sector.

The utilities sector (Appendix 15) includes companies that provide electricity, natural gas, steam supply, water supply and sewage removal services. Changes are expected in the supply of natural gas, particularly as the outbreak of war means that the long-standing partnership between Europe and Russia is at risk, and there are new opportunities for U.S. suppliers of liquefied gas.

Besides strong abnormal volatility on the event day and on the following day, we found different behaviors for sector abnormal volatility. Sectors with no overall abnormal volatility: e.g., energy. Sectors with strong abnormal volatility before the event: financials, health care, and telecommunications (Appendix 16). Sectors with abnormal volatility after the event day: e.g., the consumer discretionary sector and industrials. Another type of sector behavior is when there is abnormal volatility ($AVOLA > 1$) prior to the event day. Our findings are consistent with Prasad et al. (2021), who found evidence of the stock market sector's abnormal volatility during the dot-com boom, the global financial crisis, and COVID-19.

Cumulative Abnormal Volatility

In the following section of this paper, we aim to address the second research question by investigating whether the observed abnormal volatility persists over an extended period of time after the event day. We do this by analyzing the cumulative abnormal volatility (CAVOLA), defined by equation (10). The idea here is that if the ratio between the sum of the actual volatility and the sum of the volatility predicted by GARCH(1,1) increases, then abnormal volatility > 1 occurred over that period of time. If this ratio does not change, the actual

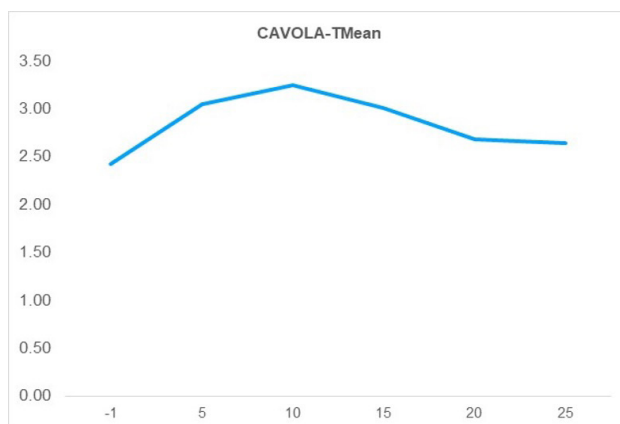
volatility is consistent with the forecast volatility. If the ratio is even lower, the actual volatility over the period under review is lower than the forecast volatility.

We start again with the analysis of the mean value. For consistency reasons, we also use the TMean here. We have shown our results in Table 2 and illustrated them in Figure 2.

Table 2. Cumulative Abnormal Volatility (CAVOLA) for MSCI sector indices from 02/17/22 to 03/31/22

	CD	CS	EN	FN	HC	IN
t-1	2.14	1.50	0.20	7.63	1.11	1.93
t+5	1.67	4.16	0.97	6.66	2.24	2.56
t+10	2.12	3.96	1.08	6.90	2.61	2.79
t+15	1.95	2.97	1.37	6.72	2.52	2.50
t+20	1.62	2.45	1.39	6.43	2.13	2.04
t+25	1.58	2.27	1.39	6.62	1.97	2.00
	IT	MT	RE	TC	UT	TMean
t-1	1.30	0.30	0.77	1.29	1.17	2.42
t+5	1.37	1.57	1.13	1.25	3.56	3.04
t+10	1.75	1.71	1.07	1.93	2.46	3.24
t+15	1.44	1.67	1.01	1.85	2.11	3.01
t+20	1.27	1.44	0.90	1.65	1.94	2.68
t+25	1.23	1.28	0.99	1.60	2.01	2.64

Source: Authors' own calculations, Matlab



Source: Authors' own illustration

Figure 2. CAVOLA-TMean (%) for MSCI sector indices from 02/17/22 to 03/31/22

We calculated the cumulative abnormal volatility for $t-1$ (sum of AVOLA for the observations $t-5$ to $t-1$) as an initial value. This also gives us a benchmark for the abnormal volatility before the event day. We were able to observe the following for the CAVOLA-TMean. Starting from a value of 2.42 at $t-1$, it increases to 3.04 at $t+5$. This is understandable, as although there are some sectors with increased abnormal volatility up to $t-1$, the majority can be observed at t and $t+1$, as shown in the previous analysis. What is surprising now is that the CAVOLA-TMean increases further to 3.24 at $t+10$ compared to $t+5$. This means that further abnormal volatility occurs in the periods $t+6$ to $t+10$ and that there continue to be strong price fluctuations even days after the event day. In other words, abnormal volatility is 20% higher than around the event day. This also implies a longer-term uncertainty about future developments among investors. From $t+11$ to $t+20$, we see decreasing values for the CAVOLA-TMean ($t+15$: 3.01 and $t+20$: 2.20). This suggests a calming of market participants, whose actions in the markets produce less volatility than the GARCH(1,1) model predicts. In the further observation period, we see that the CAVOLA-TMean of $t+20$ roughly corresponds to the CAVOLA of $t+25$. This means that the CAVOLA-TMean from $t+21$ to $t+25$ is approximately one, which shows that the actual volatility matches the estimated volatility and has therefore returned to its long-term level. From a mean value perspective, we were thus able to show that abnormal volatility persisted until $t+10$ and thus lasted for a longer period of time after the event day.

We will now look at the behavior of individual sectors. We can observe the CAVOLA-TMean behavior that we have just described for the following sectors: consumer staples (Appendix 17), energy (Appendix 18), health care (Appendix 19), industrials (Appendix 20), IT (Appendix 21), materials (Appendix 22) and telecommunications (Appendix 23). However, we also found different behaviors in individual sectors. The persistence was particularly strong in the following sectors: IT, telecommunications, health care, industrials and materials. In financial services (Appendix 24), a high CAVOLA value was observed at time $t-1$, followed by a sharp decline until time $t+5$, after which CAVOLA rose again, as in other sectors. We see a zig-zag movement here until $t+25$, which suggests that the uncertainty in this sector will persist for longer or will increase again after a specific period of time. We see little persistence of abnormal volatility due to a declining CAVOLA after $t+5$ in the real estate (Appendix 25) and utilities (Appendix 26) sectors. Our analysis showed that abnormal volatility was persistent in many sectors until $t+10$.

Statistically significant differences in abnormal volatility

The third research question focuses on determining whether statistically significant differences in abnormal volatility were identified across sectors. We carry out this analysis for the most prominent days, the event day t and the following day $t+1$. To evaluate statistical significance, we performed an F-test for all pairs of sectors, at t (Table 3) and $t+1$ (Table 4), respectively.

Table 3. F-Test statistics for differences between MSCI sector indices, abnormal volatility on the event day, 24 February 2022 (* it indicates statistical significance at a 95% level)

	CD	CS	EN	FN	HC	IN	IT	MT	RE	TC	UT
CD	1.00	505.71*	9.34*	514.69*	4.57*	14.93*	16.37*	56.09*	12.98*	24.14*	4.22*
CS		1.00	54.13*	1.02	110.67*	33.88*	30.90*	9.02*	38.97*	20.95*	119.81*
EN			1.00	55.09*	2.04	1.60	1.75	6.00*	1.39	2.58	2.21
FN				1.00	112.64*	34.48*	31.45*	9.18*	39.66*	21.32*	121.93*
HC					1.00	3.27*	3.58*	12.27*	2.84	5.28*	1.08
IN						1.00	1.10	3.76*	1.15	1.62	3.54*
IT							1.00	3.43*	1.26	1.47	3.88*
MT								1.00	4.32*	2.32	13.29*
RE									1.00	1.86	3.07*
TC										1.00	5.72*
UT											1.00

Source: Authors' own calculations, Matlab

Table 4. F-Test statistics for differences between MSCI sector indices, abnormal volatility on the 25th of February 2022 (* it indicates statistical significance at a 95% level)

	CD	CS	EN	FN	HC	IN	IT	MT	RE	TC	UT
CD	1.00	7.16*	1.31	2.98	9.76*	5.62*	3.47*	2.17	1.14	1.33	17.87*
CS		1.00	5.45*	2.40	1.36	1.27	2.06	3.29*	6.28*	9.53*	2.50
EN			1.00	2.27	7.43	4.28	2.64	1.66	1.15	1.75	13.60*
FN				1.00	3.28*	1.89	1.17	1.37	2.61	3.96*	6.00*
HC					1.00	1.74	2.81	4.49*	8.57*	13.00*	1.83
IN						1.00	1.62	2.59	4.93*	7.48*	3.18*
IT							1.00	1.60	3.04*	4.62*	5.15*
MT								1.00	1.91	2.89	8.22*
RE									1.00	1.52	15.68*
TC										1.00	23.78*
UT											1.00

Source: Authors' own calculations, Matlab

For example, the F-test for the equality of variances between the consumer discretionary sector and the consumer staples sector is equal to 505.71 and was rejected at a 95% level; it is thus statistically significant. As we can see, there are more significant differences in abnormal volatility between sectors on the event day than on the following day. We have already seen this in our previous analysis, where we observed various sector behaviors on the day of the event. Now, we want to quantify this a little more. Therefore, we counted the statistically significant differences in abnormal volatility between sectors and ordered them (Table 5 and Table 6).

Table 5. Frequencies (f) of rejected F-Tests for similar abnormal volatility on the event day, 24 February 2022, between MSCI sector indices

	CD	FN	MT	CS	UT	HC	IN	IT	RE	TC	EN	Avg.
f	10	9	9	8	8	7	6	6	5	5	2	6.82

Source: Authors' own calculations

Table 6. Frequencies (f) of rejected F-Tests for similar abnormal volatility on 25 February 2022 between MSCI sector indices

	UT	TC	CD	CS	HC	RE	IN	IT	FN	MT	EN	Avg.
f	8	6	5	5	5	5	4	4	3	3	2	4.55

Source: Authors' own calculations

We further define the sectors with a frequency of up to 5 significant differences in abnormal volatility as similar to other sectors in terms of abnormal volatility. Sectors with a higher frequency are dissimilar to other sectors. According to our definition, on the event day t , 8 out of 11 sectors were dissimilar in terms of abnormal volatility. This is also reflected in the mean value, 6.82 (Table 5). In contrast, only three sectors, namely real estate, telecommunications, and energy, are similar. A different picture emerges for the following day of the event. We observe only two dissimilar sectors here: utilities and telecommunications. The remaining sectors are similar in terms of abnormal volatility the day after the event. This is shown by the mean value of 4.55 (Table 6). Using this approach, we demonstrated that statistically significant differences in abnormal volatility existed between sectors on the event day and the day after. These results provide new insights into the volatility dynamics of global financial markets.

Our paper is insightful for researchers, as there is little evidence of the sector-wide volatility dynamics caused by current geopolitical shocks at the

level of financial markets. In particular, the short-term volatility behavior around the Russian attack as a geopolitical event has received little attention in the literature. The detailed view of the sectors and, thus, of different business models is particularly interesting. Our results can also be compared with past events, for example, the COVID-19 pandemic. This can provide new insights into the behavior of capital markets in crises. It is also much easier to compare the impact of geopolitical events. We provide practitioners, such as fund managers, investment advisors, or investors, with essential insights into how equities behave around geopolitical shocks. Our insights into the behavior of individual sectors can be used to assess the potential risk of market price fluctuations. This can be used to categorize individual stocks into different risk classes concerning geopolitical shocks and thus serve as a basis for portfolio weighting or as an indication of the scale of hedging positions.

The results can also serve as a benchmark for the volatility dynamics of other sector indices, such as for emerging markets or other regional markets. This, in turn, provides information about possible excess volatility, which must then be classified based on the resulting returns.

Conclusion

Russia's attack on Ukraine marks a major break in European history over the last thirty years. In addition to political consequences, this attack has significantly impacted global capital markets. We analyzed this impact on investor behavior in the MSCI market sector, representing the most prominent companies worldwide. Our research focuses on the influence of this geopolitical event on market participants' uncertainty, in the form of extraordinary market fluctuations around the event. We also wanted to determine whether any extraordinary volatility is persistent, i.e., whether it can be observed for a longer period after the event.

For this analysis, we used the event study method combined with the abnormal volatility (AVOLA) concept. To do this, we compared the volatility forecast based on a GARCH(1,1) model with the volatility that could be observed 5 days before to 25 days after the Russian attack for eleven MSCI World market sector indices.

We showed that investor uncertainty rose significantly on 24 February and 25 February 2022 through increased price fluctuations. The strongest reactions were seen in the financials, consumer staples, materials and utilities sectors. Overall, the average abnormal volatility on the event day was 8.99; the following day, it was 8.50. This means the actual volatility was roughly eight to nine times higher

than the predicted volatility. We also applied an F-test for statistical significance. With this, we were able to prove that the abnormal volatility was statistically significant in three sectors – financials, consumer staples, and materials – on the event day. The result was even more apparent on the following day. Eight out of eleven sectors experienced significant abnormal volatility: consumer staples, financials, health care, industrials, materials, IT, real estate, and utilities. The measured abnormal volatility shows market participants' reactions to the change in geopolitical conditions and their expectations regarding their sector investments. This results in the liquidation of stock portfolios and the shifting of stocks from one sector to another, considering the individual expectations of the respective business model. Our findings align with other research on the sector-specific behavior of recent geopolitical events.

We also analyzed abnormal volatility for persistence. For this, we used the cumulative abnormal volatility (CAVOLA) method. We found that, on average, abnormal volatility > 1 was recorded across all sectors up to ten trading days after the event day. The persistence was particularly strong in the IT, telecommunications, health care, industrials and materials sectors. In other sectors, such as the financial sector, we saw ups and downs of abnormal volatility, suggesting that investors' risk assessment is not yet complete. After that, we observed decreasing cumulative abnormal volatility, which indicates an AVOLA < 1 . Between the 20th and the 25th trading day after the event, we observed a certain convergence of the CAVOLA. So, the actual volatility matches the predicted volatility and thus returns to a normal level.

Finally, we analyzed market participants' reactions in terms of abnormal volatility differences between sectors on the day of the event and the day after. For this purpose, we conducted an F-test for equality of variances for the respective sector pairs. We found that the sectors are somewhat dissimilar in terms of abnormal volatility on the day of the event. On the event day, similar sectors are real estate, telecommunications, and energy. The other sectors are dissimilar. On the following day of the event, the sectors are more similar on average. Dissimilar sectors are utilities and telecommunications. All other sectors are similar.

We contribute to the literature by analyzing the impact of the Russian war on volatility at the global sector level. On the one hand, this analysis is intended to explain, in retrospect, how market participants acted during such a major geopolitical event. On the other hand, it also provides market participants with

indications of how to proceed with necessary hedging activities when investing in sector strategies. We want to point out that this article has limitations. For example, in our literature search, we only used English-language publications from the online databases Web of Science, Scopus, and Google Scholar.

Furthermore, we limited our analysis of volatility dynamics to the event study method. Other methods were not included, such as segmented regression or wavelet analysis. Such methods could be used to compare the results with ours. Moreover, the use of the MSCI World sector indices causes a bias. Due to the high proportion of U.S. companies, the results can only be used to a limited extent as a statement for the global financial market sectors. Also, only companies from developed economies are used in these indices. Last, we did not weight the sector returns because we primarily wanted to analyze the reaction of each sector to the Russian attack.

At the end of our article, we provide some pointers for further research. It may make sense to use sector indices that are more balanced in terms of country of origin than the MSCI and to compare the results with those presented here. In addition, sector indices for U.S., Asian, and European companies could be used separately to compare the country-specific differences in abnormal volatility for various sectors. Another approach would be to use different models for forecasting volatility to compare abnormal volatility results.

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Appendices

Appendix 1. MSCI World market sectors, international security number (ISIN) and abbreviation

Index name	ISIN	Abbreviation
MSCI World Index	MIWO00000PUS	MSCI
MSCI World Consumer Discretionary Index	MIWO0CD00PUS	CD
MSCI World Consumer Staples Index	MIWO0CS00PUS	CS
MSCI World Energy Index	MIWO0EN00PUS	EN
MSCI World Financials Index	MIWO0FN00PUS	FN
MSCI World Health Care Index	MIWO0HC00PUS	HC
MSCI World Industrial Index	MIWO0IN00PUS	IN
MSCI World Information Technology Index	MIWO0IT00PUS	IT
MSCI World Materials Index	MIWO0MT00PUS	MT
MSCI World Real Estate Index	MIWO0RE00PUS	RE
MSCI World Telecommunications Index	MIWO0TC00PUS	TC
MSCI World Utilities Index	MIWO0UT00PUS	UT

Source: MSCI (2024a)

Appendix 2. Summary statistics of MSCI sector index log returns (%) for pre-event phase 03/04/21 – 02/16/22

	MSCI	CD	CS	EN	FN	HC	IN	IT	MT	RE	TC	UT
Min	-2.22%	-2.92%	-2.36%	-4.54%	-3.41%	-1.92%	-2.55%	-2.22%	-2.82%	-2.22%	-5.85%	-2.20%
1.Q	-0.31%	-0.47%	-0.22%	-0.77%	-0.47%	-0.34%	-0.37%	-0.33%	-0.47%	-0.33%	-0.44%	-0.40%
Med.	0.10%	0.12%	0.07%	0.13%	0.10%	0.06%	0.02%	0.09%	0.08%	0.11%	0.01%	0.12%
Mean	0.04%	0.03%	0.05%	0.11%	0.06%	0.05%	0.02%	0.03%	0.03%	0.04%	-0.01%	0.03%
3.Q	0.50%	0.68%	0.40%	1.00%	0.70%	0.45%	0.56%	0.50%	0.61%	0.50%	0.57%	0.53%
Max	2.12%	3.20%	1.55%	3.38%	2.42%	1.68%	1.71%	2.12%	2.17%	2.12%	2.54%	1.64%
Std	0.73%	1.00%	0.54%	1.47%	0.90%	0.66%	0.77%	0.73%	0.92%	0.74%	1.01%	0.70%

Source: Robus et al. (2024)

Appendix 3. Summary statistics of MSCI sector index log returns (%) for event phase 02/17/22 – 03/03/22

	MSCI	CD	CS	EN	FN	HC	IN	IT	MT	RE	TC	UT
Min	-1.69%	-2.51%	-2.82%	-1.46%	-3.41%	-1.25%	-1.63%	-1.69%	-2.63%	-1.69%	-2.63%	-1.97%
1.Q	-1.13%	-2.15%	-0.72%	-0.79%	-1.64%	-0.42%	-1.14%	-1.13%	-0.72%	-1.13%	-1.12%	-0.45%
Med.	-0.74%	-0.91%	-0.23%	-0.17%	-0.62%	-0.29%	-0.86%	-0.74%	-0.46%	-0.74%	-0.88%	-0.11%
Mean	-0.36%	-0.77%	-0.14%	0.27%	-0.77%	-0.01%	-0.29%	-0.36%	-0.09%	-0.32%	-0.37%	0.05%
3.Q	-0.10%	0.48%	0.13%	0.88%	-0.30%	-0.10%	0.23%	-0.10%	0.50%	0.06%	0.29%	0.22%
Max	2.52%	2.25%	3.20%	2.79%	2.95%	3.07%	2.94%	2.52%	3.24%	2.52%	1.87%	3.50%
Std	1.19%	1.55%	1.36%	1.38%	1.73%	1.09%	1.29%	1.19%	1.43%	1.20%	1.30%	1.31%

Source: Robus et al. (2024)

**Appendix 4. Summary statistics of MSCI sector index log returns (%)
for post event phase 03/04/22 – 03/31/22**

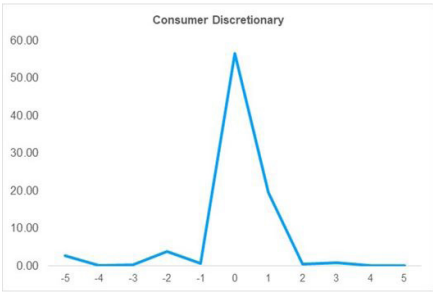
	MSCI	CD	CS	EN	FN	HC	IN	IT	MT	RE	TC	UT
Min	-2.69%	-4.58%	-2.28%	-2.48%	-3.46%	-1.68%	-2.11%	-2.69%	-1.84%	-2.69%	-3.56%	-0.67%
1.Q	-0.81%	-1.25%	-0.89%	-0.74%	-0.46%	-0.47%	-0.47%	-0.81%	-0.59%	-0.81%	-1.08%	-0.12%
Med.	0.12%	0.12%	0.36%	-0.04%	0.15%	0.36%	0.02%	0.12%	0.25%	0.12%	-0.03%	0.45%
Mean	0.18%	0.26%	0.03%	0.24%	0.14%	0.21%	0.14%	0.18%	0.19%	0.18%	0.12%	0.33%
3.Q	1.10%	1.87%	0.63%	1.70%	1.21%	0.85%	0.51%	1.10%	0.81%	1.10%	1.41%	0.89%
Max	2.96%	3.80%	2.14%	3.37%	4.04%	2.22%	2.72%	2.96%	2.41%	2.96%	3.43%	1.32%
StD	1.39%	2.13%	1.12%	1.80%	1.71%	1.07%	1.18%	1.39%	1.15%	1.39%	1.74%	0.61%

Source: Robus et al. (2024)

**Appendix 5. Levene’s test for equality of sample variances between
pre-event and event phase (* indicates that test was rejected on a 5% level)**

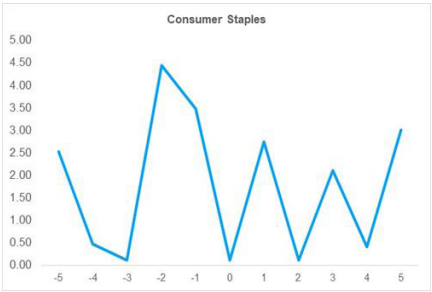
	MSCI	CD	CS	EN	FN	HC	IN	IT	MT	RE	TC	UT
Levene’s test	2.66*	2.40*	6.34*	0.88	3.69*	2.73*	2.81*	2.66*	2.42*	2.63*	1.66	3.50*

Source: Robus et al. (2024)



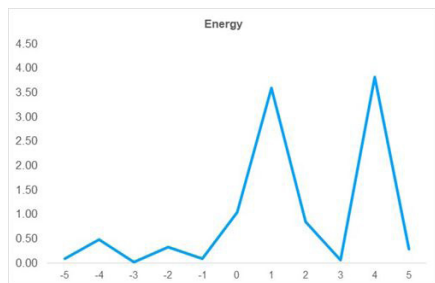
Source: Authors’ own illustration

**Appendix 6. Abnormal volatility (%) of
Consumer Discretionary sector index
from 02/17/22 – 03/03/22**



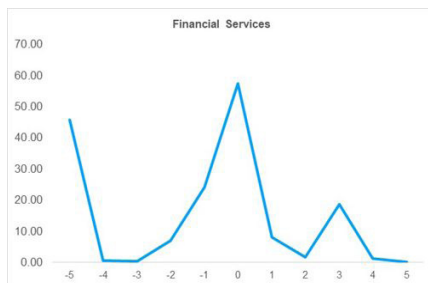
Source: Authors’ own illustration

**Appendix 7. Abnormal volatility (%)
of Consumer Staples sector index from
02/17/22 – 03/03/22**



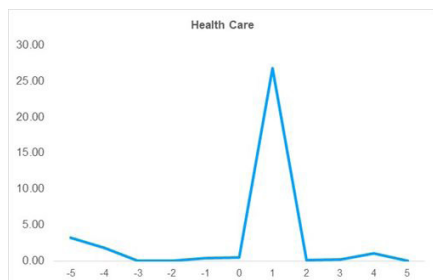
Source: Authors' own illustration

Appendix 8. Abnormal volatility (%) of Energy sector index from 02/17/22 – 03/03/22



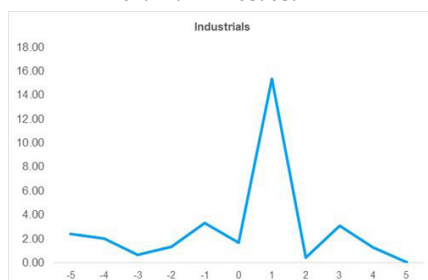
Source: Authors' own illustration

Appendix 9. Abnormal volatility (%) of Financial Services sector index from 02/17/22 – 03/03/22



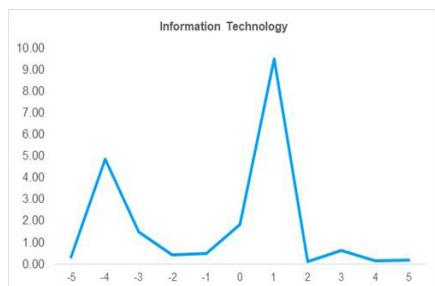
Source: Authors' own illustration

Appendix 10. Abnormal volatility (%) of Health Care sector index from 02/17/22 – 03/03/22



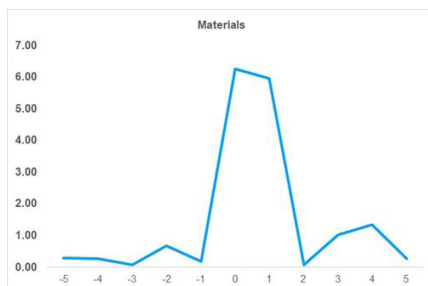
Source: Authors' own illustration

Appendix 11. Abnormal volatility (%) of Industrials sector index from 02/17/22 – 03/03/22



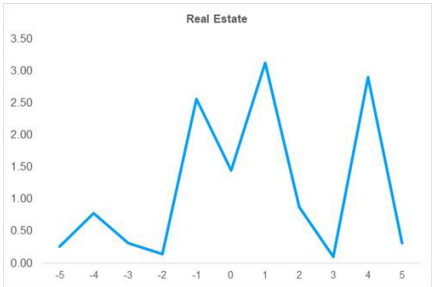
Source: Authors' own illustration

Appendix 12. Abnormal volatility (%) of Information Technology sector index from 02/17/22 – 03/03/22



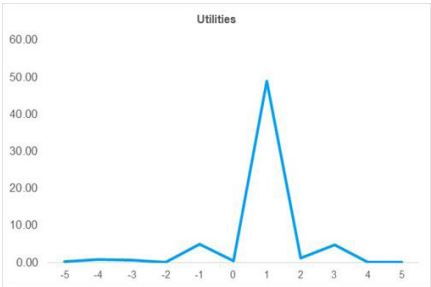
Source: Authors' own illustration

Appendix 13. Abnormal volatility (%) of Materials sector index from 02/17/22 – 03/03/22



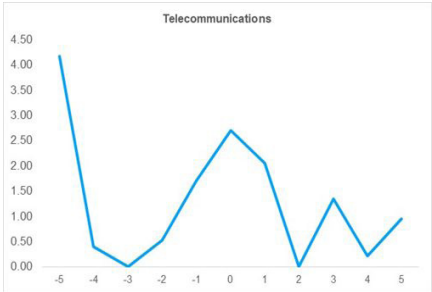
Source: Authors' own illustration

Appendix 14. Abnormal volatility (%) of Real Estate sector index from 02/17/22 – 03/03/22



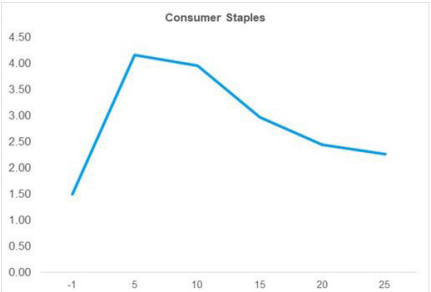
Source: Authors' own illustration

Appendix 15. Abnormal volatility (%) of Utilities sector index from 02/17/22 – 03/03/22



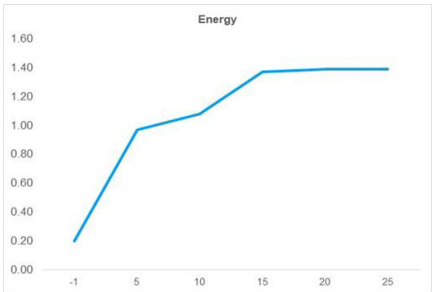
Source: Authors' own illustration

Appendix 16. Abnormal volatility (%) of Telecommunication sector index from 02/17/22 – 03/03/22



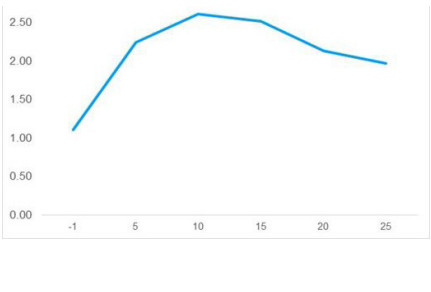
Source: Authors' own illustration

Appendix 17. Cumulated abnormal volatility (%) of Consumer Staples sector index from 02/17/22 – 03/31/22



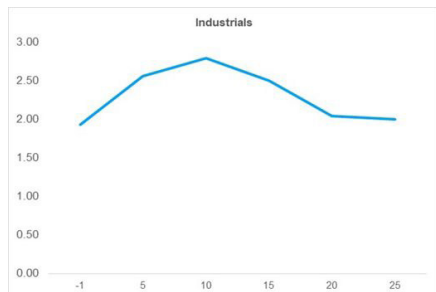
Source: Authors own illustration

Appendix 18. Cumulated Abnormal volatility (%) of Energy sector index from 02/17/22 – 03/31/22



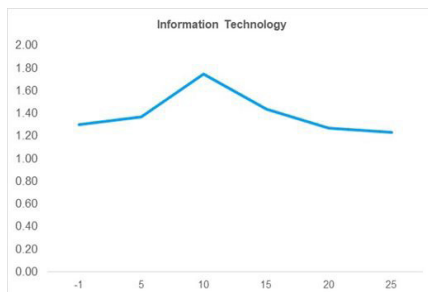
Source: Authors own illustration

Appendix 19. Cumulated abnormal volatility (%) of Health Care sector index from 02/17/22 – 03/31/22



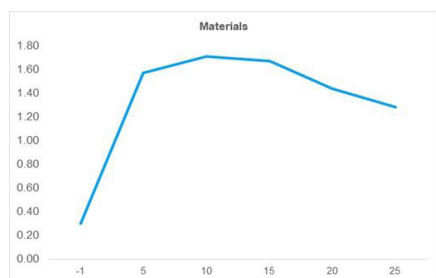
Source: Authors own illustration

Appendix 20. Cumulated Abnormal volatility (%) of industrials sector index from 02/17/22 – 03/31/22



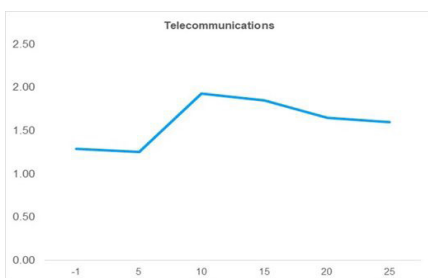
Source: Authors own illustration

Appendix 21. Cumulated abnormal volatility (%) of Information Technology sector index from 02/17/22 – 03/31/22



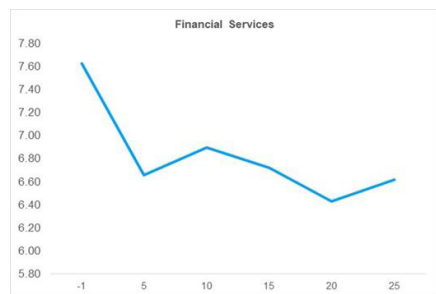
Source: Authors own illustration

Appendix 22. Cumulated abnormal volatility (%) of Materials sector index from 02/17/22 – 03/31/22



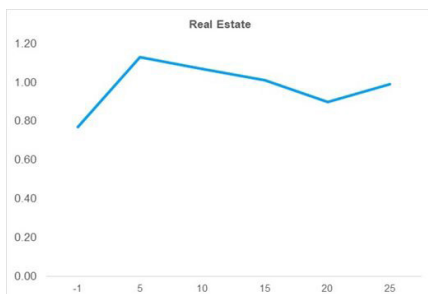
Source: Authors own illustration

Appendix 23. Cumulated Abnormal volatility (%) of Telecommunications sector index from 02/17/22 – 03/31/22



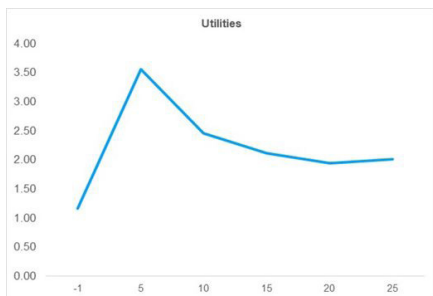
Source: Authors own illustration

Appendix 24: Cumulated Abnormal volatility (%) Financial Services sector index from 02/17/22 – 03/31/22



Source: Authors own illustration

Appendix 25. Cumulated Abnormal volatility (%) of Real Estate sector index from 02/17/22 – 03/31/22



Source: Authors own illustration

**Appendix 26. Cumulated Abnormal
volatility (%) of Utilities sector index
from 02/17/22 – 03/31/22**