Vaasan yliopisto
UNIVERSITY OF VAASA

Joonas Heikkilä

Russia-Ukraine War and Stock Market

A Sector-Specific Event Study on the Finnish Stock Market

School of Accounting and Finance
Master’s thesis in Finance
Master’s Degree Programme in Finance

Vaasa 2026

UNIVERSITY OF VAASA			
School of Accounting and Finance			
Author:	Joonas Heikkilä		
Title of the thesis:	Russia-Ukraine War and Stock Market: A Sector-Specific Event Study on the Finnish Stock Market		
Degree:	Master of Science in Economics and Business Administration		
Degree Programme:	Master’s Degree Programme in Finance		
Supervisor:	Timo Rothovius		
Year:	2026	**Pages:**	103

ABSTRACT:

This thesis examines the impact of the Russian invasion of Ukraine on 24 February 2022 on the Finnish stock market (Nasdaq Helsinki). Given Finland's geographic proximity to the conflict region and its historical economic ties with Russia, the outbreak of the war represents a significant geopolitical shock with potential implications for the financial markets. The primary objective of this study is to determine whether the beginning of the war generated abnormal returns and volatility changes across the overall market and eleven industry portfolios.

The empirical analysis employs a short-term event study methodology utilizing daily data for 139 Finnish listed companies. To isolate genuine event-driven market reactions from normal market movements, expected returns are estimated using both the Market Model (MM) and the Fama-French Five-Factor Model (FFM). In addition, cross-sectional regression models are utilized to control for the potential confounding effects of firm-specific information announcements during the event window. Furthermore, a text-based Russia-Ukraine War News Index (RUWNI) is constructed using sentiment analysis to evaluate the relationship between global Russia-Ukraine war related news flow and stock price movements in the Finnish market.

The empirical results indicate that the market reaction to the outbreak of the war was heterogenous across sectors. Rather than a uniform market decline, the event was associated with a reallocation of capital across industries. Positive abnormal returns were observed in the Energy and Basic Materials sectors, whereas negative abnormal returns were identified in sectors such as Utilities, Consumer Staples and Health Care. A comparison of the asset pricing models suggests that part of the observed abnormal performance can be attributed to changes in systematic risk factors rather than purely event-specific effects.

Volatility analysis further reveals a substantial increase in market uncertainty, with volatility rising across all sectors following the outbreak of the war. Finally, the analysis of the RUWNI indicates that the Finnish stock market reacted rapidly to geopolitical developments, indicating a high degree of market responsiveness to new information.

Overall, the findings contribute to the growing literature on geopolitical risk and financial markets by providing evidence on how the onset of this specific major military conflict affected the stock market of a small open economy. The results highlight the importance of considering geopolitical factors when evaluating market dynamics and investor behaviour during periods of global uncertainty.

KEYWORDS: Event study, Geopolitical risk, Russia-Ukraine war, abnormal returns, stock market volatility, Nasdaq Helsinki, OMX Helsinki

VAASAN YLIOPISTO
School of Accounting and Finance

Tekijä:	Joonas Heikkilä
Tutkielman nimi:	Russia-Ukraine War and Stock Market: A Sector-Specific Event Study on the Finnish Stock Market
Tutkinto:	Kauppatieteiden maisteri
Oppiaine:	Rahoitus
Työn ohjaaja:	Timo Rothovius
Valmistumisvuosi:	2026 **Sivumäärä:** 103

TIIVISTELMÄ:

Tämä tutkielma tarkastelee Venäjän 24. helmikuuta 2022 aloittaman Ukrainan hyökkäyssodan vaikutuksia Suomen osakemarkkinoihin (Nasdaq Helsinki). Suomen maantieteellinen läheisyys konfliktialueeseen sekä historialliset taloudelliset yhteydet Venäjään tekevät sodan puhkeamisesta merkittävän geopoliittisen tapahtuman, jolla voi olla huomattavia vaikutuksia Suomen osakemarkkinoihin. Tutkimuksen päätavoitteena on selvittää, aiheuttiko sodan alkaminen epänormaaleja tuottoja sekä volatiliteetin kasvua markkinatasolla ja yhdellätoista eri toimialalla.

Empiirinen analyysi toteutetaan lyhyen aikavälin tapahtumatutkimusmenetelmällä käyttäen päivittäistä hintadataa 139 suomalaisesta pörssiyhtiöstä. Tapahtumasta johtuvien markkinareaktioiden erottamiseksi normaaleista markkinaliikkeistä odotetut tuotot arvioidaan sekä markkinamallin (MM) että Faman ja Frenchin viiden faktorin mallin (FFM) avulla. Lisäksi poikkileikkausregressiota käytetään tapahtumaikkunan aikana esiintyvien yrityskohtaisten tiedotteiden aiheuttamien mahdollisten vaikutusten kontrolloimiseksi. Tutkimuksessa luodaan myös tekstipohjainen Venäjä-Ukraina SotaUutiset Indeksi (RUWNI), joka perustuu uutisten sisällön sävyanalyysiin koskien kansainvälisiä uutisia kyseiseen sotaan liittyen. Tämän indeksin avulla tarkastellaan uutisvirran sekä Suomen osakemarkkinoiden hintakehityksen välistä yhteyttä.

Tutkielman tulokset osoittavat, että markkinareaktiot sodan alkamiseen vaihtelivat toimialojen välillä. Yhtenäisen reaktion sijaan tapahtuma johti pääoman uudelleenjakoon eri toimialojen välillä. Positiivisia epänormaaleja tuottoja esiintyi Energia ja Perusmateriaalien toimialoilla, kun taas negatiivisia epänormaaleja tuottoja havaittiin esimerkiksi kulutustavaroiden ja terveydenhuollon toimialoilla. Mallien vertailu viittaa siihen, että osa havaituista epänormaaleista tuotoista johtui systemaattisten riskitekijöiden muutoksista, eikä ainoastaan tapahtuman aiheuttamista vaikutuksista.

Volatiliteettianalyysi osoittaa volatiliteetin kasvaneen kaikilla toimialoilla sodan alkamisen jälkeen, mikä viittaa epävarmuuden kasvuun Suomen osakemarkkinoilla. RUWNI-indeksin tarkastelu puolestaan osoittaa Suomen osakemarkkinoiden reagoineen viiveettä kyseiseen tapahtumaan, mikä viittaa markkinoiden kykyyn reagoida nopeasti uuteen informaatioon.

Tutkimus täydentää geopoliittisen riskin ja osakemarkkinoiden välisen yhteyden tutkimuskirjallisuutta tarjoamalla empiiristä näyttöä siitä, miten kyseisen sodan puhkeaminen vaikutti Suomen osakemarkkinoihin. Tulokset korostavat geopoliittisten tekijöiden vaikutusta osakemarkkinoihin ja sijoittajakäyttäytymiseen globaalin epävarmuuden aikana.

AVAINSANAT: Event study, Geopolitical risk, Russia-Ukraine war, abnormal returns, stock market volatility, Nasdaq Helsinki, OMX Helsinki

Contents

Figures

Tables

Abbreviations

APT	Arbitrage Pricing Theory
AR	Abnormal Return
AV	Abnormal Volatility
CAR	Cumulative Abnormal Returns
CAPM	Capital Asset Pricing Model
EMH	Efficient Market Hypothesis
FFM	Fama and French Five-Factor Model
GPR	Geopolitical Risk Index
MM	Market Model
RWT	Random Walk Theory
RUWNI	Russia Ukraine War News Index

1 Introduction

Financial markets continuously process large amounts of information, and asset prices adjust in response to new developments that alter expectations regarding future cash flows and risk (Scott, 1991). Geopolitical shocks and especially armed conflicts can simultaneously affect economic stability, investors sentiment, and global trade dynamics, which may cause stock market reactions through multiple channels (Dugbartey, 2025). Unlike macroeconomic developments, wars represent rare and extreme events that cause sudden and profound uncertainty into financial markets.

On 24 February 2022, Russia launched a full-scale invasion of Ukraine, starting the most significant military conflict in Europe since the Second World War. The outbreak of the war constituted a major geopolitical shock with widespread economic and political implications. The conflict immediately raised concerns regarding energy security, supply chains, inflationary developments, and regional stability. The invasion caused not only a humanitarian and political crisis but also a potential economic downturn for European countries and especially for Finland, which shares a 1343-kilometre border with Russia.

The Finnish economy is closely integrated with European and global markets, and geopolitical instability in the region may therefore have significant effects on domestic firms and investors. While aggregate market indices provide an overview of overall market reactions, they may hide the variation across industries. Different sectors are exposed to geopolitical shocks in distinct ways, which may lead to asymmetric market responses. Thus, examining industry-level responses is essential for understanding the full scope of market adjustments.

Historically, major geopolitical conflicts have been associated with abnormal price movements and heightened volatility in financial markets (Hudson & Urquhart, 2015; Suleman, 2012; Boubaker et al., 2023; Gkillas et al., 2018). However, the magnitude, direction, and persistence of such effects are not uniform and may depend on market structure, economic exposure and the market efficiency. The outbreak of the Russia-Ukraine war therefore provides a unique opportunity to examine how a small open economy's stock market responds to a sudden and significant geopolitical shock.

By focusing specifically on the beginning of the war as a clearly defined event, this thesis examines whether the Finnish stock market exhibited Abnormal Returns (AR) or (and) Abnormal Volatility (AV) following the invasion, whether these effects differed across industries, and what factors may explain the observed reactions. Understanding these dynamics contributes to the broader discussion on how efficiently financial markets incorporate geopolitical information and whether such shocks generate systematic deviations from expected performance.

1.1 Purpose of the Study

The purpose of this study is to examine the impact of the Russian invasion of Ukraine on the Finnish stock market at the industry level, with particular emphasis on abnormal returns and abnormal volatility. The outbreak of the war in February 2022 constituted a major geopolitical shock with potentially significant economic implications for Europe and small open economies such as Finland. Given Finland's geographic proximity to Russia and its economic ties within the European Union, the event provides a relevant setting for analysing how geopolitical uncertainty is transmitted into financial markets.

More specifically, this study examines whether the war generated abnormal returns in the Finnish stock market and whether the magnitude and direction of these effects differed across industries. In addition to price effects, the study evaluates whether the event led to an increase in volatility. By combining return and volatility analyses, the study provides a comprehensive view of how investors processed the geopolitical shock.

To enhance robustness, the analysis employs both the Market Model (MM) and the Five-Factor Model (FFM) to estimate expected returns. This dual model approach allows for the examination of whether observed abnormal performance reflects event-driven effects or compensation for systematic risk exposures. The study also tests whether a custom geopolitical uncertainty index (RUWNI, see Methodology) explains abnormal returns and volatility.

The contribution of this study could be divided into two main parts. First, it provides empirical evidence on how the outbreak of the Russia-Ukraine war affected the Finnish stock market. Second, it evaluates sectoral heterogeneity in market reactions, thereby offering insights into differential industry exposure to geopolitical risk.

Overall, this study seeks to deepen the understanding of how the Russia-Ukraine war is incorporated into asset prices and whether such events generate systematic abnormal performance.

1.2 Hypotheses

Based on the theoretical framework and prior empirical evidence on geopolitical risk, war, and financial market reactions, the following hypotheses are formulated.

Empirical research shows that military conflicts consistently generate identifiable stock market reactions (Guidolin and La Ferrara, 2005). Furthermore, major geopolitical shocks are found to influence investor expectations regarding economic growth, trade conditions, energy prices, and financial stability (Caldara and Iacoviello, 2022). According to asset pricing theory, such changes affect stock prices through adjustments in expected future cash flows and discount rates. Given Finland’s geographical proximity to the conflict and its historic economic ties with Russia, the war’s outbreak constitutes a major geopolitical shock with potential impact on the stock market. Therefore, the event is expected to generate negative abnormal returns in the Finnish stock market during the event window, through changes in investor expectations regarding future cash flows and risk perception.

Thus, the first hypothesis examines whether the outbreak of the Russia-Ukraine war generated negative abnormal returns in the Finnish stock market:

H_1: The outbreak of the Russia-Ukraine war generated negative abnormal returns in the Finnish stock market.

$H_{0,1}$: The outbreak of the Russia-Ukraine war did not generate negative abnormal returns in the Finnish stock market.

Prior research suggests that the economic consequences of geopolitical conflicts are unlikely to affect all industries uniformly, as sectors differ in their exposure to international trade, commodity prices, and macroeconomic uncertainty (Guidolin and La Ferrara, 2005). Consequently, the same conflict can trigger vastly different reactions across specific markets and industries, and recent evidence regarding the Russia-Ukraine war highlights this divergence. For example, Martins et al. (2024) recorded positive abnormal returns for companies in the Energy sector after the outbreak of the Russia-Ukraine war. These reactions were mainly driven by increases in oil and commodity prices, caused by the war. On the other hand, Höhler et al. (2024) found agriculture companies to react negatively to the war, while trade links to Russia or Ukraine were found to be the main cause for these reactions. Taken together, the previous evidence regarding the sectoral heterogeneity leads to the second hypothesis of this paper.

H_2: The abnormal return response to the Russia-Ukraine war differed across industries in the Finnish stock market.

$H_{0,2}$: There were no differences in abnormal return responses to the Russia-Ukraine war across industries in the Finnish stock market.

Specifically, based on the evidence provided by Martins et al. (2024) and Höhler et al. (2024) this study anticipates a clear directional split among Finnish industries. First, the Energy and Basic Materials sectors are expected to exhibit positive abnormal returns, driven by increases in oil and commodity prices. Conversely, the Consumer Staples, Consumer Discretionary, and Utilities sectors are expected to exhibit negative abnormal returns due to heightened uncertainty regarding input energy costs, regulatory exposure, and limitations in passing rising costs to consumers.

Finally, geopolitical conflicts increase uncertainty regarding future economic and political conditions. According to financial theory, heightened uncertainty should be reflected in increased market volatility, as investors revise expectations and reassess risk exposures. Empirical evidence supports this theory, demonstrating that the outbreak of wars typically triggers sharp increases in stock market volatility (Zhou & Wang, 2025; Caldara & Iacoviello, 2022; Wu et al., 2023). Since this paper investigates the effect of the outbreak of the Russia-Ukraine war, a corresponding increase in market volatility is therefore anticipated.

Thus, the third hypothesis evaluates whether the war led to abnormal volatility.

H_3: The outbreak of the Russia-Ukraine war led to an increase in stock market volatility.

$H_{0,3}$: The outbreak of the Russia-Ukraine war did not lead to an increase in stock market volatility.

Because the analysis focuses on a single major geopolitical event, the hypotheses are interpreted as event-specific expectations rather than universally generalizable predictions across all conflict settings.

1.3 Structure of the Study

This thesis is structured into seven main chapters.

Chapter 1 introduces the research topic, outlines the purpose of the study, and presents the research hypotheses.

Chapter 2 establishes the theoretical framework introducing the foundational asset pricing theories and key behavioural finance concepts relevant to the study.

Chapter 3 provides a comprehensive review of existing literature on how financial markets respond to macroeconomic, firm-specific, and geopolitical events, with particular emphasis on price and volatility reactions.

Chapter 4 presents the data and descriptive statistics.

Chapter 5 describes the empirical methodology, including the event study framework, the definition of estimation and event windows, expected return models, volatility analysis, and regression specifications used to control for confounding events. The construction and use of the RUWNI are also explained.

Chapter 6 reports the empirical results, including abnormal returns, volatility, regression results controlling for firm announcements, and evaluation of the RUWNI.

Finally, chapter 7 concludes the thesis by summarizing the key findings, discussing methodological limitations, and providing suggestions for future research.

2 Theoretical Framework

The impact of geopolitical shocks and news dynamics on stock market behaviour can be analysed through several financial theories. The theoretical framework of this thesis builds primarily on the Efficient Market Hypothesis (EMH), which posits that asset prices adjust rapidly to new publicly available information. Within this framework, both discrete events and continuous information flows may influence asset prices and volatility. Event study methodology provides a structured empirical approach to isolate and quantify abnormal returns and volatility associated with such events.

2.1 Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH), introduced by Fama (1970), proposes that stock prices fully reflect all available information. The EMH assumes that investors are rational and profit-maximizing, that information is freely available to all market participants, that prices adjust quickly and correctly to new information, and that transaction costs do not exist. Under this framework, the EMH suggests that it is impossible to systematically generate excess returns without taking additional risk.

According to Fama, the price reflection is such a generalizing definition that it needs to be further defined to make it examinable. Therefore, the efficiency is divided into three forms that are weak-form, semi-strong form, and strong-form. The weak-form states that stock prices reflect historical information, the semi-strong form states that all publicly available information is priced in, and finally, the strong-form states that the prices reflect all information, including both public and insider information.

This thesis assumes the semi-strong form of market efficiency. According to this framework, asset prices should adjust rapidly and unbiasedly to publicly available information, such as geopolitical developments, macroeconomic announcements, or firm-level news.

If semi-strong efficiency holds, the economic consequences of Russia's invasion of Ukraine should be incorporated into Finnish stock prices immediately once the relevant information is available. Therefore, any statistically significant deviation from expected returns during the event window may be attributed to the economic impact of the invasion rather than to random market movements.

2.2 Event Study Methodology

Event study methodology was formalized by Fama, Fisher, Jensen and Roll (FFJR), who examined the stock price reactions to stock split announcements (Fama et al., 1969). Their work introduced a systematic empirical framework for analysing how financial markets respond to new information. The methodology is based on the semi-strong form of market efficiency, which assumes that asset prices incorporate publicly available information immediately.

In an event study framework, expected returns are first estimated using data from an estimation window prior to the event. Abnormal returns are then calculated as then difference between realized returns and expected returns during the event window. The main idea is to isolate the effect of the event from normal market behaviour.

Brown and Warner (1980, 1985) further refined the statistical foundations of event study methodology, demonstrating that under market efficiency, the effects of an event should be reflected rapidly in asset prices. Consequently, the economic impact of an event can be measured by analysing security price behaviour over a relatively short event window and comparing it to an estimation window that proxies for normal return dynamics. MacKinlay (1997) later standardized this framework by clearly defining the estimation window, event window, and the concept of abnormal returns (AR) as the primary metric of analysis.

Binder (1998) highlights the importance of methodology introduced by Fama et al (1969) and discusses its widespread use in testing market efficiency and event-driven price reactions. He also addresses potential sources of statistical error in event studies, primarily arising from the choice of expected return models. However, Binder argues that many of these issues can be mitigated through careful sample selection, appropriate event-date specification, and robust model choice.

Armitage (1995) reviews expected return models commonly used in event studies and evaluates their relative accuracy. His findings suggest that the market model performs well in estimating normal returns, while the CAPM may serve as a useful complementary approach. Armitage further recommends an estimation window of at least 100 trading days and the use of daily return data for estimation if possible.

Although early event studies focused primarily on firm-specific events, the methodology has increasingly been applied to other types of events as well. Aggregating abnormal returns across portfolios or industries reduces idiosyncratic noise and improves the identification of systematic event effects.

In the context of this thesis, the Russian invasion of Ukraine on 24 February 2022 represents a clearly defined geopolitical shock, making it well suited for analysis using the event study framework

2.3 Random Walk Theory

The statistical implication of the EMH is that stock prices should follow a random walk, meaning that price changes are unpredictable. This concept forms the foundation of the Random Walk Theory (RWT).

RWT builds on the early work of French mathematician Louis Bachelier (1900), who presented a theory about the randomness of stock price developments. Later on, the

RWT was popularized by economist Burton Malkiel (1973) in a book named "A Random Walk Down Wall Street". The theory proposes that the stock price movements are both random and unpredictable with efficiency assumption stating that the stock market reflects all available information. Thus, the RWT implies that only forthcoming information could have an impact on the stock prices since currently available information is already priced in the intrinsic value of a stock. Furthermore, the intrinsic value reflects the analysis of fundaments and expected future performance of the company by discounting all the presumed earnings to this day.

The RWT further suggests that the market will price in the new information through a mechanism that randomizes the deviations from an intrinsic value and thus inefficiencies would not occur in the market. According to the theory, if systematic deviations from the fundamental value would occur, the agents in the market would recognize such inefficiencies and eliminate the non-random deviations by trying to profit through arbitrage.

Thus, RWT reinforces the core implication of the EMH, which is that price movements are unpredictable by nature, and consistent abnormal returns cannot be achieved without additional risk.

2.4 Capital Asset Pricing Model

The Capital Asset Pricing Model (CAPM), developed by William Sharpe (1964), explains the relationship between the expected return of an asset and its systematic risk. The model assumes that investors are rational, risk-averse, and able to diversify away unsystematic risk, meaning that only systematic (market) risk is priced in. Furthermore, based on this theory, investors are compensated through the risk-free rate, which reflects the time value of money and a risk premium that depends on the asset's sensitivity to market risk. This relationship is expressed in the following equation:

$$\mathrm{E}(R_i) = R_f + \beta_i\left[E(R_m) - R_f\right], \quad (1)$$

Where $\mathrm{E}(R_i)$ is the expected return of asset i, R_f is the risk-free rate (time value of money), β_i is the sensitivity to market risk of asset i (beta of an asset), $E(R_m)$ is the expected market return, and $\left[E(R_m) - R_f\right]$ is the market risk premium.

Graphically, this relationship is illustrated by the security market line (SML), which shows the expected return of an asset in relation to its systematic risk. According to the CAPM framework, investors can eliminate unsystematic risk by diversifying their portfolio. Thus, by combining market portfolio with a risk-free asset, investors can then construct portfolios that lie on the capital market line (CML), which represents the best risk-return combinations available. Therefore, the SML demonstrates how an individual asset should be priced relative to its contribution to the risk of a diversified portfolio.

Although the CAPM provide a framework for estimating expected returns, empirical evidence suggests that additional risk factors may explain return variation more accurately. This has led to the development of multifactor asset pricing models.

2.5 Multi-Factor Models

While the CAPM explains expected returns using a single market factor, multifactor models extend the framework by including additional systematic risk factors. These models aim to capture return deviations that cannot be fully explained by market beta alone.

2.5.1 Arbitrage Pricing Theory

The Arbitrage Pricing Theory (APT), introduced by Ross (1976), proposes that expected returns are determined by exposure to multiple systematic risk factors rather than a single market factor.

Furthermore, the APT assumes that if mispricing of securities occurs in the market, it is quickly eliminated by rationally operating market participants, meaning that the absence of arbitrage opportunities is the prevailing state in the market. The general form of the APT regarding the expected return of an asset can be expressed as:

$$E(R_i) = R_f + \beta_{i1}F_1 + \beta_{i2}F_2 + \cdots + \beta_{in}F_n, \tag{2}$$

Where $E(R_i)$ is the expected return of asset i, R_f is the risk-free rate, β_{in} is the sensitivity of asset i to factor n, and F_n is the risk premium associated with factor n.

This equation shows that the expected return of an asset is the risk-free rate together with the sum of the risk premium associated with each factor, weighted by the asset's sensitivity to said factor.

While the expected return model provides the theoretical price of an asset based on risk exposures, actual realized return of an asset can deviate from this expectation due to unexpected changes in the risk factors and idiosyncratic shocks. The realized return can be expressed as:

$$R_i = E(R_i) + \beta_{i1}f_1 + \beta_{i2}f_2 + \cdots + \beta_{in}f_n + \epsilon_i, \tag{3}$$

Where R_i is the realized return of asset i, $E(R_i)$ is the expected return of asset i, β_{in} is the sensitivity of asset i to factor n, and f_n is the realized deviation from the expected systematic risk-factor, and ϵ_i is the firm-specific risk.

The CAPM can be considered a special case of the ATP, where the market portfolio as a single factor is assumed to explain the expected return.

2.5.2 Three-Factor Model

The three-factor model, introduced by Fama and French (1992), complements the CAPM by adding two additional risk factors beyond the market portfolio. They argue that market beta is not sufficient enough to explain the deviation of expected returns, and that additional company characteristics also play a role in price estimations. In their research, variables such as market equity (ME), leverage, book value of equity (BE), the book-to-market ratio (BE/ME), and the earnings-price ratio (E/P) were examined.

From this analysis, Fama and French identified firm size and BE/ME as two additional systematic factors to include alongside the market factor. Empirical evidence showed that small-cap firms tend to earn higher returns than large-cap firms, and that high book-to-market-value firms tend to outperform low book-to-market firms. These findings led to the formulation of the Fama-French three-factor model, which incorporates market risk, size, and value as explanatory variables for expected return. The model can be expressed as:

$$R_i - R_f = \alpha + \beta_{i1}\left(R_m - R_f\right) + \beta_{i2}(SMB) + \beta_{i3}(HML) + \epsilon_i \text{ ,} \tag{4}$$

Where $R_i - R_f$ is the excess return of asset i, α is the abnormal return not explained by the model, $\beta_{i1}, \beta_{i2}, \beta_{i3}$ are the factor sensitivity of asset i to the respective factors, $\left(R_m - R_f\right)$ is the excess return on the market portfolio, $(SMB)$is the return difference between small-cap and large-cap firms, $(HML)$is the return difference between high and low book-to-market firms, and ϵ_i is the firm-specific risk.

2.5.3 Four-Factor Model

Four-factor model by Carhart (1997) extends the Fama-French three-factor model (1992) by adding a momentum factor. This factor captures the momentum anomaly, documented by Jegadeesh and Titman (1993), which shows that investment strategies that purchase well-performing stocks and short losing stocks, based on their past performance, tend to earn significant positive returns over a three- to twelve-month holding period. In other words, the momentum factor represents the difference between past well-performing and poorly performing stocks. Thus, the equation of the four-factor model is:

$$R_i - R_f = \alpha + \beta_{i1}\left(R_m - R_f\right) + \beta_{i2}(SMB) + \beta_{i3}(HML) + \beta_{i4}(MOM) + \epsilon_i \qquad (5)$$

Where, all the factors are equal to the equation (4), except (MOM) (sometimes up minus down (UMD)), which captures the return difference between past winners and past losers. The four-factor model is widely used both in academic research for asset pricing and in practice, particularly for the performance evaluation of portfolios and investment funds.

2.5.4 Five-Factor Model

Five-Factor Model (FFM) by Fama & French (2015) is an extension to their prior three factor model and the FFM was developed based on observations from that model. For example, Titman, Wei and Xie (2004) provides insight on how firms investing behaviour affects the return. Another important observation was made by Novy-Marx (2013) who found that profitability plays a role of approximately similar magnitude as BE/ME in explaining stock returns. As a result, Fama and French (2015) decided to add both profitability and investment factors into the model to further capture the cross-sectional variation in stock returns.

The two new factors introduced were robust minus weak (RMW) and conservative minus aggressive (CMA). Firstly, the RMW factor represents the return spread between firms with high (robust) and low (weak) operating profitability. Based on the evidence provided by Novy-Marx (2013) firms with lower profitability tends to achieve significantly lower returns than their profitable peers. Secondly, the CMA factor reflects the return spread between firms that executes conservative investment policies and those that invest more aggressively. Based on the evidence by Titman, Wei and Xie (2004) companies that execute aggressive investment policies tend to gain worse benchmark-adjusted returns than their conservative peers. This leads to the following equation of the model:

$$R_i - R_f = \alpha + \beta_{i1}(R_m - R_f) + \beta_{i2}(SMB) + \beta_{i3}(HML) + \beta_{i4}(RMW) + \beta_{i5}(CMA) + \epsilon_i \qquad (6)$$

Where, all the factors are equal to the equation (4), except (RMW) is the profitability factor, and (CMA) is the investment factor.

By Including profitability and investment factors, the FFM significantly improves explanatory power compared to the three-factor model. However, one key limitation is that value factor (HML) often becomes less significant once RMW and CMA are included, raising questions about the necessity of all five factors.

2.6 Behavioural Finance

While traditional asset pricing models assume rational investors and efficient markets, behavioural finance challenges this assumption by incorporating psychological and cognitive biases into financial decision making. Behavioural finance argues that investors are not always fully rational and that deviations from rationality may influence asset prices, particularly during periods of heightened uncertainty.

Geopolitical shocks, such as wars, represent emotionally charged and highly uncertain events. Under such circumstances, investor behaviour may be influenced not only by fundamental information but also fear, overconfidence, and other behavioural factors. Thus, markets may temporarily deviate from the predictions of the EMH.

The following behavioural theories provide alternative explanations for abnormal returns and increased volatility surrounding geopolitical events.

2.6.1 Limits to Arbitrage

The concept of limits to arbitrage challenges the fundamental assumption of the EMH, which assumes that rational investors exploit mispricing until prices reflect all available information. In reality, several factors prevent arbitrage from functioning perfectly, and deviations from fundamental values can persist. Shleifer and Vishny (1997) explained this phenomenon by limits to arbitrage, which refers to frictions that prevent traders form correcting mispricing even if they identify it.

Arbitrage requires capital, access to information, and usually the ability to take leveraged or short positions. In practice, arbitrageurs face risks and costs that may discourage trading even when profitable opportunities exist. One key friction is fundamental risk that forms from unexpected market movements before the asset price is corrected. Arbitrageurs often operate with borrowed capital, which exposes them to margin calls or liquidity constraints when markets move unexpectedly (Shleifer & Vishny, 1997). Thus, even if prices are expected to revert in the long run, short-term losses can force investors to exit positions early.

Transaction and short-selling costs also play a role. Certain assets may be costly or difficult to short, and trading may involve significant market-impact or borrowing fees, making arbitrage less attractive. Additionally, institutional frictions, such as portfolio mandates or risk limits imposed by investors, can restrict arbitrage activity, especially during periods of heightened uncertainty (Pontiff, 2006).

Taken together, these limits help explain why mispricing can persist, even in highly developed markets. They also provide a foundation for behavioural finance, where investor sentiment and psychological biases shape asset prices.

2.6.2 Prospect Theory

Prospect theory, introduced by Kahneman and Tversky (1979), suggests that decision-making of individuals is not rational. It challenges the expected utility theory by Von Neumann and Morgenstern (1944), which assumes that individuals (investors) make rational choices to maximize their expected utility of final wealth (return). Prospect theory argues that individuals evaluate potential gains and losses in relation to a certain reference point, which often is their current wealth.

One of the key elements of the prospect theory is loss aversion, which states that losses are perceived more intensely than gains of similar magnitude. Another important concept of the prospect theory is a concept of value function which is concave for gains, convex for losses, and steeper for losses than gains. This function reflects the risk-averse behaviour in gains and risk-seeking behaviour in losses. In practice, this means that investors may take excessive risks to avoid realizing a loss, even if doing so is irrational from a financial perspective. This asymmetry helps explaining common biases in financial markets, such as disposition effect by Shefrin and Statman (1985), according to which investors tend to sell winning assets too early while holding onto losing positions for too long.

In the context of this thesis, prospect theory is highly relevant because it provides insight into how investors may react asymmetrically to events. For instance, war-related news or geopolitical shock may cause more fear and trigger strong selling pressure, even if that would not be rational from a financial perspective.

2.6.3 Overreaction and Underreaction Hypotheses

De Bondt and Thaler (1985) examined if stock prices overreact to new information. The overreaction hypothesis is drawn on the concept that most individuals are prone to overreact to shocking or unexpected information. The concept is based on research by Kahneman and Twersky (1977) where they evaluate psychological biases regarding decision making and future forecasting. They state that distributional (historical) data is often ignored when making predictions, while the singular (case-specific) data is emphasized.

De Bondt and Thaler (1985) also found that investors sometimes place too much weight on recent information, causing the asset prices to deviate significantly from their fundamental values. Moreover, it was found that a portfolio of prior poor-performing stocks clearly outperformed its competing portfolio consisting of prior well-performing stocks. Interestingly, the betas of the stocks of the portfolio consisting of past winners were significantly higher, which indicates that according to CAPM they should be riskier than the better performing portfolio consisting of past losing stocks. This can be all explained by the overreaction hypothesis, which, suggests that investors overemphasize recent negative information, causing losing stock to become undervalued, while recent winners become overvalued. As prices eventually correct toward their fundamental values, past losers tend to outperform past winners.

In the context of this thesis, the overreaction hypothesis may provide an explanation for why abnormal returns might occur around the event. Investors facing unexpected and emotionally charged events may overemphasize the negative consequences, leading to selloffs, or alternatively overestimate positive developments, leading to steep increases in stock prices. In both cases, prices may deviate significantly from fundamentals in the short term and later correct, creating patterns of abnormal returns that can be detected through event study methodology.

2.6.4 Herding Behaviour

Herding behaviour refers to the tendency of individuals to imitate the actions of others rather than relying on their own information or analysis. In financial markets, this can lead to collective movements in asset prices that are not fully justified by fundamentals. For instance, Banerjee (1992) examined the effect of other people's choices on individual's decision making and he found evidence that herding behaviour occurs.

In the context of finance, an article by Bikhchandani and Sharma (2001) offers a comprehensive overview of what is meant by herding behaviour and what it may cause. In general, they suggest that herding in the financial context means that investors will adapt their choices based on the actions of others. This may cause cumulative reactions in the market which may lead to suboptimal investment decisions for all participants. Additionally, when the herding investors notice the consequences of their decisions, they may herd in the opposite direction, which increases the market volatility.

In the context of this thesis, herding is particularly relevant for studying the effects of news events and geopolitical shocks. For instance, war-related news may trigger strong emotional responses that causes reactions that are driven by other's actions. Such behaviour can amplify collective selloffs or rallies, creating abnormal returns and increased volatility in the short term.

2.6.5 Noise Trader Theory

Noise Trader Theory developed by De Long et al. (1990), challenges the assumption that all investors act rationally and base their investment decisions purely on fundamental information. Instead, the theory introduces the idea of noise traders who make decisions based on noise, such as irrelevant or misleading information, rumours, or market sentiment.

While traditional finance assumes that irrational traders are quickly eliminated from the market by arbitrage, De Long et al. (1990) suggests that noise traders can even influence prices. This happens due to risky and limited nature of arbitrage which causes rational investors to face uncertainty about the duration of mispricing and whether prices will move further away from fundamentals before correcting. As a result, noise trading can create temporary price distortions and excess volatility, even in markets that appear liquid and competitive.

In the context of this thesis, Noise Trader Theory is particularly relevant for understanding short-term market movements following the outbreak of the war. For instance, war-related news may trigger waves of sentiment-driven trading, where investors react emotionally to information rather than analysing fundamental impacts. Such behaviour can cause stock prices to temporarily deviate from their intrinsic values, leading to abnormal returns and volatility patterns.

2.7 Quantification of Qualitative Information

Financial markets react to real-time information, including news, and other online sources. Since such information is qualitative in nature, researchers have developed methods to extract numerical measures from text. This process allows sentiment, uncertainty, and geopolitical tensions to be measured directly from news content. In this thesis, I follow this approach by applying sentiment analysis to news regarding Russia-Ukraine war.

2.7.1 Sentiment Analysis

Sentiment analysis is a way of analysing the tone and meaning of digital text. It uses natural language processing (NLP) methods to analyse the use of words and their tone or emotional content in observed text (Wankhade et al., 2022). In financial markets, sentiment analysis can help to transform qualitative information into numerical indicators that capture the emotions embedded in writing. Since investor behaviour is influenced not only by fundamentals but also by expectations and emotions, sentiment measures have become increasingly relevant in explaining financial market phenomena.

In practice, sentiment analysis techniques classify text as positive, negative or neutral, and often assign a numerical score representing the magnitude of the sentiment. These methods can be rule-based, for example using predefined sentiment dictionaries that score words based on polarity, or data-based, where machine learning models are trained to detect sentiment patterns from the observed text (Mejova, 2009).

Previous research shows that sentiment analysis of financial news can provide predictive information about returns and volatility. For instance, according to previous research it has been found that pessimistic language in news media increases market volatility and decreases prices temporarily (Tetlock, 2007). Similarly, another study by Engle et al. (2020) suggest that firm-level news sentiment has significant explanatory power for short-term idiosyncratic volatility and return variation. These findings indicate the importance of sentiment analysis in financial context.

However, while sentiment analysis offers a systematic method to quantify information expressed in text form, its accuracy depends on keyword selection, context interpretation and the ability of the model to detect sarcasm for instance. Moreover, sentiment tools may struggle with geopolitical language, where negative terms do not always imply negative economic impact (Vanshika et al., 2024). Therefore, sentiment measures should be interpreted carefully.

In this thesis, sentiment analysis is applied to international news coverage of the Russia-Ukraine conflict in order to construct a summary of the daily tone of the war-related news. This analysis is then used to construct the Russia-Ukraine Warn News Index (RUWNI) which is then used for identifying major events of the war. The construction, validation, and limitations of the RUWNI are discussed in detail in the methodology section.

2.7.2 Geopolitical Risk Index

Geopolitical developments, such as wars, diplomatic conflicts, and terrorism, can create significant uncertainty in financial markets. To quantify this uncertainty, Caldara and Iacoviello (2022) developed the Geopolitical Risk Index (GPR), which is based on the frequency of newspaper articles regarding geopolitical tensions and related risks. The index captures how often terms linked to geopolitical threats appears in major international newspapers, turning qualitative data into a measurable time-series indicator.

In more detail, the sample of news used to construct the GPR consists of nearly 25 million articles collected from 10 major newspapers, covering the period from 1900 to this day. The news sources include six U.S. outlets, three from the United Kingdom and one from Canada. To analyse these articles a set of certain keywords and keyword combinations related geopolitical tensions and conflicts are defined. The frequency of these terms is then measured through an automated text-scanning process.

Based on these results two components of GPR are formed, which are the geopolitical threats (GPT) and the geopolitical acts (GPA). The GPT component captures perceived risk of future geopolitical escalations, such as military mobilization, threats of invasion and rising terrorism concerns. The GPA component measures realized geopolitical events, such as the outbreak of a war, the start of military operations, or terrorist attacks.

Together, these components allow the GPR to measure both expectations and realized geopolitical risks and events.

The GPR has been shown to rise during major geopolitical events, such as military conflicts or terrorist attacks, which tend to increase uncertainty about future economic outcomes. Higher GPR values generally reflect heightened global risk sentiment, and previous research shows that increases in geopolitical risk are associated with higher market volatility, lower investment and reduced economic activity. Therefore, the GPR serves as a useful benchmark for analysing how geopolitical news affects financial markets.

While, the GPR is used to capture the global geopolitical risk perceptions, this thesis applies a conceptually similar text-based methodology to a narrower context by constructing the RUWNI. The RUWNI captures changes in sentiment and conflict related news linked to the Russia-Ukraine war. The use and construction of the RUWNI is explained in detail in the methodology and data sections.

3 Literature Review

Stock markets continuously incorporate new information into asset prices, but the speed and magnitude of adjustment depend on the nature of the information shock and firm characteristics (Sochi, 2015). While routine macroeconomic announcements and firm-specific information have been widely studied, geopolitical shocks represent a distinct and more extreme category of events. Such shocks are typically sudden, uncertain, and extensively impactful, affecting multiple sectors and markets simultaneously. Understanding how these events are priced is essential for evaluating market efficiency and investor behaviour under conditions of heightened uncertainty.

From an asset pricing perspective, a central question is whether market reactions following a geopolitical event reflect genuine abnormal performance or simply compensation for systematic risk exposures. Event study methodology, combined with models such as the Market Model (MM) and multifactor asset pricing models, provides a framework for isolating event-specific effects. If abnormal returns persist after controlling for systematic risk factors, this suggests that the event introduced new information that may not be explained by general market movements.

In addition to returns, major geopolitical events are expected to affect market uncertainty. Volatility responses may capture shifts in investor risk perception that are not fully reflected in price changes alone. Moreover, recent research has introduced news-based geopolitical risk indices to quantify uncertainty related to conflicts and political instability, allowing researchers to assess whether geopolitical risk holds explanatory power for stock market dynamics. Accordingly, one empirical question is whether a news-based uncertainty index, Russia-Ukraine War News Index (RUWNI) explains stock returns and volatility.

Although, prior studies document market reactions to wars and geopolitical crises, limited evidence exists on how small open European market with geopolitical proximity to a conflict price such an event. This literature review therefore examines prior research on price and volatility reactions to macroeconomic, firm-specific, and geopolitical events, providing the theoretical foundation for analysing the Finnish stock market's response to the outbreak of the Russia-Ukraine war.

3.1 The Effect of Information Events on Stock Prices

The relationship between news announcements and stock prices has been widely studied in financial economics. According to the semi-strong form of the EMH (Fama, 1970), stock prices should immediately adjust to all publicly available information, leaving no opportunity for investors to earn abnormal returns after a news release. However, extensive empirical research has shown that markets often exhibit short-term deviations from this principle.

Early studies such as Ball and Brown (1968) and Fama, Fisher, Jensen, and Roll (1969) provided some of the first evidence that stock prices react systematically to earnings announcements and other public information such as stock split announcements. Later research has extended this to a wide range of events, including macroeconomic announcements, political developments, and news in general. For instance, Cutler, Poterba, and Summers (1988) found that fundamental news could not fully explain stock price movements. They also discovered that notable stock price changes often occurred on days when no major news related to future cash flows or interest rates was published.

The way information spreads and affects markets has evolved significantly over time. Especially, the rise of the internet and digital news outlets has accelerated the speed at which information reaches investors. For example, Tetlock (2007) studied the relationship between media tone and the stock market performance and found that high levels of media negativity anticipate a descendent trend in stock prices that then returns to their fundamental values. Moreover, atypically high or low levels of media negativity forecasts increased trading volume. The effect on price of small stocks seems to be bigger and slower to reverse than the effect on bigger stocks. These findings align with the Noise Trader Theory, which suggests that temporary price asymmetries can arise when investors react to market “noise” rather than to fundamental information.

It is evident that the type of news and events plays a significant role in determining how markets react. Different categories of information affect investor expectations and sentiment in distinct ways. While some news directly impacts the fundamental outlook of companies or economies, other events influence markets primarily through behavioural channels, such as uncertainty, fear, or optimism. Therefore, the following sections review prior research on how various types of news affect stock prices, focusing on macroeconomic, firm-specific, and geopolitical information, as well as sentiment-driven market reactions.

Taken together, prior research shows that stock prices react systematically to new information, but the speed and magnitude of these reactions vary across news types and market conditions. While some information is incorporated rapidly, empirical evidence suggests that investor sentiment, attention, and behavioural biases can lead to delayed or asymmetric price responses. These findings motivate the use of event study methodology to examine short-term market reactions to clearly defined information shocks.

3.1.1 Macroeconomic Information and Stock Prices

McQueen and Roley (1993) examined the effect of macroeconomic news on stock prices and found that market responses vary depending on the overall state of the economy. Specifically, their results suggest that better than anticipated macroeconomic news leads to lower stock prices, when the economy is already strong, while the same news leads to higher stock prices when the economy is in a weak state. The reason for such variation seems to be related to changes in expected cash flows, whereas the responses to interest rates appear to vary less between different economic conditions.

Flannery and Protopapadakis (2002) examined the effect of 17 macroeconomic announcements on equity returns and volatility. They identified six variables that significantly affect stock returns, which are the consumer price index (CPI), producer price index (PPI), monetary aggregate, balance of trade, employment report and housing starts. Interestingly, they could not find significant relationship between important macroeconomic indicators, such as industrial production or gross national product (GNP) and equity returns.

Similarly, Birz and Lott (2011) provided evidence consistent with these findings. They studied the effect of macroeconomic news on stock returns through analysis of newspaper coverage. Their results suggest that news considering gross domestic product (GDP), and unemployment have an impact on stock prices. Importantly, their results indicate that not only do the surprises themselves matter, but investor reactions and interpretations of such unexpected news also play a significant role in shaping market responses.

In addition to these studies, Chen et al. (2015) examined the amount of attention investors pay to scheduled macroeconomic announcements in the Chinese Stock Index futures market. Similar to Flannery and Protopapadakis (2002) they found that the CPI receives the most investor attention and has a notable short-term effect on stock prices. Another important finding suggests that the price effect of a CPI announcement is stronger when it gains more investor attention, indicating that investor attention itself amplifies market reactions. Finally, their results show that price impact is stronger in case of bad news, more volatile during periods of high inflation and less distinct on Fridays. These findings align with those of McQueen and Roley (1993), who observed that the economic state shapes market reactions, and they also support the overreaction hypothesis, which suggests that market responses tend to appear stronger following negative news.

Overall, the evidence suggests that macroeconomic news affects stock prices. Moreover, the magnitude and direction of reactions are shaped by economic conditions, investor expectations and the surprise component of an announcement. The evidence also highlights that not all macroeconomic indicators carry equal informational value, and that investor attention can amplify market responses. These findings underline the importance of carefully selecting events and controlling for market conditions when analysing price reactions to macroeconomic information.

3.1.2 Firm-Specific Events and Stock Prices

Crucially for event study research, the strong price and volatility effects generated by firm-specific news create methodological challenges when analysing macroeconomic or geopolitical shocks. If a major geopolitical event coincides with the traditional corporate earnings season, it becomes difficult to determine if the geopolitical shock itself caused the price and volatility reactions. Therefore, to accurately isolate the pricing of geopolitical risk, controlling for confounding firm-specific events is needed.

Firm-specific news has been among the most widely studied information types affecting stock prices. For instance, earnings announcements, dividend changes, profit warnings, and other news concerning the fundamentals are known to have notable effects on stock prices. Unlike macroeconomic announcements, which influence entire markets, firm-level news primarily affects the valuation of individual companies. Nevertheless, these effects can also spill over to sector or market levels during periods of high uncertainty or when the news concerns large or influential firms.

One of the earliest studies in this area was conducted by Ball and Brown (1968) who examined the relationship between accounting earnings and stock prices. They found that stock prices tend to react to the realized forecasting error, and that the direction of the reaction aligns with the surprise component of the earnings. However, their results also suggest that much of the earnings information is incorporated into prices before the official report is released. This implies that investors anticipate a notable portion of the earnings-related news in advance, reflecting a degree of market efficiency.

Similarly, Beaver (1968) examined the informational value of earnings announcements by studying stock price and trading volume reactions to such reports around announcement dates. The emphasis of the study is on realized investor reactions, rather than on whether such reactions are rational. The findings suggest that there is a significant increase in trading volume during the announcement week compared to other periods of the year. Interestingly, trading volume seems to be lower than normally eight weeks before the announcement date. This finding indicates that investors might wait for the announcements to be released before making their investment decisions. Abnormal price changes were also recorded around earning announcements, reflecting atypical trading activity driven by the publication of new financial information. This evidence indicates that earnings announcements hold substantial informational value.

Ryan and Taffler (2004) also examined the effect of firm-specific news on both stock prices and trading volumes with using a sample of FTSE350 companies and found results that were broadly consistent with Beaver’s (1968) findings. Specifically, they report results that show firm-specific information to explain at least 65% of share price movements and variation in trading volumes around the announcement. Their results indicate that sell-side analyst suggestions and earning forecast updates are the most influential sources of information in explaining the reported market reactions. Hence, the findings suggest that a majority of significant price changes can be attributed to firm-specific information, while noise and unrelated market factors play a relatively smaller role in driving these reactions.

Chan (2001) examined how news publications concerning companies affect their share prices and compared them to corresponding firms with no notable information releases. Chan reports a significant difference between the stock price movements of companies with public news coverage and those without any released information. The evidence also shows a drift in share prices after the information release, which indicates investor underreaction. This drift appears to be stronger following negative news, indicating that bad news might be initially ignored or discounted by investors. This leads to delayed price reactions as the information becomes more widely recognized. The findings challenge the semi-strong form of the EMH, which assumes that all publicly available information is fully and immediately included into prices. Overall, the evidence highlights the role of investor behaviour and sentiment in shaping market reactions to firm-specific information.

Finally, Tetlock et al. (2007) analysed the impact of firm-specific news sentiment on stock returns of companies from S&P500 by using textual analysis of financial news articles. Their results show that negative words in company-specific news predict lower stock returns over the following days, and that the effect is strongest when the news concerns a company’s fundamentals. However, investors appear to slightly underreact to such information, which is reflected by a delay of the price movement. The findings of the study further highlight the usefulness of quantifying qualitative information to predict market movements and investor behaviour.

In conclusion, existing literature provide strong evidence that firm-specific news plays a significant role in explaining stock price movements. Especially, earning announcements and analyst-related disclosures are found to drive stock price fluctuations. While markets appear to anticipate part of this information, delayed price adjustments and post announcement drifts suggest that investors do not always react fully or immediately. This supports the view that behavioural factors and information processing frictions influence short term stock price dynamics.

3.1.3 Geopolitical and War-Related Events and Stock Prices

Geopolitical events and war-related news represent a distinct category of market-relevant information. Often characterized by high uncertainty, emotional responses, and broad societal and economic impacts, geopolitical and war-related news can affect markets as whole. Unlike macroeconomic or firm-specific announcements, these events are typically unexpected and can trigger immediate price reactions. Geopolitical shocks such as wars, terrorist attacks, or political crises may not directly influence company fundamentals but still have significant implications for risk perception, capital flows, and overall market stability. Therefore, understanding how markets respond to such events provides valuable insights into investor behaviour under conditions of stress and uncertainty.

Hudson and Urquhart (2015) examined the effect of World War Two on the stock market of Britain by utilizing an event-study methodology on a dataset consisting of positive and negative major events of the war. Their results suggest that the positive events caused insignificant positive price reaction lasting for one day, whereas negative events cause significant negative declines in market prices that persisted for two days following the event. Importantly, these results are consistent with the overreaction hypothesis, which proposes that investors are prone to react more strongly to negative than to positive news. Contextually, it is important to note that Britain was an active participant in the war, and thus the observed effects are likely to be stronger than in markets of countries not directly involved in the conflict.

Suleman (2012) studied the effect of positive and negative political news on stock market using daily stock price data for eighteen years from Karachi Stock Exchange. The paper found that both positive and negative political news affect the price and volatility of a stock. In case of positive news, it seems that the stock prices tend to go up and volatility decreases, while in case of negative news the stock prices tend to fall, and volatility increases. However, the research suggests that the effect on the volatility and price is stronger in the case of bad news, the effect being almost two times greater. Moreover, the paper reports differing effects that varies between industries, causing asymmetric reactions across the market.

He (2023) examined the impact of geopolitical risk (GPR) on investor sentiment in the stock market of United States. The GPR data were gathered from the GPR index which is generated through automated analysis tool that counts the monthly number of news publications related to geopolitical developments. The index includes two components that are geopolitical threats (GPT) and geopolitical acts (GPA) and the concept of the GPR index used is based on Caldara and Iacoviello's (2022) work. The results by He (2023) indicate that geopolitical surprises have a notable impact on investor sentiment, which is reflected in decreased investment activity, and overall poorer performance of stock markets. However, the reactions appear to be stronger for short and medium periods, indicating that ongoing conflicts may not trigger equally significant responses as they persist. Furthermore, the study found no significant differences between the market reactions to GPR, GPT, or GPA events.

Boubaker et al. (2023) examined the stock price reactions of the global banking sector to the Russia-Ukraine war. They report significant decline of approximately 1.5% in banking industry stock prices on the first day of the conflict. The effect is strongest in the European market, where prices fell by around 4%, while Asia and North America also experienced notable decreases. The widespread reactions reflect heightened risk perceptions among investors toward the banking sector, and thus the whole financial system. Furthermore, the study found evidence of investors overreacting to new information and war-related developments with the magnitude of reaction varying according to the geopolitical proximity of the conflict. Moreover, the authors observed that investors tend to delay their investment decisions when they expect further developments in the near future. This effect was also recorded by Beaver (1968) in the context of firm-specific news releases.

While Boubaker et al. (2023) reported a 4% decline in European banking sector, the impact is likely to be heterogenous based on expectations regarding economic consequences, future political and financial stability, and geopolitical proximity to the conflict (Schneider & Troeger, 2006). Prior research on the proximity of the war suggests that countries sharing a border with the conflict zone face the strongest price reactions due to the risk of spill over and possible trade relations (Boungou and Yatié, 2022; Aguiar Rodrigues et al., 2025). Similarly, Kumari et al. (2023) found equivalent evidence on stock market reactions to the Russia-Ukraine war being strongest in countries closest to the conflict.

Additionally, Aguiar Rodrigues et al. (2025) and Nerlinger & Utz (2022) discovered varying price reactions between industries. While the overall reaction was found to be mostly negative across markets, military sector gained significant abnormal returns due to the Russian invasion of Ukraine (Aguiar Rodrigues et al., 2025). On the other hand, banking and tourism sectors experienced significant negative abnormal returns simultaneously. These differences are mainly explained by future uncertainty and development expectations regarding the industries. Nerlinger & Utz (2022) report energy sector to be another winner since the war began. They report positive CARs of energy companies around the event day, February 24 2022, and the reaction seems to be stronger for US firms than for their European and Asian counterparts. Once again, the outperformance of the energy sector is explained by future perceptions of the industry.

Similarly, Melnychenko (2024) studied the impact of the Russia-Ukraine war on stock prices by analysing the war developments using artificial intelligence (AI) models. The study combined news data with stock market information to capture timely investor reactions. The evidence show instantaneous and notable price impacts when the war first started, the effect being strongest in the industry of defence. However, as the conflict progressed, no distinct correlation was found between developments on the battlefield and movements in financial markets. The author also suggests that future research could apply alternative methodologies to better identify significant war-related developments and their correlations with market behaviour.

The literature indicates that geopolitical and war-related news can trigger strong and immediate price reactions, particularly during the early stages of conflicts. Rather than a uniform market decline, wars trigger reallocation of capital, which causes some industries to underperform, while other industries might benefit from the shock. In addition, these effects tend to be asymmetric, with negative events generating larger and more persistent responses than positive developments. However, as conflicts continue, market reactions often weaken, suggesting that investors incorporate ongoing geopolitical risk into asset prices over time. This motivates a focused analysis of sector-level reactions to the beginning of the Russia-Ukraine war as a distinct event.

3.2 The Effect of Information Events on Volatility

In addition to stock prices, various events also influence market uncertainty, which is reflected in changes in volatility. Prior research show that volatility responses often capture shifts in investor risk perception and disagreement that may not be fully reflected in price movements alone. Analysing volatility therefore provides complementary insights into how markets process new information, particularly during periods of heightened uncertainty.

3.2.1 Macroeconomic Information and Volatility

Chan and Gray (2018) examined the impact of macroeconomic news releases on volatility of the S&P500 index, bonds, and notes. Their findings provide clear evidence that macroeconomic announcements significantly influence market volatility, and they cause volatility changes through at least two distinct sources. Firstly, the correlation between volatility and scheduled macroeconomic information publications appears strong, indicating that investors anticipate these announcements. Secondly, the magnitude of the volatility change is linked to the surprise factor of the news, meaning that unexpected information drives the largest volatility reactions. Moreover, the reactions between realized volatility (RV) and implied volatility (IV) clearly differs from each other around the event. On announcement days, RV tends to increase substantially as prices adjust to new information, whereas IV often decreases as the uncertainty previously priced into options unravels.

Nikkinen and Sahlström (2004) examined the impact of both domestic and US macroeconomic information publications on European stock markets by analysing IVs in the German and Finnish equity markets. Their results highlight the dominant role of US macroeconomic information in shaping volatility reactions, as domestic announcements were found to have no significant effects on the IV of either market. Especially, US employment reports and Federal Open Market Committee (FOMC) meetings appears to influence the volatility on both Finnish and German markets, while the Producer Price Index (PPI) report affected the Finnish market but not the German one. Furthermore, the authors state that the magnitude of reactions to the US macroeconomic information was generally stronger in Finland. They suggest that it may be caused by greater proportion of foreign ownership, size, and export dependent nature of the Finnish market. Thus, the results indicate that domestic macroeconomic announcements have no impact on market uncertainty, while the US announcements hold significant informational value.

In addition, Arshanapalli et al. (2006) found similar evidence regarding the effect of macroeconomic information on volatility, using data from the US stock and bond markets. Consistent with previous studies, they report that volatility tends to increase on days with macroeconomic announcements. Once again, the employment report and the PPI effects are identified as key drivers affecting the volatility of both stocks and bonds. However, their results also suggest that the effect is relatively short-lived, as volatility typically reverts to its expected level through a correction of similar magnitude shortly after the announcement.

Empirical evidence consistently shows that macroeconomic announcements are associated with increase in market volatility, especially when the released information deviates from expectations. The magnitude of volatility reactions appears to depend on the type of announcement and its perceived importance, with labour market and inflation related news playing a particularly significant role. These findings suggest that macroeconomics events and news affect markets not only through prices but also by shaping uncertainty and risk assessments.

3.2.2 Firm-Specific Events and Volatility

Firm-specific news, such as earnings reports, management changes, mergers or other company-level disclosures, often generate distinct volatility changes. Unlike macro-economic shocks, these announcements directly affect the firm's expected cash flows and risk profile, leading to idiosyncratic market reactions. Previous literature shows that volatility typically increases around earnings announcements and other major firm specific events, reflecting heightened uncertainty and information asymmetry among investors (Boudoukh et al., 2018).

DeLisle et al. (2016) investigated the relationship between firm-specific news releases and idiosyncratic volatility. Their findings show that when firms release news, idiosyncratic volatility increases and stock prices tend to react positively. However, when volatility increases without any firm-level news, stock prices usually react negatively. This suggests that the price reaction differs depending on whether volatility is supported by information. The authors also highlight that the price effect of volatility linked to news appears stronger than the theoretical limit of arbitrage, meaning that information plays a major role in how investors price stocks.

Engle et al. (2020) provide recent evidence from the U.S. market that public information plays a meaningful role in explaining changes in idiosyncratic volatility, with an average explanatory power of 26%. They also found that firm-level volatility explains more than

50% of five-minute return variation during trading hours. These results suggest that firm-specific news announcements lead to significant volatility responses, which then translate into short-term return movements. In other words, news events appear to be an important driver of firm-level volatility and price fluctuations.

Li et al. (2023) examined the relationship between firm-specific news and volatility using data from the Chinese stock market. Their results show that the predictive power of firm-specific volatility for future returns increases around periods with news announcements, compared to periods with no news. Furthermore, their results show that news sentiment has stronger predictive power when the announcements contain negative information rather than positive news. This finding aligns with investor overreaction and underreaction hypotheses, which suggest that investors tend to overreact to negative news while underreacting to positive developments.

The literature demonstrates that firm-specific news is a key driver of idiosyncratic volatility, reflecting increased uncertainty and information asymmetry around major corporate events. Volatility tends to rise when news is released and differs in its market impact depending on whether it is information driven or unrelated to fundamentals. This highlights the role of firm-level information in shaping short-term volatility dynamics and investor behaviour.

3.2.3 Geopolitical Events and Volatility

Geopolitical shocks tend to increase uncertainty regarding future cash flows, discount rates, and funding conditions. That uncertainty transfers quickly into financial markets, typically resulting in higher volatility and stronger price fluctuations. Furthermore, recent research, such as the GPR by Caldara & Iacoviello (2022), has introduced tools to systematically measure geopolitical risk from news. These tools help quantifying the qualitative information news hold and link geopolitical development to market movements.

Zhou and Wang (2025) examined the relationship between war risk and stock market volatility using U.S. stock market data. Their findings show that a war discourse index has strong explanatory power for future stock market volatility over a 12-month horizon, and it outperforms its standard autoregressive benchmark model.

Similarly, Manela and Moreira (2017) constructed a news implied volatility index (NVIX) to examine how unexpected events reported in the news relate to stock market volatility and returns. The NVIX is created by collecting headlines and summaries from The Wall Street Journal over the period from July 1889 to December 2009 and connecting them to VIX and VXO implied volatility indices. This enables them to capture periods when news reflects heightened uncertainty.

After constructing the NVIX, it is combined with U.S stock market data to assess the impact of risk perception on stock prices. Their results show that the NVIX rises during periods of heightened uncertainty, including financial crashes, geopolitical crises, and wars. Furthermore, they find that war-related news is one of the primary news categories affecting the risk premium. Higher NVIX values are associated with higher expected future returns and variations in the risk premium during normal market conditions. However, steep increases in NVIX values may also anticipate an upcoming economic crash.

Gkillas et al. (2018) examined the relationship between geopolitical events and volatility jumps in the Dow Jones Industrial Average (DJIA). Their analysis uses the GPR by Caldara and Iacoviello (2017) together with daily DJIA return data from January 1889 to December 2017. After combining the GPR and return data, they investigate whether geopolitical risks can explain volatility jumps in the DJIA. Using standard linear Granger causality test, they do not find reliable evidence that geopolitical risk predicts volatility jumps. However, the authors highlight that this result may be misleading, because the relationship between GPR and market volatility may be nonlinear. When they apply a non-parametric causality-in-quantiles approach, they find strong evidence that GPR significantly affects volatility jumps and holds predictive power. Thus, their results suggest that GPR can help predict unusual volatility spikes and that they have a non-linear correlation.

Overall, prior research show that geopolitical events play an important role in shaping market volatility and risk perceptions. However, the speed at which financial markets process this information remains debated. While news-based indices like the GPR or NVIX successfully capture broad periods of heightened uncertainty, their day-to-day predictive power needs further examination. These findings motivate a more targeted analysis of conflict-specific information flows, such as those related to the Russia-Ukraine war, and highlight the potentially usefulness of using news-based indices to track market-relevant geopolitical sentiment. Additionally, the evidence supports the relevance of analysing volatility reactions to major geopolitical shocks, such as the outbreak of the Russia-Ukraine war.

3.3 Stock Market Reactions to Wars

This section summarizes the common stock market reactions documented in previous research, with particular emphasis on the Russia-Ukraine war. Wars and military conflicts represent significant geopolitical shocks that can affect financial markets through increased uncertainty, disruptions in trade and energy markets, and changes in investor risk perceptions.

A substantial body of literature has examined how stock markets react to military conflicts. Early studies suggest that the outbreak of the war often leads to negative abnormal returns and increased volatility due to heightened uncertainty. For example, Schneider and Troeger (2006) find that stock market reactions to international conflicts are mostly negative, and the volatility tends to increase during the war events. However, they also note that positive stock price reactions to wars are not unheard of, which highlight the heterogenous nature of market responses. Similarly, an article by Guidolin and La Ferrara (2005) document that military conflicts can have significant effects on financial markets. Interestingly, their results support the existence of positive reactions to conflicts, particularly in the United States. Nevertheless, they emphasize that the magnitude and direction of market reactions depend heavily on factors such as economic and geographic proximity to the conflict region.

More recent studies focusing on the Russia-Ukraine war provide further evidence on how proximity to the conflict influences market reactions. Federle et al. (2024) show that countries geographically closer to Ukraine experienced more negative stock market returns around the outbreak of the war. Blasco et al. (2024) report similar findings and provide evidence of herding behaviour in markets that are geographically or economically close to the conflict region. According to their results, heightened uncertainty and the risk of conflict spillovers can cause investors to herd, which amplifies negative market reactions.

The heterogeneity of these impacts can be observed across multiple levels, including countries, markets, industries, and individual firms. Martins et al. (2024) examine the effects of the Russian invasion of Ukraine on 100 of the largest oil and gas companies in the world. Their results show that the reactions within the energy sector differed significantly, largely depending on firm’s dependence on Russian resources. Overall, the sector experienced positive abnormal returns due to rising global energy prices following the outbreak of the war. However, companies with stronger economic ties to Russia experienced negative abnormal returns at the start of the conflict.

While the energy sector benefited from rising energy prices, other industries experienced negative market reactions. For example, Höhler et al (2024) document negative stock price reactions among agribusiness companies. Their evidence is bas on firms from Europe, Japan, and the United States, and it shows particularly strong negative reactions among European and Japanese firms. Within the sector, reactions also varied substantially across subindustries. Breweries, packaged food and meat producers, soft drink manufacturers, and Tobacco companies experienced the most significant reactions, while other agribusiness firms showed limited market impacts. These findings further highlight the importance of industry-level analysis, as broader market indices may hide substantial variation in sectoral responses to the war.

Kiesel and Kolaric (2023) examine the market reaction to the Russia-Ukraine war from a different perspective. After confirming the overall negative abnormal returns documented in previous literature, they investigate whether firms' stock market influenced their decisions to continue operating in Russia. Their results suggest that negative performance did not significantly affects these decisions. However, firms that chose to abandon Russian operations experienced slightly better return performance after the event. Overall, their findings illustrate the complexity of firm and market responses to the war.

All in all, existing literature suggests that wars and military conflicts can have significant but heterogenous effects on financial markets. While many studies document negative abnormal returns and increased volatility following the outbreak of conflicts, the magnitude and direction of market reactions depend on factors such as geographic proximity, economic exposure, and industry characteristics. Despite the growing body of research on the financial market impacts of the Russia-Ukraine war, relatively little attention has been given to the industry-level effects. Thus, evidence from the Russia-Ukraine war further highlights the importance of sector-specific analysis, as different industries may experience different outcomes. These findings motivate the industry-level event study conducted in this thesis, which examines how the outbreak of the Russia-Ukraine war affected different sectors of the Finnish stock market.

4 Data and Descriptive Statistics

This section introduces the data used to analyse the effect of the Russia-Ukraine war on Helsinki stock market and the descriptive statistics of the data. The first part concentrates on data used in the event study and the second part concentrates on the data used in RUWNI.

4.1 Data

The empirical analysis is based on daily closing price data for 139 companies listed on the Helsinki Stock Exchange (Nasdaq Helsinki), along with the OMXH25 and MSCI Europe indices, which serves as the market proxy. The OMXH25 index is used to capture developments in the Finnish equity market, while the MSCI Europe index serves as a broader European market benchmark in the estimation of expected return models. The closing price data for the 139 companies and the OMXH25 is downloaded from Datastream database, while the MSCI Europe data is downloaded from MSCI website. To allow for a detailed cross-sectional analysis, the sample firms have been categorized into eleven distinct industries according to the Nasdaq Helsinki industry categorization. The data covers the period from 22 July 2021 to 3 March 2022, including only trading days. All daily closing prices were converted into continuous daily logarithmic returns.

The 139 stocks were classified into 11 industries according to the Nasdaq Helsinki industry classification. The industry distribution is as follows: Energy (1 stock), Basic Materials (14 stocks), Industrials (38 stocks), Consumer Staples (9 stocks), Consumer Discretionary (27 stocks), Health Care (9 stocks), Telecommunications (4 stocks), Utilities (3 stocks), Financials (15 stocks), Technology (14 stocks), and Real Estate (5 stocks). The complete industry listing can be seen in Appendix 1. This industry-level grouping enables sector-specific analysis of abnormal returns and volatility responses to the event, allowing for the identification of heterogeneous market reactions across economically distinct segments.

For the FFM, five systematic risk factors are included, and they capture additional sources of systematic risk beyond the market portfolio. The factors gathered are the market risk premium ($R_m - R_f$), the size factors (SMB), the value factor (HML), the profitability factor (RMW), and the investment factor (CMA). The factor data are obtained from the publicly available Kenneth R. French data library. The factor data covers the same period as the stock price data and includes only trading days.

To control for confounding firm-specific events, data regarding official corporate announcements was collected from Nasdaq Helsinki Company News database. This dataset tracks the daily volume of stock market announcements released by the 139 sample companies. This data was used to construct the ANN dummy variable utilized in the regression analysis.

Finally, the construction of the RUWNI relied on large-scale text data scraped from Google News RSS feeds. The raw dataset comprises over 340 000 international news articles. The articles were filtered using a predefined set of Russia-Ukraine war-related keywords.

4.2 Descriptive Statistics

Table 1 presents descriptive statistic for daily logarithmic returns across sectors and benchmark indices during the estimation window. This period serves as a benchmark for normal return behaviour prior to the event and is therefore crucial for validating the assumptions underlying the event study methodology.

Table 1. Descriptive statistics of logarithmic returns over the estimation window.

Descriptive statistics of logarithmic returns over the estimation window 22.7.2021-16.2.2022.

Estimation window	Mean	SE	Median	SD	Kurtosis	Skewness	Range	Min.	Max.	Count
Energy	-0,0023	0,002	-0,0004	0,022	1,96	-0,53	0,16	-0,0887	0,0667	150
Basic Materials	0,0000	0,001	0,0001	0,013	1,88	-0,90	0,07	-0,0485	0,0257	150
Industrials	-0,0006	0,001	0,0002	0,013	3,85	-1,13	0,09	-0,0610	0,0315	150
Consumer Stap.	-0,0013	0,001	-0,0004	0,009	2,53	-0,83	0,06	-0,0418	0,0202	150
Consumer Discr.	-0,0007	0,001	0,0000	0,012	4,57	-1,06	0,09	-0,0609	0,0339	150
Health Care	-0,0012	0,001	0,0000	0,012	3,12	-1,03	0,08	-0,0595	0,0253	150
Telecommunications	-0,0005	0,001	0,0008	0,009	2,46	-1,06	0,06	-0,0385	0,0233	150
Utilities	-0,0005	0,001	0,0001	0,011	1,39	-0,64	0,07	-0,0372	0,0295	150
Financials	0,0002	0,001	0,0008	0,011	3,37	-0,98	0,08	-0,0494	0,0289	150
Technology	-0,0003	0,001	0,0001	0,014	2,03	-1,04	0,09	-0,0624	0,0254	150
Real Estate	-0,0003	0,001	0,0000	0,009	3,68	-0,89	0,07	-0,0471	0,0249	150
OMXH25	-0,0004	0,001	0,0000	0,011	2,84	-0,67	0,08	-0,0439	0,0364	150
MSCI Europe	0,0003	0,001	0,0010	0,009	3,57	-1,08	0,06	-0,0381	0,0238	150

In table 1, mean returns across sectors are close to zero, which is consistent with expectations for daily returns over a non-event period. This supports the assumption that no systematic abnormal performance is present during the estimation window. Minor differences across sectors are observable, with energy industry exhibiting the most negative abnormal return, while financials industry and MSCI Europe display slightly positive means.

Return volatility, as measured by the standard deviation (SD), varies across sectors. Energy and technology sectors display the highest standard deviations, indicating greater baseline uncertainty and sensitivity to market conditions. The OMXH25 index shows volatility slightly higher than the European benchmark which indicates the higher idiosyncratic risk of the Finnish market.

The distributional characteristics of returns deviate from normality across all sectors. Kurtosis values are reported as excess kurtosis and differs from the benchmark of 0 for all industries. The correlation between raw kurtosis and excess kurtosis can be presented with the following equation:

$$Raw\ kurtosis = excess\ kurtosis + 3, \tag{7}$$

Thus, the distribution is leptokurtic across all industries and indices. The high kurtosis indicates the presence of fat tails and an increased probability of extreme returns. At the same time, skewness is mostly negative and ranging from moderate to high, implying that large negative return realizations occur more frequently than positive ones.

Table 2 presents descriptive statistics for the event window, and it reveals a pronounced deterioration in return performance and a sharp increase in volatility across all sectors and market indices. Mean returns are negative for every sector, as well as for both OMXH25 and MSCI Europe, indicating a broad market decline rather than sector-specific effects alone.

Table 2. Descriptive statistics of logarithmic returns over the event window.

Descriptive statistics of logarithmic returns over the event window 17.2.2022-3.3.2022.

Event window	Mean	SE	Median	SD	Kurtosis	Skewness	Range	Min.	Max.	Count
Energy	-0,00670	0,018	-0,0202	0,060	2,82	0,96	0,24	-0,108	0,133	11
Basic Materials	-0,00578	0,008	-0,0083	0,027	4,86	1,85	0,11	-0,040	0,065	11
Industrials	-0,01433	0,008	-0,0166	0,025	3,17	1,20	0,09	-0,048	0,046	11
Consumer Stap.	-0,01202	0,007	-0,0126	0,025	3,16	1,18	0,10	-0,049	0,047	11
Consumer Discr.	-0,01059	0,008	-0,0120	0,026	2,20	0,71	0,10	-0,049	0,048	11
Health Care	-0,01093	0,009	-0,0144	0,030	2,15	1,05	0,11	-0,055	0,058	11
Telecommunications	-0,00855	0,006	-0,0082	0,020	1,56	1,01	0,07	-0,035	0,036	11
Utilities	-0,01378	0,008	-0,0126	0,025	0,13	0,38	0,08	-0,054	0,030	11
Financials	-0,00796	0,006	-0,0110	0,021	1,11	0,58	0,08	-0,042	0,036	11
Technology	-0,00542	0,007	-0,0096	0,023	0,85	0,97	0,08	-0,034	0,044	11
Real Estate	-0,00314	0,005	-0,0040	0,018	2,03	0,39	0,07	-0,037	0,036	11
OMXH25	-0,01204	0,007	-0,0120	0,023	0,99	0,53	0,08	-0,047	0,035	11
MSCI Europe	-0,00595	0,005	-0,0066	0,017	1,52	0,72	0,07	-0,033	0,032	11

As seen in table 2 the most negative average returns are observed in industrials, utilities, consumer staples and OMXH25 index. Also, volatility increases substantially relative to the estimation window, as reflected in higher SDs. The energy sector exhibits the highest volatility (SD 6,00%), combined with the widest return range of 24%. Elevated volatility is also observed in all other industries, and for many industries the SD has doubled in comparison with the estimation window.

Return distributions during the event window display strong departures from normal distribution. Interestingly, positive skewness occurs in all sectors, implying that despite the large negative returns, occasional sharp positive rebounds were also presents. Kurtosis values have both elevated and decreased depending on the industry. Especially, basic materials and consumer staples experienced increase in kurtosis, which indicates fat-tailed distributions and an increased likelihood of extreme returns. However, for example utilities industry showed a decrease in kurtosis, while the skewness got also closer to zero indicating return distribution that is closer to normal distribution during the event window.

Overall, the descriptive statistics support the suitability of the data for the event study methodology applied in this thesis. During the estimation window, returns across sectors and market indices exhibit relatively stable means and moderate volatility, providing an appropriate basis for estimating benchmark returns models. The return distributions in the estimation window deviate from normality, as observed from the non-zero skewness and excess kurtosis across industries and indices. These features suggest the presence of asymmetry and fat tails, which are well documented characteristics of daily financial return data (Mandelbrot, 1963; Fama, 1965). Importantly, return volatility and distributional properties remain relatively stable during the estimation window, supporting its use for estimating benchmark return models.

5 Methodology

This section describes the empirical methodology applied to examine the impact of the outbreak of the Russia-Ukraine war on the Finnish stock market. The analysis is based on an event study framework and focuses on industry-level stock market reactions to the beginning of the war on 24 February 2022. Industry portfolios are used instead of individual firms in order to reduce idiosyncratic noise and capture systematic sectoral responses to a major geopolitical shock.

5.1 Event Study Methodology

This thesis employs a standard event study methodology, as introduced in the theory framework section, to assess how the Finnish stock market reacted to the outbreak of Russia's full-scale invasion of Ukraine. The analysis examines both abnormal returns and abnormal volatility, enabling an assessment of not only price reactions but also changes in market uncertainty around the event. The event study framework is well suited for this purpose, as it allows for the isolation of abnormal stock market reactions attributable to a clearly identified and unexpected information shock.

The event day analysed in this thesis is 24 February 2022 (t_0), which marks the beginning of Russia's full-scale invasion of Ukraine. This event represents a major and largely unexpected geopolitical shock with significant implications for the Finnish economy and the global financial markets.

An estimation window of 150 trading days ($t_{-155} - t_{-6}$), ranging from 22 July 2021 until 16 February 2022, is used to estimate normal stock price behaviour. The estimation window ends prior to the event window to avoid contamination from event-related information. The event window is defined to be 10 trading days ($t_{-5} - t_{+5}$) ranging from 17 February 2022 until 3 March 2022 and surrounding the event date (24 February 2022), allowing for the possibility of information effect before the event and delayed market reactions after the event.

5.2 Return Calculations

Daily returns are calculated using logarithmic returns, defined as:

$$R_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{8}$$

Where, $R_{i,t}$ is the daily return of stock i at time t, $P_{i,t}$ is a price of stock i at time t and $P_{i,t-1}$ is the price of stock i at time t minus one day.

Industry-level returns are constructed as equally weighted averages of the returns of constituent firms within each Nasdaq Helsinki industry classification. This equal-weighting approach prevents large-cap firms from dominating sector-level results and improves comparability across industries.

To ensure robustness, expected returns are estimated using two alternative models. The models used in this thesis are (1) the market model and (2) the Fama-French Five-factor model. Using multiple models for estimations reduces the sensitivity of results to model-specific assumptions and errors.

To estimate expected returns for the OMXH25 index, the MSCI Europe Index is utilized as the proxy for the market return. This approach mitigates the mechanical correlation between the dependent variable and the benchmark index and allows the analysis to isolate country-specific abnormal performance during the war-related shock. The MSCI Europe index provides a comprehensive representation of general European market movements while remaining external to the Finnish stock market. Conversely, for the industry-level return estimations, the OMXH25 index is used as the benchmark. This specification is designed to capture the deviation of specific sectors from the general trend of the Finnish stock market, thus isolating the industry-specific reaction to the event.

The market model assumes a linear relationship between industry returns and the overall market return, with following equation:

$$ER_{i,t} = \alpha_i + \beta_i \times R_{m,t} + \varepsilon_{i,t} \tag{9}$$

Where, $ER_{i,t}$ is the expected return of industry i, $R_{m,t}$ is the return on the OMX Helsinki 25 index, α_i is the industry-specific intercept of industry i, β_i is the sensitivity of industry i returns to market movements, and $\varepsilon_{i,t}$ is the error term.

The parameters α_i and β_i are estimated using ordinary least squares (OLS) regression over the estimation window as follows.

$$\beta_i = \frac{\sum(R_m - \overline{R_m})(R_i - \overline{R_i})}{\sum(R_m - \overline{R_m})^2} \tag{10}$$

Where, $R_i$is the sample mean of industry returns, $\overline{R_i}$ is the average industry return, R_m is the sample mean of market returns, and R_m is the average market return.
The equation for estimating $\alpha_i$is following:

$$\alpha_i = R_i - \beta_i R_m \tag{11}$$

As a more comprehensive method, expected returns are also estimated using the Fama-French five-factor model, which can be illustrated with equation (6) introduced in the theory framework section. The European daily factor returns are obtained from the Kenneth. R. French data library. Coefficients are estimated separately for each industry using a multivariate Ordinary Least Squares (OLS) regression, yielding factor loadings and an intercept term a_i, which captures average industry-specific performance after controlling for systematic risk factors.

5.3 Abnormal Returns and Volatility Analysis

To address the effects of the war, the abnormal returns are calculated as deviation between expected and realized returns. Additionally, volatility around the event is analysed by comparing estimation window volatility to the volatility of the event window.

Abnormal returns represent the portion of realized returns that cannot be explained by normal market movements and are therefore attributed to the event under study. For each industry i and trading day t within the event window, abnormal returns are calculated as difference between the observed return and the expected return estimated from the pre-event estimation window:

$$AR_{i,t} = R_{i,t} - ER_{i,t} \tag{12}$$

Where $R_{i,t}$ denotes the realized return of industry i on day t, and $ER_{i,t}$ is the expected return generated by either the market model or the five-factor model.

To summarize the average daily impact of the event over multi-day window, this thesis computes average abnormal returns (AAR) by averaging abnormal returns over the event window for each industry

For a review window ranging from $t_1$to t_2, the AAR for industry i is defined as:

$$AAR_i(t_1, t_2) = \frac{1}{L}\sum_{t=t_1}^{t_2} AR_{i,t} \tag{13}$$

Where $L = t_2 - t_1 + 1$ denotes the number of trading days in review window.

To capture the total impact of the event over multiple trading days, cumulative abnormal returns (CAR) are computed by combining abnormal returns over a specified review period:

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{i,t} \tag{14}$$

Where t_1 and t_2 define the start and the end of the review window. In this study CARs are calculated for several symmetric windows around the event date, allowing assessment of immediate, delayed or anticipatory reactions.

To examine the impact of the Russia-Ukraine war on market stability, this study analyses shift in return volatility between estimation window and event window. While abnormal returns measure the directional price impact, volatility captures the uncertainty and risk associated with the event.

The volatility is calculated for each industry as the sample standard deviation of daily realized logarithmic returns. This calculation is performed separately for the estimation window ($t_{-155} - t_{-6}$) and the event window ($t_{-5} - t_{+5}$) to allow for a direct comparison of market risk levels before and during the shock.

The volatility (σ_i) for industry i over a specific window N of days is calculated as:

$$\sigma_i = \sqrt{\frac{\sum_{t=1}^{N}(R_{i,t} - \bar{R}_i)^2}{N-1}} \tag{15}$$

Where $R_{i,t}$ is the daily realized logarithmic return of industry i on day t, $\bar{R}_i$ is the average return of industry i over the respective window, and N is the number of trading days in the window.

An increase in σ_i during the event window relative to the estimation window indicates a surge in idiosyncratic risk of an industry and investor uncertainty triggered by the invasion.

5.4 Controlling for Firm Announcements

To distinguish the effect of the outbreak of the Russia-Ukraine war from firm-level information releases, this study employs a regression-based framework using daily industry-level abnormal return data. The analysis is conducted separately for abnormal returns and abnormal volatility in order to capture both price reactions and changes in market uncertainty.

Daily abnormal returns are calculated as presented earlier in the methodology section. These abnormal returns serve as the dependent variable in the first set of regressions. In the second set of regressions, abnormal volatility is used as the dependent variable to assess whether the beginning of the war and the firm announcements primarily affect the return variability rather than the direction of price movements.

For each industry i, the following regression model is estimated:

$$Y_{i,t} = \alpha_i + \beta_1 ANN_t + \beta_2 WAR_t + \varepsilon_{i,t}, \tag{16}$$

Where $Y_{i,t}$ is either the daily abnormal return or abnormal volatility for industry i on day t, WAR_t is a dummy variable equal to one during the event window after 24 February 2022 and zero otherwise, ANN_t captures periods of heightened firm-level announcement activity on Nasdaq Helsinki and takes the value of one on trading days in which the number of firm-level announcements belongs to the top 10% of the distribution, and zero otherwise, and α_i captures the average abnormal returns or volatility in non-event periods.

The regressions are estimated using daily observations over the combined estimation and event window. Employing daily abnormal returns rather than the cumulative abnormal returns allows the analysis to preserve time-series variation and to identify average daily effects of announcements and the war. Consequently, the estimated coefficients should be interpreted as average daily impacts rather than cumulative event-window effects.

An important feature of the data is that the early post event period $t_0 - t_{+5}$ coincides with elevated firm announcement activity, resulting in overlap between WAR and ANN dummy variables. Including both variables in the same regression provides a conservative identification strategy, as the estimated coefficients capture the incremental effect of each type of event while controlling for the presence of the other. While this overlap may reduce the statistical precision of individual coefficient estimates, this approach helps reduce omitted variable bias and improves the interpretation of the estimated effects.

An examination of historical announcement activity indicates that the event window is typically characterized by an elevated number of firm announcements. While this may limit the ability to fully isolate war-related effects from firm-level information, the estimation window includes periods of both high and low announcement activity, allowing the average impact of firm announcements to be captured in the regression.

5.5 RUWNI Index

To complement the event study, a custom Russia-Ukraine War News Index (RUWNI) is constructed to quantify the intensity of the information environment surrounding the conflict. While the primary analysis focuses on the invasion date on February 24, 2022, the RUWNI serves as an attempt to validate the link between news flow and market behaviour.

Specifically, the RUWNI is utilized to examine whether the observed Abnormal Returns (AR) or Abnormal Volatility (AV) in stock prices correlates with the volatility of the news cycle. A correlation between these measures would support the idea that the market's risk perception may be driven by the intensity of war-related information flows.

The RUWNI is based on large-scale text data collected from Google News RSS feeds, ensuring broad international media coverage. Articles are gathered using fixed keywords that represent the ongoing war narrative. The number of keywords is limited to ensure the relevance of the news fetched and to keep the dataset in manageable size.

Each news article's headline and summary detected by the RUWNI are analysed using the VADER (Valence Aware Dictionary and sEntiment Reasoner) sentiment analysis tool. Vader assigns a compound sentiment score ranging from -1 (very negative) to +1 (very positive). For each day t, the RUWNI score is computed as the average sentiment of all articles published on that day:

$$Sentiment_t = \frac{1}{N_t}\sum_{i=1}^{N_t} S_{i,t} \quad (17)$$

Where $S_{i,t}$ is the sentiment score of an article i on day t, and N_t is the total number of articles collected that day. This produces continuous time series that reflects the prevailing tone of war-related news coverage on a daily basis.

A value close to -1 indicates highly negative media tone (e.g. reports of attacks, casualties, or escalations), while values closer to +1 represent more positive developments (e.g. ceasefire discussions, or peace negotiations). Since most war-related coverage is initially negative, the sentiment value typically lies below the neutral baseline of zero, with occasional positive spikes corresponding with relatively positive developments.

To make the index easier to interpret and visually comparable across time, the value is rescaled as follows:

$$RUWNI_t = 50\ x\ (Sentiment_t + 1) \tag{18}$$

Where value of 50 represents neutral sentiment, values below 50 indicate negative media tone, and values above 50 indicate positive tone. This transformation keeps the sign and magnitude of sentiment changes but expresses them on a more intuitive scale.

Furthermore, to reduce noise and capture persistent shifts in news tone, a 7-day rolling average is computed:

$$RUWNI_t^{(7)} = \frac{1}{7}\sum_{j=1}^{6} RUWNI_{t-j} \tag{19}$$

This rolling index smooths daily volatility caused by uneven news volume or spiking reactions.

To ensure the stability and reliability of the RUWNI, several robustness tests were conducted. First, the daily sentiment was recalculated using mean, median and a 10% trimmed mean to assess the impact of deviations. Correlations among these series all exceeded 0.8, confirming that extreme or misleading sentiment values do not significantly affect the index.

Second, the sentiment analysis was performed separately using headlines only and full article summaries. The two versions showed correlation coefficient of 0.985, demonstrating that RUWNI captures media tone consistently, regardless of text length or phrasing

5.6 Limitations of the RUWNI

While the RUWNI provides a novel and consistent approach to quantifying war-related news sentiment, several limitations should be stated. First, sentiment analysis based on dictionaries like VADER may misclassify the news tone, since it does not take context into account. For instance, news headlines reporting "Russia claims victory" might be scored positively despite being interpreted negatively in the geopolitical context.

Second, RUWNI depends on the selection of keywords. Thus, the chosen keywords may not capture every relevant war-relevant article or could occasionally include unrelated topics with overlapping terminology.

Third, as the number of daily articles varies considerably over time, the volume of news may reflect the intensity of events. Therefore, while RUWNI captures sentiment tone, it does not account for variations in attention or reporting frequency. Another limitation related to the amount of daily news, is that RUWNI does not take the timing of the event into account. This creates a possibility that old news affects the RUWNI value and thus RUWNI may show delayed reactions to the new developments.

Considering these mentioned limitations, the RUWNI is not used as an explaining factor in estimation regression, but it's significance will be tested with correlation and regressions analysis.

6 Empirical Results

This section presents the empirical results obtained from the event-study stock market analysis examining the impact of the Russia-Ukraine war on the Nasdaq Helsinki companies. The analysis focuses on abnormal returns and volatility around the starting date of the war, 24 February 2022, using both the market model and Fama-French five-factor model to enhance robustness. Results are reported at the market and industry levels to capture potential heterogeneity in the market response.

6.1 Abnormal Returns

Table 3 reports daily AR for each industry over the event window before the event [-5, 0] estimated using the market model.

Table 3. MM abnormal returns prior to the event.

Market model (MM) daily abnormal returns (AR) for period [-5, 0] 17.2.2022-3.3.2022.

	N	-5	-4	-3	-2	-1	0
Energy	1	-1,80 %	-3,43 %**	1,98 %	-0,57 %	-1,17 %	3,37 %**
		(-1,11)	(-2,12)	(1,23)	(-0,35)	(-0,72)	(2,09)
Basic Materials	14	-0,49 %	0,07 %	-0,94 %	0,35 %	0,95 %	-0,11 %
		(-0,66)	(0,09)	(-1,28)	(0,47)	(1,29)	(-0,15)
Industrials	38	-0,49 %	-0,82 %	-0,45 %	-0,36 %	0,42 %	-0,59 %
		(-0,77)	(-1,29)	(-0,71)	(-0,57)	(0,66)	(-0,93)
Consumer Staples	9	-0,86 %	-0,13 %	-0,71 %	0,72 %	-0,37 %	-0,78 %
		(-1,45)	(-0,22)	(-1,18)	(1,20)	(-0,61)	(-1,30)
Consumer Discretionary	27	-0,25 %	-0,51 %	-0,27 %	0,30 %	0,04 %	-1,17 %*
		(-0,36)	(-0,72)	(-0,38)	(0,42)	(0,06)	(-1,65)
Health Care	9	-1,47 %*	1,54 %*	-0,43 %	0,24 %	-0,13 %	-2,20 %***
		(-1,75)	(1,83)	(-0,51)	(0,29)	(-0,15)	(-2,62)
Telecommunications	4	-0,72 %	-0,32 %	-0,89 %	0,13 %	-0,40 %	-0,87 %
		(-1,25)	(-0,56)	(-1,55)	(0,23)	(-0,70)	(-1,52)
Utilities	3	0,41 %	-0,58 %	-1,46 %**	-0,04 %	-1,57 %**	-1,68 %**
		(0,54)	(-0,78)	(-1,93)	(-0,05)	(2,08)	(-2,23)
Financials	15	-1,26 %*	-0,78 %	0,64 %	-0,22 %	0,84 %	-1,17 %*
		(-1,82)	(-1,12)	(0,93)	(-0,32)	(1,21)	(-1,69)
Technology	14	-0,70 %	-0,23 %	-1,25 %	2,24 %**	0,51 %	0,66 %
		(-0,74)	(-0,25)	(-1,33)	(2,37)	(0,54)	(0,70)
Real Estate	5	-1,21 %	1,17 %	-0,39 %	0,32 %	0,84 %	-1,59 %**
		(1,58)	(1,53)	(-0,51)	(0,42)	(1,09)	(-2,08)
OMXH25	25	-0,73 %	0,17 %	0,22 %	-1,19 %***	-0,18 %	-0,30 %
		(-1,61)	(0,39)	(0,48)	(-2,62)	(-0,39)	(-0,67)

The T-statistics are in parentheses.
* Statistically sginificant at the 10% level
** Statistically significant at the 5% level
*** Statistically significant at the 1% level

The most distinguished market reaction before the event occurred on day t_{-2} (22.02.2022), which is one day after Putin recognized the independence of Donetsk and Luhansk (BBC, 2022). On that day both OMXH25 index (-1,19%) and Technology industry (2,24%) experienced significant AR, although the sign of the AR differs between these two observations.

When looking at the individual industries, Utilities exhibit several statistically significant negative ARs prior to the event, suggesting sector-specific sensitivity to geopolitical risk. Statistically significant ARs were recorded on day -3 (-1,46%), day -1 (-1,57%), and day 0 (-1,68%). This may indicate that investors partially anticipated escalating political tensions. Interestingly, the timing of statistically significant negative AR trend of the industry is correlated with the Putin's recognition of independence of Donetsk and Luhansk. This news might have caused investors to prepare for the worst before the realization of the event.

On day 0 (February 24), the reaction intensified and became more sector specific. While the aggregate market index was relatively stable, specific sectors reacted strongly and diversely to the event. On day 0, abnormal returns are predominantly negative across industries, with the Health Care, Utilities, Financials, and Real Estate appearing statistically significant. In contrast, the Energy sector shows significant positive AR on 24 February 2022.

Table 4 reports corresponding ARs estimated with the FFM to control for systematic risk factors.

Table 4. FFM abnormal returns prior to the event.

Five-factor model (FFM) daily abnormal returns (AR) for period [-5, 0] 17.2.2022-3.3.2022.

	N	-5	-4	-3	-2	-1	0
Energy	1	-2,41 %	-2,80 %	3,03 %*	-2,71 %	-0,93 %	2,39 %
		(-1,36)	(-1,58)	(1,71)	(-1,53)	(-0,52)	(1,35)
Basic Materials	14	-0,46 %	0,43 %	0,26 %	-1,29 %	1,17 %	0,71 %
		(-0,58)	(0,53)	(0,32)	(-1,61)	(1,46)	(0,88)
Industrials	38	-0,54 %	-0,24 %	0,56 %	-2,15 %***	0,58 %	-0,67 %
		(-0,69)	(-0,31)	(0,73)	(-2,77)	(0,75)	(-0,86)
Consumer Staples	9	-1,06 %*	0,17 %	-0,07 %	-0,37 %	-0,35 %	-0,98 %
		(-1,69)	(0,27)	(-0,11)	(-0,58)	(-0,55)	(-1,55)
Consumer Discretionary	27	-0,28 %	0,09 %	0,65 %	-1,28 %*	0,18 %	-1,41 %*
		(-0,36)	(0,12)	(0,84)	(-1,65)	(0,24)	(-1,82)
Health Care	9	-1,78 %**	2,04 %**	0,48 %	-1,14 %	-0,15 %	-2,91 %***
		(-2,17)	(2,48)	(0,59)	(-1,39)	(-0,19)	(-3,55)
Telecommunications	4	-1,01 %	-0,06 %	-0,52 %	-1,01 %	-0,25 %	-1,17 %*
		(-1,44)	(-0,09)	(-0,73)	(-1,43)	(-0,36)	(-1,67)
Utilities	3	0,23 %	-0,40 %	-0,78 %	-1,19 %	-1,56 %*	-1,70 %**
		(0,27)	(-0,47)	(-0,92)	(-1,41)	(-1,84)	(-2,01)
Financials	15	-0,89 %	-0,11 %	1,54 %**	-1,42 %**	1,10 %	-1,11 %
		(-1,30)	(-0,17)	(2,24)	(-2,07)	(1,60)	(-1,62)
Technology	14	-0,69 %	0,58 %	-0,33 %	0,42 %	0,63 %	0,02 %
		(-0,73)	(0,61)	(-0,34)	(0,44)	(0,66)	(0,02)
Real Estate	5	-1,33 %*	1,37 %*	0,16 %	-0,55 %	0,87 %	-1,64 %**
		(-1,66)	(1,72)	(0,20)	(-0,68)	(1,08)	(-2,05)
OMXH25	25	-0,33 %	0,37 %	0,80 %	-1,77 %***	0,15 %	0,00 %
		(-0,60)	(0,67)	(1,44)	(-3,20)	(0,27)	(-0,01)

The T-statistics are in parentheses.
* Statistically sginificant at the 10% level
** Statistically significant at the 5% level
*** Statistically significant at the 1% level

The comparison between the MM and the FFM indicates broadly consistent timing of the market reactions, while revealing notable differences in sector-specific sensitivities. Under the FFM, the most pronounced market reaction prior to the invasion remains concentrated on day -2, supporting the MM findings. The aggregate OMXH25 index shows even stronger and statistically significant negative abnormal return of -1,77%, which might indicate market-wide repricing following the geopolitical escalation.

However, the industries that reacted significantly on day -2 differs between the models. Under the FFM settings, statistically significant results are reported on Industrials (-2,15%), Consumer Discretionary (-1,28%), Financials (-1,42%), and OMXH25 (-1,77%), all of which reacted negatively.

A critical divergence between the models is observed in the Technology sector on day -2. Under the MM, Technology industry appeared to experience a significant positive AR of 2,24%. However, the FFM reports only an insignificant AR of 0,42% for technology sector on day -2. The disappearance of significance under the FFM suggests that the positive abnormal return estimated under the MM may reflect exposure to systematic size or value-related factors rather than even-specific abnormal performance.

Among individual industries, Health Care exhibits the most volatile pre-event behaviour, recording statistically significant ARs on three separate days. The sector experienced significant ARs on day -5 and day 0, combined with significant positive correction on day -4. Finally, consistent with the MM, Utilities continued to show signs of anticipatory price reaction, with a significant negative AR of -1,56% on day -1, indicating possible early investor concerns over Russian exposure prior to the full-scale war.

6.1.1 Abnormal Returns Around the Event

Table 5 presents the immediate and cumulative reactions to the war, reporting the abnormal returns (AR) for the event day (t_0) and cumulative abnormal returns (CAR) for two periods [-1,+1] and [-5,+5].

Table 5. MM abnormal returns and cumulative abnormal returns around the event date.

Market model abnormal return on day [0] 24.2.2022 and cumulative abnormal returns for periods [-1, +1] 23.2.-25.2.2022 and [-5, +5] 17.2.-3.3.2022.

Industry	N	Day 0 AR		CAR [-1, +1]		CAR[-5, +5]	
Energy	1	3,37 %	**	1,30 %		12,61 %	**
		(2,09)		(0,46)		(2,35)	
Basic Materials	14	-0,11 %		3,71 %	***	6,63 %	***
		(-0,15)		(2,93)		(2,73)	
Industrials	38	-0,59 %		0,70 %		-1,46 %	
		(-0,93)		(0,63)		(-0,69)	
Consumer Staples	9	-0,78 %		1,46 %		-3,81 %	*
		(-1,30)		(1,41)		(-1,92)	
Consumer Discretionary	27	-1,17 %	*	0,43 %		1,12 %	
		(-1,65)		(0,35)		(0,48)	
Health Care	9	-2,20 %	***	0,72 %		-0,23 %	
		(-2,62)		(0,50)		(-0,08)	
Telecommunications	4	-0,87 %		-0,07 %		-0,20 %	
		(-1,52)		(-0,07)		(-0,10)	
Utilities	3	-1,68 %	**	-3,07 %	**	-5,49 %	**
		(-2,23)		(-2,34)		(-2,19)	
Financials	15	-1,17 %	*	0,48 %		0,95 %	
		(-1,69)		(0,40)		(0,41)	
Technology	14	0,66 %		1,96 %		7,61 %	**
		(0,70)		(1,20)		(2,43)	
Real Estate	5	-1,59 %	**	0,98 %		3,62 %	
		(-2,08)		(0,74)		(1,42)	
OMXH25	25	-0,30 %		-0,33 %		-5,52 %	***
		(-0,67)		(-0,42)		(-3,67)	

The T-statistics are in parentheses.
* Statistically sginificant at the 10% level
** Statistically significant at the 5% level
*** Statistically significant at the 1% level

As reported in table 5, most industries exhibit negative ARs on the event day, indicating an immediate adverse reaction to the invasion. Under the MM, Health Care (-2,20%), Utilities (-1,68%), Real Estate (-1,59%), Financials (-1,17%), and Consumer Discretionary (-1,17%) show statistically significant losses. Although most remaining industries also record negative ARs, these effects are not statistically significant. In contrast, the Energy sector records a positive and significant AR of 3,37% on the event day, consistent with expectation of rising energy prices and supply disruptions following the geopolitical escalation.

When expanding the window to [-1, +1], the reaction appears less uniform across industries. The Basic Materials sector exhibits strongly positive and statistically significant CAR (3,71%), suggesting that this sector benefited from anticipated commodity price increases. Conversely, Utilities continue to experience significant negative cumulative effects (-3,07%), indicating sustained investor concerns.

Over the longer [-5, +5] window, sectoral differences become more pronounced. Under the market model Energy (12,61%), Technology (7,61%), and Basic Materials (6,63%) display significant positive CARs, while Utilities (-5,49%) and Consumer Staples (-3,81%) show persistent and significant losses. The aggregate OMXH25 index also records a significant negative CAR (-5,52%), indicating a broader market impact.

Table 6 presents the corresponding ARs and CARs estimated using the FFM to control for risk factors such as size, value and profitability. Comparing the two specifications allows assessment of whether the observed effects are sensitive to the choice of expected return model.

Table 6. FFM abnormal returns and cumulative abnormal returns around the event date.

Five-factor model abnormal return on day [0] 24.2.2022 and cumulative abnormal returns for periods [-1, +1] 23.2.-25.2.2022 and [-5, +5] 17.2.-3.3.2022.

Industry	N	Day 0 AR		CAR [-1, +1]		CAR[-5, +5]	
Energy	1	2,39 %		0,40 %		6,76 %	
		(1,35)		(0,13)		(1,15)	
Basic Materials	14	0,71 %		4,69 %	***	6,56 %	***
		(0,88)		(3,38)		(2,47)	
Industrials	38	-0,67 %		1,06 %		-3,80 %	
		(-0,86)		(0,79)		(-1,48)	
Consumer Staples	9	-0,98 %		1,32 %		-6,06 %	***
		(-1,55)		(1,21)		(-2,90)	
Consumer Discretionary	27	-1,41 %	*	0,53 %		-1,37 %	
		(-1,82)		(0,39)		(-0,53)	
Health Care	9	-2,91 %	***	-0,03 %		-4,51 %	*
		(-3,55)		(-0,02)		(-1,65)	
Telecommunications	4	-1,17 %	*	-0,16 %		-2,44 %	
		(-1,67)		(-0,13)		(-1,05)	
Utilities	3	-1,70 %	**	-2,75 %	*	-7,39 %	***
		(-2,01)		(-1,88)		(-2,64)	
Financials	15	-1,11 %		1,00 %		0,34 %	
		(-1,62)		(0,84)		(0,15)	
Technology	14	0,02 %		1,84 %		4,06 %	
		(0,02)		(1,11)		(1,28)	
Real Estate	5	-1,64 %	**	1,06 %		2,11 %	
		(-2,05)		(0,76)		(0,80)	
OMXH25	25	0,00 %		0,01 %		-2,74 %	
		(0,00)		(0,01)		(-1,49)	

The T-statistics are in parentheses.
* Statistically sginificant at the 10% level
** Statistically significant at the 5% level
*** Statistically significant at the 1% level

The FFM results broadly confirm the main patterns observed under the MM. On the event day, most industries again exhibit negative abnormal returns, with Health Care (-2,91%), Utilities (-1,70%), Real Estate (-1,64%), and Consumer Discretionary (-1,41%) remaining statistically significant. As a difference the negative AR of financials do not appear statistically significant under the FFM, while Telecommunications exhibit negative AR (-1,17%) that is statistically significant at the 10% level.

While the FFM reports positive AR and CARs for both windows for the Energy sector, the results are no longer statistically significant under the FFM specification. However, the effect on Basic Materials appears similar with both models and it gains positive car of 4,69% over the [-1, +1] window with statistical significance at the 1% level under the FFM specification.

Also, other divergences emerge between the models. First, the Technology industry, which appeared to gain significant positive CAR under the MM (7,61%) loses its statistical significance under the FFM (4,06%) over the [-5, +5] window. This suggests that a substantial portion of the aggregate market decline can be attributed to systematic risk factor exposures rather than abnormal performance attributable solely to the invasion.

Second and most critically, the aggregate OMXH25 decline loses its statistical significance under the FFM (CAR -2,74%) over the [-5, +5] window. This implies that much of the market’s downturn can be explained by standard risk factors rather than a pure unexplained surprise reaction. However, this divergence may partly reflect the methodological differences between the models. The MM evaluates performance relative to the MSCI Europe benchmark, whereas the FFM controls directly for systematic risk exposures such as size, value, and profitability. Consequently, the estimated abnormal component differs across specifications.

6.1.2 Abnormal Returns After the Event

Table 7 reports daily abnormal returns (AR) for the post-event window [0, +5] estimated using the Market Model (MM). Compared to the pre-event period, the post-event dynamics are considerably more pronounced, both in magnitude and statistical significance

Table 7. MM abnormal returns after the event.

Market model daily abnormal returns for period [0, +5] 24.2.-3.3.2022.

	N	0	+1	+2	+3	+4	+5
Energy	1	3,37 %**	-0,90 %	4,19 %***	-4,22 %***	11,93 %***	3,22 %**
		(2,09)	(-0,56)	(2,59)	(-2,61)	(7,38)	(1,99)
Basic Materials	14	-0,11 %	2,87 %***	0,89 %	2,50 %***	-0,54 %	1,08 %
		(-0,15)	(3,93)	(1,21)	(3,42)	(-0,73)	(1,47)
Industrials	38	-0,59 %	0,87 %	-0,73 %	0,37 %	-1,28 %**	1,62 %**
		(-0,93)	(1,37)	(-1,15)	(0,57)	(-2,01)	(2,54)
Consumer Staples	9	-0,78 %	2,60 %***	-0,40 %	-1,80 %***	-0,86 %	-1,24 %**
		(-1,30)	(4,36)	(-0,67)	(-3,01)	(-1,43)	(-2,07)
Consumer Discretionary	27	-1,17 %*	1,56 %**	0,26 %	-0,39 %	-0,06 %	1,62 %**
		(-1,65)	(2,21)	(0,36)	(-0,56)	(-0,09)	(2,29)
Health Care	9	-2,20 %***	3,05 %***	-0,36 %	0,34 %	0,02 %	-0,85 %
		(-2,62)	(3,63)	(-0,43)	(0,41)	(0,03)	(-1,01)
Telecommunications	4	-0,87 %	1,20 %**	0,88 %	1,33 %**	0,43 %	-0,97 %*
		(-1,52)	(2,09)	(1,54)	(2,32)	(0,75)	(-1,70)
Utilities	3	-1,68 %**	0,19 %	-0,38 %	-2,01 %***	2,19 %***	-0,55 %
		(-2,23)	(0,25)	(-0,50)	(-2,66)	(2,89)	(0,73)
Financials	15	-1,17 %*	0,81 %	1,25 %*	1,03 %	-0,52 %	0,32 %
		(-1,69)	(1,17)	(1,80)	(1,49)	(-0,75)	(0,46)
Technology	14	0,66 %	0,79 %	1,73 %*	2,82 %***	0,13 %	0,93 %
		(0.70)	(0,83)	(1,83)	(2,98)	(0,14)	(0,99)
Real Estate	5	-1,59 %**	1,73 %**	0,23 %	1,44 %**	-0,11 %	1,19 %
		(-2,08)	(2,26)	(0,30)	(1,88)	(-0,14)	(1,55)
OMXH25	25	-0,30 %	0,15 %	-1,02 %**	-2,15 %***	0,30 %	-0,80 %*
		(-0,67)	(0,33)	(-2,26)	(-4,76)	(0,67)	(-1,76)

The T-statistics are in parentheses.
* Statistically sg
ificant at the 10% level
** Statistically significant at the 5% level
*** Statistically significant at the 1% level

On the event day, the sector-specific pattern observed earlier persist, but a notable pattern emerges on day +1, where several industries record statistically significant positive ARs. Basic Materials (2,87%), Consumer Staples (2,60%), Consumer Discretionary (1,56%), Telecommunications (1,20%), Health Care (3,05%) and Real Estate

(1,73%) all exhibit significant abnormal performance. The widespread positive movement one day after the event may reflect a short-term rebound or correction following the initial uncertainty driven reaction on the event date. Interestingly, the possible rebound effect is not seen on the OMXH25 index which experienced only a weak and insignificant positive AR on day t +1.

However, the adjustment process does not appear to be complete on day +1. On day +3, the OMXH25 index records statistically significant AR of -2,15%, suggesting a broader market repricing. At the industry level, both negative (Energy -4,22%, Utilities -2,01%, Consumer Staples -1,80%) and positive (Technology 2,82%, Basic Materials 2,50%, Telecommunications 1,33%, Real Estate 1,44%) significant ARs are observed, indicating heterogenous sectoral responses as investors reassessed the economic implications of the invasion.

Overall, the post-event window reveals that the market reaction was neither instantaneous nor uniform. Instead, the results suggest a multistage adjustment process characterized by an initial sector-specific shock, a short term rebound, and finally broader risk evaluation.

Table 8 reports corresponding ARs during the post-event window [0. +5] estimated with the FFM, to assess the robustness of the post-event ARs, and whether they are affected by additional risk factors.

Table 8. FFM abnormal returns after the event.

Five-factor model daily abnormal returns for period [0, +5] 24.2.-3.3.2022.

	N	0	+1	+2	+3	+4	+5
Energy	1	2,39 %	-1,06 %	2,75 %	-6,31 %***	12,15 %***	2,66 %
		(1,35)	(-0,60)	(1,55)	(-3,56)	(6,85)	(1,50)
Basic Materials	14	0,71 %	2,81 %***	0,92 %	1,65 %**	-0,07 %	0,44 %
		(0,88)	(3,51)	(1,15)	(2,06)	(-0,09)	(0,55)
Industrials	38	-0,67 %	1,14 %	-1,70 %**	-1,08 %	-0,61 %	0,91 %
		(-0,86)	(1,47)	(-2,20)	(-1,40)	(-0,79)	(1,17)
Consumer Staples	9	-0,98 %	2,65 %***	-1,27 %**	-2,76 %***	-0,45 %	-1,57 %**
		(-1,55)	(4,19)	(-2,01)	(-4,37)	(-0,72)	(-2,48)
Consumer Discretionary	27	-1,41 %*	1,76 %**	-0,94 %	-1,73 %**	0,53 %	1,06 %
		(-1,82)	(2,26)	(-1,21)	(-2,23)	(0,68)	(1,37)
Health Care	9	-2,91 %***	3,04 %***	-2,35 %***	-1,11 %	0,56 %	-1,18 %
		(-3,55)	(3,69)	(-2,85)	(-1,36)	(0,68)	(-1,43)
Telecommunications	4	-1,17 %*	1,27 %*	0,74 %	0,33 %	0,59 %	-1,35 %*
		(-1,67)	(1,81)	(1,06)	(0,47)	(0,84)	(-1,93)
Utilities	3	-1,70 %**	0,51 %	-0,92 %	-3,11 %***	2,71 %***	-1,19 %
		(-2,01)	(0,60)	(-1,08)	(-3,67)	(3,20)	(-1,41)
Financials	15	-1,11 %	1,01 %	0,30 %	0,18 %	-0,06 %	-0,20 %
		(-1,62)	(1,47)	(0,43)	(0,26)	(-0,08)	(-0,28)
Technology	14	0,02 %	1,19 %	-0,13 %	1,10 %	0,96 %	0,31 %
		(0,02)	(1,24)	(-0,13)	(1,16)	(1,00)	(0,32)
Real Estate	5	-1,64 %**	1,83 %**	-0,34 %	0,67 %	0,23 %	0,83 %
		(-2,05)	(2,29)	(-0,42)	(0,84)	(0,29)	(1,03)
OMXH25	25	0,00 %	-0,13 %	-0,33 %	-1,26 %**	0,29 %	-0,52 %
		(-0,01)	(-0,24)	(-0,59)	(-2,27)	(0,52)	(-0,94)

The T-statistics are in parentheses.
* Statistically sginificant at the 10% level
** Statistically significant at the 5% level
*** Statistically significant at the 1% level

Overall, the post-event dynamics are broadly consistent across the Market Model and the Five-Factor Model. In particular, the significant positive rebound observed on day +1 appears in both specification across multiple industries, suggesting that the short-term correction is not driven by omitted systematic risk factors. The significant positive ARs were recorded in exactly the same industries (Basic Materials 2,81%, Consumer Staples 2,65%, Consumer Discretionary 1,76%, Health Care 3,04%, Telecommunications 1,27%, Real Estate 1,83%) under both models, indicating that the rebound effect is unlikely to be fully explained by exposure to systematic risk factors.

However, several sectoral effects weaken or disappear once additional risk factors are controlled for. For example, the Technology sector, which exhibited statistically significant positive ARs under the MM on days +2 and +3, no longer shows significant results over the post-event period. This suggests that part of the initially observed abnormal performance may reflect exposure to systematic factors rather than purely event-driven effects.

Under the FFM, several industries recorded ARs on day +3, which supports the MM findings. As a difference, the ARs under the FFM on day +3 are mostly negative (OMXH25 -1,26%, Energy -6,31%, Consumer Staples -2,76%, Consumer Discretionary -1,73%, Utilities -3,11%), while only Basic Materials show positive AR of 1,65%. The set of industries exhibiting statistically significant reactions on day +3 is broadly similar across models, although direction and magnitude of certain effects differ. Specifically, positive ARs of Real Estate, Technology, and Telecommunications sectors losing their statistical significance and negative AR of Consumer Discretionary gaining statistical significance, appearing as a difference. Notably, controlling for systematic risk factors reduces the number of positive significant ARS on day +3 while strengthening several negative effects. This suggests that part of the positive performance observed under the MM may be attributed to common factor exposure rather than purely event-driven dynamics.

Furthermore, the extreme idiosyncratic volatility of the Energy sector is highly visible in its return behaviour, as it plummeted on day +3 (-6,31%) and gained a highly significant positive AR of 12,15% on day +4.

Taken together, the comparison between the two models suggests that while timing of the market reaction remains mostly consistent, the magnitude and statistical significance of certain sectoral effects are sensitive to model specification. The persistence of several key findings across both models strengthens the evidence of a genuine event-driven market adjustment, whereas differences highlight the importance of controlling for systematic risk exposures when evaluating abnormal returns. The results indicate that while the invasion triggered economically meaningful abnormal returns, part of the observed cross-sectional variation reflects differences in systematic risk exposures across industries.

6.2 Volatility Around the Event

As seen in the descriptive statistics, the volatility reaction to the invasion was pronounced across the industries as measured with standard deviation comparison between the estimation and event windows. The following table 9 provides volatility measures during the estimation and event windows and F-test analysis to examine the equality of variances.

Table 9. Volatility reaction to the event.

Return volatility during the estimation window [-155,-6] 22.7.2021-16.2.2022 and the event window [-5, +5] 17.2.-3.3.2022

Industry	Est. Volatility	Event Volatility	F-stat	P-value
Energy	2,16 %	6,01 %	7,73	0,000***
Basic Materials	1,29 %	2,71 %	4,39	0,000***
Industrials	1,29 %	2,50 %	3,77	0,000***
Consumer Staples	0,89 %	2,45 %	7,58	0,000***
Consumer Discretionary	1,21 %	2,62 %	4,66	0,000***
Health Care	1,20 %	3,00 %	6,23	0,000***
Telecommunications	0,92 %	1,98 %	4,67	0,000***
Utilities	1,06 %	2,55 %	5,73	0,000***
Financials	1,08 %	2,07 %	3,72	0,000***
Tehcnology	1,44 %	2,27 %	2,50	0,009***
Real Estate	0,95 %	1,82 %	3,69	0,000***
OMXH25	1,06 %	2,28 %	4,65	0,000***

The T-statistics are in parentheses.
* Statistically sginificant at the 10% level
** Statistically significant at the 5% level
*** Statistically significant at the 1% level

As seen in table 9, the findings reveal a universal and statistically significant surge in volatility across every industry (P<0,01), indicating that the invasion was associated with a pronounced and systematic increase in return volatility across all industries.

The most striking results are observed in Energy and Consumer Staples sectors. For both industries, the F-statistics show that the event period variance of returns was over seven times higher than during normal times. An interesting difference occurs when both volatility and price reactions of those two industries are examined. During the event window, the Energy sector gained positive CAR with both models over the [-5, +5] period, while the result was not statistically significant under the FFM. In contrast, Consumer Staples sector experienced negative CAR over the [-5, +5] period and the result appear statistically significant under both models. This contrast highlights an important characteristic of the invasion shock. The war generated elevated market-wide uncertainty that led to both positive and negative abnormal price adjustments across sectors, combined with a substantial increase in volatility.

The aggregate OMXH25 index experienced its F-statistics to rise to 4,65, implying a more than four times greater return variance during the event window. Taken together, these findings suggest that the shock was not limited to sectors with direct Russian exposure but rather reflected a broad increase in market-wide uncertainty.

6.3 Regression Analysis: Controlling for Confounding Events

To enhance the robustness of the previous findings, this section presents the results of a regression analysis that controls for confounding events. By accounting for the days when firms in our industry portfolios released informational announcements, we can better isolate the effect of the examined event on return behaviour and volatility.

6.3.1 Regression Analysis on Abnormal Returns

Table 10 reports the variable coefficients with the Market Model Abnormal Returns.

Table 10. Coefficients between MM abnormal returns and war and announcement dummies.

Regression analysis coefficients between abnormal returns estimated with the market model and the war and announcement dummies.

	α_i	β_1	β_2
Energy	0,000 (0,12)	-0,006 (-1,16)	0,034*** (3,92)
Basic Materials	0,000 (-0,52)	0,004 (1,83)*	0,008** (2,36)
Industrials	0,000 (-0,38)	0,001 (0,62)	0,000 (-0,11)
Consumer Staples	0,000 (-0,07)	-0,001 (-0,32)	-0,004 (-1,18)
Consumer Discretionary	0,000 (-0,36)	0,002 (1,03)	0,002 (0,45)
Health Care	0,000 (-0,57)	0,005* (1,95)	-0,004 (-0,87)
Telecommunications	0,000 (-0,31)	0,000 (0,10)	0,003 (1,20)
Utilities	0,000 (-0,12)	-0,002 (-0,69)	-0,002 (-0,64)
Financials	0,000 (-0,12)	0,000 (0,13)	0,003 (0,83)
Technology	0,000 (0,26)	-0,002 (-0,78)	0,013*** (2,98)
Real Estate	0,000 (-0,05)	0,001 (0,45)	0,004 (1,09)
OMXH25	0,000 (0,11)	-0,002 (1,36)	-0,005** (2,19)

The T-statistics are in parentheses.
* Statistically sgnificant at the 10% level
** Statistically significant at the 5% level
*** Statistically significant at the 1% level

The intercept coefficients are statistically insignificant across all industries, indicating the absence of systematic abnormal performance outside the defined specifications.

The announcement dummy exhibits limited statistical significance. While Basic Materials (0,004) and Health Care (0,005) display marginally positive coefficients, the majority of industries do not show statistically significant abnormal returns associated with the announcements once the war period is controlled for. This suggests that the heightened announcement activity did not trigger a broad market-wide repricing.

In contrast, the war dummy produces statistically significant effects in several sectors. Energy exhibits a strong positive coefficient (0,034, t=3,92), indicating substantial abnormal gains during the war period. Basic Materials (0,008) and Technology (0,013) also show positive and statistically significant abnormal performance. However, the OMXH25 index displays a significant negative coefficient (-0,005), suggesting that while certain industries benefited, the aggregate market experienced downward movement during the war period. These findings support the event study results indicating heterogenous sectoral responses.

Table 11 reports the corresponding coefficients between the dummies and the Five-Factor Model Abnormal Returns.

Table 11. Coefficients between FFM abnormal returns and war and announcement dummies.

Regression analysis coefficients between abnormal returns estimated with the five-factor model and the war and announcement dummies.

	α_i	β_1	β_2
Energy	0,000	-0,008	0,027***
	(0,17)	(-1,36)	(2,83)
Basic Materials	0,000	0,003	0,009**
	(-0,31)	(1,13)	(2,34)
Industrials	0,000	0,000	-0,003
	(-0,16)	(-0,02)	(-0,86)
Consumer Staples	0,000	-0,002	-0,006*
	(0,03)	(-0,78)	(-1,86)
Consumer Discretionary	0,000	0,001	-0,002
	(-0,18)	(0,43)	(-0,51)
Health Care	0,000	0,003	-0,009**
	(-0,38)	(1,20)	(-2,08)
Telecommunications	0,000	0,000	0,001
	(-0,28)	(-0,08)	(0,29)
Utilities	0,000	-0,003	-0,004
	(-0,00)	(-1,10)	(-0,90)
Financials	0,000	-0,001	-0,001
	(0.12)	(-0,34)	(0,21)
Technology	0,000	-0,003	0,008*
	(0,38)	(1,17)	(1,84)
Real Estate	0,000	0,000	0,003
	(0,04)	(0,03)	(0,67)
OMXH25	0,000	-0,001	-0,003
	(0,04)	(-0,49)	(-0,98)

The T-statistics are in parentheses.
* Statistically sginificant at the 10% level
** Statistically significant at the 5% level
*** Statistically significant at the 1% level

Comparing the regression results across the Market Model and the Five-Factor Model reveals both consistencies and differences. The war-period abnormal return in the Energy and Basic Materials sectors remain positive under both specifications. This indicates that the observed effects are robust and cannot be explained solely by exposure to common risk factors.

In contrast, the Technology sector exhibits weaker statistical significance under the FFM, suggesting that part of the abnormal performance observed under the MM may reflect compensation for systematic risk exposures. This result was also noted in the earlier findings, where the positive AR of Technology sector lost its statistical significance under the FFM estimations.

The Health Care sector displays a statically significant negative war-period coefficient und ether Fama-French specification, implying relative underperformance after controlling for risk factors. This effect is less pronounced under the MM, indicating that risk adjustment alters the interpretation of sectoral performance.

At the aggregate level, the OMXH25 index does not exhibit statistically significant abnormal returns under the FFM. This suggests that the overall market reaction may reflect changes in systematic risk rather than pure abnormal performance.

Overall, the results demonstrate that while certain sectoral effects are robust across model specifications, others are sensitive to the inclusion of additional risk factors.

6.3.2 Regression Analysis on Abnormal Volatility

The following table 12 shows the results of regressions analysis between the war and announcement dummies and daily abnormal volatility estimated with the market model.

Table 12. Coefficients between MM abnormal volatility and war and announcement dummies.

Regression analysis coefficients between abnormal volatility estimated with the market model and the war and announcement dummies.

	α_i	β_1	β_2
Energy	0,0002**	0,0003	0,0028***
	(2,57)	(1,04)	(5,50)
Basic Materials	0,0000***	0,0000	0,0002***
	(5,83)	(1,46)	(4,15)
Industrials	0,0000***	0,0000	0,0000**
	(6,99)	(-0,32)	(2,03)
Consumer Staples	0,0000***	0,0000	0,0002***
	(5,82)	(1,39)	(5,10)
Consumer Discretionary	0,0000***	0,0000	0,0001
	(6,99)	(0,10)	(1,58)
Health Care	0,0001***	0,0000	0,0002***
	(6,65)	(-0,16)	(3,10)
Telecommunications	0,0000***	0,0000	0,0000**
	(8,36)	(2,86)	(2,00)
Utilities	0,0001***	0,0000	0,0001***
	(6,75)	(0,51)	(2,83)
Financials	0,0000***	0,0000	0,0000
	(8,41)	(-0,22)	(1,19)
Technology	0,0001***	0,0000	0,0001*
	(6,26)	(-0,41)	(1,70)
Real Estate	0,0001***	0,0000	0,0001*
	(7,95)	(-0,88)	(2,57)
OMXH25	0,0000***	0,0000	0,0001***
	(5,19)	(0,48)	(3,78)

The T-statistics are in parentheses.
* Statistically sginificant at the 10% level
** Statistically significant at the 5% level
*** Statistically significant at the 1% level

The intercept coefficients are positive and statistically significant across all industries, reflecting the baseline level of abnormal return volatility outside the event periods.

The announcement dummy exhibits limited statistical significance across sectors, suggesting that the heightened announcement activity did not substantially increase abnormal return volatility.

In contrast, the war dummy is positive and statistically significant across the majority of industries, including Energy, Basic Materials, Industrials, Consumer Staples, Health Care, Telecommunications, Utilities, Technology, and Real Estate. The OMXH25 index also exhibits a significant increase in abnormal volatility during war period.

These findings indicate that the invasion led to a broad increase in uncertainty across the Finnish stock market. Importantly, this increase in volatility occurred even in sectors that experienced positive abnormal returns, such as Energy and Basic Materials, suggesting that the war generated both sectoral reallocation effects and heightened market wide uncertainty.

The following table 13 shows corresponding results of the regression analysis with abnormal volatility estimated with the Five-Factor Model. The results show consistencies, while some differences also occur.

Table 13. Coefficients between FFM abnormal volatility and war and announcement dummies.

Regression analysis coefficients between abnormal volatility estimated with the five-factor model and the war and announcement dummies.

	α_i	β_1	β_2
Energy	0,0003***	0,0004	0,0029***
	(2,87)	(1,22)	(5,10)
Basic Materials	0,0001***	0,0000	0,0001***
	(7,99)	(1,04)	(2,76)
Industrials	0,0001***	0,0000	0,0001
	(7,08)	(0,14)	(1,10)
Consumer Staples	0,0000***	0,0000	0,0003***
	(5,24)	(1,20)	(6,91)
Consumer Discretionary	0,0001***	0,0000	0,0001***
	(7,36)	(-0,50)	(2,71)
Health Care	0,0001***	0,0000	0,0004***
	(6,10)	(-0,19)	(5,69)
Telecommunications	0,0000***	0,0000	0,0000
	(7,60)	(1,04)	(0,93)
Utilities	0,0001***	0,0000	0,0003***
	(7,28)	(-0,18)	(5,53)
Financials	0,0000***	0,0000	0,0000
	(8,45)	(0,11)	(-0,33)
Technology	0,0001***	0,0000	0,0000
	(8,10)	(-0,45)	(-0,24)
Real Estate	0,0001***	0,0000	0,0001
	(7,60)	(-0,43)	(1,40)
OMXH25	0,0000***	0,0000	0,0000
	(6,84)	(0,43)	(0,25)

The T-statistics are in parentheses.
* Statistically sginificant at the 10% level
** Statistically significant at the 5% level
*** Statistically significant at the 1% level

Overall, the results from the MM and the FFM are broadly similar in terms of the direction and significance of the war effect, while the announcement effect remains largely insignificant across both models. However, the magnitude and statistical significance of some sectoral effects change once additional risk factors are controlled for in the FFM.

In both the MM and the FFM, the announcement variable is statistically insignificant across nearly all sectors. The war dummy coefficient remains positive and statistically significant for several industries in both models, particularly, Energy, Basic Materials, Consumer Staples, Health Care, and Utilities.

Compared to the MM, the magnitude of some war coefficients changes slightly under the FFM specification, indicating that part of the abnormal return captured in the MM may be explained by risk exposures. For certain sectors, statistical significance weakens under the FFM (e.g., Industrials, Telecommunications and Real Estate), suggesting that the abnormal returns identified by the MM may partly reflect systematic risk factors rather than pure event driven effects.

Comparing the MM and the FFM reveals that the aggregate market effect (OMXH25) becomes insignificant once size and value factors are included. This suggest that the war-related abnormal returns observed under the MM may be explained by systematic risk exposures rather than abnormal performance.

In contrast, the Energy sector remains strongly positive and statistically significant across both models, indicating a robust sector-specific response to the war shock. Defensive sectors such as Consumer Staples also exhibit significant positive war coefficients under the FFM specification, suggesting that their performance is not solely attributable to factor structure.

6.4 RUWNI Discussion

A secondary objective of this thesis was to evaluate the predictive power of information intensity regarding the Russia-Ukraine war. Ideally, if the RUWNI accurately captures escalating geopolitical risk in real time, it could serve as a forecasting tool for equity market movements and volatility. Under this ideal scenario, a surge in the RUWNI volatility would show as abnormal returns or volatility spikes in the Finnish market.

To further illustrate the relationship between the RUWNI and OMXH25, Figure 1 shows the daily percentage change in the RUWNI and the daily logarithmic returns of the OMXH25 index over the event window

Figure 1. Daily Change of the RUWNI and the OMXH25 Over Event Window.

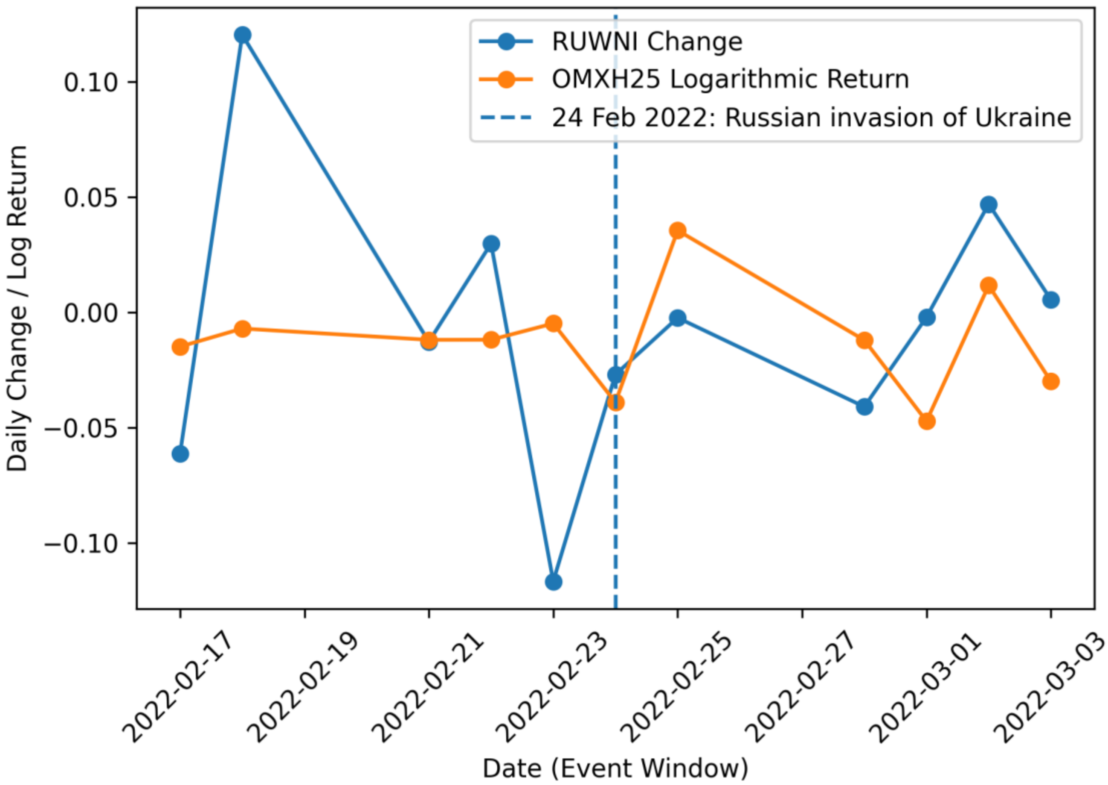

Figure 1 shows that the days before the event day demonstrate a notable divergence between the RUWNI and the OMXH25. However, as the event window progresses, the two trendlines begin to be more synchronized and move into a same direction. This suggests that once the initial shock occurred, daily news flow and market performance aligned more to reflect the ongoing conflict. This observation shows that the RUWNI acts primarily as a concurrent or lagging indicator rather than a predictive forecasting tool. However, this raises questions regarding the predictive power of a news-based index in context of ongoing conflict.

Table 14 shows the same day correlations between the daily RUWNI volatility and the daily abnormal returns (AR) or abnormal volatility (AV) of the OMXH25 and industry portfolios are largely weak, noisy, or generally negative. This indicates that in its current form, the raw daily volatility of war news is a poor forecaster for Finnish stock price movements.

Table 14. Correlation between the RUWNI volatility and abnormal return and abnormal volatility.

Correlation between the RUWNI volatility and the abnormal returns and abnormal volatility.

	RUWNI (Vol) Market Model	RUWNI (Vol) Five-Factor Model
Energy (AR)	-0,33	-0,21
Energy (AV)	-0,09	-0,14
Basic Materials (AR)	-0,15	-0,02
Basic Materials (AV)	-0,32	-0,23
Industrials (AR)	-0,17	0,16
Industrials (AV)	-0,18	-0,35
Consumer Staples (AR)	0,00	0,14
Consumer Staples (AV)	-0,40	-0,42
Consumer Discretionary (AR)	-0,26	0,08
Consumer Discretionary (AV)	-0,35	-0,60
Health Care (AR)	0,18	0,31
Health Care (AV)	-0,14	-0,17
Telecommunications (AR)	-0,22	0,02
Telecommunications (AV)	-0,57	-0,55
Utilities (AR)	-0,11	0,01
Utilities (AV)	-0,07	-0,21
Financials (AR)	-0,16	0,15
Financials (AV)	0,00	-0,16
Technology (AR)	-0,30	0,08
Technology (AV)	-0,39	-0,12
Real Estat (AR)	0,18	0,31
Real Estate (AV)	-0,12	0,09
OMXH25(AR)	0,34	0,36
OMXH25 (AV)	-0,31	-0,28

The correlations between RUWNI volatility and ARs are generally weak and inconsistent across sectors and model specifications. Similarly, the relationship between RUWNI and AVs ranges from non-existent to moderate and is mostly negative. Additional regression analysis including RUWNI as an explanatory variable does not indicate statistically significant effects on abnormal returns nor volatility. The coefficient remains insignificant across specifications, suggesting that RUWNI-based uncertainty does not provide explanatory power beyond the invasion event.

More importantly, lead-lag analysis indicates that the strongest correlations are observed when the stock market leads RUWNI, rather than the other way around. In other words, stock market movements appear to precede changes in the RUWNI index. This suggests that the market may incorporate geopolitical more rapidly than RUWNI captures it.

This finding is consistent with the forward-looking nature of financial markets. If investors react immediately to new geopolitical information, asset prices may adjust before uncertainty measures fully capture those developments. From the perspective of market efficiency, the results align with the semi-strong form of the EMH, according to which publicly available information is rapidly incorporated into asset prices. In this context, RUWNI does not appear to provide substantial forecasting power for Finnish stock returns during the sample period.

Several methodological factors may also contribute to the limited predictive performance of RUWNI. First, the analysis relies on linear correlation measures, which may fail to capture non-linear or asymmetric responses to uncertainty shocks. Second, the global nature of RUWNI may not perfectly align with the specific exposure of a small open economy such as Finland, where sector-level sensitivities may differ from global patterns. Third, the RUWNI does not take the timing of the news events into account, which causes the RUWNI to react news concerning older events.

Although RUWNI does not function as a strong standalone forecasting tool in this study, its usefulness could potentially be enhanced through methodological refinements. Future research could examine lagged effects of uncertainty, employ changes rather than levels of RUWNI, or apply dynamic models to capture feedback mechanisms. Additionally, quantile regression approaches could be used to investigate whether geopolitical uncertainty primarily affects the tails of the return distribution rather than average outcomes. Such extensions may provide a more detailed understanding of the relationship between geopolitical uncertainty and stock market behaviour.

Overall, the results suggest that while RUWNI reflects broader geopolitical developments, it does not serve as a reliable predictor of abnormal returns of abnormal volatility in the Finnish stock market within the examined framework. Instead, the evidence indicates that stock market movements may anticipate changes in measured uncertainty rather than being driven by them.

7 Conclusions

This thesis examined the impact of the outbreak of the Russia-Ukraine war on the Finnish stock market. Using an event study methodology, the study analysed abnormal returns and abnormal volatility across Finnish industry portfolios around the invasion of Ukraine on 24 February 2022. In addition, the analysis controlled for systematic risk factors using both the market model and the five-factor model to ensure that the observed market reactions were not driven by common risk exposures. Additionally, stock market announcements were controlled for by conducting additional dummy regression analysis.

The empirical results indicate that the market reaction was not uniform across industries. While most sectors experienced negative abnormal returns on the event day, the magnitude and persistence of these effects varied. The strongest negative reactions were observed in Health Care, Utilities and Real Estate sectors, suggesting heightened investor concerns about economic uncertainty and potential exposure to geopolitical risk. In contrast, the Energy sector recorded positive abnormal returns around the event, consistent with expectations of rising energy prices and supply disruption following the escalation of the conflict. Basic Materials also showed positive cumulative abnormal returns over the event window, indicating that investors anticipated higher commodity prices and increased demand for raw materials.

Beyond structural return effects, the results reveal a significant increase in market volatility across all industries during the event period. The volatility analysis shows that return variance rose significantly in every sector, suggesting that the invasion generated a broad spike in uncertainty, rather than affecting only industries with direct exposure to Russia or Ukraine. This finding highlights the systematic nature of geopolitical shocks and their widespread impact on market instability.

Comparing the two expected return models shows that the overall timing of market reactions is consistent across specifications. However, the magnitude and statistical significance of some sectoral effects differ once additional risk factors are controlled for in the Fama-French model. In particular, several positive abnormal returns identified under the market model lose significance under the five-factor model. This finding suggests that part of the initially observed reactions can be explained by exposure to systematic risk factors. Nevertheless, most of the sectoral responses remain robust across model specifications.

The regression analysis controlling for confounding announcements further supports these findings. The war dummy exhibits statistically significant effects in several sectors, whereas announcement coefficients remain mostly insignificant. This suggests that the observed abnormal returns and volatility increases are primarily caused by the geopolitical shock rather than firm-specific information releases.

Finally, the analysis of the Russia-Ukraine War News Index (RUWNI) indicates limited correlation with the Finnish stock market movements. The lead-lag analysis suggests that stock market movements tend to precede changes in the RUWNI, implying that financial markets incorporate geopolitical information more rapidly than the uncertainty measure captures it.

In addition to these contributions, the study is subject to several limitations. First, the analysis focuses on short-term market reactions surrounding the beginning of the war and therefore does not capture potential longer-term effects of the conflict. Second, the event study methodology assumes that the observed market reactions are primarily driven by the selected event, although other confounding macroeconomic developments may have influenced market behaviour during the sample period. Third, the outbreak of the war coincided with the annual earnings season, when the firm-specific announcement activity is heightened, and might cause price and volatility reactions in the markets. Finally, the controlling for confounding firm announcements only took the overall activity into account, while the originator itself was not addressed. This may lead to a situation where the announcement coefficient might not fully reflect the impact of information. It is also important to mention that since the analysis focuses on a single geopolitical event, the results should be interpreted as evidence of market responses to this specific shock rather than as universally generalizable effects across all conflicts.

Based on the mentioned limitations, future research could extend this analysis by examining longer time horizons to capture longer term reactions of the war. Second, it might be beneficial to explore the role of additional factors, such as geopolitical risk indices or news-based uncertainty measures, in explaining market reactions to geopolitical shocks. Third, it could be beneficial to extend the analysis beyond the beginning of the conflict. Such an extension could help enhance understanding of the mechanisms through which wars affect financial markets. Fourth, the robustness could be enhanced by creating more efficient and precise methods for isolating the true impact of the war.

Artificial intelligence (AI) tools were used in a limited supporting role during the writing process, primarily for grammar checking and improving the clarity and smoothness of the language. All AI-generated suggestions were critically assessed by the author before inclusion. The research design, theoretical framework, empirical analysis, interpretation of results, and conclusions were produced independently by the author.

References

Aguiar Rodrigues, I. F., Gomes, L. M. P., & Pereira, C. M. F. (2025). How do neighbouring stock markets and sensitive sectors discount the Russia-Ukraine military conflict? *Cogent Economics & Finance*, *13*(1). https://doi.org/10.1080/23322039.2025.2555411

Armitage, S. (1995). EVENT STUDY METHODS AND EVIDENCE ON THEIR PERFORMANCE. *Journal of Economic Surveys*, *9*(1), 25–52. https://doi.org/10.1111/j.1467-6419.1995.tb00109.x

Arshanapalli, B., d’Ouville, E., Fabozzi, F., & Switzer, L. (2006). Macroeconomic news effects on conditional volatilities in the bond and stock markets. *Applied Financial Economics*, *16*(5), 377–384. https://doi.org/10.1080/09603100500511068

Bachelier, L. (1900). Théorie de la spéculation. *Annales Scientifiques de l’École Normale Supérieure*, *17*, 21–86. https://doi.org/10.24033/asens.476

Ball, R., & Brown, P. (1968). An Empirical Evaluation of Accounting Income Numbers. *Journal of Accounting Research*, *6*(2), 159–178. https://doi.org/10.2307/2490232

Banerjee, A. V. (1992). A Simple Model of Herd Behavior. *The Quarterly Journal of Economics*, *107*(3), 797–817. https://doi.org/10.2307/2118364

BBC News (2022, February 21). *BBC News*. Putin announces Donetsk and Luhansk recognition. https://www.bbc.com/news/av/world-europe-60470900

Beaver, W. H. (1968). The Information Content of Annual Earnings Announcements. *Journal of Accounting Research*, *6*, 67–92. https://doi.org/10.2307/2490070

Bikhchandani, S., & Sharma, S. (2001). Herd Behavior in Financial Markets. *SSRN Electronic Journal*, *47*(3). https://doi.org/10.2139/ssrn.228343

Binder, J. (1998). The Event Study Methodology Since 1969. *Review of Quantitative Finance and Accounting*, *11*(2), 111–137. https://doi.org/10.1023/a:1008295500105

Birz, G., & Lott, J. R. (2011). The effect of macroeconomic news on stock returns: New evidence from newspaper coverage. *Journal of Banking & Finance*, *35*(11), 2791–2800. https://doi.org/10.1016/j.jbankfin.2011.03.006

Blasco, N., Casas, L., & Ferreruela, S. (2024). Does war spread the herding effect in stock markets? Evidence from emerging and developed markets during the Russia-Ukraine war. *Finance Research Letters*, *63*, 105365–105365. https://doi.org/10.1016/j.frl.2024.105365

Boubaker, S., Nguyen, N., Trinh, V. Q., & Vu, T. (2023). Market reaction to the Russian Ukrainian war: a global analysis of the banking industry. *Review of Accounting and Finance*. https://doi.org/10.1108/raf-10-2022-0294

Boudoukh, J., Feldman, R., Kogan, S., & Richardson, M. (2018). Information, Trading, and Volatility: Evidence from Firm-Specific News. *The Review of Financial Studies*, *32*(3), 992–1033. https://doi.org/10.1093/rfs/hhy083

Boungou, W., & Yatié, A. (2022). The Impact of the Ukraine–Russia War on World Stock Market Returns. *Economics Letters*, *215*. https://doi.org/10.1016/j.econlet.2022.110516

Brown, S. J., & Warner, J. B. (1985). Using daily stock returns: the case of event studies. *Journal of Financial Economics*, *14*(1), 3–31. https://doi.org/10.1016/0304-405X(85)90042-X

Brown, S. J., & Warner, J. B. (1980). Measuring security price performance. *Journal of Financial Economics*, *8*(3), 205–258. https://doi.org/10.1016/0304-405X(80)90002-1

Burton, M. (1973). A random walk down Wall Street. W. W. Norton & Company.

Caldara, D., & Iacoviello, M. (2022). Measuring Geopolitical Risk. *American Economic Review*, *112*(4), 1194–1225. https://doi.org/10.1257/aer.20191823

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance*, *52*(1), 57–82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x

Chan, K. F., & Gray, P. (2018). Volatility jumps and macroeconomic news announcements. *Journal of Futures Markets*, *38*(8), 881–897. https://doi.org/10.1002/fut.21922

Chan, W. S. (2001). Stock Price Reaction to News and No-news: Drift and Reversal After Headlines. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.262452

Chen, J., Liu, Y.-J., Lu, L., & Tang, Y. (2015). Investor Attention and Macroeconomic News Announcements: Evidence from Stock Index Futures. *Journal of Futures Markets*, *36*(3), 240–266. https://doi.org/10.1002/fut.21727

Cutler, D. M., Poterba, J. M., & Summers, L. H. (1988, March 1). *What Moves Stock Prices?*Www.nber.org. https://doi.org/10.3386/w2538

De Bondt, W. F. M. D., & Thaler, R. (1985). Does the Stock Market Overreact? *The Journal of Finance*, *40*(3), 793–805. https://doi.org/10.2307/2327804

DeLisle, R. J., Mauck, N., & Smedema, A. R. (2016). Idiosyncratic Volatility and Firm-Specific News: Beyond Limited Arbitrage. *Financial Management*, *45*(4), 923–951. https://doi.org/10.1111/fima.12135

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise Trader Risk in Financial Markets. *Journal of Political Economy*, *98*(4), 703–738. https://www.jstor.org/stable/2937765?seq=1

Dugbartey, A. N. (2025). Systemic financial risks in an era of geopolitical tensions, climate change, and technological disruptions: Predictive analytics, stress testing and crisis response strategies. *International Journal of Science and Research Archive*, *14*(02), 1428–1448. https://doi.org/10.30574/ijsra.2025.14.2.0563

Guidolin, M., & La Ferrara, E. (2005). The Economic Effects of Violent Conflict: Evidence from Asset Market Reactions. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.825889

Engle, R. F., Hansen, M. K., Karagozoglu, A. K., & Lunde, A. (2020). News and Idiosyncratic Volatility: The Public Information Processing Hypothesis*. *Journal of Financial Econometrics*, *19*(1), 1–38. https://doi.org/10.1093/jjfinec/nbaa038

Fama, E. F. (1965). The Behavior of Stock-Market Prices. *The Journal of Business*, *38*(1), 34–105. https://doi.org/10.1086/294743

Fama, E. (1970). Efficient Capital markets: a Review of Theory and Empirical Work. *The Journal of Finance*, *25*(2), 383–417. https://doi.org/10.2307/2325486

Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance*, *47*(2), 427–465. https://doi.org/10.1111/j.1540-6261.1992.tb04398.x

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1–22. https://doi.org/10.1016/j.jfineco.2014.10.010

Fama, E. F., Fisher, L., Jensen, M. C., & Roll, R. (1969). The Adjustment of Stock Prices to New Information. *International Economic Review*, *10*(1), 1–21. https://doi.org/10.2307/2525569

Federle, J., Meier, A., Müller, G. J., & Sehn, V. (2024). Proximity to War: The Stock Market Response to the Russian Invasion of Ukraine. *Journal of Money Credit and Banking*. https://doi.org/10.1111/jmcb.13226

Flannery, M. J., & Protopapadakis, A. (2002, October 3). *Macroeconomic Factors Do Influence Aggregate Stock Returns*. Papers.ssrn.com. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=314261

Gkillas, K., Gupta, R., & Wohar, M. E. (2018). Volatility jumps: The role of geopolitical risks. *Finance Research Letters*, *27*, 247–258. https://doi.org/10.1016/j.frl.2018.03.014

He, Z. (2023). Geopolitical risks and investor sentiment: Causality and TVP-VAR analysis. *The North American Journal of Economics and Finance*, *67*, 101947–101947. https://doi.org/10.1016/j.najef.2023.101947

Hudson, R., & Urquhart, A. (2015). War and stock markets: The effect of World War Two on the British stock market. *International Review of Financial Analysis*, *40*, 166–177. https://doi.org/10.1016/j.irfa.2015.05.015

Höhler, J., Harmens, I., & Oude Lansink, A. (2024). The impact of the Russia–Ukraine war on stock prices, profits and perceptions in the food supply chain. *Agribusiness*. https://doi.org/10.1002/agr.21964

Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance*, *48*(1), 65–91. https://doi.org/10.1111/j.1540-6261.1993.tb04702.x

Kahneman, D., & Tversky, A. (1977, June 1). *Intuitive Prediction: Biases and Corrective Procedures*. Apps.dtic.mil. https://apps.dtic.mil/sti/citations/ADA047747

Kahneman, D., & Tversky, A. (1979). Prospect theory: an Analysis of Decision Under Risk. *Econometrica*, *47*(2), 263–292. https://doi.org/10.2307/1914185

Kenneth R. French - Data Library. (n.d.). Retrieved on 10.12.2025 Mba.tuck.dartmouth.edu. https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#International

Kiesel, F., & Kolaric, S. (2023). Should I stay or should I go? Stock market reactions to companies' decisions in the wake of the Russia-Ukraine conflict. *Journal of International Financial Markets, Institutions and Money*, *89*, 101862. https://doi.org/10.1016/j.intfin.2023.101862

Kumari, V., Kumar, G., & Pandey, D. K. (2023). Are the European Union stock markets vulnerable to the Russia–Ukraine war? *Journal of Behavioral and Experimental Finance*, *37*, 100793. https://doi.org/10.1016/j.jbef.2023.100793

Li, Y., Hoang, V. H., Sun, C., & Lee, J. (2023). Idiosyncratic volatility and firm-specific news: evidence from the Chinese stock market. *Economic*

Research-Ekonomska Istraživanja, *36*(2). https://doi.org/10.1080/1331677x.2023.2173630

MacKinlay, A. C. (1997). Event Studies in Economics and Finance. *Journal of Economic Literature*, *35*(1), 13–39. https://www.jstor.org/stable/2729691?seq=1

Mandelbrot, B. (1963). The Variation of Certain Speculative Prices. *The Journal of Business*, *36*(4), 394–419. JSTOR. https://doi.org/10.2307/2350970

Manela, A., & Moreira, A. (2017). News implied volatility and disaster concerns. *Journal of Financial Economics*, *123*(1), 137–162. https://doi.org/10.1016/j.jfineco.2016.01.032

Martins, A. M., Correia, P., & Gouveia, R. (2024). Heterogeneous stock market impact of Russia–Ukraine War for oil and gas companies. *International Journal of Islamic and Middle Eastern Finance and Management*. https://doi.org/10.1108/imefm-03-2024-0131

McQueen, G., & Roley, V. V. (1993). Stock Prices, News, and Business Conditions. *Review of Financial Studies*, *6*(3), 683–707. https://doi.org/10.1093/rfs/5.3.683

Mejova, Y. (2009). Sentiment Analysis: An Overview. *Www.academia.edu*. https://www.academia.edu/291678/Sentiment_Analysis_An_Overview

Melnychenko, O. (2024). Utilising AI Models to Analyse the Relationship between Battlefield Developments in the Russian-Ukrainian War and Fluctuations in Stock Market Values. *Forum Scientiae Oeconomia*, *12*(4), 83–98. https://doi.org/10.23762/FSO_VOL12_NO4_5

Neumann, von, Morgenstern, O., & Rubinstein, A. (1944). *Theory of Games and Economic Behavior (60th Anniversary Commemorative Edition)*. Princeton University Press; JSTOR. https://doi.org/10.2307/j.ctt1r2gkx

Nerlinger, M., & Utz, S. (2022). The impact of the Russia-Ukraine conflict on energy firms: A capital market perspective. *Finance Research Letters*, *50*(103243), 103243. https://doi.org/10.1016/j.frl.2022.103243

Nikkinen, J., & Sahlström, P. (2004). Scheduled domestic and US macroeconomic news and stock valuation in Europe. *Journal of Multinational Financial Management*, *14*(3), 201–215. https://doi.org/10.1016/j.mulfin.2003.01.001

Vanshika, Rani, N., & Walia, R. (2024). *A Comprehensive Review of Sentiment Analysis: Techniques, Datasets, Limitations, and Future Scope*. https://doi.org/10.1109/ccict62777.2024.00072

Novy-Marx, R. (2013). The Other Side of value: the Gross Profitability Premium. *Journal of Financial Economics*, *108*(1), 1–28. https://doi.org/10.1016/j.jfineco.2013.01.003

Pontiff, J. (2006). Costly arbitrage and the myth of idiosyncratic risk. *Journal of Accounting and Economics*, *42*(1-2), 35–52. https://doi.org/10.1016/j.jacceco.2006.04.002

Ross, S. A. (1976). The Arbitrage Theory of Capital Asset Pricing. *Journal of Economic Theory*, *13*(3), 341–360. sciencedirect. https://doi.org/10.1016/0022-0531(76)90046-6

Ryan, P., & Taffler, R. J. (2004). Are Economically Significant Stock Returns and Trading Volumes Driven by Firm-specific News Releases? *Journal of Business Finance Accounting*, *31*(1-2), 49–82. https://doi.org/10.1111/j.0306-686x.2004.0002.x

Schneider, G., & Troeger, V. E. (2006). War and the World Economy. *Journal of Conflict Resolution*, *50*(5), 623–645. https://doi.org/10.1177/0022002706290430

Scott, L. O. (1991). Financial Market Volatility: A Survey. *IMF Staff Papers*, *38*(3), 582–625. https://doi.org/10.5089/9781451973136.024

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, *19*(3), 425–442. https://doi.org/10.2307/2977928

Shefrin, H., & Statman, M. (1985). The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence. *The Journal of Finance*, *40*(3), 777–790. https://doi.org/10.2307/2327802

Shleifer, A., & Vishny, R. W. (1997). The Limits of Arbitrage. *The Journal of Finance*, *52*(1), 35–55. https://doi.org/10.1111/j.1540-6261.1997.tb03807.x

Sochi, M. H. (2015, August). *An Analysis of Speed of Stock Price Adjustment to Market Wide Information*. ResearchGate; unknown. https://www.researchgate.net/publication/398110800_An_Analysis_of_Speed_of_Stock_Price_Adjustment_to_Market_Wide_Information

Suleman, M. T. (2012). Stock Market Reaction to Good and Bad Political News. *Asian Journal of Finance & Accounting*, *4*(1). https://doi.org/10.5296/ajfa.v4i1.1705

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

Tetlock, P. C., Saar-Tsechansky, M., & Macskassy, S. (2007). More than Words: Quantifying Language to Measure Firms' Fundamentals. *SSRN Electronic Journal*, *63*(3). https://doi.org/10.2139/ssrn.923911

Titman, S., Wei, K. C. J., & Xie, F. (2004). Capital Investments and Stock Returns. *Journal of Financial and Quantitative Analysis*, *39*(4), 677–700. https://doi.org/10.1017/s0022109000003173

Wankhade, M., Rao, A. C. S., & Kulkarni, C. (2022). A Survey on Sentiment Analysis Methods, Applications, and Challenges. *Artificial Intelligence Review*, *55*(55). https://doi.org/10.1007/s10462-022-10144-1

Wu, F., Zhan, X., Zhou, J., & Wang, M. (2023). *Stock market volatility and Russia-Ukraine conflict*. 103919–103919. https://doi.org/10.1016/j.frl.2023.103919

Zhou, Z., & Wang, K. (2025). War discourse predicts stock market volatility: A century of evidence. *Finance Research Letters*, *82*, 107567. https://doi.org/10.1016/j.frl.2025.107567

Appendices

Appendix 1. Stocks Included in the Analysis and Industry Classification.

Industry Portfolio	Company Name	Ticker Symbol
Energy (1)	NESTE	NESTE
Basic Materials (14)	AFARAK GROUP A	AFAGR
	COMPONENTA	CTH1V
	ENDOMINES FINLAND	ENDOM
	KEMIRA	KEMIRA
	KOSKISEN CORPORATION	KOSKI
	METSA BOARD A	METSA
	METSA BOARD B	METSB
	OUTOKUMPU 'A'	OUT1V
	SOTKAMO SILVER (HEL)	SOSI1
	SSAB A (HEL)	SSABAH
	SSAB B (HEL)	SSABBH
	STORA ENSO A	STEAV
	STORA ENSO R	STERV
	UPM-KYMMENE	UPM
Industrials (38)	ASPO	ASP
	BOREO	BOREO
	CONSTI	CONSTI
	DOVRE GROUP	DOV1V
	EEZY	EEZY
	ELECSTER A	ELEAV
	ENERSENSE INTERNATIONAL	ESENSE
	ETTEPLAN	ETTE
	EXEL COMPOSITES	EXL1V
	GLASTON	GLA1V
	GRK INFRA	GRK
	HIAB CORPORATION B	HIAB
	HUHTAMAKI	HUH1V
	INCAP	ICP1V
	KALMAR CORPORATION B	KALMAR
	KEMPOWER	KEMPOWR
	KESLA A	KELAS
	KH GROUP	KHG
	KONE B	KNEBV
	KONECRANES	KCR

	KREATE GROUP	KREATE
	LEHTO GROUP	LEHTO
	METSO CORPORATION	METSO
	NURMINEN LOGISTICS	NLG1V
	PONSSE	PON1V
	RAUTE A	RAUTE
	REKA INDUSTRIAL	REKA
	ROBIT	ROBIT
	SCANFIL	SCANFL
	SITOWISE GROUP	SITOWS
	SRV YHTIOT	SRV1V
	TALENOM	TNOM
	TULIKIVI A	TULAV
	VAISALA A	VAIAS
	VALMET	VALMT
	WULFF-GROUP	WUF1V
	WARTSILA	WRT1V
	YIT	YIT
Consumer Staples (9)	ANORA GROUP	ANORA
	APETIT	APETIT
	ATRIA A	ATRAV
	HKFOODS A	HKFAS
	KESKO A	KESKOA
	KESKO B	KESKOB
	OLVI A	OLVAS
	RAISIO	RAIVV
	SUOMINEN	SUY1V
Consumer Discretionary (27)	ALMA MEDIA	ALMA
	TALLINK GRUPP GDR	TALLINK
	FINNAIR	FIA1S
	FISKARS A	FSKRS
	HARVIA	HARVIA
	HONKARAKENNE B	HONBS
	ILKKA	ILKKA
	KAMUX	KAMUX
	KESKISUOMALAINEN A	KSLAV
	LINDEX GROUP SHARE B	LINDEX
	MARIMEKKO	MEKKO
	MARTELA A	MARAS
	MUSTI GROUP	MUSTI
	NOHO PARTNERS	NOHO

	NOKIAN RENKAAT	TYRES
	ORTHEX	ORTHEX
	PUUILO	PUUILO
	RAPALA VMC	RAP1V
	REBL GROUP	REBL
	RELAIS GROUP	RELAIS
	REMEDY ENTERTAINMENT	REMEDY
	SAGA FURS C	SAGCV
	SANOMA	SAA1V
	TOKMANNI GROUP CORP.	TOKMAN
	VERKKOKAUPPA COM	VERK
	VIKING LINE	VIK1V
	WETTERI	WETTERI
Health Care (9)	BIOHIT B	BIOBV
	NIGHTINGALE HEALTH B	NGHTB
	OPTOMED	OPTOMED
	ORIOLA	OKDBV
	ORION A	ORNAV
	ORION B	ORNBV
	PIHLAJALINNA	PIHLIS
	REVENIO GROUP	REG1V
	TERVEYSTALO	TTALO
Telecommunications (4)	ELISA	ELISA
	NOKIA	NOKIA
	TELESTE	TLT1V
	TELIA COMPANY (HEL)	TELIA1
Utilities (3)	FORTUM	FORTUM
	LAMOR CORPORATION	LAMOR
	LASSILA & TIKANOJA	LAT1V
Financials (15)	AKTIA BANK A	AKTIA
	ALISA BANK ORD	ALISA
	CAPMAN B	CAPMAN
	ENENTO GROUP	ENENTO
	EQ	EQV1V
	EVLI B	EVLI
	MANDATUM	MANTA
	NORDEA BANK (HEL)	NDA FI
	OMA SAASTOPANKKI	OMASP
	PANOSTAJA	PNA1V
	SAMPO A	SAMPO
	TAALERI	TAALA

	UNITED BANKERS	UNIB
	ALANDSBANKEN A	ALBAV
	ALANDSBANKEN B	ALBBV
Technology (14)	ASPOCOMP GROUP	ACG1V
	BITTIUM	BITTI
	DIGIA	DIGIA
	DIGITALIST GROUP	DIGIGR
	F SECURE OYJ	FSECURE
	GOFORE	GOFORE
	QPR SOFTWARE	QPR1V
	QT GROUP	QTCOM
	SIILI SOLUTIONS	SIILI
	SOLTEQ	SOLTEQ
	SSH COMMUNICATIONS SECURITY	SSH1V
	TECNOTREE	TEM1V
	TIETOEVRY	TIETO
	TRAINERS HOUSE	TRH1V
Real Estate (5)	CITYCON	CTY1S
	INVESTORS HOUSE	INVEST
	KOJAMO	KOJAMO
	OVARO KIINTEISTOSIJOITUS	OVARO
	TOIVO GROUP	TOIVO