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The effect of the Russian invasion of Ukraine in 2022 on the American, European and Chinese stock market

Author: J.R.F.O Tiemessen
Student number: 606437jt
Thesis supervisor: Dr. J.J.G. Lemmen
Second reader: Professor Dr. O.W. Steenbeek
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PREFACE AND ACKNOWLEDGEMENTS

Personally, I really enjoyed writing my master thesis about the impact of the Russian invasion of Ukraine in 2022 on several stock markets. Multiple times a day I checked several news channels to get to know more and more about the situation in Ukraine. Every day there were new developments concerning the situation in Ukraine, which made it a very interesting topic to investigate. I am really curious where this situation will be heading to. In the end, I hope this war will end soon. Moreover, I very grateful for the excellent support and guidance of my supervisor Jan Lemmen in writing my thesis. Furthermore, I want to thank the Erasmus University of Rotterdam for providing all the tools and facilities I needed for writing my master thesis. Lastly, I appreciate my family and friends for their support during the process of writing my thesis.

ABSTRACT

This paper performs an event study to observe the impact of Russia's invasion of Ukraine in 2022 on the American, European and Chinese stock market. In the paper a specific focus will be given to the effect of the Ukraine war on the performance of defense related stocks. The results show that the Russian invasion of Ukraine led to significant negative abnormal returns on the European & Chinese stock market while there were significant positive abnormal returns on the American stock market on the day of the invasion. The American & Chinese defense-related stocks obtained significant positive abnormal returns while the European defense-related stocks obtained significant negative abnormal returns on the event date. Based on the significant abnormal returns on the event date, one can conclude that investors were not able to anticipate the invasion and that the market was in a semi-strong form of efficiency. For the American, European & Chinese stock market it was difficult to find variables that could explain differences in abnormal returns. For the defense related stocks, a larger distance from Ukraine's capital Kiev explained differences in abnormal returns between the American, European and Chinese defense stocks. A larger distance from Kiev had a significantly positive influence on the abnormal returns of the defense-related stocks that were obtained on the day of the invasion. Furthermore, a larger firm size of a defense-related stock, had a significant positive influence on the abnormal return on the event date as well.

Keywords: Ukraine War, Stock Market Performance, Defense Industry Performance, Event Study Methodology

JEL Classification: F50, F51, G10, G14, G15, N4

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1 Introduction

1.1 Introduction

This study performs an event study of the impact of the war in Ukraine in 2022 on the American, European and Chinese stock market and how this war affected their defense industry related stocks. So far there is hardly any academic research done on the impact of this war on various stock markets and their specific industries. The whole world was in shock when the Russian president Vladimir Putin invaded Ukraine on the 24th of February, 2022 (BBC, 2022). Many countries in the world did not expect that Putin would invade Ukraine at all nor did they expect that Putin would use so much violence for his invasion by bombing cities and killing innocent people. The war in Ukraine and the sanctions imposed by other countries on Russia had a major impact on financial markets in the world (Smith, 2022).

Prior literature has mainly focused on the impact of violent events like terrorist attacks on stock markets' performance. The magnitude of impact of a war is often much higher than that of a terrorist attack. There is limited literature on the impact of wars on financial markets and its specific industries. Especially there is limited research done on the impact of a war on stock markets in which large world powers are opposed to each other. The Ukraine war is the first real war since WWII in which large world powers like Russia and U.S and European Union (EU) are involved and opposed to each other. The contribution of this paper to the existing literature is to show how the war in Ukraine, that has the involvement of several world powers, affects different global stock markets and its specific industries. A specific focus will be given on the impact of the war on the stock market performance of firms in the defense industry.

The research question of this paper will be: *"How did the Russian invasion of Ukraine in 2022 affect the European, American and Chinese stock markets and their defense-related stocks?"*

1.2 Background information Russia-Ukraine war

The Russia-Ukraine conflict started back in November 2013, there were large protest in Ukraine's capital Kiev against former Ukraine's president Yanukovich because of his decision to suspend trade and talks with the EU and opts to revive economic ties with Moscow (Reuters, 2022). In February 2014, the parliament of Ukraine voted to remove president Yanukovich. Shortly after that, the Russian-Ukraine conflict changed into an armed conflict. In March 21, 2014, the Russian Federation moved military troops to Crimea, an area of Ukraine and annexed this area (Grant, 2015). The annexation caused international outrage and let to a breakdown of diplomatic relations between Russia and EU and U.S (Myers & Barry, 2014). In May 2014, pro-Russian separatists held a referendum and declared that the majority of the people in the eastern part of Ukraine, in the regions Donetsk and Luhansk, are in favor of a declaration of independence for these regions. The Russian Federation gave the pro-Russian separatists in these regions financial and military support for separation from Ukraine. Ukraine and the rest of the world did not support the declaration of these regions to become independent nations.

In January 2021, the incumbent Ukraine's president Zelensky appealed to U.S president Joe Biden to let Ukraine join the North Atlantic Treaty Organization (NATO). In the spring of 2021, Russia started to move troops to Ukraine's borders for a so-called military training exercise. In December 2021, the Russian president Vladimir Putin demanded security guarantees that included that the NATO pulls back troops and weapons from eastern Europe and that Ukraine will never join NATO (Fitzgerald, 2015). The Biden administration rejects Putin's security guarantees. On 21st of February 2022, Putin recognized the regions of Donetsk and Luhansk as independent states and sent in troops to "keep peace". On the 24th of February 2022, Putin shocked the world by invading Ukraine for a "special military operation" to "demilitarise and de-Nazify Ukraine" (Kirby, 2022). Russian troops began missile and artillery attacks, striking major Ukraine cities and killing innocent people.

World Bank Vice President Bjerde (2022) said that "The magnitude of the humanitarian crisis unleashed by the war is staggering. The Russian invasion is delivering a massive blow to Ukraine's economy and it has inflicted enormous damage to infrastructure," (para. 4). The economy of Ukraine is expected to shrink by almost half (The World Bank, 2022). The European Union (EU), the U.S and the rest of the world have imposed economic and all other kind of sanctions on Russia to stop the aggressive invasion of Ukraine (Bown, 2022). These sanctions had a tremendous impact on the Russian economy. The Russian ruble is seesawing in value against the US dollar and the Russian economy is facing an economic contraction (Ivanovo, 2022). According to the Institute of International Finance (IIF) Russia's GDP will shrink by 15 % in 2022 (Reuters, 2022). The war in Ukraine is causing a food and fuel crises and is damaging global trade (WEF, 2022). This will have implications for economies all around the globe. In this paper, the effect of the Russian invasion in Ukraine on the American, European and Chinese stock market returns will be analyzed.

The main findings of this paper show that the Russian invasion of Ukraine led to significant negative abnormal returns on the European & Chinese stock market while there were significant positive abnormal returns on the American stock market on the day of the invasion. The American & Chinese defense-related stocks mainly showed significant positive abnormal returns while the European defense-related stocks showed significant negative abnormal returns on the event date. Based on the significant abnormal returns obtained on the day the Ukraine war started, one can conclude that investors were not able to anticipate the invasion and that the market was in a semi-strong form of efficiency. For the S&P500, the STOXX 600 and the SSE Composite it was difficult to find variables to explain the differences in abnormal returns. For the defense-related stocks, a larger distance from Ukraine's capital Kiev had a significant positive influence on the abnormal returns. This is in line with research done by Brounen & Derwall (2010) who showed that financial markets further away from the location of a terrorist attack have less severe negative price reactions. Furthermore, the results of this paper are also in line with researches done by Schneider & Tröger (2004) and Berrebi & Klor (2010) who both showed that the defense sector profits from an intensification of a conflict or from terroristic attacks. Furthermore, the results in the robustness section show that a larger firm size of the defense-related stock, had a significant positive influence on the abnormal returns as well. Based on this, one can conclude that the distance and firm size explain some of the variation in abnormal returns of the American, European and Chinese defense stocks.

The remainder of this paper is structured as follows: Chapter 2, the literature review, provides more information about the Efficient Market Hypothesis (EMH) (Fama, 1970) and the Even Study Market Model (Fama, 1970). Next to that, it looks at related research about the impact of wars and violent events on stock market performance. Several hypotheses will be set up based on the information given in the literature review. These hypotheses will be tested so the research question can be answered. In Chapter 3, more details will be given about the data that is used to conduct the research. In Chapter 4, the method, more information will be given about the event study methodology that is used to test the hypothesizes. Next to that, a multiple regression model will be explained in more detail as this model might have some explanatory power for the results obtained in the event study. In Chapter 5, the results will be compared to the hypotheses. Next to that, a robustness check will be conducted and an economic interpretation of the results will be given. For the multivariate regression, issues related to heteroskedasticity, multicollinearity and endogeneity will be discussed. In Chapter 6, a final answer will be given to the research question. Lastly, some limitations of this research will be discussed and some recommendations for future research will be given.

CHAPTER 2 Literature Review

In the literature review, first the literature related to event studies and efficient markets will be analyzed. Furthermore, the literature of the impact of violent events on stock market performance will be discussed. At the end of the literature review, a meta table summarizes the main findings of the papers discussed in this literature review.

2.1 Event studies and efficient markets

Economists frequently evaluate the impact of events on the value and returns of companies. This can easily be done using an event study methodology of Fama (1970). In the event study methodology, financial market data is used to measure the impact of a specific event on the value of a firm. The usefulness of such a study comes from the Efficient Market Hypothesis (EMH). The EMH of Fama (1970) states that markets are efficient and that security prices fully reflect all available information. The measure of the event's economic impact can be constructed using security prices as according to EMH the effects of an event will be reflected immediately in security prices. The EMH has played an important role in explaining abnormal returns. According to the EMH there are three forms of market efficiency: weak, semi-strong and strong. The weak-form test if all information from historic prices is incorporated in the current stock price. The semi-strong form tests if all historic and public information is reflected in stock's current price. The strong-form tests whether all information, public or private, is fully reflected in the current stock price. The event study methodology can be used to analyze the semi-strong form of market efficiency at a certain point in time.

According to Jensen (1968) a weaker but a more sensible economic interpretation of the efficient market hypothesis states that the prices reflect information to the point where the marginal benefits of acting on information do not exceed the marginal costs. The strong-form of the EMH preconditions that information and trading costs, the cost of getting prices to reflect information, are always zero (Grossmann and Stiglitz, 1980). This form of efficiency is false as there are information and trading costs. However, EMH can still be used to analyze how prices adjust to various kinds of information. The cleanest evidence of market efficiency comes from event studies on daily stock returns (Fama, 1991). When information can be dated precisely and the event has a large effect, one can use expected returns to measure abnormal daily returns as a second-order consideration. These returns can help in an event study to give a clear picture of the speed of adjustment of prices to information.

According to Shiller (2003) academic finance has evolved a long way from the days when the efficient market theory was widely considered to be proven beyond doubts. He argues that behavioral finance, finance including psychology and sociology, is now one of the most vital research programs and stand in contradiction to much of the efficient market theory. Lo (2007) explains in his paper that the most enduring critique on EMH comes from phycologists and behavioral economists. They argue that the EMH is based on rationality which is a counterfactual assumption regarding human behavior. According to Lo (2007) recent advances in evolutionary psychology and the cognitive neurosciences may be able to reconcile the EMH with behavioral anomalies. In contrast to Shiller (2003), Malkier (2003) makes a strong case for the continuation of the EMH. He examined the attacks on the EMH and the relationship between stock price predictability and efficiency. He found that our stock markets are far more efficient and far less predictable than some recent academic papers told us. In line with this, Ball (2009) shows in his research that the impact of efficient market theory is durable, and seems likely to continue to do so, despite its inevitable and obvious limitations.

2.2 Impact of violent events on stock markets

In the existing literature there is limited research done on the impact of wars on stock markets. However, there is a lot of research done on the effect of violent events like terrorist attacks on stock market performance. Although the magnitude of impact and the use of violence of these events is lower than a war, the literature and research done on these violent events is relevant for this paper.

Hoffman & Neuenkirch (2017) analyzed the impact of the pro-Russian conflict on stock returns in Russia and the Ukraine during the period November 21, 2013 to September 29, 2014. They find that escalation of the conflict is bad news for investors in both stock markets. Russian returns decrease by as much as 21 basis points after a one percentage point increase in escalation and Ukraine returns drop by 30 basis points. Next to that, news from international sources is more relevant for investors in the Russian stock market than in news from Russian sources. Following on this conflict, sanctions were imposed against Russia. Ankudinov et al. (2017) found that the sanctions imposed let to an increase in volatility in returns for all sectoral indices. In line with this research, Biblaiser and Lektzian (2020) show that sanctions can have a negative effect on stock market value in targeted countries, but that their effectiveness is limited in practice due to the overuse of sanctions. There is a marginal decrease in the negative effect on the target's stock market as the number of sanctions increases.

International political crises reduce world market stock returns by approximately four percent per year. An international crisis causes large negative stock market returns in the first month, lower than average returns during the remaining months and partial recovery when they end. The start of a crisis increases monthly world market volatility by more than a third and the end of a crisis decreases volatility by slightly less than a third. Furthermore, the stock market reactions and the volatility changes are significant stronger when an international crisis starts with violence, involves more severe value threats, or when a major world power is involved on both sides of a conflict. The financial consequences are even more devastating for investors in the country where the crisis is taking place (Berkman & Jacobsen, 2006). Schneider and Troeger (2006) analyzed the influence that political developments within three war regions had on global financial markets (CAC, Dow Jones, FTSE) from 1990 to 2000. They embed a framework within commercial liberalism, a theoretical perspective that tries to assess the interrelationship between war and economic changes. They show that conflicts affected the financial markets in the Western world negatively. The impact of the political events depends on two factors: (1) the severity of conflictive events and (2) the degree to which economics agents could anticipate both cooperative and conflictive events. Conflictive events influenced the volatility of the stock market much more than cooperative ones. Economic agents detest war because it endangers mutually profitable exchange.

A prior study has analyzed the quarterly prices of the Dow Jones Industrial Average (DJIA) index from 1960 to 2015 to determine the effects on stock prices on U.S war involvement. The results showed that the entry of the United States into war has a positive effect on the quarterly returns from the DJIA index. However, the different type of wars can have an increasing or decreasing impact on DJIA real returns (Simeunovic, 2016). Brune et al. (2015) has shown that an increase in the likelihood of a war tends to decrease stock prices, but the ultimate outbreak of a war increases them. However, wars that occur "out of the blue" show a different pattern as their sudden outbreaks tend to decrease stock market prices. Furthermore, research done by Piccolo and Chaudhury (2018) has shown that extreme market movements are by construction low probability events. When they do occur, they elicit the emotion of 'surprise' leading to overweighting of the incidence and hence overreaction. This effect is more pronounced when investor sentiment is low rather than high. This is because when investor sentiment is low, an extreme event appears to the investors with a greater contrast. Hudson and Urguhart (2015) analyzed the effect of World War Two (WWII) on the British stock market. They found support for the 'negative effect', documented by Akthar et al. (2011). The returns in WWII showed signs of negative effects, where stock returns reacted significantly to bad news but insignificantly to good news.

Chesney et al. (2011) analyzed the impact of terrorism on financial markets. Their results show that approximately two-thirds of the terrorist attacks considered lead to a significant negative impact on at least one stock market. Research done by Nikkenen et al. (2008) following the 9/11 attacks show that stock returns experienced significant negative returns in the short-run but recovered quickly afterwards. Nikkenin and Vähäma (2010) analyzed the effect of terrorism on stock market sentiment of the FTSE 100 index. They found that terrorist attacks have a strong adverse impact on stock market sentiment, cause a downward shift in the expected value of the FTSE 100 index and significantly increases the stock market uncertainty. An event study analysis conducted by Karolyi and Martel (2006) uncovers evidence that around the day of a terrorist attack there is significant negative stock price reaction of -

0.83%, which corresponds to an average loss per firm per attack of $401 million in firm market capitalization. Besides that, they show that terrorist attacks in countries that are wealthier and more democratic are associated with larger negative stock price reactions. Furthermore, human capital losses are associated with larger negative stock price reactions than physical losses like destruction of buildings. In research conducted by Markoulis and Katsikides (2020), one of their most important findings was that recent events do not seem to influence local or international markets, suggesting that investors have learnt to better assess terror events and react more calmy to them. This is probably not true for the Russia-Ukraine war as Brune et al. (2015), previously mentioned, found that wars "out of the blue" tend to decrease stock prices. Based on the existing literature, the first null-hypothesis of this paper will be:

$H_{1,0}$: The Russian invasion of Ukraine in 2022 did not lead to abnormal returns on the American, European and Chinese stock markets.

Jayakody (2017) analyzed the impact of the Sri Lankan civil war on the stock market performance and showed that terrorist attacks have significant different impact across industries. Brounen and Derwall (2010) compared price responses to terrorist attacks internationally and for separate industries. They found that the price reactions are the strongest for local markets and for industries that are directly affected by the attack. The impact of a terrorist attack on stock market returns is also stronger when the market is performing extremely well or poor (Park and Newaz, 2018). War opponents claim that the economic interests of the defense industry and other sectors drive conflicting parties into the use of violence. Schneider and Tröger (2004) evaluated this claim and identified the sectors that loose or gain during intensification of the hostilities. Their results show that the defense sector occasionally profits from an intensification of a conflict, while other sectors like aviation and hotels lose under an escalation of hostilities. In line with this research, Berrebi and Klor (2010) showed that terrorism has a significant negative impact of 5 % on the expected returns of non-defense-related companies while it had a significantly positive overall effect of 7% on expected stock returns on defense-related companies. Based on the literature on the impact of war and hostile events on specific industries, the second null-hypothesis of this paper will be:

$H_{2,0}$: The Russian invasion of Ukraine in 2022 did not affect the abnormal returns of American, European and Chinese defense-related stocks.

The existing literature has shown that the magnitude of impact of war and terrorist attacks on stock market returns may differ based on specific factors. Specific factors that might play a role are: democracy, wealth of a country, direct affection of country or industry, distance from the place of event, direct relations to place of event, phase of business cycle, human capital and physical losses, investor sentiment, severity of the event, cooperative or conflictive events and the involvement of world powers. In research done by Ferguson (2008) he explains that any lessons investors might have taken from the last war could have limited relevance for the next or could be forgotten after a generation of relative peace that has led to complacency. Based on the literature, the third null-hypothesis of this paper will be:

$H_{3,0}$: There are no factors that can explain the difference in abnormal returns on the American, European and Chinese stock markets.

To see if there are factors that explain difference in abnormal returns between defense-related stocks on the different stock markets, the fourth null-hypothesis will be:

$H_{4,0}$: There are no factors that can explain the difference in abnormal returns of American, European and Chinese defense-related stocks.

Table 1: Meta table of the literature review

This meta table summarizes the most important findings of the literature review. The papers are in chronological order so one can see the development of the relevant literature over time. At the end of the meta table, the most salient developments in literature are shortly discussed.

Author(s) (Publication year)	**Time period**	**Region**	**Method**	**Control variables**	**Results**
Fama (1970)	2021-2022	U.S., EU, China	Efficient Market Hypothesis		Form of market efficiency
Jensen (1978)	1945-1964	U.S.	OLS regression		Prices reflect information to the point where the marginal benefits of acting on information do not exceed the marginal cost
Grossmann & Stiglitz (1980)	1980	Model for all markets	Extension of the noisy rational expectations model		Strong form of market efficiency is false as there are information and trading costs
Shiller (2003)	2003		Critical review		Behavioral finance is now one of the most vital research programs and stand in contradiction to much of the efficient market theory
Malkier (2003)	2003	All markets	Literature review of critics on EMH		Our stock markets are far more efficient and far less predictable than some recent academic papers told us

Schneider and Tröger (2004)	1990-1999	France, U.K. and U.S.	GARCH model		Defense sector occasionally profits from an intensification of a conflict, while other sectors like aviation and hotels lose
Berkman & Jacobsen (2006)	1918-2002	International	GARCH model	Crisis triggers, gravity of crisis, great power involvement	International crises reduce stock market return by 4 percent per annum
Schneider, & Troeger (2006)	1990-2000	France, U.S. & UK	E-GARCH & T-GARCH model	Neutral countries	International conflicts affect Western financial markets negatively
Lo (2007)	2007	All markets	Critical review		Recent advances in evolutionary psychology and neurosciences may be able to reconcile the EMH with behavioral anomalies
Nikkinen, Omran, Sahlström & Äijö (2008)	2001-2002	Global stock markets	GARCH-model		The 9/11 attacks show that stock returns experienced significant negative returns in the short-run but recovered quickly afterwards
Ferguson (2008)	1945-2001	U.S.	Comparative analysis		Any lessons investors might have taken from the last war could have limited relevance for the next
Ball (2009)	2009	All markets	Critical review		The impact of efficient market theory is durable, and seems likely to continue to do so, despite its inevitable and obvious limitation
Nikkinen, & Vähämaa (2010)	2000-2005	U.K.	Multivariate regression, GARCH-model		Terrorist attacks have a strong adverse impact on stock market sentiment
Karolyi & Martell (2010)	1995-2002	International markets	Event Study Approach		Around the day of a terrorist attack there is significant negative stock price reaction of -0.83%, which corresponds to an average loss per firm per attack of $401 million in firm market capitalization
Brounen & Derwall (2010)	1990-2005	International markets	Event study methodology	Control sample of extreme events unrelated to terrorism	Price reactions are the strongest for local markets and for industries that are directly affected by the attack

Berrebi & Klor (2010)	1998-2001	Israel	Event study methodology, CAPM	Control group of American companies	Terrorism negative impact of 5 % on the expected returns of non-defense-related companies, positive effect of 7% on expected stock returns on defense-related companies
Chesney, Reshetar & Karaman (2011)	1994-2005	International markets	Event-study approach, a non-parametric methodology and a filtered GARCH–EVT approach	Interest rates, equity market integration, spillover and contemporaneous effects	Two-thirds of the terrorist attacks considered lead to significant negative impact on at least one stock market under consideration
Brune, Hens, Rieger& Wang (2015)	1939-2003	U.S.	Time series model		Increase likelihood war decrease stock price, outbreak of war increases stock prices
Hudson & Urquhart (2015)	1939-1945	U.K.	GARCH-model		Returns in WWII signs of negative effects: stock returns reacted significantly to bad news but insignificantly to good news
Simeunovic (2016)	1960-2015	U.S.	Time series model	Inflation	Entry U.S of in different wars have a different type of impact on DJIA real returns
Hoffman & Neuenkirch (2017)	2013-2014	Russia, Ukraine	Event Study	Monetary policy, day-of-the-week effects	1% ↑ escalation = 21BPS decrease returns Russia, 30BPS decrease returns Ukraine
Ankudinov, Ibragimov & Lebedev (2017)	2010-2016	Russia	OLS regression		Increased sanctions lead to an increase in volatility of returns
Jayakody (2017)	2006-2009	Sri Lanka	Event study methodology		Terrorist attacks have significant different impact across industries
Park & Newaz (2018)	1996-2015	Foreign exchange markets in 36 countries	Meta-analysis of event studies, GARCH model and quantile regression model	Returns on the MSCI World Index	Impact of a terrorist attack on stock market returns is stronger when the market is performing extremely well or poor
Piccoli & Chaudhury (2018)	1962-2010	U.S.	Event Study, OLS regression	Macro-conditions	Much stronger stock price reactions when investor sentiment is low rather than high

Biglaiser & Lektzian (2020)	1990-2005	Targeted countries & G20 countries	Autoregressive distributive lag model	Consumer price index, exchange rates	Marginal decrease in target's stock market return as number of sanction increase
Markoulis & Katsikides (2020)	1915-2011	EU, Russia and U.S.	Event study methodology		Recent events do not seem to influence local or international markets, suggesting that investors have learnt to better assess terror events

The paper of Fama (1970) is one of the most salient papers of the meta table. His efficient market hypothesis theory is an investment theory that is widely used in the financial literature. Even though there is a lot of criticism on his theory, most event studies still rely on the EMH. The paper of Schneider and Tröger (2004) is another important finding in the literature. They are one of the first papers to show that some sectors like the defense sectors profit from an intensification of an armed conflicts while other sectors lose. Nikkinen et al. (2008) uncovered important evidence after the 9/11 attacks. They showed that stock returns experienced significant negative returns in the short-run but recovered quickly afterwards. Lastly, the paper of Markoulis & Katsikides (2020) is an important development in the literature. They showed that recent terrorist attacks do not seem to influence local or international markets, suggesting that investors have learnt to better assess terror events. Even though the magnitude of impact of a war is way bigger, it might be interesting to investigate if investors also have learnt to better assess wars and international conflicts.

CHAPTER 3 Data

The stock prices of the stock markets S&P 500, STOXX 600 and the SSE Composite are obtained from the Thomson Reuters Eikon Datastream. This Datastream contains over 35 million individual instruments or indicators across all major asset classes and it features 70 years of data across 175 countries. The database has the information and tools one needs to interpret market trends, economic cycles and the impact of world events. The stock prices of each stock market are put in a separate excel sheet each so the stock market returns of each index can be calculated individually. In this way, the descriptive statistics of the different stock markets can be compared. In table 2, the data filtering criteria are shown to obtain the data from Thomson Reuters Eikon Datastream. The S&P 500, STOXX 600 and SSE Composite consist of 504, 600 and 2592 companies respectively. Overall, this brings the total sample size to 3696 stock-listed companies. The main datasets contain the stock prices of the indices from the 24th of November 2021 till the 25th of February 2022. In an extra dataset the stock prices of the indices are extended to the period of 17th of February till the 3rd of March. The extension of the period is needed for a robustness test, which will be explained in more detail in the chapter of the methodology.

To calculate the stock market return, the formula of continuous compounded returns is used. The advantage of this formula is that it takes into account that investors reinvest their returns. Furthermore, taking the logarithm of returns ensures that the returns approximately have a normal distribution. The formula of continuous compounded returns is as follows:

$$r_{it} = ln(\frac{P_{it}}{P_{it-1}}) \tag{1}$$

Where r_{it} is the continues compounded return of stock *i* in period *t*, $ln\ (\cdot)$ is the natural log function, P_{it} is the stock price of stock *i* at time *t* and P_{it-1} is the stock price of stock *i* the day prior to *t*. Based on these stock prices, the returns of the stocks on the stock markets are calculated. The general descriptive statistics of the returns of companies on the S&P 500, STOXX 600 and the SSE Composite are described in table 6 on the next page. One can see that the returns of the STOXX 600 are the lowest over the whole window of the event study.

Table 6: Descriptive statistics of the daily returns of companies on the stock markets of interest								

Where μ is the mean return of the stock listed companies of a specific stock market over the whole time period (estimation window and event window), M is the median, σ is the standard deviation, Min and Max are the minimum and maximum return, Skewness is a measure of symmetry, Kurtosis determines the heaviness of the distribution tails and N is the number of observations.

Estimation window: 3 months								
Variables	μ	M	σ	Min	Max	Skewness	Kurtosis	N
S&P 500	-0.067%	0%	2.106%	-30.694%	23.012%	-0.24533	11.31061	33728
STOXX 600	-0.132%	0%	2.434%	-35.968%	20.646%	-0.984627	12.4612	40188
SSE Composite	-0.040%	0%	3.088%	-24.747%	86.977%	0.6353114	13.65191	172583

For the defense related stocks, tables 3, 4, 5 in the appendix describe the data filtering to obtain defense stocks' prices on American, European and Chinese stock markets from the Eikon Datastream. To find SIC and NAICS codes for companies only related to military and defense is really difficult and only results in a total sample of 10 stocks across all stock markets. This sample size is way too small to conduct proper research. In the Eikon Datastream, a filter named "sector Aerospace & Defense" is applied to find more stock listed companies related to the defense industry. A lot of companies that operate in the aerospace market, operate in the defense industry as well. By applying this sector filter, the total sample size is way bigger and is feasible for research. Once all the data is retrieved, all the duplicates and all the stocks for which there is no data are removed from the data set. This brings the sample size of American, European and Chinese defense stocks to 105, 57 and 40 respectively and brings the total sample size to 202 defense stocks. The general descriptive statistics of the returns of defense companies on American, European and Chinese stock markets are described in table 7. One can see that the returns of the U.S. defense stocks are the lowest over the whole window of the event study.

Table 7: Descriptive statistics of the daily returns of defense companies on American, European and Chinese stock markets

Where μ is the mean return of the defense-related stock listed companies over the whole time period (estimation window and event window), M is the median, σ is the standard deviation, Min and Max are the minimum and maximum return, Skewness is a measure of symmetry, Kurtosis determines the heaviness of the distribution tails and N is the number of observations.

Estimation window: 3 months								
Variables	μ	M	σ	Min	Max	Skewness	Kurtosis	N
U.S. Defense	-0.448%	0%	16.489%	-845.532%	236.712%	-38.269	1973.069	7019
EU Defense	-0.054%	0%	3.924%	-69.315%	69.315%	0.592	72.047	3782
China Defense	-0.207%	0%	2.513%	-13.867%	18.312%	0.1360	6.0372	2680

For the multivariate regression analysis, which will be discussed at a later stage, some firm specific data of the stock listed firms is obtained from the Eikon Reuters dataset as well. In table 2, the datatypes that are given in between brackets in the filtering table represent the market value, price-to-book ratio, price-earnings ratio and the dividend yield. These search entries are used to find firm specific information about the stock listed companies on the S&P 500, STOXX 600 and the SSE Composite during the estimation window and event window. Furthermore, some country specific information about America, the European countries on the STOXX 600 and China is obtained from the Organisation for Economic Co-operation and Development (OECD) website. It is interesting that the OECD has information about China in its database as China is not an OECD country. Based on this, one could argue that the data obtained from OECD database about China is not as accurate as the information about OECD countries. The descriptive statistics of the dependent variable and the independent variables that are used in the first regression analysis are presented in table 8.

Table 8: Descriptive statistics of dependent variable and independent variables used in the multivariate regression of the abnormal returns of the S&P 500, STOXX 600 and SSE Composite

Where μ is the mean, M is the median, σ is the standard deviation, Min and Max are the minimum and maximum, Skewness is a measure of symmetry, Kurtosis determines the heaviness of the distribution tails and N is the number of observations. AR_0 is the abnormal return on the day of the invasion, *PE* is the price-earnings ratio, *PB* is the price-to-book ratio, *MV* is the market value of a firm, *DY* is the dividend yield, *D* is the distance in miles from Ukraine's capital Kiev, DEP_{GAS} is the dependence of a firm on Russian gas and *CCI* is the Consumer Confidence Indicator of a country.

Variables	μ	M	σ	Min	Max	Skewness	Kurtosis	N
AR_0	-.024	-.025	0.039	-.341	.162	-.308	7.399	1830
PE	42.019	24.85	106.831	1.3	2654.2	14.583	280.305	1830
PB	5.27	2.716	46.963	-397.345	1685.652	29.364	993.904	1830
MV	28895.86	7027.26	105934.29	305.39	2655825	15.876	334.348	1830
DY	1.818	1.28	2.002	0	22.38	2.669	18.489	1830
D	3462.882	4006	1402.052	506.5	4864	-.821	2.083	1830
DEP_{GAS}	.125	0	0.331	0	1	2.266	6.134	1830
CCI	100.882	101.24	2.498	97.53	103.37	-.202	1.314	1830

Based on the data that is available, the total sample size of firms that is used in the regression is 1830 stock listed companies. The Central Limit Theorem (CLT) states that when the sample size is large, the sampling distribution of the standardized sample average, is approximately normal (Stock & Watson, 2019). The CLT holds for both the dependent as the intendent variables. Often it is assumed that if the sample size has more than 100 observations, the Central Limit Theorem holds. Based on this, one does not have to worry about the non-normal distribution of variables used in the regression analysis. As a robustness check, some independent variables in the regression will be winsorized or the logarithm of the independent variables will be taken if the data of the variables are likely to have a non-normal distribution. Both techniques are often used in finance to normalize the data of variables. Winsorization is the transformation of the data by limiting the extreme values, which reduces the effect of outliers in the regression. In this paper a 90% winsorization is applied, which means that the extreme outliers below the 5th percentile and above the 95th percentile are replaced by the minimum and maximum values at the given thresholds respectively. Hair et al. (2010) and Bryne (2010) argued that data is considered to be normal in a multivariate regression if skewness is between -2 to +2 and kurtosis is between -7 to +7. These benchmark values will be used in this paper to check if an independent variable needs to be normalized. Based on the descriptive statistics in table 8, independent variables *PE*, *PB*, *MV* and *DY* need to be normalized. For variables *PE* and *MV*, the logarithm is taken to normalize data of the variables. For variables *PB* and *DY*, the winsorization technique is applied to normalize the data. In table 9 in the appendix, one can see the normalized descriptive statistics of the independent variables.

The firm specific data of the defense-related stocks is obtained in a similar way as for the stock markets and these search requests can be found in tables 3, 4 and 5. Some data on the defense budgets of America, European countries and China is obtained from the SIPRI Military Expenditure Database, which will be used for the multivariate regression of the defense-related stocks. Based on the data available, 152 defense-related stocks are used in the regression model. The descriptive statistics of the dependent variable and the independent variables that are used in the multivariate regression of the defense-stocks' abnormal returns are given in table 10.

Table 10: Descriptive statistics of dependent variable and independent variables used in the multivariate regression of the abnormal returns of the American, European and Chinese defense-related stocks

Where μ is the mean, M is the median, σ is the standard deviation, Min and Max are the minimum and maximum, Skewness is a measure of symmetry, Kurtosis determines the heaviness of the distribution tails and N is the number of observations. AR_0 is the abnormal return on the day of the invasion, *D* is the distance in miles of a defense-company from Ukraine's capital Kiev, *S* is a dummy for military support given to Ukraine, *MV* is the market value of a firm and *DY* is the dividend yield.

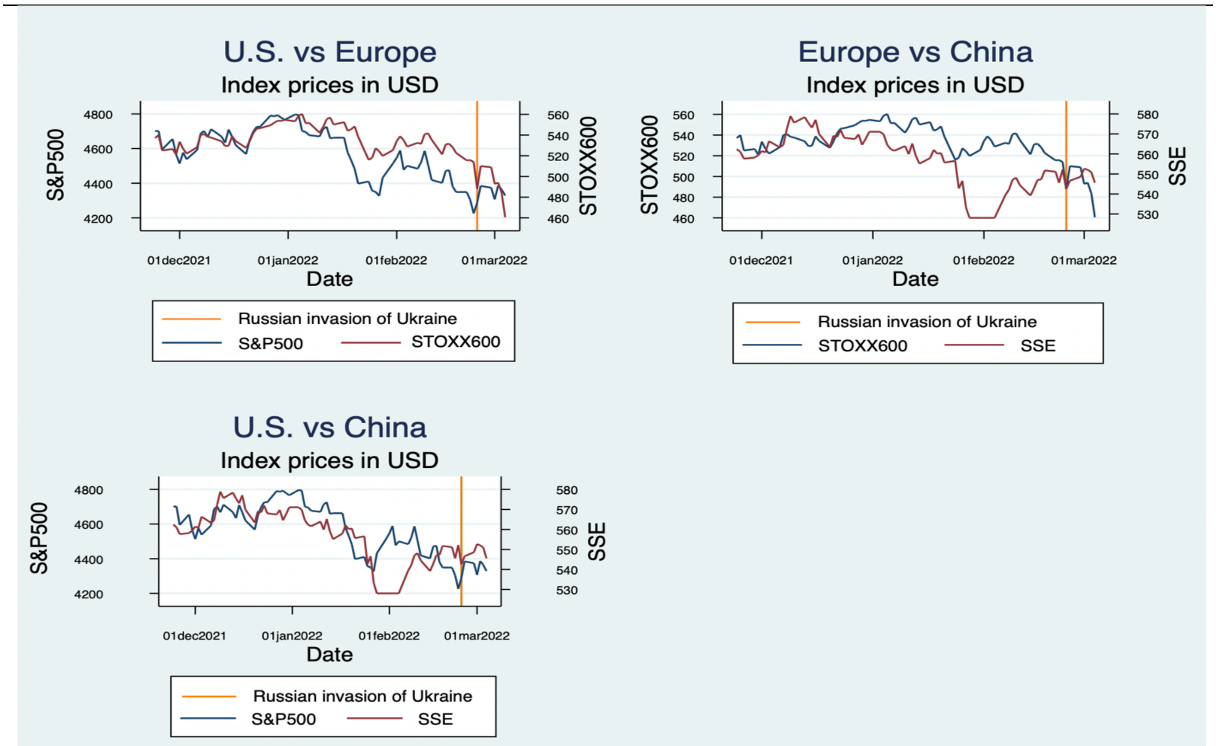
Variables	μ	M	σ	Min	Max	Skewness	Kurtosis	N
AR_0	.013	.004	0.092	-.299	.591	2.576	17.893	152
D	3373.243	4006	1630.172	464	4864	-.551	1.56	152
S	.757	1	0.431	0	1	-1.196	2.43	152
MV	2841.139	238.885	9619.471	0	95161.89	7.006	61.446	152
DY	2.823	0	24.774	0	300	11.554	138.236	152

The sample size is larger than 100 observations, which means that the Central Limit Theorem holds and that there is an approximate normal distribution of the dependent variable and independent variables. Nevertheless, similar to the first regression, a robustness check will be performed by winsorizing the independent variable or taking the logarithm of the independent variable if the variable is likely to have a non-normal distribution. Similar as in the previous regression, one looks at the skewness and kurtosis of the independent variables in table 10 to see if the variable has a non-normal distribution. Based on this data, the logarithm of variable *MV* is taken and the variable *DY* is winsorized at a 90%-level. By taking the logarithm of the variable *MV*, two observations are dropped out of the regression. This means that the total sample size is reduced to 150 observations, which means that the central limit theorem still holds. The descriptive statistics of the normalized data are given in table 11 in the appendix.

Lastly, Figure 1 represents some general data on how the stock markets moved respectively to each other during the estimation window and event window. The orange straight line indicates the Russian invasion of Ukraine.

Figure 1: Stock market movements financial markets during estimation window and event window

Stock market movements of S&P 500, STOXX 600 and the SSE Composite relatively to each other during the estimation window and the event window. The orange line represents the moment Russia invaded Ukraine (24th of February 2022).



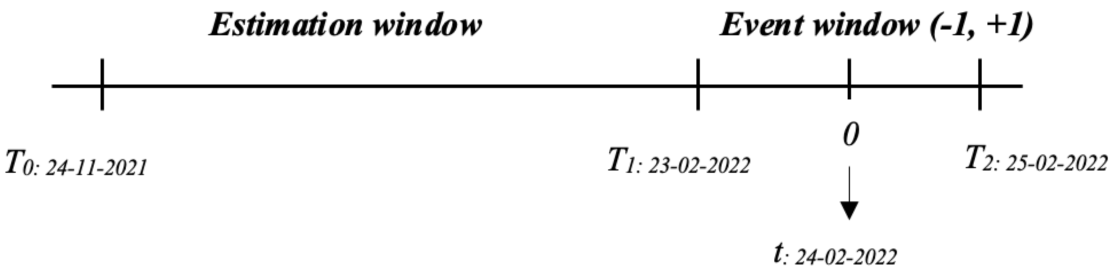
CHAPTER 4 Method

The event study methodology of Fama (1970) will be used to test hypotheses 1 and 2, which will be explained in this section. Assuming there is rationality in the market, the effects on an event will be reflected immediately in the stock prices. An event study methodology is used to measure an event's economic impact by using the stock prices observed over a short period of time. An event like this Russian invasion of Ukraine is seen as something exogeneous and this is why it lends itself to be used for an event study. Additionally, event studies could be used to test the strong and semi-strong form of market efficiency and how fast markets process new information. The main focus of this event study is to measure the impact of the Russian invasion of Ukraine in 2022 on the abnormal returns of American, European and Chinese stock listed-companies. The invasion of Ukraine shocked the world as most people thought that an invasion was unlikely. The news of the invasion came as a total surprise for investors, which makes this exogenous event suitable for an event study. Next to that, people did not expect that Putin would use so much violence by not only attacking military targets but also targeting innocent civilians from Ukraine. People within and outside Ukraine are economically and psychologically affected by the invasion. Furthermore, the invasion has caused a drastic shift in the geopolitical relationships around the globe. The unpredictability of the event, the surprise reaction of investors caused by the news, the enormous economic and phycological impact and the geopolitical shift that the Russian invasion in Ukraine in 2022 has brought along, makes the event suitable for an event study. Due to the fact that that this event is exogenous, a causal interpretation can be given on how this event influenced the (cumulative) abnormal returns.

The first task in conducting an event study is to define the event of interest and identify the period over which the stock prices of the firms involved will be examined. The time period of interest is called the event window and includes at least the day of the event and the day after the event. The time interval prior to the event period might be of interest as well and is called the estimation window. In general, the event window is not included in the estimation window to prevent the event from influencing the normal performance model parameters estimates. In this paper the estimation window starts 3 months prior to the event date and ends one day before the event window. So, the estimation window starts on the 24th of November 2021 and will end on the 22nd of February 2022. The event window $L_2=T_2-T_1$, consists of three days and will look at the day prior to the invasion, the day of the invasion and the day after the invasion (-1, +1). The event date is the 24st of February 2022 and will be $t=0$. An overview of the event study is given in figure 2. The market portfolio of firms listed on the S&P 500, STOXX 600 and the SSE Composite Index will be used for this event study.

Figure 2: Timeline of the event study

This figure gives an overview of the estimation window and the event window that is used for this event study.



The impact of the Russian invasion in Ukraine is analyzed by measuring the abnormal returns. The abnormal return is the actual ex post return of the stock over the event window minus the normal return of the firm over the event window. The normal return is defined as the expected return if the event would not take place. There are a number of approaches to calculate the normal returns of a stock. In this paper, two statistical approaches will be used to calculate the abnormal return: The constant mean return model and the market model as robustness check. For both models the assumptions is imposed that the stock returns are jointly multivariate normal and independently and next to that identically distributed through time. The constant mean market return model is one of the simplest models and yields similar results to more sophisticated models. The constant mean return model is needed for the abnormal returns and is given by the formula:

$$\overline{R_\imath} = \frac{1}{T_1 - T_0} \sum\nolimits_{t \in [T_0, T_1]} R_{it} \qquad (2)$$

Where R_{it} is the return of stock *i* in period *t*. To get to the constant mean return $\overline{R_\imath}$of a security *i,* the average returns of stock *i* in the estimation window $(T_{0,}T_1)$ are taken. The market model is a model which relates the returns of any given security to the return of the market portfolio. The market model is used as robustness check and the formula is as follows:

$$R_{it} = \alpha_i + \beta_i * R_{mt} + \varepsilon_{it} \qquad \textbf{(3)}$$

Where R_{it} is the stock market return of security *i* in period t, R_{mt} the return of the market portfolio in period t, α_i is the alpha of the market model, β_i is the stocks market risk and ε_{it} is the error term with an expected value of zero and a finite variance. The market model requires to calculate alphas and betas of individual stocks over the estimation window. The alphas and betas of the estimation window are obtained by an Ordinary Least Squared (OLS) regression with R_{it} as dependent variable and R_{mt} as independent variable. Both formulas (2) and (3) will be used to calculate the abnormal returns for stocks and defense-related stocks on the American, European and Chinese stock market. The constant mean return model is more often used in the literature due to its simplicity and will therefore be used as main formula to calculate abnormal returns. The COVID-19 crisis and the rising interest rates have led a lot of uncertainty and volatility in the market and might bias the alpha and the beta over the estimation window. Therefore, the market model will only be used as a robustness check. To calculate the expected abnormal returns, the following formulas are used:

$$\widehat{AR}_{it} = R_{it} - \bar{R}_i \quad \textbf{(4)}$$

$$\widehat{AR_{it}} = R_{it} - (\widehat{\alpha}_i + \hat{\beta}_i * R_{mt}) \quad \textbf{(5)}$$

Where $\widehat{AR_{it}}$ are the expected abnormal returns of stock *i* in period *t*, $R_{it}$is the return of stock *i* in period *t*, R_{mt} is the return of the market portfolio in period t. $\bar{R}_i$ is the mean return of security *i* in the estimation window $(T_{0,}T_1)$. The abnormal returns show the impact of the Russian invasion of Ukraine in 2022 on the American, European and Chinese stock market and its defense-related stocks. To analyze this, the average abnormal returns will be used. The formula of the expected average abnormal returns is:

$$\widehat{AAR_{it}} = \frac{1}{N}\sum_i^N \widehat{AR_{it}} \quad \textbf{(6)}$$

Where N represents the total numbers of firms on stock market or total amount of firms related to the defense industry. To analyze the overall impact of the invasion on the stock markets, the abnormal returns have to be aggregated to get to the cumulative abnormal returns. The formula of the expected cumulative abnormal returns is:

$$\widehat{CAR}_i(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} \widehat{AR_{i\tau}} \quad \textbf{(7)}$$

Where $\widehat{CAR}_i$ is the sum of the expected abnormal returns between period τ_1 and τ_2, in which τ_1 will have a value of -1 or 0 and τ_2 will have a value equal to 1. The cumulative abnormal returns that will be used are (-1, +1) and (0, +1). To analyze the overall impact on the stock markets and the defense related stocks, the cumulative average abnormal returns will be analyzed. The formula of the expected cumulative average abnormal returns is as follows:

$$\widehat{CAAR_{it}} = \frac{1}{N}\sum_{i}^{N} \widehat{CAR_{it}} \quad \textbf{(8)}$$

Where N represents the total numbers of firms on stock market or total amount of firms related to the defense industry. The $\widehat{CAAR_i}$ and $\widehat{AAR_{it}}$ will be used to test the first and second hypotheses of this paper. To test these two hypotheses and know if the results are statically significant, a parametric test will be conducted. To test the significance of this event study a t-test has to be conducted. For a t-test, there is always a null-hypothesis and an alternative hypothesis. Where the first $H_{1,0}$ means that the Russian invasion of Ukraine in 2022 did not lead to abnormal returns on the American, European and Chinese stock markets.

$$H_{1,0}: \widehat{(C)AAR_{ct}} = 0$$
$$H_{1,1}: \widehat{(C)AAR_{ct}} \neq 0$$

Where small $\widehat{(C)AAR_c}$ are the expected (cumulative) average abnormal returns of stock market *c* at time *t*. The second $H_{2,0}$ means that the Russian invasion in Ukraine in 2022 did not affect the abnormal returns of the American, European and Chinese defense-related stocks.

$$H_{2,0}: \widehat{(C)AAR_{def-ct}} = 0$$
$$H_{2,1}: \widehat{(C)AAR_{def-ct}} \neq 0$$

Where $\widehat{(C)AAR_{def-c}}$ are the expected (cumulative) average abnormal returns of defense stocks *(def)* on the stock market *c* at time *t*. To know if the results are statistically significant and to know if the null-hypotheses can be rejected, a two-sided t-test has to be conducted. It is a two-tailed t-test as the abnormal returns can either be negative, zero or positive. The formula for a t-test is as follows:

$$t - stat = \frac{\overline{(C)AAR_t} - \mu H_0}{\frac{\sigma}{\sqrt{N}}} = \frac{\overline{(C)AAR_t}}{\frac{\sigma}{\sqrt{N}}} \sim N(0,1) \quad \textbf{(9)}$$

Where $\overline{(C)AAR_t}$ is the observed mean of the (cumulative) abnormal return in period *t*, μ is the theoretical mean, σ is the standard deviation and $\sqrt{N}$ is the square root of the sample size. The t-statistic will be compared to the critical t-value. Based on this comparison, one can reject or fail to reject the null hypothesis. Given that result, an economic interpretation of the impact of the Russian invasion of Ukraine on the different stock markets and their defense-related stocks can be given. Based on this, one can conclude how fast investors price new information and what kind of form of market efficiency is present in the market.

Next to the parametric test, a non-parametric test will be conducted as a robustness check for the parametric test. These non-parametric tests are free of assumptions about the distributions of returns. In this paper, the sign test and the Wilcoxon signed-rank test will be used as non-parametric tests. Both non-parametric will be two-sided as abnormal returns can be negative or positive. The sign test requires that the (cumulative) abnormal returns are independent across stocks and that the expected proportion of positive or negative abnormal returns is equal to 0.5. Under the null-hypothesis there is an equal probability that the abnormal returns are positive or negative. Let θ_2 be the test statistic of the sign test so the formula will be:

$$\theta_2 = \left[\frac{N^{+-}}{N} - 0.5\right]\frac{\sqrt{N}}{0.5} \sim N(0,1) \qquad \textbf{(10)}$$

Where N^{+-} is the number of negative or positive abnormal returns. The H_0 is rejected if the portion of negative or positive abnormal returns on the stock markets is higher or lower than 0.5. The second non-parametric test is the test by Frank Wilcoxon (1945), which is the Wilcoxon signed-rank test. This test is more powerful than the sign test as it makes use of the magnitude of the differences rather than just their signs (King and Eckersley, 2019). This test does require that the data sample that is being tested has a distribution of differences that is symmetric. To reject this H_0, the difference between the abnormal returns and median of the abnormal returns, need to be different from zero. The difference between the abnormal returns and the median of the abnormal returns are ranked according to their magnitude in difference. Next the ranks of positive and negative differences are summed and the minimum of the sums is taken as test statistic *T= min* (T^-, T^+). If *T* is smaller than the critical value, the null hypothesis that there were no abnormal returns on the stock markets and no abnormal returns for defense-related stocks will be rejected. In this paper, the sample is larger and the following formula is used to obtain a Z-value:

$$Z = \frac{T-\mu_T}{\sigma_T} \qquad \textbf{(11)}$$

Where *T* is *T= min* (T^-, T^+), $\mu_T = \frac{n(n+1)}{4}$ and $\sigma_T = \sqrt{\frac{n(n+1)(2n+1)}{24}}$. The critical Z-value, which is based on the level of significance, will be compared to the Z-value. Based on this, one can see at which level of significance the null-hypothesis can be rejected.

Hypotheses 3 and 4 can be tested with a multivariate regression method, which will be explained in more detail in the next paragraphs. This multivariate regression analysis suits itself to test the impact of different variables on the abnormal return. The goal of a multivariate regression analysis is look at which degree independent variables and the dependent variable have a relationship. The relation is said to be linear due to the correlation between variables. The assumptions of a multivariate regression analysis are that the relationship between the dependent variable and independent variables should be linear and all observations should be independent. Furthermore, for each value of the independent variable, the distribution of the dependent variable must be normal. Lastly, the variance of the distribution of the dependent variable should be constant for all values of the independent variable. In short, the assumptions are: independence, linearity, normality and homoscedasticity (Alexopoulos, 2010). In this paper, several independent variables will be tested if they are significantly predictive for explaining differences in abnormal returns on the stock markets. Based on the abnormal returns, a cross sectional dataset will be constructed to run a multiple linear regression. The following multiple linear regression model will be used for finding predicting variables for the abnormal returns on the American, European and Chinese stock markets due the Russian invasion in Ukraine:

$$\widehat{AR_{\iota 0}} = \beta_0 + \beta_1 PE_{it} + \beta_2 PB_{it} + \beta_3 MV_{it} + \beta_4 DY_{it} + \beta_5 D + \beta_6 DEP_{gas} + \beta_7 UN + \\ + \beta_8 CCI_k + \varepsilon_i \quad \textbf{(12)}$$

Where AR_{it} are the expected abnormal returns during the event window of stock listed company i at time *0* in the event window. β_0 is the intercept of the regression line, PE_i is the price-earnings ratio of an individual stock *i* on one of the 3 stock markets on the day of the invasion *(t=0)*, PB_i is the price-to-book ratio of an individual stock *i* on the event date, MV_{it} is the market value of an individual stock in thousand US Dollars on the event date and is often used as a size indicator of a firm. Variable DY_{it} is the dividend yield of an individual stock i. The dividend yield is a ratio that tells how much an individual company i pays out in dividend relative to its current stock price. The current stock price, is the stock price of a company on the day of the Russian invasion of Ukraine. The variables PE_{it}, PB_{it}, MV_{it} and DY_{it} are all firm-specific independent variables that might explain something about the differences in the abnormal returns between companies on the day of the invasion.

Variable *D* represents the distance in miles from the capital of a stock market index to Ukraine's capital Kiev. For the S&P 500 this is Washington, for STOXX 600 the capital of a firms' country of origin is taken and for the SSE Composite this is Beijing. The distance variable is based on the gravity model of trade of Jan Tinbergen (1962). This gravity equation states that the bilateral trade between two countries is proportional to their size, measured by their GDP, and proportional to the geographic distance between two countries. Unfortunately, one cannot include the GDP as the GDP is measured per quarter and not for a specific day. Variable DEP_{gas} is a dummy variable for the dependence of a country on Russian gas. If a country is dependent for more than 20% of its import on Russian gas, the dummy variable is 1 and otherwise the dummy equals zero. The gas dependence dummy is used as variable as the boycott of Russian gas has led to a quick rise of gas prices, which is one of the main drivers of inflation.

Furthermore, the rise of the gas prices has significantly impacted companies' operations and their returns. For simplicity, it is assumed that all individual stocks from a specific country have similar dependency on Russian gas. The variable UN is a dummy variable as well and represents the United Nations support for Ukraine. The United States, China and European countries are members of the United Nations. Immediately after the Russian invasion of Ukraine, the United Nations adopted a statement to support Ukraine in this international conflict. However, China declared that they would stay 'neutral' in this international conflict. The UN dummy equals 1 for the United States and the European countries as they give United Nations support. For China this dummy equal zero as they stay neutral and do not provide support to Ukraine or Russia in this conflict. Variable CCI_k is the Consumer Confidence Index and indicates how optimistic/pessimistic consumers are regarding their financial situation in specific country k. The CCI_k indicator prior to the Russian invasion is used, so there is no impact of the invasion incorporated in the CCI indicator. The independent variables D, DEP_{gas}, UN and CCI_k are country specific variables that might have some explanatory power in explaining the difference in abnormal returns on the specific stock markets. Lastly, ε_i represents the error-term of the residuals.

The betas $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7$ and β_8 represent the regression coefficients of the independent variables PE_{it}, PB_{it}, MV_{it}, DY_{it}, D, DEP_{gas}, UN and CCI_k respectively. For some of stock-listed companies, especially from China, the independent variables are not available. The firms for which the independent variables are not available, are dropped out of the regression. Due to this, the sample shrinks from 3696 firms to 1830 firms that are used in the analysis. This is a large shrink in the sample size. However, the sample size stays large enough to get a decent interpretation of the regression coefficients. To test the third hypothesis of this paper, one needs to conduct a test of significance of the multiple regression model. This is done via an analysis of variance which makes use of the F-test. The F-test is used to check if there is a statistical linear correlation between the dependent variable and the independent variables and if the regression model provides a better fit with the dataset than with no independent variables. The F-test can be used to test significance of several coefficients but can also be used to test the significance of an individual coefficient. The formula of the F-test is as follows:

$$F_0 = \frac{MS_R}{MS_E} \quad \textbf{(13)}$$

Where MS_R is the mean square regression and MS_E is the mean square error. In essence, the F-test tests if the regression model as a whole is useful.

To test the third hypothesis, the null hypothesis and the alternative hypothesis will be:

$$H_{3,0}: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8 = 0$$
$$H_{3,1}: B_j \neq 0 \; for\ at\ least\ one\ j$$

If the P value for the F-test of the significance test is lower than significance level that is set, the null hypothesis can be rejected. Based on this, one can conclude that the regression model fits the data better with independent variables than without and furthermore the chosen independent variables in the model actually improve the fit of the model. However, if none of the independent variables in the model are statistically significant, the overall F-statistic is also not statistically significant.

To test the fourth hypothesis, similarly to the third hypothesis, a multivariate regression model will be set up to test if there are predicting variables to explain differences in abnormal returns of defense-related stocks on the American, European and Chinese stock market. Based on a cross-sectional data design, the following regression model for the abnormal returns of defense-related stocks will be tested:

$$AR_{\widehat{def-\iota 0}} = \beta_0 + \beta_1 DEFB_i + \beta_2 S + \beta_3 D + \beta_4 DEP_{gas} + \beta_5 MV_{it} + \beta_6 DY_{it} + \varepsilon_i \qquad \textbf{(14)}$$

Where AR_{def-i0} is the expected abnormal returns of defense-related stocks i at time *0,* which is the event date during the event window. β_0 is the intercept of the regression line, $DEFB_i$ is the total government spending on defense relative to the country's GDP (Defense budget/GDP). S is a dummy which equals 1 if a country gives military support to Ukraine and otherwise the dummy equals zero. For simplicity it is assumed that defense-related stocks of a specific country give similar military support to Ukraine as the government of a country. Variable D is the distance in miles from the capital of a stock market index to Ukraine's capital Kiev. For the S&P 500 this is Washington, for STOXX 600 the capital of a firms' country of origin is taken and for the SSE Composite this is Beijing. Variable DEP_{gas} is the same dummy variable as in the previous regression, which represents the dependency on Russian gas. Variables $DEFB$, S, D and DEP_{gas} are country specific variables, which might explain differences in abnormal returns between American, European and Chinese defense stocks.

Furthermore, like in the first regression, some firm specific variables will be used to analyze the difference in abnormal returns between defense-related stocks. Unfortunately, the data of the P/B and P/E ratios of most defense-related stocks is not available on the Thomson Reuters Eikon dataset. To maintain enough observations in the regression, these variables are left out. Fortunately, there is enough data on the market values and the dividend yields of defense-related stocks. Like in the previous regression, the variable MV_{it} presents the market value of an individual defense-related stock i on the event date (*t=0)* in thousand US Dollars. The variable DY_{it} represents the dividend yield of an individual defense stock *i* on the event date. The betas $\beta_1, \beta_2, \beta_{3,}\beta_4, \beta_5$ and β_6 represent the regression coefficients of the independent variables $DEFB_i$, S, D, DEP_{gas}, MV_{it} and DY_{it} respectively. For some defense related stocks there are missing variables and therefore these defense-related stocks are left out of the sample. The sample size shrinks from 203 defense-stocks to 153 defense-stocks. The sample size is not really large after the shrinkage, however still large enough to run a multivariate regression. Similarly, to other regression model, this multivariate regression model will be tested on the overall significance and on the significance of responsive variables by means of a F-test. The fourth hypothesis will be:

$$H_{4,0}: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = 0$$
$$H_{4,1}: \beta_j \neq 0 \; for\ at\ least\ one\ j$$

In multilinear regression models there might be the problem of perfect/imperfect multicollinearity between independent variables in the regression. Perfect/imperfect multicollinearity is a statistical concept that independent variables are perfectly/ highly correlated with each other. A high multicollinearity will result in an inconsistent estimate of at least one of the regression coefficients. This can lead to misleading results in how the independent variables affect the dependent variable. One can use a Variance Inflation Factor (VIF) to check if there is multicollinearity in the regression model. The formula of the VIF is as follows:

$$VIF = \frac{1}{1-{R_i}^2} \qquad \textbf{(15)}$$

Where ${R_i}^2$ represents the unadjusted coefficient of determination for regressing the i[th] independent variable on the remaining ones. Usually, a VIF above 4 and below 0.25 indicates that there is multicollinearity present and that further investigation is needed (Corporate Finance Institute, 2022). Next to this, the adjusted-R^2 will be reported, which measures the proportion of variation explained by only the independent variables that really help explaining the dependent variable. The formula of the adjusted R-squared is as follows:

$$\text{Adjusted } R^2 = 1 - \frac{(1-R^2)(N-1)}{N-p-1} \qquad \textbf{(16)}$$

Where R^2 is the sample R-squared which measures the proportion of the variation in your dependent variable explained by all of your independent variables in the model. N is the total sample size and p is the number of predictors.

One of the other important conditions that often is assumed in a multilinear regression model is homoskedasticity. Homoskedasticity refers to the condition that the variance of the error term is constant or the variance of the error term does not depend on the independent variable (Stock & Watson, 2019). However, this condition might be violated, which implies that the variance of the error term is not constant or the variance of the error term does depend on the independent variable, and is often referred to as heteroskedasticity. If there is heteroskedasticity, the computation of the regression coefficients is not affected but it does lead to incorrect standard errors. These standard errors are needed for the hypotheses testing with desired significance levels. If one does not take into account the possible problem of heteroskedasticity, the results of the regression analysis may be invalid. To test for the presence of heteroskedasticity, one can perform Breusch-Pagan test in the scientific data software STATA. The test uses the following hypotheses:

$$H_0: Homoskedasticity\ is\ present$$
$$H_1: Hetroskedasticity\ is\ present$$

If the p-value of the Breusch-Pagan test is less than some desired significance level, one can reject the null hypotheses and conclude that heteroskedasticity is present. In econometrics it is common to use a 5% significance level to test for heteroskedasticity (Statology, 2020). To overcome this heteroskedasticity problem, one can use heteroskedasticity-robust standard errors to get consistent standard errors and a valid statistical inference of the regression parameters.

A problem where one still has to deal with is the problem of endogeneity. Endogeneity refers to the situation where the independent variable is correlated with the error term. If there is endogeneity present, the regression coefficients of the independent variable become biased and inconsistent to predict the dependent variable. Furthermore, no causal effect of the independent variable can be given on the dependent variable. Common sources of endogeneity of are omitted variable bias, simultaneous causality, error-in-variables bias and selection bias. The first 3 sources of endogeneity will be discussed in more detail in the results. Selection bias is the distortion of statistics by the way in which a sample is selected (Nikolopoulou, 2022). This is unlikely to happen in this event study as the researcher has obtained the data of the stocks from the Thomson Eikon Reuters Dataset and did not select the stocks that are listed on the stock markets. Furthermore, the researcher did not categorize which stocks are defense-related stocks. Based on this, up to a certain degree the randomization of data is achieved and is it unlikely that selection bias causes endogeneity in this research. If there does exist endogeneity, it does not mean that the results of a regression analysis are completely useless. The regression analysis still shows how the regression coefficients of the independent variables are association or correlated with the dependent variable (Stock & Watson, 2019). In the results, in more detailed will be discussed how this research deals with endogeneity issues.

Overall, this will be the methodology to test the hypotheses of this research paper. To implement this methodology, the scientific data software STATA is used. This software can be used for data research of large data sets. In the next section, the results of this research paper will be examined.

CHAPTER 5 Results

5.1 Results event study

In the results, evidence will be provided to reject or accept the hypotheses that are set up for this paper. First, the results of hypotheses 1 and 2 will be discussed, which includes a robustness section for these results to check whether a change in parameters will change the results for these hypotheses. Next, hypotheses 3 and 4 will be rejected or accepted based on the results of the multivariate regression analysis. The results of these hypotheses will be tested on multicollinearity and problems like endogeneity will be discussed.

The first hypothesis which will be analyzed is:

$H_{1,0}$: The Russian invasion of Ukraine in 2022 did not lead to abnormal returns on the American, European and Chinese stock markets.

Tables 12, 13 and 14 show the abnormal returns and the cumulative abnormal returns of the S&P 500, the STOXX 600 and the SSE Composite during the event window using the constant mean model. The tables show that there were significant abnormal returns on all three stock markets on the day of the invasion. However, there is a difference in how the Russian invasion of Ukraine influenced the different stock markets.

In table 12, the abnormal returns of the S&P 500 are shown during the event window. On AR_{-1}, the day prior the invasion, there were negative average abnormal returns on the American stock market. The negative abnormal returns are statistically significant at a 1% level for both the t-test and the non-parametric tests. On the day of the invasion and the day after the invasion, AR_0 and AR_1, there were positive average abnormal returns on the S&P 500. AR_0 and AR_1 are both significant at a 1% level for both the parametric test and the non-parametric tests. Surprisingly, investors on the US stock market were able to obtain positive abnormal returns on the day of the invasion. A possible explanation for this could be that the US economy was not really affected by the Russian invasion in Ukraine in the first place. Another possible explanation could be that investors have learnt to assess violent events in a better way, which is in line with research done by Markoulis & Katsikides (2020). The Russian invasion of Ukraine started at 05:00 a.m. Central European Time (CET). The American stock market was closed at that time & this means that investors had more time to assess the severity of the event and anticipate the event. Looking at the standard deviation of AR_0 compared to the other abnormal returns, one can see that the standard deviation is much higher on the day of the invasion compared to the day prior and the day after the invasion. This implies there was a higher market volatility on the day of the invasion. Looking at the cumulative abnormal returns CAR $_{(-1, +1)}$ and CAR $_{(0,1)}$, one can see that the cumulative average abnormal returns were positive during the event window and that these cumulative abnormal returns are statistically significant at a 1% level for the t-test, the sign test and the Wilcoxon signed-rank test.

Table 13 shows that the average abnormal returns AR $_{-1}$ and AR $_{0}$ on the STOXX 600 are negative and statistically significant at a 1% level for both the t-test and the non-parametric tests. Looking at AR $_{0}$, one can see that on the day of the invasion the mean abnormal returns were -5.223%. This shows that the Russian invasion had a serious negative impact on the European stock market and that the magnitude of impact is way larger than on the American stock market. The magnitude is probably much bigger due to the fact that European stock listed companies are more closely related to Ukraine and closer to the battlefield in Ukraine. Furthermore, one can see that the standard deviation, which represents the market volatility, is much higher on the European stock market on the day of the invasion than on the days around the invasion. Surprisingly, AR_1 is positive and statistically significant at 1 % for the t-test, sign test and the Wilcoxon signed-rank test. An explanation for this could be that investors corrected their emotional responses to the Russian invasion in Ukraine from the day before. This would be in line with the research of Nikkinen et al. (2008) in which the researchers showed that there are significant negative returns with hostile events in the short-run but that financial markets recover quickly afterwards. Both CAR $_{(0,1)}$ and CAR $_{(-1,1)}$ are negative on the European stock market and these cumulative negative abnormal returns have a 1% significance level for the parametric and non-parametric tests.

Table 14 demonstrates the abnormal returns and the cumulative abnormal returns of the SSE Composite. On the day prior to the invasion, investors were able to obtain positive abnormal returns on the Chinese stock market. These positive abnormal returns have a 1% significance level. Like the STOXX 600, there were negative abnormal returns on the SSE Composite on the day of the invasion. These abnormal returns are statistically significant at a 1% level for both the t-test and the non-parametric tests. This shows that investors were shocked by the attack and that the Chinese economy might have been affected by the attack. Like the American stock market and the European stock market, the market volatility increased on the Chinese stock market on the day of the Russian invasion. This is in line with the research done by Berkman & Jacobsen (2006) where they showed that an international political crisis leads to an increase in market volatility. One day after the invasion one can see that the mean of the abnormal returns on the Chinese stock market is positive and significant at a 1% level. Looking at the cumulative abnormal returns over the whole event window, CAR $_{(-1,1)}$, one can see that the cumulative abnormal returns are positive. These cumulative abnormal returns are significant at 1% for the t-test ant the Wilcoxon signed-rank test and significant at a 5% level for the sign test. However, CAR $_{(0,1)}$ is negative and is statistically significant at a 1% level of all significant tests.

Overall, based on the results of tables 12, 13 and 14 one can conclude that the first hypothesis of this paper can be rejected. On the American, European and Chinese stock market there were significant abnormal returns due to the Russian invasion. However, the magnitude of the impact was different on the stock markets. Furthermore, it differed per stock market if investors were able to obtain positive or negative abnormal returns during the event window. This shows that investors priced the information differently on European and Chinese stock markets than on the American stock market. A possible explanation for this finding is the differences in opening hours of the stock market. The invasion started on the 24th of February at 05:00 a.m. Central European Time. At that time, the Chinese stock market was already open & the European stock market opened shortly after the invasion. These stock markets had less time to assess the event & this might have led to the negative abnormal returns. The American stock market was closed at that time and it would take 10 hours at that time before it would open again. This means that the investors had more time to assess the event and this might have resulted in the positive abnormal returns on the event date.

The second hypothesis that will be analyzed will be:

$H_{2,0}$: The Russian invasion of Ukraine in 2022 did not affect the abnormal returns of American, European and Chinese defense-related stocks.

Tables 15, 16 and 17 show the abnormal and cumulative abnormal returns of the American, European and Chinese defense-related stocks during the event window using the constant mean model. In the next few paragraphs, the results of each of these tables will be discussed in more detail.

Table 15 presents the abnormal and the cumulative abnormal returns of the American defense stocks during the event window. The average abnormal return the day prior to the invasion, AR $_{-1}$, is negative but statistically insignificant for the t-test and the sign-test. AR $_{-1}$ is only significant at a 5% level for the Wilcoxon signed-rank test. Looking at AR $_0$, one can see that the mean abnormal returns was 3.562% and statistically significant at a 1% for all significance tests. Similarly, AR_1 is positive as well and is statistically significant at 1% for the t-test and the non-parametric tests. Investors were probably able to obtain positive abnormal returns on American defense stocks due to the increased demand for military weapons to support Ukraine in their war against Russia. Like on the general stock markets one can see that the standard deviation is higher for AR $_0$ and AR $_1$. This implies that there was a higher market volatility for US defense stocks on the day of the attack and the day the day after. The cumulative abnormal returns $CAR_{(0,1)}$ and $CAR_{(-1,1)}$ are both positive and statistically significant at a 1% level for both parametric and non-parametric test, which implies that the Russian invasion did affect the abnormal returns over the total event window.

Table 16 demonstrates the abnormal returns and the cumulative abnormal returns of the European defense stocks. In table 16, one can see that AR_{-1} is slightly positive but statistically insignificant. On the day of the invasion, the mean abnormal return is -1.812%. The average abnormal return on this day is statistically insignificant for the parametric test, but is statistically significant at 5% and 1% for the sign test and the Wilcoxon signed-ranked test respectively. Based on this, one can assume that the negative abnormal returns on the event date are significant. These negative abnormal returns of the European defense-related stocks might be explained by the emotional response investors to the hostile invasion. The mean abnormal returns of the European defense stocks are positive on the day after the invasion. Furthermore, the positive abnormal returns are statistically significant at a 1% level for all significance tests. The positive abnormal returns might be explained by the increased demand by the NATO for military weapons to give military support to Ukraine. Once again, one can see that the market volatility of the defense stocks is really high on the day of the invasion. The cumulative abnormal returns over the whole event window, $CAR_{(-1,1)}$, is positive and significant at a 5% for the t-test and the Wilcoxon signed-rank test but insignificant for the sign test. $CAR_{(0,1)}$ is positive and significant at a 5% and a 10% for the t-test and the Wilcoxon signed-rank test but insignificant for the sign test once again. Based on these, one can conclude that the Russian invasion did affect the abnormal returns of European defense stocks.

Table 17 presents the abnormal returns and the cumulative abnormal returns of the Chinese defense stocks during the event window. The mean abnormal returns on the day prior to the invasion and on the day of the invasion are positive and are statistically significant at a 1% level for both the parametric test and the non-parametric tests. The positive abnormal returns for AR_{-1} and AR_0 might be explained by the fact that the Chinese got an increased demand from Russia for military weapons to attack Ukraine. Furthermore, there is an increased market volatility of Chinese defense stocks on the day of the attack. The mean abnormal return of the Chinese defense stocks on the day after the invasion is negative and statistically significant at a 1% for all the significance tests. The Chinese government did not disapprove the hostile attack of Russia in Ukraine. This might be the reason investors got out of Chinese defense stocks and which consequently led to negative abnormal returns on the day after the invasion. Both $CAR_{(0,1)}$ and $CAR_{(-1,1)}$ are positive and statistically significant at 1% for the t-test, the sign test and the Wilcoxon signed-rank test. All the abnormal and cumulative abnormal returns are statistically significant for the Chinese defense stocks. Based on this, one can conclude that the Russian invasion did lead to abnormal returns on Chinese defense stocks.

Overall, one can reject the second hypothesis that the Russian invasion did not affect the abnormal returns of the defense stocks. The American, European and Chinese defense-related stocks all show significant abnormal returns on the event day and the day after. Furthermore, the abnormal returns of the American, European and Chinese defense-related stocks differ in their magnitudes and differ in the fact that they are positive or negative. However, the American, European and Chinese defense-related stocks all had positive cumulative average abnormal returns over the event window. This is in line with researches done by Schneider & Tröger (2004) and Berrebi & Klor (2010) who both showed that the defense sector profits from an intensification of a conflict or from terroristic attacks.

The rejection of the first and second hypotheses show that investors were not able to anticipate to the Russian invasion of Ukraine. The negative psychological and social impact of the invasion let to irrational decision making of investors. The S&P 500, the American defense-related stocks and Chinese defense-related stocks showed significant positive abnormal returns on the event date. The STOXX 600, the SSE Composite and the European defense-related stocks had significant negative abnormal returns on the day of the invasion. The magnitude of defense-related stocks' abnormal returns is in general higher than the abnormal returns of the American, European & Chinese stock markets. Furthermore, there is a higher market volatility for the defense-related stocks on the event date than on the three stock markets. Due this higher market volatility, investors were able to lock in superior returns on the defense-related stocks compared to the general stock markets. In general, the war news resulted in a higher market volatility and higher positive (cumulative) abnormal returns for the defense-related stocks. Based on this, one might conclude that the war in Ukraine came as positive news for the defense industry. The significant abnormal returns demonstrate that investors were not able to incorporate all information in the stock prices and anticipate on the attack. The event study analysis shows that the market was in a semi-strong form of market efficiency on the day of the invasion.

5.2 Robustness section event study

In this section some robustness checks will be performed to check if a change in parameters will alter the outcome of the results and check if one of the first two hypotheses might not be rejected. First, an alternative method of calculating the abnormal returns will be used to check if this changes the results. Secondly, the event window will be expanded to see if a larger event window will change outcomes.

The market model will be used to calculate the abnormal and cumulative abnormal returns in an alternative way to check if this method of calculating changes the results. Table 18 up to and including table 20 present the abnormal and cumulative abnormal returns of the American, European and Chinese stock markets using the market model as calculation method. Table 21 up to and including table 23 demonstrate the abnormal and cumulative abnormal returns of defense stocks using the market model.

Looking at table 18, it is striking to see that the abnormal returns and the cumulative abnormal returns of the S&P 500 are much smaller in magnitude using the market model than when using the constant mean model. Furthermore, AR_{-1} is insignificant in the market model while significant at a 1% level for all significance tests in the constant mean model. Moreover, it is interesting to see that the mean abnormal returns on the day of the invasion are negative & significant using the market model while they are positive in the constant mean model. It makes more sense that these abnormal returns are negative on the day of the invasion as the Russian attack in Ukraine is seen as a terrible event and negative influences the global economy. Besides that, the European and Chinese stock market also showed significant negative abnormal returns on the day of the invasion with the constant mean model. Similarly, to the constant mean model, the market model also shows that there is an increased standard deviation on the day of the invasion, which means that there is a higher market volatility on the event date.

Table 19 shows the abnormal and cumulative abnormal returns of the STOXX 600 using the market model. A striking difference compared to the constant mean model is that almost all abnormal and cumulative abnormal returns are statistically insignificant when using the market model. Only AR_{-1} is statistically significant at 1% for the t-test. All other abnormal returns and cumulative abnormal returns are insignificant for the event window. As mentioned earlier, the COVID-19 crisis and the rising interest rates have led a lot of uncertainty and volatility in the market and might bias the alpha and the beta of the market model. These biased alphas and betas in turn might lead to unreliable results.

Table 20 demonstrates the abnormal and cumulative abnormal returns of the SSE Composite using the market model. The results of table 16 are in line with the results of table 10. Almost all abnormal and cumulative abnormal returns are statistically significant at 1%. However, the magnitude of impact is much smaller under the market model. Similarly, to the constant mean model, there is an increased market volatility on the day of the invasion. The only striking difference is that $CAR_{(-1,1)}$ is statistically insignificant using the market model while this CAR is statistically significant at 1%- or 5%- level when using the constant mean model.

Table 21 shows the abnormal and cumulative abnormal returns of American defense stocks using the market model. The results of table 21 are similar to the results of table 15. The magnitude of the (cumulative) abnormal returns is much lower when using the market model. Moreover, AR_{1} is statistically insignificant in table 21 while this AR is statistically significant in table 15 at a 1% level for all both the parametric test and the non-parametric tests. Like in table 15, table 21 shows that there is an increased market volatility of the US defense stocks on the day of the invasion and the day after the invasion.

Table 22 shows the (C)ARs of the European defense stocks using the market model. An interesting difference between table 22 and table 16 is that the abnormal returns on the event day are positive and statistically significant at a 5% level for all significant tests in table 22. In table 16, AR_0 is negative and statistically insignificant for the t-test and significant at a 5% and 1% level for the sign test and the Wilcoxon signed-rank test respectively. The results of table 22 for AR_0 make more sense as there probably was an increased demand for military weapons on the day of the Russian invasion and therefore investors were probably able to obtain positive abnormal returns on European defense stocks. Once again, the magnitude of impact of the invasion on the (C)ARs is lower and there also is an increased market volatility of the European defense stocks on the day of the invasion and the day after the invasion. Table 23 represents the abnormal and cumulative abnormal returns of the Chinese defense stocks using the market model. Tables 23 and 17 show similar results in their (C)ARs and in both tables most (C)ARs are statistically significant at a 1%-level for all the significant tests. The size of the CARs are similar and there is an increased market volatility on the day of the event.

Overall, the market model provides results which show that the Russian invasion of Ukraine had a lower magnitude of impact on the abnormal returns than in the constant mean model. Furthermore, the results are more often statistically insignificant. However, for the S&P 500 the market model provides negative abnormal returns on the event date, which makes more sense from an economic point of view as investors were shocked by the invasion of Ukraine. Furthermore, the European defense-related stocks have significant positive abnormal returns on the day of the invasion instead of negative abnormal returns in the constant mean model. This makes more sense from an economic point of view as one would expect an increase in demand for military weaponry by Ukraine which would lead to an increase in returns for defense-related stocks.

Table 24 up to and including table 29 present the results of the abnormal and cumulative abnormal returns when the event window is expanded to (-3, +3). Tables 30 up to and including table 35 present the abnormal and cumulative abnormal returns when the event window is expanded to (-5, +5). The event window is expanded to see if an expansion of the event window leads to more significant (cumulative) abnormal returns on days surrounding the event date.

Table 24 and table 30 show the results of abnormal and cumulative abnormal returns of the S&P 500 when the event window is expanded to (-3, +3) and (-5, +5). Expanding to (-3, +3) shows that there are positive abnormal returns and cumulative abnormal returns for AR_{-3} and $CAR_{(-2,2)}$ which are statistically significant at 1% for all significance tests. Furthermore, there are negative abnormal returns for AR_{-2}, AR_{2}, AR_{3} and $CAR_{(-3, +3)}$. These are returns are all significant at a 1% level for the t-test, sign test and the Wilcoxon signed-rank test. When the event window is expanded even further to (-5, +5), one can see that there are more significant abnormal returns. Values AR_{-5}, AR_{-4}, AR_{5} and $CAR_{(-5,5)}$ show negative abnormal and cumulative abnormal returns which are significant for most of the tests at a 1% level. The AR_{4} and the $CAR_{(-4,4)}$ show positive abnormal returns which are also significant at a 1% level for all significance tests. Overall, one can see that expanding the event window for the S&P 500 does not change much to the existing results and only leads to more significant abnormal and cumulative abnormal returns. Figure 3 gives a clear overview of the average abnormal returns of the S&P 500 during the event window.

In table 25 one can see what happens to the cumulative abnormal returns and the abnormal returns of the STOXX 600 if the event window is expanded to (-3, +3). The table shows that expanding the event window leads to negative abnormal returns for AR_{-3}, AR_{3} and $CAR_{(-3,3)}$ which are significant at a 1%-level for the t-test, sign test and the Wilcoxon signed rank test. Value AR_{2} has significant positive abnormal returns at a 1%-level and AR_{-2} has positive abnormal returns at a 1% and 5% significance level for the t-test and the Wilcoxon test respectively. Value $CAR_{(-2,2)}$ has negative cumulative abnormal returns but these returns are statistically insignificant. Looking at table 31, one can see what happens to the (C)ARs if the event window is expanded to (-5, +5). The abnormal and cumulative abnormal returns AR_{-5}, AR_{-4}, AR_{5}, $CAR_{(-4,4)}$, $CAR_{(-5,5)}$ all show negative abnormal returns which are significant at a 1%-level for all significant tests. Only AR_{4} has positive abnormal returns which are only significant at 10% level for the sign test. Overall, one can see that the expanding the event window for the STOXX 600 mostly leads to more significant negative abnormal returns. Figure 4 provides an overview of the average abnormal returns of the STOXX 600 during the event window.

Table 26 and table 32 show what happens to the abnormal and cumulative abnormal returns of the SSE Composite when the event window is expanded to (-3, +3) and (-5, +5). Expanding to (-3, +3) leads to positive abnormal returns for AR_{-3}, AR_{3} and $CAR_{(-3,3)}$ which are significant at a 1% level for the significance tests. It leads to negative abnormal returns and cumulative abnormal returns for values AR_{-2} and $CAR_{(-2,2)}$ and has a 1%-significance level. For AR_{2} there are also negative abnormal returns which are significant for the non-parametric tests at 1%. However, the t-test value is so low that it is doubtable if these negative abnormal returns are really significant. Expanding the window to (-5, +5) leads to significant positive abnormal returns and cumulative abnormal returns for AR_{-4}, AR_{4},

$CAR_{(-4,4)}$ and $CAR_{(-5,5)}$ at a 1% level for all significance tests. Both AR_{-5} and AR_5 are negative abnormal returns which are significant at a 1% level for the t-test, sign test and the Wilcoxon signed rank test. In contradiction to the STOXX 600, expanding the event window for the SSE Composite mostly leads to more significant positive abnormal returns. Figure 5 provides an overview of the average abnormal returns of the SSE Composite during the event window.

In table 27, the cumulative abnormal returns and the abnormal returns of the US defense stocks are given when the event window is expanded to (-3, +3). The mean abnormal returns 3 days prior to the invasion, AR_{-3}, are positive and statistically significant at 1% and 5% for the t-test and sign test and statistically insignificant for the Wilcoxon-signed rank test. The negative abnormal returns of AR_2 are statistically insignificant. The AR_3 is negative and is only significant for the sign test at 10%, so one can conclude that these abnormal returns are probably insignificant. However, the cumulative abnormal returns $CAR_{(-2, 2)}$ and $CAR_{(-3,3)}$ are positive and statistically significant at 1% for all significance tests. In table 33, the event window is expanded to (-5 +5). AR_{-5} shows a negative mean abnormal return which is statistically significant at 5% for the t-test, insignificant for the sign test and statistically significant at 1% for the Wilcoxon-signed rank test. Value AR_{-4} shows a negative abnormal return that is significant at 1% for all significance tests. The mean abnormal returns on day 4 after the invasion are positive, significant at 5% level for the t-test and the sign test and significant at a 1% level for the Wilcoxon-signed rank test. AR_5 is positive but is only significant at 5% for the Wilcoxon test. The $CAR_{(-4,4)}$ is positive and statistically significant at 5% and 1% for the parametric test and the non-parametric test respectively. However, $CAR_{-(5,5)}$ is positive but is only significant at 5% for the Wilcoxon test. Figure 6 provides an overview of the average abnormal returns of the defense-related stocks. Overall, expanding the event window especially leads to more significant positive cumulative abnormal returns for the US defense stocks.

Table 28 presents the cumulative abnormal returns and the abnormal returns of European defense stocks when the event window is expanded to (-3, +3). Variable AR_{-3} shows negative abnormal returns which are statistically significant at 1% for the t-test and statistically significant at 5% for the sign test. AR_{-2} is statistically insignificant for all significance tests. AR_2 is positive and statistically significant at 1% for all significant tests. AR_3 is negative and is statistically insignificant for the t-test, significant at 5% for the sign test and significant at 1% for the Wilcoxon sign test. The $CAR_{(-2,2)}$ is positive and statistically significant at 1% for all significance tests. $CAR_{(-3,3)}$ is only significant at 10% for the t-test and sign test. In table 34, the event window is expanded to (-5, +5) and shows the impact on the abnormal returns and cumulative abnormal returns. AR_{-5} is negative and statistically significant at 5% for the t-test, 10% at the sign test and 1% at the Wilcoxon test. AR_4 is negative is as well and is statistically significant at 5%

for t-test and the sign test and significant at 1% for the Wilcoxon-test. AR_5 is positive but only significant at 5% for the Wilcoxon-signed rank test. The $CAR_{(-5,5)}$ is positive but is only significant at 10% for all three significance tests. Values AR_4 and $CAR_{(-4,4)}$ are both statistically insignificant. An overview of the average abnormal returns of the European defense-related stocks is given in figure 7. Based on this, one can conclude that expanding the event window for the European defense stocks does not lead to more significant abnormal and cumulative abnormal returns (with exception of $CAR_{(-2,2)}$).

Finally, table 29 and table 35 demonstrate the abnormal and cumulative abnormal returns of the Chinese defense stocks when to event window is expanded to (-3, +3) and (-5, +5) respectively. Values AR_{-3}, AR_3, $CAR_{(-2,2)}$ and $CAR_{(-3,3)}$ are all positive and statistically significant at a 1% level for all significance tests when the event window is extended to (-3, +3). Value AR_{-2} is negative and is significant at 5% for the t-test and significant at 1% for the non-parametric tests. Only AR_2 shows insignificant results when the event window is expanded. Expanding the window to (-5, +5) leads to positive abnormal returns and cumulative abnormal returns for AR_{-5}, $CAR_{(-4,4)}$ and $CAR_{(-5,5)}$ which are significant at 1% for all significance tests. The AR_{-4} is negative and significant at 1% for the t-test and at 5% for the non-parametric tests. Value AR_4 is negative but is only significant at 10% for the parametric tests. The AR_5 shows a negative mean of the abnormal returns and these abnormal returns are significant at a 1% level for all significant tests. An overview of the average abnormal returns for the Chinese defense-related stocks are given in figure 8. Overall, one can conclude that expanding the event window for the Chinese defense stocks mainly leads to more significant positive abnormal returns.

In short, expanding the event window to (-3, +3) and (-5, +5) mostly led to more significant positive abnormal and on the Chinese stock market. Likewise, one can see that expanding the event window also led to more significant positive abnormal returns for Chinese defense-related stocks. Expanding the event window for the American and European stock market and their defense-related stocks led to more significant negative abnormal returns or to insignificant results. A possible explanation for this is that by expanding the event window, there is more noise and there are fewer signals in the stock prices and the (cumulative) abnormal returns. In efficient markets, one can expect that the information of the war is incorporated in stock prices in a single day. It might be the case that the Chinese stock market and the Chinese defense-related stocks are less efficient than the American and European stock markets and their defense-related stocks. Therefore, it might take more time for the Chinese stock market and the Chinese defense-related stocks to incorporate all information which in turn leads to more significant abnormal returns when expanding the event window.

5.3 Multivariate regression analysis

In this section, the results of hypotheses 3 and 4 will be discussed in more detail. Next to a detailed discussion of the result, problems like heteroskedasticity, multicollinearity and endogeneity will be discussed. An approach will be given on how to overcome these problems or minimize the impact of these problems.

The third hypothesis that will be analyzed is:

$H_{3,0}$: There are no factors that can explain the difference in abnormal returns on the American, European and Chinese stock markets.

The first multivariate regression model (12) mentioned in the method chapter will be used to answer this hypothesis. For calculating the abnormal returns, the normal returns were taken in logarithm. This helps to normalize the returns as far as possible. Based on prior research done by Dissanaike & Le Fur (2003), taking the logarithm of (cumulative) abnormal returns leads to biased results or does not portray a realistic portfolio strategy. So, by taking the logarithm of the normal returns is as far as one can go to normalize the distribution of the dependent variable, which is in this case the abnormal return on the event date. First, one runs the general multivariate regression model in STATA to see if there is any correlation between the interdepend variables and the dependent variables. Fortunately, there is some significant correlation between the independent variables and the dependent variables. However, the model might suffer from problems like heteroskedasticity, multicollinearity or endogeneity and therefore one needs to check if these problems are present in this regression model. Furthermore, extreme outliers in the regression might cause problems as well. Therefore, in the robustness section of this multivariate regression analysis, the independent variables are winsorized or the logarithm is taken to see if the results change if one removes extreme outliers and the data has an improved normalized distribution.

First of all, one needs to check if there is multicollinearity present by using the Variance Inflator Factor. The results of the test for multicollinearity between the independent variables is found in table 36A. In general, there is serious multicollinearity between the independent variables if the VIF is above 4 or below 0.25. As one can see in the table, the VIF of the *UN* and the *CCI* are really high, which implies that they have a high multicollinearity. To solve multicollinearity, the variable with the highest VIF is dropped out of the model to see if the multicollinearity is solved. In this case dummy variable *UN* is dropped out of the regression to see if the problem of multicollinearity is solved. In table 36B, one can see the test for multicollinearity without the dummy variable *UN*. The VIF factors are in between 4 and

0.25 for all the independent variables and for the mean VIF as well. This implies that the problem of multicollinearity is resolved by dropping dummy *UN*.

Table 36 A & B: Variance inflation factors of the stock market's multivariate regression

The Variance Inflator Factor (VIF) is used to check the presences of multicollinearity between independent variables in a regression. The VIF is based on the following formula (15):

$$VIF = \frac{1}{1 - {R_i}^2}$$

Where ${R_i}^2$ represents the unadjusted coefficient of determination for regressing the i^{th} independent variable on the remaining ones. Variable *UN* is a dummy variable to show if a country gives United Nations support, *CCI* is the Consumer Confidence Index, *D* is the distance in miles from Ukraine's capital Kiev, DEP_{GAS} is a dummy for the dependence of a country on Russian gas, *DY* is the dividend yield, *MV* is the market value, *PE* is the price-earnings ratio and *PB* is the price-to-book ratio.

Table 36A: Variance inflation factor

	VIF	1/VIF
UN	74.893	.013
CCI	63.774	.016
D	7.551	.132
DEP_{GAS}	2.436	.41
DY	1.139	.878
MV	1.089	.918
PE	1.022	.979
PB	1.008	.992
Mean VIF	19.114	.

Table 36B: Variance inflation factor without UN

	VIF	1/VIF
D	1.839	.544
DEP_{GAS}	1.745	.573
DY	1.138	.879
CCI	1.131	.884
MV	1.087	.92
PE	1.021	.979
PB	1.008	.992
Mean VIF	1.281	.

Secondly, a Breusch-Pagan test is performed to test for the presence of heteroskedasticity. Table 37 shows the results of the Breusch-Pagan test. The test p-value shows that there is heteroskedasticity present in the linear multivariate regression model. To solve this problem, heteroskedastic-robust standard errors have to be used to get the correct statistical inference of the regression coefficients.

Table 37: Breusch-Pagan test for heteroskedasticity
The Breusch-Pagan test is a general test used for the presence of heteroskedasticity. In this test the following assumption holds for the abnormal returns on the event date: Assumption: Normal error terms Variable: Fitted values of AR_0
H_0: Constant variance chi2(1) = 57.70 Prob > chi2 = 0.0000

Thirdly, there might be a problem of endogeneity of interdependent variables which leads to biased and inconsistent results of the regression coefficients. The Russian invasion of Ukraine is an exogenous event. This exogenous shock/event suits itself to be used for an event study. Due to this exogeneity, a causal effect of the Russian invasion on the (cumulative) abnormal effect can be identified. These causal effects of the Russian invasion on the abnormal returns of stock markets and defense-related stocks were discussed earlier. However, in this multivariate regression it is about country and firm specific variables that might explain something about the differences in abnormal returns between companies. It is not likely that this regression model suffers from errors-in-variable bias, which might cause endogeneity, as all the data that is used is from high end data sources like Thomson Eikon Reuters. Simultaneous causality is the case when the dependent variable and the independent variable simultaneously influence each other. Simultaneous causality might cause endogeneity issues. In this regression model is unlikely that the abnormal returns also influence the independent variables used in this regression. The country specific variables D, DEP_{GAS} and CCI are not influenced by abnormal returns as extreme high profits or losses do not impact these variables. The firm specific variables *PE, PB, DY* and *MV* are not directly influenced by the abnormal returns on the day of the invasion. If abnormal returns exist for a longer period of time, these firm specific variables might change in the future. However, in this case only the abnormal returns on the event day are analyzed. Therefore, this model unlikely to suffer from simultaneous causality.

A third possible way endogeneity might exist is due to omitted variables from the regression model. Relevant variables that might explain something about the dependent variable are omitted, which would result in the error term being correlated with the independent variables in the regression model. To check if there are omitted variables, a Ramsey RESET test for omitted variables is done. This test checks if there are omitted variables. The null hypothesis assumes that there are no omitted variables. The results of this test are represented in table 38.

Table 38: Ramsey RESET test for omitted variables
The Ramsey RESET (regression specification-error test) test if the model has omitted variables. This test ensures that the omitted variables are not causing model-misspecifications. The test checks the following:
Omitted: Powers of fitted values of AR0
H_0: Model has no omitted variables
F (3, 1819) = 17.38
Prob > F = 0.0000

The p-value of this test rejects the null hypothesis that there are no omitted variables in the regression models. This result thus implies that the regression model suffers from omitted variable bias. One way to deal with omitted variable bias is to include as many relevant variables as possible, if the data is available. Unfortunately, in this case there is not enough extra firm specific data available for all firms of the S&P500, the STOXX 600 and the SSE Composite on the Thomson Eikon Reuters Dataset. For some firms this data is available, however for most of the firms this firm specific variable is available over larger periods of time but not on the specific event date on the 24th of February. The same problem accounts for other datasets like Bloomberg where the data often is available over longer time periods, but not on the specific event date. One needs firm constant data or data that is specific on the event date. Most of this firm-specific data is not publicly available on the event date. In this case there is not data to keep a large enough sample for a decent regression analysis. Due to this more relevant variable which might explain something about the abnormal returns cannot be included. Similarly, most country specific data is not available on the event date or is not publicly available at all. Based on this, one can conclude that all the data that is publicly available and has enough data points for a regression, is included in the analysis.

If there is not enough data available on the event date or the data is not publicly available at all, one can use proxy variables or instrumental variables to solve the omitted variable bias. However, according to research done by Lynch & Brown in 2011 about endogeneity of cross-sectional data it is difficult finding appropriate instruments if not impossible in studies with few variables. In this research with cross sectional data there are only a few variables available & finding instrumental variables for the missing data is really difficult as well. Next to that, this dataset contains so many different kinds of firms from 3 large stock markets, which makes it extremely difficult to capture the individual heterogeneity. Due to the fact that it is cross-sectional data, one cannot make use of firm-fixed or firm-random effects which is often used in panel data to control for unobserved data/individual heterogeneity. Based on this, it seems like that the endogeneity issues cannot be ruled out in this regression. This implies that the regression coefficients of the regression are biased and inconsistent. Next to that, no causal relationship between the dependent variable and the independent variables can be given. If a causal relationship could have been analyzed, still it does not mean that a correlation between dependent variable and the independent variable means causation. In this case, only the correlation between the independent variables and the dependent variable can be analyzed. In table 39, one can see the correlation between the dependent variable and the independent variables.

Table 39: Multivariate linear regression of the abnormal returns of the S&P500, STOXX600 and SSE Composite on the event date

Model specification:

$$AR_0 = \beta_0 + \beta_1 * PE + \beta_2 * PB + \beta_3 * MV + \beta_4 * DY + \beta_5 * D + \beta_6 * DEP_{GAS} + \beta_7 * CCI \qquad (12)$$

Where PE is the price-earnings ratio, PB is the price-to-book ratio, MV is the market value of a firm, DY is the dividend yield, D is the distance in miles from Ukraine's capital Kiev, DEP_{GAS} is the dependence of a firm on Russian gas and CCI is the Consumer Confidence Indicator of a country. β_0 is the intercept and the betas β_1, β_2, β_3, β_4, β_5, β_6 & β_7 are the regression coefficients of the independent variables. The robust standard error, t-value, p-value and the 95% confidence interval of each coefficient is given in the table. The asterisks ***, **, * provide the level of significance. Furthermore, the mean and the standard deviation of the dependent variable are provided. Next to that the R^2, the adjusted-R^2, the F-test and the number of observations are given in the lower part of the table.

AR_0	Coef.	Robust St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
PE	0	.00001	0.17	.86781	-.00002	.00002	
PB	.00001	.00001	1.54	.12259	0	.00003	
MV	0	0	2.42	.01568	0	0	**
DY	-.00372	.00054	-6.91	0	-.00477	-.00266	***
D	.00001	0	18.21	0	.00001	.00002	***
DEP_{GAS}	.00539	.0035	1.54	.12302	-.00146	.01225	
CCI	-.00368	.0003	-12.24	0	-.00427	-.00309	***
Constant	.30213	.03164	9.55	0	.24007	.36419	***

Mean dependent var	-0.02380	SD dependent var	0.03889
R-squared	0.38397	Number of obs	1830
Adjusted R-squared	0.38159	Prob > F	0.00000
F-test	127.26914		

**** p<.01, ** p<.05, * p<.1*

The results in table 39 show that there is some significant correlation between the abnormal returns on the event date and some firm and country specific variables. One can see that there is a negative correlation between a dividend yield and the abnormal returns which is significant at a 1% level. This means that firms which have higher dividend yield are associated with lower abnormal returns. Furthermore, one can see that a larger distance from Kiev is associated with higher abnormal returns at a 1% significance level as well. This makes sense from an economic point of view as firms further away from the conflict are probably less likely to be influenced by Russian invasion of Ukraine. The variable CCI shows a negative correlation with the abnormal returns which is significant at a 1% level. This implies that higher consumer confidence is associated with lower abnormal returns. This might be due to the fact that if the consumer confidence is high, a violent conflict like the Russian invasion of Ukraine comes as a bigger surprise and is thus associated with a decrease in abnormal returns. The variables PE and PB are statistically insignificant and their relationships with the abnormal returns are zero or close to zero respectively. The variable MV is statistically significant at 5%, however the positive correlation with the abnormal returns is so small that it is negatable to zero. The variable D_{GAS} has a positive correlation with the abnormal returns, which does not make sense from an economic point of view. One would expect a negative correlation between abnormal returns and the dependency on Russian gas as firms are negatively impacted by the boycott of Russian gas. However, the correlation is statistically insignificant which means one cannot infer something about the true correlation between the abnormal returns and the dependency on Russian gas. Lastly, in table 40 in the appendix one can see the regression results if *CCI* would have been left out instead of *UN* because of high multicollinearity between the two independent variables. The result shows that supporting Ukraine in this conflict is positively associated with abnormal returns. This makes sense from economic point of view as most countries support Ukraine in this conflict and most investors disgust countries that do not support Ukraine or even support Russia's inhuman attacks on Ukraine's population.

Overall, based on these results one fails to reject the third hypothesis to explain the differences in the abnormal returns on the American, European and Chinese stock market. Due to endogeneity issues, one cannot give a causal interpretation of the differences in abnormal returns on the stock markets. There is some significant correlation between the independent variables *DY, D, CCI* and the abnormal returns on the event date. Unfortunately, the endogeneity issue does not make it possible to give a causal interpretation of the regression results. Otherwise, the distance from Ukraine's capital Kiev would have been a good variable to give a causal explanation of the differences in abnormal returns on the different stock markets. Next to that, the R-squared is not extremely high, which means that the independent variables do not explain that much about the variation in the abnormal returns.

A similar procedure as the third hypothesis will be used to answer the fourth hypothesis of this paper. With the help of a multivariate regression model, the following hypothesis will be analyzed:

$H_{4,0}$: There are no factors that can explain the difference in abnormal returns of American, European and Chinese defense-related stocks.

The multivariate regression of the defense-related stock consist of fewer independent variables as there is less information available about these defense-related stocks in general and less information available of these stocks on the event date. Like the previous regression, one needs to check if there is a high multicollinearity between the independent variables. This is done in a similar way, by using the Variation Inflation Factor (VIF). Table 41A in the appendix shows there is a high multicollinearity between the variables D_{GAS} and variable *D* and the mean VIF is too high as it has to be between 0.25 and 4. Therefore, the variable with the highest VIF factor is dropped out of the regression to see if the problem if multicollinearity is resolved. In this case the variable D_{GAS} is dropped out and the VIF without this independent variable is shown in table 41B (in the appendix). Without this variable, there is a high multicollinearity between the variable *DEFB* and the variable *D* and the mean VIF is still too high. Therefore, the variable DEFB is propped out of the regression as this independent variable has the highest VIF. Table 42 shows the VIF without D_{GAS} and *DEFB*. These Variance inflation factors show that there is no serious multicollinearity present in the model anymore. Therefore, the variables *D, S*, *MV* and *DY* will be used in the regression analysis.

Table 42: Correct variance inflation factor of defense-related stocks without D_{GAS} & DEFB

The Variance Inflator Factor (VIF) is used to check the presences of multicollinearity between independent variables in a regression. The VIF is based on the following formula (15):

$$VIF = \frac{1}{1 - R_i^{\ 2}}$$

Where $R_i^{\ 2}$ represents the unadjusted coefficient of determination for regressing the ith independent variable on the remaining ones. Where *D* is the distance in miles from Ukraine's capital Kiev, *S* a dummy variable if military support is given, *MV* the market value of a defense company and *DY* is the dividend yield of a defense-stock.

Variance inflation factor		
	VIF	1/VIF
D	1.106	.904
S	1.063	.94
MV	1.049	.954
DY	1.011	.989
Mean VIF	1.057	.

Next one needs to check if there is heteroskedasticity present by conducting a Breusch-Pagan test in STATA again. In table 43, one can see the Breusch-Pagan test for heteroskedasticity. Based on the p-value one fails to reject the null-hypothesis of a constant variance. This implies that the regression model does not suffer from the problem of heteroskedasticity and that reporting standard errors is sufficient to get a correct statistical inference about the regression coefficients.

Table 43: Breusch-Pagan test for heteroskedasticity for defense-related stock regression

The Breusch-Pagan test is a general test used for the presence of heteroskedasticity. In this test the following assumption holds for the abnormal returns on the event date:

Assumption: Normal error terms
Variable: Fitted values of AR_0

H_0: Constant variance
chi2(1) = 0.01
Prob > chi2 = 0.9143

Lastly, one needs to check if the model suffers from endogeneity. As explained before, three possible ways endogeneity might arise is due to errors-in-variable bias, simultaneous causality and omitted variable bias. Error-in-variable bias is unlikely as most of the data is obtained from Thomson Eikon Reuters dataset, which is a high-end dataset and it is unlikely that they do not report the correct values in their dataset. Simultaneous causality is unlikely to be present in this regression model. Variables *D* is a constant variable for each country so not influenced by the abnormal returns. The dummy military support *S* for each country is also not influenced by the abnormal returns. The firm specific variables *MV* and *DY* are not directly influenced by the abnormal returns on the event date. Like in the previous regression these firm specific variables might change in the future if abnormal returns exist for a longer period of time. However, the abnormal returns do not influence these firm specific variables directly and therefore simultaneous causality is unlikely. To check for omitted variable bias, one performs a Ramsey RESET test in STATA. The results of this test are presented in table 44.

Table 44: Ramsey RESET test for omitted variables for defense-related stock regression

The Ramsey RESET (regression specification-error test) test if the model has omitted variables. This test ensures that the omitted variables are not causing model-misspecifications. The test checks the following:

Omitted: Powers of fitted values of AR_0
H_0: Model has no omitted variables

F (3, 144) = 0.26
Prob > F = 0.8523

Table 44 shows that, based on the p-value, one fails to reject the null hypothesis that the model contains no omitted variables. Based on this test, the regression model does not suffer from omitted variable bias. Even though, one cannot completely rule out omitted variable bias is present, it is assumed in this case that it is not present. The change is small that there is endogeneity present based on the fact that there is no error-in-variable bias, simultaneous causality and no omitted variable bias. In this case again, one cannot completely rule out that endogeneity is present. However, as the main causes of endogeneity are not present in the regression model, it is assumed that endogeneity is not present as well. Based on this, one can give a causal interpretation of the regression coefficients on the dependent variable. In other words, the regression coefficients of the independent variables provide a causal effect on the abnormal returns. The results of the regression analysis are shown in table 45.

Table 45: Multivariate linear regression of the abnormal returns of the American, European and Chinese defense-related stocks on the event date

Model specification:

$$AR_0 = \beta_0 + \beta_1 * S + \beta_2 * D + \beta_3 * MV + \beta_4 * DY \quad (14)$$

Where *S* is a dummy for military support to Ukraine, *D* is the distance from Ukraine's capital Kiev, *MV* is the market value of a defense-related stock and *DY* is the dividend yield of a defense related stock. β_0 is the intercept and the betas β_1, β_2, β_3 and β_4 are the regression coefficients of the independent variables. The robust standard error, t-value, p-value and the 95% confidence interval of each coefficient is given in the table. The asterisks ***, **, * provide the level of significance. Furthermore, the mean and the standard deviation of the dependent variable are provided. Next to that the R^2, the adjusted-R^2, the F-test and the number of observations are given in the lower part of the table.

AR_0	Coef.	Robust St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
S	-.01312	.0176	-0.75	.4571	-.0479	.02166	
D	.00001	0	2.61	.00996	0	.00002	***
MV	0	0	-0.54	.58791	0	0	
DY	.00007	.0003	0.22	.82307	-.00052	.00066	
Constant	-.01757	.02477	-0.71	.47911	-.06652	.03137	

Mean dependent var	0.01323	SD dependent var	0.09202
R-squared	0.06264	Number of obs	152
Adjusted R-squared	0.03713	Prob > F	0.04825
F-test	2.45600		

**** p<.01, ** p<.05, * p<.1*

Due to the fact that there are no endogeneity issues, a causal interpretation can be given of the regression coefficients. Variables *S* has a negative impact on the abnormal returns, which does not make sense from economic point of view as one would expect higher abnormal returns for defense- related stocks if military support is given to Ukraine. However, the coefficient is statistically insignificant which means that the interpretation is unreliable. Variables *MV* and *DY* are zero or close to zero respectively and both are statistically insignificant as well. The variable D, which is the distance from a defense-related stock its capital to Ukraine in miles, is positive and statistically significant at 1%. A 1000-mile increases from Ukraine's capital, leads to a 0.01 increase in abnormal returns or stated differently, a 1000-mile increase leads to a 1 percentage point increase in abnormal returns. This makes sense from an economic point of view as if a military firm is further away from the war in Ukraine, it is less likely that these defense-related stocks are directly affected by the conflict in a negative way. America & China defense-related stocks are influenced less by the fact that gas and oil prices are so high, which is caused by this war. However, these defense-related stocks are able to take advantages of this military conflict by providing military weaponry. By seizing the opportunities of this military conflict, higher abnormal returns can be obtained. Even though the R-squared and the adjusted R-squared are not really high in this model, there is a variable in the model that is statistically significant and has some economic significance as well to explain differences in abnormal returns. Overall, based on these results the null hypothesis that there are no factors that can explain the difference in abnormal returns of American, European and Chinese defense-related stocks can be rejected. The distance from the conflict in Ukraine has some significant power in explaining differences in abnormal returns. Tables 15, 16 and 17 support this result as the average abnormal return of the American and Chinese defense related stocks are positive on the event date while the cumulative average abnormal returns of European defense stocks are negative.

5.4 Robustness section multivariate regression analysis

In this section, a robustness check is done for the two regressions previously conducted. In the first two regressions, the Central Limit Theorem was applied. This theorem states that when the sample size is large, the sampling distribution of the standardized sample average, is approximately normal (Stock & Watson, 2019). For both regressions, the total sample size was larger than 100 observations which implies that the Central Limit Theorem holds. Nevertheless, in this robustness section some independent variables are winsorized or the logarithm of the independent variable is taken to remove extreme outliers and ensure that the independent variables have an improved normalized distribution. Next, the multivariate regression is conducted once more to see if there are large differences in the results.

First, the extreme outliers are removed for the multivariate regression of the abnormal returns of the American, European & Chinese stock market. The independent variables *PE*, *PB, MV* and *DY* are normalized and extreme outliers are removed. For variables *PE* and *MV*, the logarithm is taken to normalize data of the variables. For variables *PB* and *DY*, the winsorization technique is applied to normalize the data. The problem of multicollinearity is resolved in a similar way as the first regression. The model suffers from heteroskedasticity and therefore robust-standard errors are used. Lastly, the regression model still suffers from endogeneity. This means that it is still not possible to infer a causal relationship between the dependent & independent variables and one can only look at the correlation between variables. In table 46, the results of the regression are provided with winsorized and logarithmic independent variables.

Table 46: Multivariate linear regression of the abnormal returns of the S&P500, STOXX 600 and SSE Composite on the event date with winsorized & logarithmic variables

Model specification:

$$AR_0 = \beta_0 + \beta_1 * LN\_PE + \beta_2 * PB_{W05} + \beta_3 * LN\_MV + \beta_4 * DY_{W05} + \beta_5 * D + \beta_6 * DEP_{GAS} + \beta_7 * CCI$$

Where *LN_PE* is the logarithm of the price-earnings ratio, PB_{W05} is the price-to-book ratio winsorized at 90%-level, *LN_MV* is logarithm of the market value of a firm, DY_{W05} is the dividend yield winsorized at 90%-level, *D* is the distance in miles from Ukraine's capital Kiev, DEP_{GAS} is the dependence of a firm on Russian gas and *CCI* is the Consumer Confidence Indicator of a country. β_0 is the intercept and the betas $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6$ & β_7 are the regression coefficients of the independent variables. Furthermore, the robust standard error, t-value, p-value and the 95% confidence interval are given in the table. The asterisks ***, **, * provide the level of significance. Furthermore, the mean and the standard deviation of the dependent variable are provided in the lower part of the table. Next to that the R^2, the adjusted-R^2, the F-test and the number of observations are given in the lower part of the table.

AR_0	Coef.	Robust St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
LN_PE	.00155	.00115	1.35	.17873	-.00071	.00381	
PB_{W05}	.00196	.00032	6.08	0	.00133	.00259	***
LN_MV	.00194	.00067	2.88	.00404	.00062	.00326	***
DY_{W05}	-.00386	.00059	-6.55	0	-.00501	-.0027	***
D	.00001	0	18.45	0	.00001	.00002	***
DEP_{GAS}	.00403	.00344	1.17	.2407	-.00271	.01078	
CCI	-.00286	.00041	-6.99	0	-.00366	-.00206	***
Constant	.19312	.04545	4.25	.00002	.10397	.28227	***

Mean dependent var	-0.02380	SD dependent var	0.03889
R-squared	0.42098	Number of obs	1830
Adjusted R-squared	0.41875	Prob > F	0.00000
F-test	147.83841		

**** p<.01, ** p<.05, * p<.1*

One can see in table 46 that by removing extreme outliers there are more independent variables with a significant correlation with the abnormal returns on the event date. Furthermore, the coefficients are for most of the variables higher. Variable *LN_PE* now has a coefficient that is larger than zero. Previously it had a coefficient that was negatable to zero. The correlation with AR_0 is still statistically insignificant. By winsorizing variable *PB* to $PB_{W05,}$ the price-to-book value of a firm has a significant positive correlation with the abnormal returns on the event date. Previously variable *MV* had a correlation with AR_0 that was negatable to zero. Now it has a significant positive correlation of 0.00002 with AR_0 at a 1% significance level. Even though the magnitude of change is still very small, the robustness check does show that the results change somewhat when removing extreme outliers. Variable *D* has the same significant correlation as previously. Variable DEP_{GAS} has a slightly lower positive correlation which still is statistically insignificant. Variable *CCI* has a slightly lower significant negative correlation with the dependent variable. Winsorizing and taking the logarithm of the independent variables mostly led to a stronger and significant association with the dependent variable.

In the second regression of abnormal returns of the defense-related stocks, similar to the first regression, extreme outliers are removed and independent variables have an improved normalized distribution. In this regression, the logarithm of variable *MV* is taken and the variable *DY* is winsorized. Like in the previous regression of the defense related-stocks, the problem of multicollinearity is resolved. However, due to the transformation of variables and the removal of extreme outliers the model suffers from heteroskedasticity. Therefore, robust standard errors are used to resolve this problem. Fortunately, this model still does not suffer from endogeneity. This means that a causal interpretation can be given about the relationship between the dependent variable and the independent variable. In table 47, one can see the results of the regression with winsorized & logarithmic independent variables.

The first striking difference compared to the results in table 45 is that dummy variable *S* previously had an insignificant negative correlation with AR_0. In this regression the dummy variable has a positive insignificant correlation with AR_0. Even though it is still insignificant, it makes more sense that if a country gives military support to Ukraine that this is associated with higher abnormal returns for defense-related stocks. Secondly, the magnitude of impact of the variable *D* is higher in this regression and is still significant at a 1%-level. This implies that a larger distance from Ukraine's capital Kiev leads to even higher abnormal returns for defense-related stocks. Now a 1000-mile increase leads to a 2-percentage point increase in abnormal returns. This shows that distance has some significant power in explaining differences in abnormal returns between defense-related stocks. Thirdly, the previous variable *MV* which is *LN_MV* now, has become statistically significant at a 10% level. Market value is often used as a size indicator. This implies that defense-related stocks of a larger size obtained larger abnormal returns than smaller defense-related stocks. This makes sense from economic point of view as these large defense-related stocks are capable of delivering more, better and heavier military weaponry to Ukraine. Due to the war, there is an increased demand for this weaponry and this thus probability resulted in higher abnormal returns. A thousand US dollar increase in market value leads to a 0.004-percentage point increase in abnormal returns, or stated differently, a one unit increase in market value leads to a 0.004 percentage point increase in abnormal returns. Lastly for the variable DY_{W05} the coefficient became much larger but it remained statistically insignificant.

Table 47: Multivariate linear regression of the abnormal returns of the American, European and Chinese defense-related stocks on the event date with winsorized & logarithmic variables

Model specification:

$$AR_0 = \beta_0 + \beta_1 * S + \beta_2 * D + \beta_3 * LN\_MV + \beta_4 * DY_{W05}$$

Where S is a dummy for military support to Ukraine, D is the distance from Ukraine's capital Kiev, LN_MV is the logarithm of the market value of a defense-related stock and DY_{W05} is the dividend yield of a defense related stock winsorized at a 90%-level. β_0 is the intercept and the betas β_1, β_2, β_3 and β_4 are the regression coefficients of the independent variables. The robust standard error, t-value, p-value and the 95% confidence interval of each coefficient is given in the table. The asterisks ***, **, * provide the level of significance. Furthermore, the mean and the standard deviation of the dependent variable are provided in lower part of the table. Next to that the R^2, the adjusted-R^2, the F-test and the number of observations are given in the lower part of the table.

AR_0	Coef.	Robust St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
S	.00812	.01638	0.50	.62072	-.02425	.0405	
D	.00002	.00001	2.66	.00858	0	.00003	***
LN_MV	.00426	.00224	1.90	.05877	-.00016	.00868	*
DY_{W05}	.00432	.00801	0.54	.58996	-.0115	.02015	
Constant	-.07512	.03851	-1.95	.05303	-.15123	.00099	*

Mean dependent var	0.01267	SD dependent var	0.09229
R-squared	0.07930	Number of obs	150
Adjusted R-squared	0.05390	Prob > F	0.00455
F-test	3.94258		

**** p<.01, ** p<.05, * p<.1*

Overall, due to endogeneity issues the first multivariate regression analysis is limited in explaining differences in abnormal returns on the American, European and Chinese stock markets. Even if extreme outliers are removed, the model still suffers from the endogeneity issues. This makes it difficult to give a causal interpretation about the results of the model. Therefore, one fails to reject the third hypothesis of this research paper. The second multivariate regression analysis demonstrates that the distance from

Ukraine's capital Kiev has some significant power in explaining the differences in abnormal returns of the American, European and Chinese defense-related stocks on the event date. Next to that, the robustness section showed that by removing outliers and normalizing the data, the independent variable market value also had some explanatory power in explaining the differences in abnormal returns. Defense-related stocks of a larger size obtained higher abnormal returns on the day of the invasion. Based on these results, one can reject the fourth hypothesis that was set up for this paper.

CHAPTER 6 Conclusion

In the conclusion a final answer will be given to the research question based on the hypotheses that were set up for this paper. Furthermore, some limitations will be given to this research and recommendations will be given for some further research. The research question that was set up for this paper was:

"How did the Russian invasion of Ukraine in 2022 affect the European, American and Chinese stock markets and their defense related stocks?"

Based on the hypotheses in this research, a final answer will be given to the research question of this paper. The four hypotheses that were set up for this paper were as follows:

- $H_{1,0}$: *The Russian invasion of Ukraine in 2022 did not lead to abnormal returns on the American, European and Chinese stock markets.*
- $H_{2,0}$: *The Russian invasion in Ukraine in 2022 did not affect the abnormal returns of American, European and Chinese defense-related stocks.*
- $H_{3,0}$: *There are no factors that can explain the difference in abnormal returns on the American, European and Chinese stock markets.*
- $H_{4,0}$: *There are no factors that can explain the difference in abnormal returns of American, European and Chinese defense-related stocks.*

The first hypothesis can be rejected as the Russian invasion mostly led to significant abnormal return on the S&P 500, STOXX 600 and the SSE Composite. On the day of the invasion there were significant negative abnormal returns on the STOXX 600 and the SSE Composite while there were significant positive returns on the S&P 500. Similarly, the second hypothesis can be rejected as the American and Chinese defense-related stocks obtained significant positive abnormal returns on the day of the invasion. The European defense-related stocks had significant negative abnormal returns on the day of the invasion. Based on the significant abnormal returns, event study analysis shows that the market was in a semi-strong form of market efficiency on the day of the invasion.

The third hypothesis that there are no factors that can explain the difference in abnormal returns on the American, European and Chinese stock markets could not be rejected due to endogeneity issues in the multivariate regression analysis. One was able to reject the fourth hypothesis as the variable distance from Ukraine's capital Kiev and firm size showed some significant explanatory power in explaining differences in abnormal returns between American, European and Chinese defense stocks.

Overall, based on the acceptation or rejection of the hypotheses, a final answer can be given to the research question. Surprisingly, the Russian invasion of Ukraine affected the S&P 500 positively as significant positive abnormal returns were obtained. This might be due to differences opening hours of the stock markets & that investors on the American stock market had more time to anticipate to the situation. Furthermore, the invasion also positively affected the American and Chinese defense-related stocks. This is probably due to the fact that there was an increased demand by both Ukraine and Russia for military weaponry. Investors were able to anticipate on this increased demand and obtained significant positive abnormal returns. The European stock market and European defense-related stocks both showed that they were negatively affected by the Russian invasion of Ukraine. Both showed significant negative abnormal returns on the day of the invasion. The reason that European stocks were affected negatively might be due to the closer relationship with Ukraine and Russia. Furthermore, European investors might have shown more irrational behavior because they were closer to the event & psychologically more affected due to personal ties with friends and family in Ukraine. The SSE Composite was also negatively affected by the Russian invasion of Ukraine. Investors might have been shocked by the attack and the Chinese economy might have been affected by the attack as China is an important trading partner of Russia. The variable distance from the Ukraine's capital explained how the invasion affected the American, European and Chinse stocks differently.

One of the big limitations to this research is that one failed to reject the third hypothesis of this paper. Due to a lack of data available for the large sample size of stock listed companies, the regression model suffers from omitted variable bias. This results in endogeneity issues, which makes a causal interpretation of the regression not possible. It would have been interesting to have a variable that had some causal explanatory power in explaining the differences in abnormal returns on the S&P 500, STOXX 600 and the SSE Composite. A second limitation is that the event study methodology of a specific event restricts the researcher to a cross-sectional data set for the multivariate regression analysis. Due to the fact that an event study is often done for a specific moment in time, it restricts the researcher to obtain different sections across time. If a researcher is able to construct the dataset as panel data, fixed or random effect can be used to explain individual heterogeneity between stock listed companies. These fixed or random effects might explain something about the differences in abnormal returns on the event date. A recommendation for further research could be to investigate if it is possible to set up a panel dataset of several event studies to analyze if there are some significant variables that always have some causal explanatory power in explaining differences in abnormal returns. Another possible recommendation for further research could be how the Russian invasion of Ukraine affected all the American, European and Chinese industry sectors specifically. This would require a lot of data gathering before one can obtain a consistent and unbiased measure. However, it would provide a good overview of how each sector is affected by war or an international conflict. Lastly, a recommendation for further research could be how the unforeseen war might has changed the long-term equilibrium of the stock market and has changed the long-term fundamental values of stocks.

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APPENDIX

Table 2: Data filtering for the S&P 500, STOXX 600 and SSE Composite	
This table provides all the data filtering criteria that were used to find the stock prices, market value, price-earnings ratios, price-to-book ratios and dividend yield of stock listed companies on the S&P 500, STOXX 600 and the SSE Composite	
Request	Time Series Request
Series	LDJSTOXX, LS&PCOMP, LCHZCOMP
Datatypes	NAME, X(P)~U$, (X(MV)~U$, PE, 553E (PB), DY)
Start Date	24/11/2021
End date	25/02/2022
Frequency	Daily

Table 3: Data filtering for the U.S. defense stocks	
This table provides all the data filtering criteria that were used to find the stock prices, market value, price-earnings ratios, price-to-book ratios and dividend yield of stock listed companies of U.S. defense-related stocks.	
Request	Time Series Request
Category	Equities
Sector	Aerospace and Defense
Markets	U.S.
Exchange	NASDAQ or NON NASDAQ OTC, NYSE, NSYE MKT
Type	Equity
Activity	Active
Datatypes	X(P)~U$, (X(MV)~U$, PE , 553E (PB), DY)
Start Date	24/11/2021
End Date	25/02/2022
Frequency	Daily

Table 4: Data filtering of the EU defense-related stocks	
This table provides all the data filtering criteria that were used to find the stock prices, market value, price-earnings ratios, price-to-book ratios and dividend yield of stock listed companies of European defense-related stocks.	
Request	Time Series Request
Category	Equities
Sector	Aerospace and Defense
Markets	Austria, Czech Republic, Denmark, France, Germany, Italy, Norway, Poland, Romania, Spain, Sweden, Switzerland, UK
Exchange	Berlin, Berne, Deutsche Boerse AG, Dusseldorf, Euronext. Liffe Paris, London, Mercado Continuo Espanol, Milan, Munich, OMX Nordic Exchange Copenhagen, Oslo Bors, Praque, Six Swiss, Spot Regulated Market, Stockholm, Stuttgart, Vienna Stock Exchange, Warsaw, Xetra
Type	Equity
Activity	Active
Datatypes	X(P)~U$, (X(MV)~U$, PE, 553E (PB), DY)
Start Date	24/11/2021
End Date	25/02/2022
Frequency	Daily

Table 5: Data filtering for Chinese defense stocks	
This table provides all the data filtering criteria that were used to find the stock prices, market value, price-earnings ratios, price-to-book ratios and dividend yield of stock listed companies of Chinese defense-related stocks.	
Request	Time Series Request
Category	Equities
Sector	Aerospace and Defense
Markets	China
Exchange	HKSE Connect Equity, HKSZ Connect Equity, Shanghai, Shenzhen, SSE Connect Equities, SZHK Connect Equities
Type	Equity
Activity	Active
Datatypes	X(P)~U$, (X(MV)~U$, PE, 553E (PB), DY)
Start Date	24/11/2021
End Date	25/02/2022
Frequency	Daily

Table 9: Descriptive statistics of dependent variable and normalized independent variables used as robustness check in the multivariate regression of the abnormal returns of the S&P 500, STOXX 600 and SSE Composite

Where μ is the mean, M is the median, σ is the standard deviation, Min and Max are the minimum and maximum, Skewness is a measure of symmetry, Kurtosis determines the heaviness of the distribution tails and N is the number of observations. AR_0 is the abnormal return on the day of the invasion, *LN_PE* is the logarithm of the price-earnings ratio, PB_{W05} is the price-to-book ratio winsorized at 90%, *LN_MV* is the logarithm of the market value of a firm, DY_{W05} is the dividend yield winsorized at a 90%-level, *D* is the distance in miles from Ukraine's capital Kiev, DEP_{GAS} is the dependence of a firm on Russian gas and *CCI* is the Consumer Confidence Indicator of a country.

Variables	μ	M	σ	Min	Max	Skewness	Kurtosis	N
AR_0	-.024	-.025	0.039	-.341	.162	-.308	7.399	1830
LN_PE	3.233	3.213	0.857	.262	7.884	.576	5.188	1830
PB_{W05}	3.625	2.716	2.814	.711	11.069	1.313	3.887	1830
LN_MV	8.941	8.858	1.561	5.722	14.792	.296	2.622	1830
DY_{W05}	1.716	1.28	1.614	0	5.56	.919	2.885	1830
D	3462.882	4006	1402.052	506.5	4864	-.821	2.083	1830
DEP_{GAS}	.125	0	0.331	0	1	2.266	6.134	1830
CCI	100.882	101.24	2.498	97.53	103.37	-.202	1.314	1830

Table 11: Descriptive statistics of dependent variable and normalized independent variables used as robustness check in the multivariate regression of the abnormal returns of the American, European and Chinese defense-related stocks

Where μ is the mean, M is the median, σ is the standard deviation, Min and Max are the minimum and maximum, Skewness is a measure of symmetry, Kurtosis determines the heaviness of the distribution tails and N is the number of observations. AR_0 is the abnormal return on the day of the invasion, *D* is the distance in miles of a defense-company from Ukraine's capital Kiev, *S* is a dummy for military support given to Ukraine, LN_*MV* is the logarithm of the market value of a firm and DY_{W05} is the dividend yield winsorized at a 90%-level.

Variables	μ	M	σ	Min	Max	Skewness	Kurtosis	N
AR_0	.013	.004	0.092	-.299	.591	2.599	17.983	150
D	3353.367	4006	1631.841	464	4864	-.53	1.539	150
S	.753	1	0.433	0	1	-1.175	2.381	150
LN_MV	4.666	5.582	3.693	-4.605	11.463	-.822	3.237	150
DY_{W05}	.453	0	0.800	0	2.75	1.831	5.139	150

Table 12: The effect of the Russian invasion of Ukraine in 2022 on the average abnormal returns and the cumulative average abnormal returns of the S&P 500 using constant mean model

This table reports the result of the constant mean return model (4), model (6) and model (8). Where μ is the mean of the (C)AR_t of the stock listed companies on the S&P500 on day *t* during the event window. The event date is when *t=0*. The standard errors are given in the parentheses and σ describes the standard deviation. The T-statistic gives the t-stat of the t-test (9). θ_2 is the test statistic of the non-parametric sign test (10). The numbers in Wilcoxon signed-rank test (11) represent the Z-values of the test. N presents the number of observations. The asterisks ***, **, * next to the t-statistic, θ_2 and the Z-value denote a 1%, 5% or 10% level of significance respectively.

Estimation window: 3 months						
Variables	$\boldsymbol{\mu}$	$\boldsymbol{\sigma}$	**T-statistic**	**Sign test $\boldsymbol{\theta_2}$**	**Wilcoxon signed-rank test (Z-Value)**	**N**
AR_{-1}	-1.568% (0.067)	1.501%	-23.449 ***	-17.194 ***	-16.916 ***	504
AR_0	1.185% (0.137)	3.074%	8.654 ***	-6.949 ***	7.851 ***	504
AR_1	2.761% (0.070)	1.582%	39.168 ***	-21.114 ***	19.201 ***	504
$CAR_{(-1,1)}$	2.378% (0.146)	3.288%	16.236 ***	-14.076 ***	15.004 ***	504
$CAR_{(0,1)}$	3.946% (0.148)	3.336%	26.552 ***	-19.243 ***	18.397 ***	504

Table 13: The effect of the Russian invasion of Ukraine in 2022 on the average abnormal returns and the cumulative average abnormal returns of the STOXX 600 using constant mean model

This table reports the result of the constant mean return model (4), model (6) and model (8). Where μ is the mean of the (C)AR_t of the stock listed companies on the STOXX 600 on day *t* during the event window. The event date is when *t=0*. The standard errors are given in the parentheses and σ describes the standard deviation. The T-statistic gives the t-stat of the t-test (9). θ_2 is the test statistic of the non-parametric sign test (10). The numbers in Wilcoxon signed-rank test (11) represent the Z-values of the test. N presents the number of observations. The asterisks ***, **, * next to the t-statistic, θ_2 and the Z-value denote a 1%, 5% or 10% level of significance respectively.

Estimation window: 3 months						
Variables	$\boldsymbol{\mu}$	$\boldsymbol{\sigma}$	**T-statistic**	**Sign test** $\boldsymbol{\theta_2}$	**Wilcoxon signed-rank test (Z-Value)**	**N**
AR_{-1}	-0.531% (0.084)	2.048%	-6.3453 ***	-5.307 ***	-6.774 ***	600
AR_{0}	-5.223% (0.168)	4.122%	-31.053 ***	-21.311***	-20.085 ***	600
AR_{1}	4.577% (0.093)	2.284%	49.079 ***	-23.515 ***	20.794 ***	600
$CAR_{(-1,1)}$	-1.179% (0.197)	4.822%	-5.990 ***	-5.634 ***	-6.295 ***	600
$CAR_{(0,1)}$	-0.649 % (0.167)	4.084%	-3.892 ***	-4.164 ***	-4.320 ***	600

Table 14: The effect of the Russian invasion of Ukraine in 2022 on the average abnormal returns and the cumulative average abnormal returns of the SSE Composite using constant mean model

This table reports the result of the constant mean return model (4), model (6) and model (8). Where μ is the mean of the (C)AR_t of the stock listed companies on the SSE Composite on day *t* during the event window. The event date is when *t=0*. The standard errors are given in the parentheses and σ describes the standard deviation. The T-statistic gives the t-stat of the t-test (9). θ_2 is the test statistic of the non-parametric sign test (10). The numbers in Wilcoxon signed-rank test (11) represent the Z-values of the test. N presents the number of observations. The asterisks ***, **, * next to the t-statistic, θ_2 and the Z-value denote a 1%, 5% or 10% level of significance respectively.

Estimation window: 3 months						
Variables	$\boldsymbol{\mu}$	$\boldsymbol{\sigma}$	**T-statistic**	**Sign test** $\boldsymbol{\theta_2}$	**Wilcoxon signed-rank test (Z-Value)**	**N**
AR_{-1}	1.888% (0.056)	2.894%	33.196 ***	-30.050 ***	31.936 ***	2,589
AR_{0}	-2.600% (0.065)	3.329%	-39.734 ***	-36.889 ***	-34.551 ***	2,589
AR_{1}	1.103% (0.049)	2.519%	22.276 ***	-25.176 ***	25.743 ***	2,589
$CAR_{(-1,1)}$	0.391% (0.103)	5.219%	3.810 ***	-2.417 **	4.115 ***	2,589
$CAR_{(0,1)}$	-1.496% (0.079)	4.023%	-18.936 ***	-24.193 ***	-23.513 ***	2,589

Table 15: The effect of the Russian invasion of Ukraine in 2022 on the average abnormal returns and the cumulative average abnormal returns of US defense stocks using constant mean model

This table reports the result of the constant mean return model (4), model (6) and model (8). Where μ is the mean of the (C)AR_t of the US defense stocks on day t during the event window. The event date is when $t=0$. The standard errors are given in the parentheses and σ describes the standard deviation. The T-statistic gives the t-stat of the t-test (9). θ_2 is the test statistic of the non-parametric sign test (10). The numbers in Wilcoxon signed-rank test (11) represent the Z-values of the test. N presents the number of observations. The asterisks ***, **, * next to the t-statistic, θ_2 and the Z-value denote a 1%, 5% or 10% level of significance respectively.

Estimation window: 3 months						
Variables	$\boldsymbol{\mu}$	$\boldsymbol{\sigma}$	**T-statistic**	**Sign test $\boldsymbol{\theta_2}$**	**Wilcoxon signed-rank test (Z-Value)**	**N**
AR_{-1}	-0.424% (0.368)	3.767%	-1.154	-0.488	-2.269 **	105
AR_{0}	3.562% (0.872)	8.940%	4.083 ***	-4.587 ***	6.349 ***	105
AR_{1}	2.335% (0.707)	7.248%	3.300 ***	-4.782 ***	6.215 ***	105
$CAR_{(-1,1)}$	5.421% (1.145)	11.788%	4.735 ***	-4.468 ***	6.127 ***	105
$CAR_{(0,1)}$	5.841% (1.035)	10.660%	5.642 ***	-5.050 ***	6.981 ***	105

Table 16: The effect of the Russian invasion of Ukraine in 2022 on the average abnormal returns and the cumulative average abnormal returns of European defense stocks using constant mean model

This table reports the result of the constant mean return model (4), model (6) and model (8). Where μ is the mean of the (C)AR_t of the European defense stocks on day *t* during the event window. The event date is when *t=0*. The standard errors are given in the parentheses and σ describes the standard deviation. The T-statistic gives the t-stat of the t-test (9). θ_2 is the test statistic of the non-parametric sign test (10). The numbers in Wilcoxon signed-rank test (11) represent the Z-values of the test. N presents the number of observations. The asterisks ***, **, * next to the t-statistic, θ_2 and the Z-value denote a 1%, 5% or 10% level of significance respectively.

Estimation window: 3 months						
Variables	$\boldsymbol{\mu}$	$\boldsymbol{\sigma}$	**T-statistic**	**Sign test** $\boldsymbol{\theta_2}$	**Wilcoxon signed-rank test (Z-Value)**	**N**
AR_{-1}	0.025% (0.462)	3.490%	0.0545	-0.397	0.326	57
AR_{0}	-1.812% (1.128)	8.520%	-1.606	-3.046**	-3.138 ***	57
AR_{1}	4.223% (0.545)	4.118%	7.743 ***	-6.225 ***	5.896 ***	57
$CAR_{(-1,1)}$	2.435 % (1.012)	7.675%	2.407 **	-0.662	2.082 **	57
$CAR_{(0,1)}$	2.410% (1.035)	7.831%	2.327 **	-0.132	1.923 *	57

Table 17: The effect of the Russian invasion of Ukraine in 2022 on the average abnormal returns and the cumulative average abnormal returns of Chinese defense stocks using constant mean model

This table reports the result of the constant mean return model (4), model (6) and model (8). Where μ is the mean of the (C)AR_t of the Chinese defense stocks on day *t* during the event window. The event date is when *t=0*. The standard errors are given in the parentheses and σ describes the standard deviation. The T-statistic gives the t-stat of the t-test (9). θ_2 is the test statistic of the non-parametric sign test (10). The numbers in Wilcoxon signed-rank test (11) represent the Z-values of the test. N presents the number of observations. The asterisks ***, **, * next to the t-statistic, θ_2 and the Z-value denote a 1%, 5% or 10% level of significance respectively.

Estimation window: 3 months						
Variables	**Mean**	$\boldsymbol{\sigma}$	**T-statistic**	**Sign test** $\boldsymbol{\theta_2}$	**Wilcoxon signed-rank test (Z-Value)**	**N**
AR_{-1}	3.631% (0.317)	2.005%	11.454 ***	-6.325 ***	5.511 ***	40
AR_{0}	3.163% (0.659)	4.165%	4.803 ***	-4.111 ***	4.476 ***	40
AR_{1}	-1.049% (0.321)	2.034%	-3.263 ***	-3.479 ***	-3.293 ***	40
$CAR_{(-1,1)}$	5.744% (0.597)	3.774%	9.625 ***	-6.008 ***	5.430 ***	40
$CAR_{(0,1)}$	2.112% (0.644)	4.073%	3.281 ***	-2.539 **	3.387 ***	40

Table 18: The effect of the Russian invasion of Ukraine in 2022 on the average abnormal returns and the cumulative average abnormal returns of the S&P 500 using market model

This table reports the result of the market model (5), model (6) and model (8). Where μ is the mean of the (C)AR_t of the stock listed companies on the S&P500 on day *t* during the event window. The event date is when *t=0*. The standard errors are given in the parentheses and σ describes the standard deviation. The T-statistic gives the t-stat of the t-test (9). θ_2 is the test statistic of the non-parametric sign test (10). The numbers in Wilcoxon signed-rank test (11) represent the Z-values of the test. N presents the number of observations. The asterisks ***, **, * next to the t-statistic, θ_2 and the Z-value denote a 1%, 5% or 10% level of significance respectively.

Estimation window: 3 months						
Variables	$\boldsymbol{\mu}$	$\boldsymbol{\sigma}$	**T-statistic**	**Sign test** $\boldsymbol{\theta_2}$	**Wilcoxon signed-rank test (Z-Value)**	**N**
AR_{-1}	-0.0240% (0.063)	1.414%	-0.380	-1.425	-0.921	504
AR_{0}	-0.271% (0.121)	2.718%	-2.237 **	-3.920 ***	-3.464 ***	504
AR_{1}	0.652% (0.088)	1.978%	7.4015 ***	-7.572 ***	7.611 ***	504
$CAR_{(-1,1)}$	0.357% (0.138)	3.104%	2.5829 **	-1.960 *	2.260 **	504
$CAR_{(0,1)}$	0.381% (0.130)	2.911%	2.940 ***	-2.673 ***	2.985 ***	504

Table 19: The effect of the Russian invasion of Ukraine in 2022 on the abnormal average returns and the cumulative average abnormal returns of the STOXX 600 using market model

This table reports the result of the market model (5), model (6). and model (8) Where μ is the mean of the (C)AR_t of the stock listed companies on the STOXX600 on day *t* during the event window. The event date is when *t=0*. The standard errors are given in the parentheses and σ describes the standard deviation. The T-statistic gives the t-stat of the t-test (9). θ_2 is the test statistic of the non-parametric sign test (10). The numbers in Wilcoxon signed-rank test (11) represent the Z-values of the test. N presents the number of observations. The asterisks ***, **, * next to the t-statistic, θ_2 and the Z-value denote a 1%, 5% or 10% level of significance respectively.

Estimation window: 3 months

Variables	$\boldsymbol{\mu}$	$\boldsymbol{\sigma}$	**T-statistic**	**Sign test** $\boldsymbol{\theta_2}$	**Wilcoxon signed-rank test (Z-Value)**	**N**
AR_{-1}	-0.213% (0.0826)	2.022%	-2.589 ***	-1.143	-1.643	600
AR_0	0.153% (0.183)	4.476%	0.834	-0.245	0.897	600
AR_1	-0.130% (0.105)	2.574%	-1.232	-0.408	-0.982	600
$CAR_{(-1,1)}$	-0.189% (0.197)	4.816%	-0.9638	-0.408	-0.329	600
$CAR_{(0,1)}$	0.0240% (0.167)	4.106%	0.1430	0.000	0.412	600

Table 20: The effect of the Russian invasion of Ukraine in 2022 on the average abnormal returns and the cumulative average abnormal returns of the SSE Composite using market model

This table reports the result of the market model (5), model (6) and model (8). Where μ is the mean of the (C)AR$_t$ of the stock listed companies on the SSE Composite on day *t* during the event window. The event date is when *t=0*. The standard errors are given in the parentheses and σ describes the standard deviation. The T-statistic gives the t-stat of the t-test (9). θ_2 is the test statistic of the non-parametric sign test (10). The numbers in Wilcoxon signed-rank test (11) represent the Z-values of the test. N presents the number of observations. The asterisks ***, **, * next to the t-statistic, θ_2 and the Z-value denotes a 1%, 5% or 10% level of significance respectively.

Estimation window: 3 months						
Variables	$\boldsymbol{\mu}$	$\boldsymbol{\sigma}$	**T-statistic**	**Sign test** $\boldsymbol{\theta_2}$	**Wilcoxon signed-rank test (Z-Value)**	**N**
AR $_{-1}$	0.527% (0.057)	2.918%	9.2068 ***	-8.509 ***	9.756 ***	2589
AR $_{0}$	-0.726% (0.065)	3.339%	-11.058 ***	-18.022 ***	-16.641 ***	2589
AR $_{1}$	0.226% (0.050)	2.559%	4.513 ***	-3.282 ***	4.827 ***	2589
CAR $_{(-1,1)}$	0.029 (0.103)	5.227%	0.2840	1.492	-0.301	2589
CAR $_{(0,1)}$	-0.498 (0.079)	3.996%	-6.346 ***	-9.467 ***	-9.679 ***	2589

Table 21: The effect of the Russian invasion of Ukraine in 2022 on the average abnormal returns and the cumulative average abnormal returns of US defense stocks using market model

This table reports the result of the market model (5), model (6) and model (8). Where μ is the mean of the (C)AR_t of US defense stocks on day *t* during the event window. The event date is when *t=0*. The standard errors are given in the parentheses and σ describes the standard deviation. The T-statistic gives the t-stat of the t-test (9). θ_2 is the test statistic of the non-parametric sign test (10). The numbers in Wilcoxon signed-rank test (11) represent the Z-values of the test. N presents the number of observations. The asterisks ***, **, * next to the t-statistic, θ_2 and the Z-value denote a 1%, 5% or 10% level of significance respectively.

Estimation window: 3 months						
Variables	$\boldsymbol{\mu}$	$\boldsymbol{\sigma}$	**T-statistic**	**Sign test** $\boldsymbol{\theta_2}$	**Wilcoxon signed-rank test (Z-Value)**	**N**
AR_{-1}	0.542% (0.423)	4.334%	1.2394	0.488	1.050	105
AR_{0}	2.668% (0.867)	8.880%	3.0788 ***	-2.049 **	4.151 ***	105
AR_{1}	1.039% (0.861)	8.825%	1.2063	0.878	0.682	105
$CAR_{(-1,1)}$	4.191% (1.211)	12.468%	3.461 ***	-2.525 **	4.630 ***	105
$CAR_{(0,1)}$	3.672% (1.202)	12.380%	3.0536 ***	-1.554	3.677 ***	105

Table 22: The effect of the Russian invasion of Ukraine in 2022 on the average abnormal returns and the cumulative average abnormal returns of European defense stocks using market model

This table reports the result of the market model (5), model (6) and model (8). Where μ is the mean of the (C)AR_t of European defense stocks on day *t* during the event window. The event date is when *t=0*. The standard errors are given in the parentheses and σ describes the standard deviation. The T-statistic gives the t-stat of the t-test (9). θ_2 is the test statistic of the non-parametric sign test (10). The numbers in Wilcoxon signed-rank test (11) represent the Z-values of the test. N presents the number of observations. The asterisks ***, **, * next to the t-statistic, θ_2 and the Z-value denote a 1%, 5% or 10% level of significance respectively.

Estimation window: 3 months						
Variables	$\boldsymbol{\mu}$	$\boldsymbol{\sigma}$	**T-statistic**	**Sign test** $\boldsymbol{\theta_2}$	**Wilcoxon signed-rank test (Z-Value)**	**N**
AR_{-1}	0.270% (0.461)	3.484%	0.586	-1.722 **	1.645	57
AR_{0}	2.356% (1.136)	8.578%	2.074 **	-1.722 **	1.970 **	57
AR_{1}	0.574% (0.547)	4.129%	1.0498	-1.722 **	1.676 **	57
$CAR_{(-1,1)}$	3.200% (1.012)	7.640%	3.1628 ***	-1.987 **	2.987 ***	57
$CAR_{(0,1)}$	2.930% (1.037)	7.827%	2.8265 ***	-1.192	2.654 ***	57

Table 23: The effect of the Russian invasion of Ukraine in 2022 on the abnormal returns and the cumulative abnormal returns of Chinese defense stocks using market model

This table reports the result of the market model (5), model (6) and model (8). Where μ is the mean of the (C)AR_t of Chinese defense stocks on day t during the event window. The event date is when $t=0$. The standard errors are given in the parentheses and σ describes the standard deviation. The T-statistic gives the t-stat of the t-test (9). θ_2 is the test statistic of the non-parametric sign test (10). The numbers in Wilcoxon signed-rank test (11) represent the Z-values of the test. N presents the number of observations. The asterisks ***, **, * next to the t-statistic, θ_2 and the Z-value denote a 1%, 5% or 10% level of significance respectively.

Estimation window: 3 months						
Variables	$\boldsymbol{\mu}$	$\boldsymbol{\sigma}$	**T-statistic**	**Sign test $\boldsymbol{\theta_2}$**	**Wilcoxon signed-rank test (Z-Value)**	**N**
AR_{-1}	2.504% (0.302)	1.971%	8.3071***	-5.376 ***	5.309 ***	40
AR_{0}	4.718% (0.638)	4.035%	7.394 ***	-5.692 ***	5.430 ***	40
AR_{1}	-1.775% (0.322)	2.036%	-5.514 ***	-4.427 ***	-4.315 ***	40
$CAR_{(-1,1)}$	5.446% (0.599)	3.788%	9.090 ***	-6.008 ***	5.403 ***	40
$CAR_{(0,1)}$	2.942% (0.633)	4.002%	4.650 ***	-4.111 ***	4.274 ***	40

Table 24: The effect of the Russian invasion of Ukraine in 2022 on the average abnormal returns and the cumulative average abnormal returns of the S&P 500 using constant mean model for an extended event window (-3, +3)

This table reports the result of the constant mean return model (4), model (6) and model (8). Where μ is the mean of the (C)AR_t of the stock listed companies on the S&P500 on day *t* during the event window. The event date is when *t=0*. The standard errors are given in the parentheses and σ describes the standard deviation. The T-statistic gives the t-stat of the t-test (9). θ_2 is the test statistic of the non-parametric sign test (10). The numbers in Wilcoxon signed-rank test (11) represent the Z-values of the test. N presents the number of observations. The asterisks ***, **, * next to the t-statistic, θ_2 and the Z-value denote a 1%, 5% or 10% level of significance respectively.

Estimation window: 3 months						
Variables	$\boldsymbol{\mu}$	$\boldsymbol{\sigma}$	**T-statistic**	**Sign test** $\boldsymbol{\theta_2}$	**Wilcoxon signed-rank test (Z-Value)**	**N**
AR_{-3}	0.073% (0.011)	0.250%	6.585 ***	-3.653 ***	5.773 ***	504
AR_{-2}	-0.913% (0.071)	1.588%	-12.902 ***	-10.958 ***	-12.222 ***	504
AR_{2}	-0.594% (0.161)	3.608%	-3.6958 ***	-8.641 ***	-7.953 ***	504
AR_{3}	-1.808% (0.120)	2.687%	-15.107 ***	-13.541 ***	-13.972 ***	504
$CAR_{(-2,2)}$	0.765% (0.264)	5.915%	2.905 ***	-2.761 ***	4.070 ***	504
$CAR_{(-3,3)}$	-0.969% (0.325)	7.309%	-2.978 ***	-2.673 ***	-3.277 ***	504

Table 25: The effect of the Russian invasion of Ukraine in 2022 on the abnormal average returns and the cumulative average abnormal returns of the STOXX 600 using constant mean model for an extended event window (-3, +3)

This table reports the result of the constant mean return model (4), model (6) and model (8). Where μ is the mean of the (C)AR_t of the stock listed companies on the STOXX 600 on day t during the event window. The event date is when $t=0$. The standard errors are given in the parentheses and σ describes the standard deviation. The T-statistic gives the t-stat of the t-test (9). θ_2 is the test statistic of the non-parametric sign test (10). The numbers in Wilcoxon signed-rank test (11) represent the Z-values of the test. N presents the number of observations. The asterisks ***, **, * next to the t-statistic, θ_2 and the Z-value denote a 1%, 5% or 10% level of significance respectively.

Estimation window: 3 months						
Variables	$\boldsymbol{\mu}$	$\boldsymbol{\sigma}$	**T-statistic**	**Sign test** $\boldsymbol{\theta_2}$	**Wilcoxon signed-rank test (Z-Value)**	**N**
AR_{-3}	-1.149 % (0.065)	1.593%	-22.963 ***	-17.473 ***	-18.189 ***	600
AR_{-2}	0.289% (0.093)	2.229%	3.0938 ***	-0.734	1.989 **	600
AR_{2}	0.458% (0.152)	3.722%	3.014 ***	-3.756 ***	3.225 ***	600
AR_{3}	-3.505% (0.145)	3.545%	-24.222 ***	-17.800 ***	-18.582 ***	600
$CAR_{(-2,2)}$	-0.308% (0.358)	8.759 %	-0.863	-0.408	-0.816	600
$CAR_{(-3,3)}$	-5.307% (0.453)	11.098%	-11.714 ***	-9.063 ***	-11.268 ***	600

Table 26: The effect of the Russian invasion of Ukraine in 2022 on the average abnormal returns and the cumulative average abnormal returns of the SSE Composite using constant mean model for an extended event window (-3, +3)

This table reports the result of the constant mean return model (4), model (6) and model (8). Where μ is the mean of the (C)AR_t of the stock listed companies on the SSE Composite on day *t* during the event window. The event date is when *t=0*. The standard errors are given in the parentheses and σ describes the standard deviation. The T-statistic gives the t-stat of the t-test (9). θ_2 is the test statistic of the non-parametric sign test (10). The numbers in Wilcoxon signed-rank test (11) represent the Z-values of the test. N presents the number of observations. The asterisks ***, **, * next to the t-statistic, θ_2 and the Z-value denote a 1%, 5% or 10% level of significance respectively.

Estimation window: 3 months

Variables	$\boldsymbol{\mu}$	$\boldsymbol{\sigma}$	**T-statistic**	**Sign test** $\boldsymbol{\theta_2}$	**Wilcoxon signed-rank test (Z-Value)**	**N**
AR_{-3}	1.511% (0.053)	2.698%	28.499 ***	-24.665 ***	28.487 ***	2,589
AR_{-2}	-1.116% (0.052)	2.624%	-22.415 ***	-29.224 ***	-27.292 ***	2,589
AR_{2}	-0.004% (0.050)	2.550%	-0.076	-4.146 ***	-3.784 ***	2,589
AR_{3}	0.811% (0.046)	2.323%	17.724 ***	-17.786 ***	20.105 ***	2,589
$CAR_{(-2,2)}$	-0.826% (0.127)	6.466%	-6.504 ***	-10.331 ***	-9.480 ***	2,589
$CAR_{(-3,3)}$	1.493% (0.141)	7.163%	10.615 ***	-8.834 ***	10.958 ***	2,589

Table 27: The effect of the Russian invasion of Ukraine in 2022 on the average abnormal returns and the cumulative average abnormal returns of US defense stocks using constant mean model for an extended event window (-3, +3)

This table reports the result of the constant mean return model (4), model (6) and model (8). Where μ is the mean of the (C)AR_t of the US defense stocks on day *t* during the event window. The event date is when *t=0*. The standard errors are given in the parentheses and σ describes the standard deviation. The T-statistic gives the t-stat of the t-test (9). θ_2 is the test statistic of the non-parametric sign test (10). The numbers in Wilcoxon signed-rank test (11) represent the Z-values of the test. N presents the number of observations. The asterisks ***, **, * next to the t-statistic, θ_2 and the Z-value denote a 1%, 5% or 10% level of significance respectively.

Estimation window: 3 months						
Variables	$\boldsymbol{\mu}$	$\boldsymbol{\sigma}$	**T-statistic**	**Sign test** $\boldsymbol{\theta_2}$	**Wilcoxon signed-rank test (Z-Value)**	**N**
AR_{-3}	0.450% (0.165)	1.699%	3.013 ***	-2.049 **	4.618	105
AR_{-2}	-0.382% (0.478)	4.902%	-0.7993	-1.073	-2.685	105
AR_{2}	1.262% (0.840)	8.609%	1.5023	-3.220 ***	5.139 ***	105
AR_{3}	-0.905% (0.463)	4.743%	-1.9559 *	0.487	-1.582	105
$CAR_{(-2,2)}$	6.196% (1.242)	12.785%	4.989 ***	-3.885 ***	5.728 ***	105
$CAR_{(-3,3)}$	5.794% (1.540)	15.856%	3.762 ***	-2.720 ***	4.488 ***	105

Table 28: The effect of the Russian invasion of Ukraine in 2022 on the average abnormal returns and the cumulative average abnormal returns of European defense stocks using constant mean model for an extended event window (-3, +3)

This table reports the result of the constant mean return model (4), model (6) and model (8). Where μ is the mean of the (C)AR_t of European defense stocks on day *t* during the event window. The event date is when *t=0*. The standard errors are given in the parentheses and σ describes the standard deviation. The T-statistic gives the t-stat of the t-test (9). θ_2 is the test statistic of the non-parametric sign test (10). The numbers in Wilcoxon signed-rank test (11) represent the Z-values of the test. N presents the number of observations. The asterisks ***, **, * next to the t-statistic, θ_2 and the Z-value denote a 1%, 5% or 10% level of significance respectively.

Estimation window: 3 months						
Variables	$\boldsymbol{\mu}$	$\boldsymbol{\sigma}$	**T-statistic**	**Sign test** $\boldsymbol{\theta_2}$	**Wilcoxon signed-rank test (Z-Value)**	**N**
AR_{-3}	-1.979% (0.491)	3.707%	-4.030 ***	-2.252 **	-4.028 ***	57
AR_{-2}	0.163% (0.584)	4.406%	0.280	-0.927	1.351	57
AR_{2}	5.042% (1.072)	8.094%	4.703 ***	-3.576 ***	4.354 ***	57
AR_{3}	-0.418% (1.050)	7.931%	-0.398	-2.252 **	-1.812 *	57
$CAR_{(-2,2)}$	7.582% (1.199)	15.096 %	3.792 ***	-1.987 **	3.575 ***	57
$CAR_{(-3,3)}$	5.184% (2.763)	20.859%	1.876 *	-0.132 *	1.549	57

Table 29: The effect of the Russian invasion of Ukraine in 2022 on the average abnormal returns and the cumulative average abnormal returns of Chinese defense stocks using constant mean model for an extended event window (-3, +3)

This table reports the result of the constant mean return model (4), model (6) and model (8). Where μ is the mean of the (C)AR_t of Chinese defense stocks on day t during the event window. The event date is when $t=0$. The standard errors are given in the parentheses and σ describes the standard deviation. The T-statistic gives the t-stat of the t-test (9). θ_2 is the test statistic of the non-parametric sign test (10). The numbers in Wilcoxon signed-rank test (11) represent the Z-values of the test. N presents the number of observations. The asterisks ***, **, * next to the t-statistic, θ_2 and the Z-value denote a 1%, 5% or 10% level of significance respectively.

Estimation window: 3 months						
Variables	$\boldsymbol{\mu}$	$\boldsymbol{\sigma}$	**T-statistic**	**Sign test $\boldsymbol{\theta_2}$**	**Wilcoxon signed-rank test (Z-Value)**	**N**
AR_{-3}	0.779% (0.1768)	1.118%	4.405 ***	-3.162 ***	3.629 ***	40
AR_{-2}	-0.756% (2.021)	2.022%	-2.364 **	-3.1622 ***	-3.132 ***	40
AR_{2}	0.158% (0.444)	2.809%	0.357	-0.632	0.820	40
AR_{3}	2.282% (0.329)	2.081%	6.937 ***	-5.375 ***	5.081 ***	40
$CAR_{(-2,2)}$	5.162% (0.763)	4.828%	6.762 ***	5.3756 ***	4.772 ***	40
$CAR_{(-3,3)}$	8.223% (0.828)	5.238%	9.928 ***	-5.692 ***	5.282 ***	40

Table 30: The effect of the Russian invasion of Ukraine in 2022 on the average abnormal returns and the cumulative average abnormal returns of the S&P 500 using constant mean model for an extended event window (-5, +5)

This table reports the result of the constant mean return model (4), model (6) and model (8). Where μ is the mean of the (C)AR_t of the stock listed companies on the S&P 500 on day *t* during the event window. The event date is when *t=0*. The standard errors are given in the parentheses and σ describes the standard deviation. The T-statistic gives the t-stat of the t-test (9). θ_2 is the test statistic of the non-parametric sign test (10). The numbers in Wilcoxon signed-rank test (11) represent the Z-values of the test. N presents the number of observations. The asterisks ***, **, * next to the t-statistic, θ_2 and the Z-value denote a 1%, 5% or 10% level of significance respectively.

Estimation window: 3 months						
Variables	$\boldsymbol{\mu}$	$\boldsymbol{\sigma}$	**T-statistic**	**Sign test** $\boldsymbol{\theta_2}$	**Wilcoxon signed-rank test (Z-Value)**	**N**
AR_{-5}	-1.810% (0.096)	2.161%	-18.808 ***	-16.125 ***	-16.166 ***	504
AR_{-4}	-0.409 % (0.0598)	1.341%	-6.850 ***	-6.860 ***	-6.835 ***	504
AR_{4}	2.252% (0.082)	1.857%	27.213 ***	-19.154 ***	18.218 ***	504
AR_{5}	-0.234% (0.087)	1.961%	-2.682 ***	-0.535	-1.866 *	504
$CAR_{(-4,4)}$	0.732% (0.291)	6.541%	2.514 ***	-3.563 ***	3.562 ***	504
$CAR_{(-5,5)}$	-1.312% (0.357)	8.019%	-3.674 ***	-1.693 *	-3.080 ***	504

Table 31: The effect of the Russian invasion of Ukraine in 2022 on the average abnormal returns and the cumulative average abnormal returns of the STOXX 600 using constant mean model for an extended event window (-5, +5)

This table reports the result of the constant mean return model (4), model (6) and model (8). Where μ is the mean of the (C)AR_t of the stock listed companies on the STOXX 600 on day *t* during the event window. The event date is when *t=0*. The standard errors are given in the parentheses and σ describes the standard deviation. The T-statistic gives the t-stat of the t-test (9). θ_2 is the test statistic of the non-parametric sign test (10). The numbers in Wilcoxon signed-rank test (11) represent the Z-values of the test. N presents the number of observations. The asterisks ***, **, * next to the t-statistic, θ_2 and the Z-value denote a 1%, 5% or 10% level of significance respectively.

Estimation window: 3 months						
Variables	$\boldsymbol{\mu}$	$\boldsymbol{\sigma}$	**T-statistic**	**Sign test** $\boldsymbol{\theta_2}$	**Wilcoxon signed-rank test (Z-Value)**	**N**
AR_{-5}	-0.810% (0.086)	2.103%	-9.435 ***	-10.696 ***	-11.764 ***	600
AR_{-4}	-1.240% (0.083)	2.026%	-14.990 ***	-15.513 ***	-16.441 ***	600
AR_{4}	0.055% (0.107)	2.628%	0.513	-1.960 *	1.373	600
AR_{5}	-2.360% (0.118)	2.879%	-20.082 ***	-17.636 ***	-18.219 ***	600
$CAR_{(-4,4)}$	-6.656% (0.459)	11.249%	14.495 ***	-11.758 ***	-13.380 ***	600
$CAR_{(-5,5)}$	-9.827% (0.514)	12.599%	-19.105 ***	-14.615 ***	-16.375 ***	600

Table 32: The effect of the Russian invasion of Ukraine in 2022 on the average abnormal returns and the cumulative average abnormal returns of the SSE Composite using constant mean model for an extended event window (-5, +5)

This table reports the result of the constant mean return model (4), model (6) and model (8). Where μ is the mean of the (C)AR_t of the stock listed companies on the SSE Composite on day *t* during the event window. The event date is when *t=0*. The standard errors are given in the parentheses and σ describes the standard deviation. The T-statistic gives the t-stat of the t-test (9). θ_2 is the test statistic of the non-parametric sign test (10). The numbers in Wilcoxon signed-rank test (11) represent the Z-values of the test. N presents the number of observations. The asterisks ***, **, * next to the t-statistic, θ_2 and the Z-value denote a 1%, 5% or 10% level of significance respectively.

Estimation window: 3 months						
Variables	$\boldsymbol{\mu}$	$\boldsymbol{\sigma}$	**T-statistic**	**Sign test** $\boldsymbol{\theta_2}$	**Wilcoxon signed-rank test (Z-Value)**	**N**
AR_{-5}	-0.330% (0.056)	2.838%	-5.906 ***	-13.210 ***	-11.443 ***	2,589
AR_{-4}	0.945% (0.046)	2.365%	20.322 ***	-20.758 ***	22.464 ***	2,589
AR_{4}	0.463% (0.044)	2.214%	10.631 ***	-7.312 ***	9.738 ***	2,589
AR_{5}	-0.509% (0.049)	2.509%	-10.320 ***	-14.664 ***	-15.355 ***	2,589
$CAR_{(-4,4)}$	2.936% (0.158)	8.052%	18.560 ***	-18.817 ***	20.607 ***	2,589
$CAR_{(-5,5)}$	2.099% (0.185)	9.417%	11.346 ***	-12.571 ***	13.683 ***	2,589

Table 33: The effect of the Russian invasion of Ukraine in 2022 on the average abnormal returns and the cumulative average abnormal returns of the US defense stocks using constant mean model for an extended event window (-5, +5)

This table reports the result of the constant mean return model (4), model (6) and model (8). Where μ is the mean of the (C)AR_t of US defense stocks on day *t* during the event window. The event date is when *t=0*. The standard errors are given in the parentheses and σ describes the standard deviation. The T-statistic gives the t-stat of the t-test (9). θ_2 is the test statistic of the non-parametric sign test (10). The numbers in Wilcoxon signed-rank test (11) represent the Z-values of the test. N presents the number of observations. The asterisks ***, **, * next to the t-statistic, θ_2 and the Z-value denote a 1%, 5% or 10% level of significance respectively.

Estimation window: 3 months						
Variables	$\boldsymbol{\mu}$	$\boldsymbol{\sigma}$	**T-statistic**	**Sign test** $\boldsymbol{\theta_2}$	**Wilcoxon signed-rank test (Z-Value)**	**N**
AR_{-5}	-0.984% (0.405)	4.145%	-2.433 **	-1.464	-3.107 ***	105
AR_{-4}	-1.595% (0.515)	0.515%	-3.100 ***	-2.245 **	-4.688 ***	105
AR_{4}	0.873% (0.369)	3.781%	2.366 **	-1.854 **	3.491 ***	105
AR_{5}	-0.651% (0.474)	4.860%	-1.372	-0.097	-2.282 **	105
$CAR_{(-4,4)}$	4.844% (1.892)	19.481%	2.560 **	-2.914 ***	4.327 ***	105
$CAR_{(-5,5)}$	3.224% (2.261)	23.275%	1.426	-1.166	2.163 **	105

Table 34: The effect of the Russian invasion of Ukraine in 2022 on the average abnormal returns and the cumulative average abnormal returns of the European defense stocks using constant mean model for an extended event window (-5, +5)

This table reports the result of the constant mean return model (4), model (6) and model (8). Where μ is the mean of the (C)AR_t of European defense stocks on day t during the event window. The event date is when $t=0$. The standard errors are given in the parentheses and σ describes the standard deviation. The T-statistic gives the t-stat of the t-test (9). θ_2 is the test statistic of the non-parametric sign test (10). The numbers in Wilcoxon signed-rank test (11) represent the Z-values of the test. N presents the number of observations. The asterisks ***, **, * next to the t-statistic, θ_2 and the Z-value denote a 1%, 5% or 10% level of significance respectively.

Estimation window: 3 months						
Variables	$\boldsymbol{\mu}$	$\boldsymbol{\sigma}$	**T-statistic**	**Sign test** $\boldsymbol{\theta_2}$	**Wilcoxon signed-rank test (Z-Value)**	**N**
AR_{-5}	-0.969% (0.403)	3.044%	-2.403 **	-1.722*	-2.995 ***	57
AR_{-4}	-0.637% (0.264)	1.991%	-2.417 **	-1.987 **	-2.654 ***	57
AR_{4}	0.886% (1.072)	8.093%	0.826	-0.132	-0.127	57
AR_{5}	0.473% (1.870)	14.122	0.253	-1.192	-1.986 **	57
$CAR_{(-4,4)}$	5.404% (3.211)	24.234%	1.683 *	-0.397	1.279	57
$CAR_{(-5,5)}$	4.908% (3.560)	26.875%	1.379	-0.132	0.699	57

Table 35: The effect of the Russian invasion of Ukraine in 2022 on the average abnormal returns and the cumulative average abnormal returns of the Chinese defense stocks using constant mean model for an extended event window (-5, +5)

This table reports the result of the constant mean return model (4), model (6) and model (8). Where μ is the mean of the (C)AR_t of Chinese defense stocks on day *t* during the event window. The event date is when *t=0*. The standard errors are given in the parentheses and σ describes the standard deviation. The T-statistic gives the t-stat of the t-test (9). θ_2 is the test statistic of the non-parametric sign test (10). The numbers in Wilcoxon signed-rank test (11) represent the Z-values of the test. N presents the number of observations. The asterisks ***, **, * next to the t-statistic, θ_2 and the Z-value denote a 1%, 5% or 10% level of significance respectively.

Estimation window: 3 months

Variables	μ	σ	**T-statistic**	**Sign test** θ_2	**Wilcoxon signed-rank test (Z-Value)**	**N**
AR_{-5}	1.515% (0.326)	2.063%	4.644 ***	-3.795 ***	4.476 ***	40
AR_{-4}	-0.437% (0.155)	0.982%	-2.816 ***	-1.581	-2.285 **	40
AR_{4}	-0.344% (0.238)	1.509%	-1.442	-1.897 *	-1.949 *	40
AR_{5}	-2.451% (0.223)	1.413%	-10.975 ***	-5.692 ***	-5.430 ***	40
$CAR_{(-4,4)}$	7.223% (0.968)	6.124%	7.459 ***	-5.0560 ***	4.825 ***	40
$CAR_{(-5,5)}$	6.287% (1.138)	7.195%	5.526 ***	-4.743 ***	4.288 ***	40

Figure 3: Average Abnormal Returns S&P 500 during the event window (-5, + 5)

This diagram summarizes the average abnormal returns of the S&P 500 during the event window. The constant mean model is used to calculate the average abnormal returns.

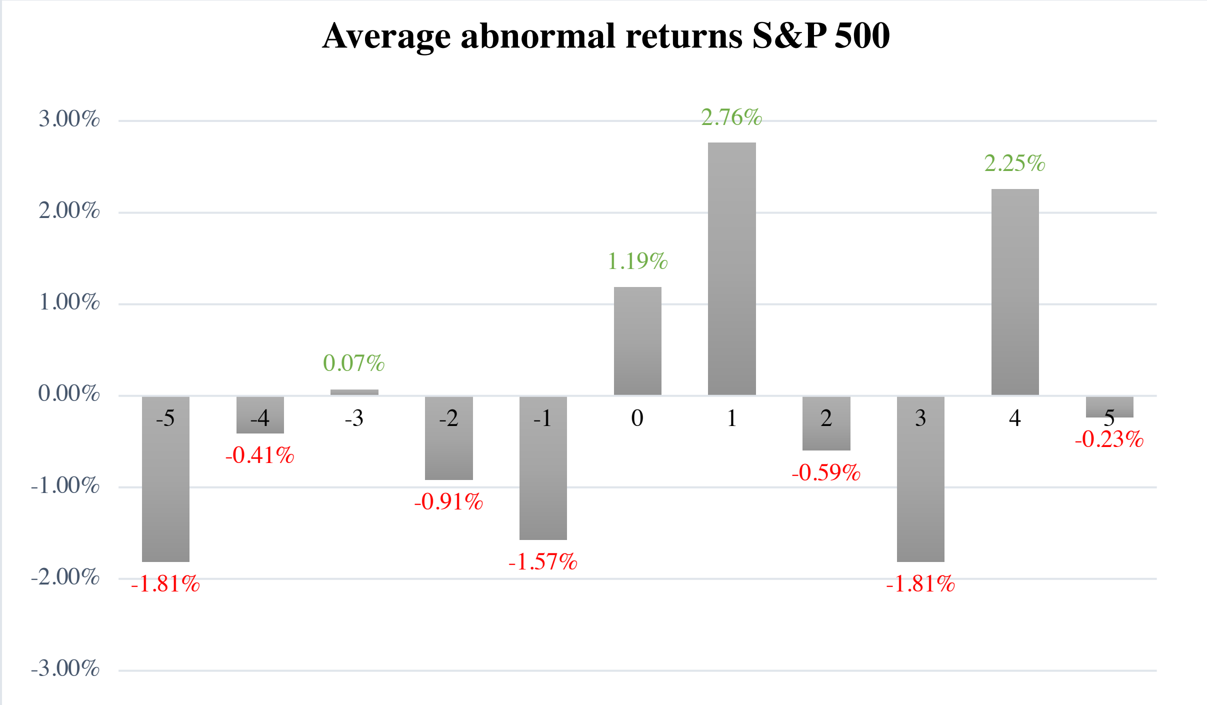

Figure 4: Average Abnormal Returns STOXX 600 during the event window (-5, + 5)

This diagram summarizes the average abnormal returns of the STOXX 600 during the event window. The constant mean model is used to calculate the average abnormal returns.

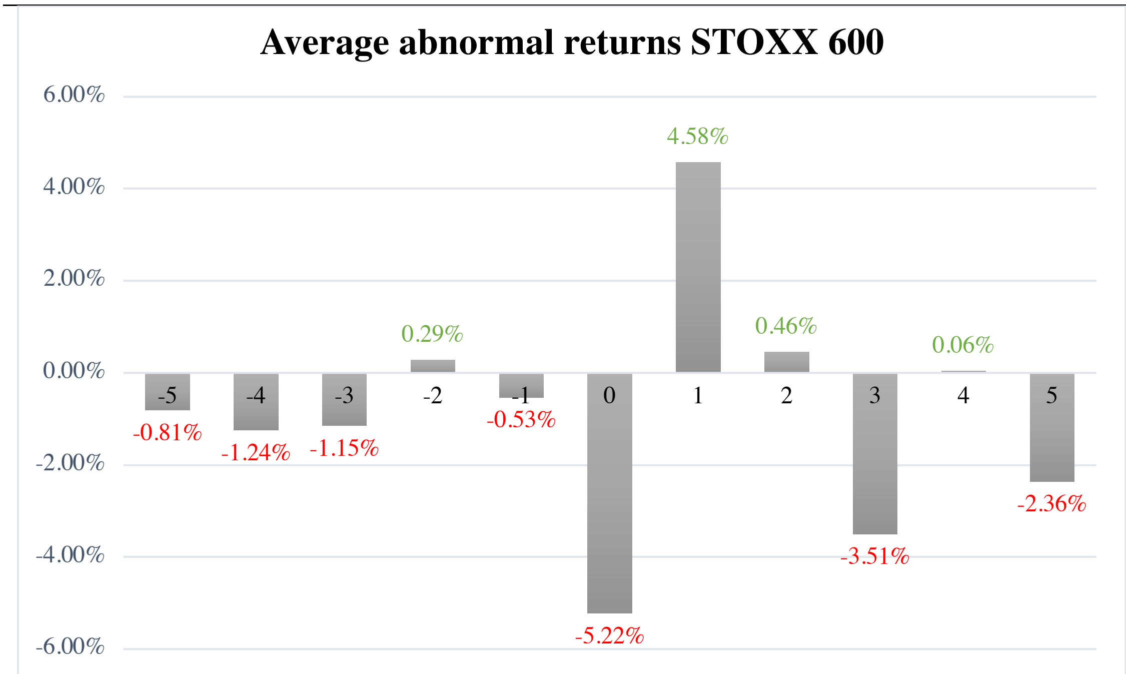

Figure 5: Average Abnormal Returns SSE Composite during the event window (-5, + 5)

This diagram summarizes the average abnormal returns of the SSE Composite during the event window. The constant mean model is used to calculate the average abnormal returns.

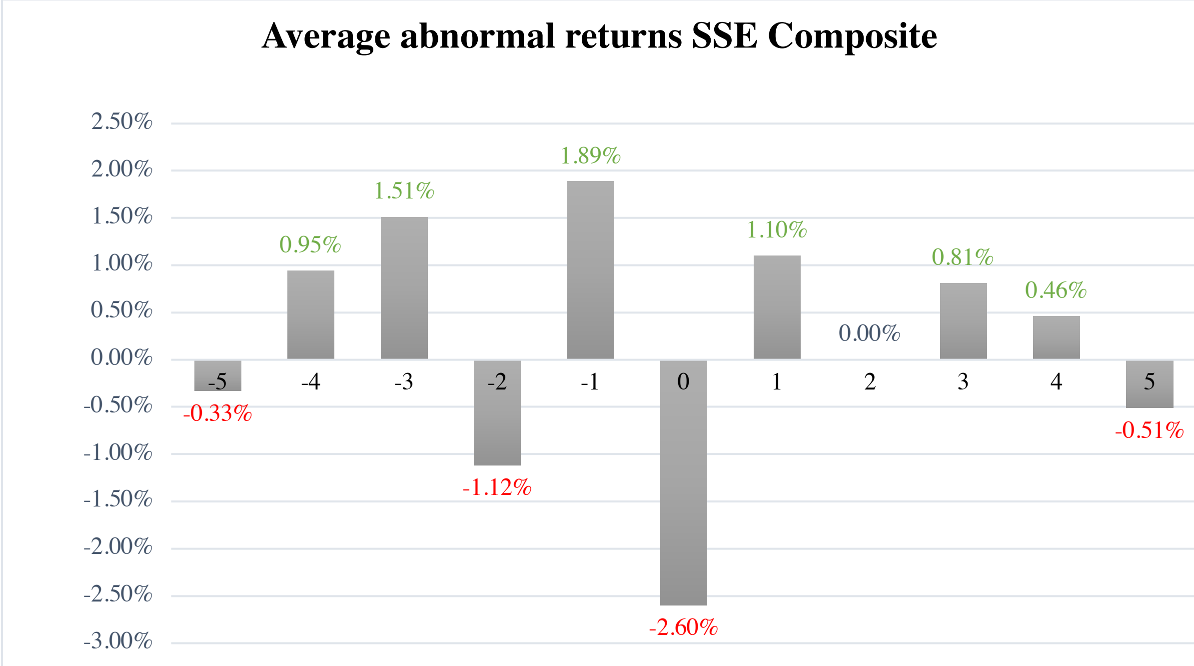

Figure 6: Average Abnormal Returns American defense-related stocks during the event window (-5, + 5)

This diagram summarizes the average abnormal returns of the American defense stocks during the event window. The constant mean model is used to calculate the average abnormal returns.

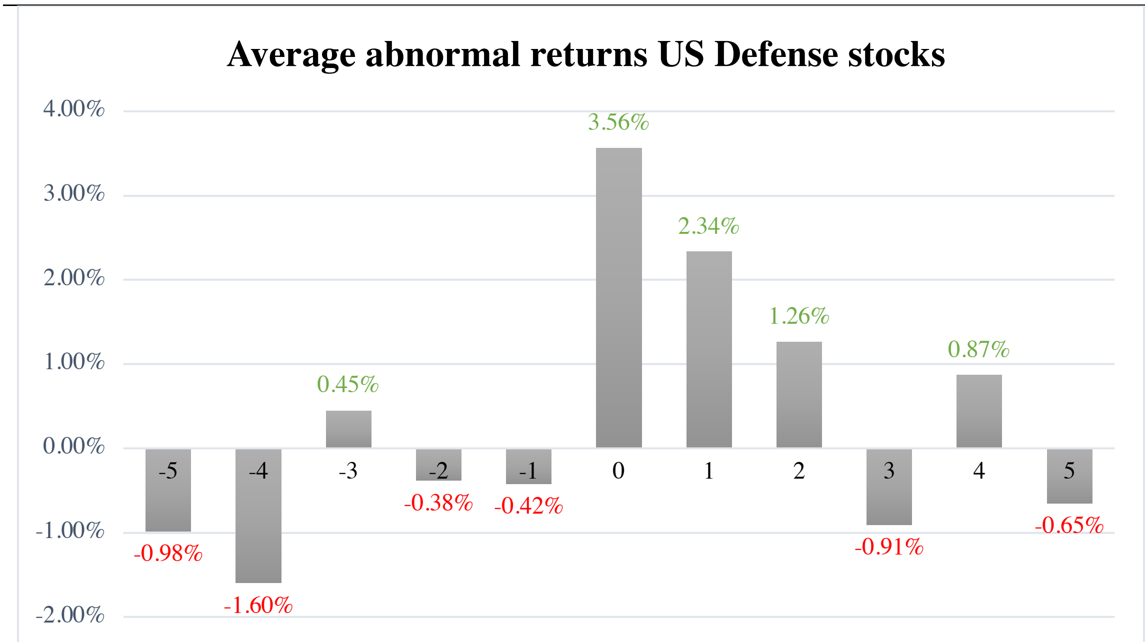

Figure 7: Average Abnormal Returns European defense-related stocks during the event window (-5, + 5)

This diagram summarizes the average abnormal returns of the European defense stocks during the event window. The constant mean model is used to calculate the average abnormal returns.

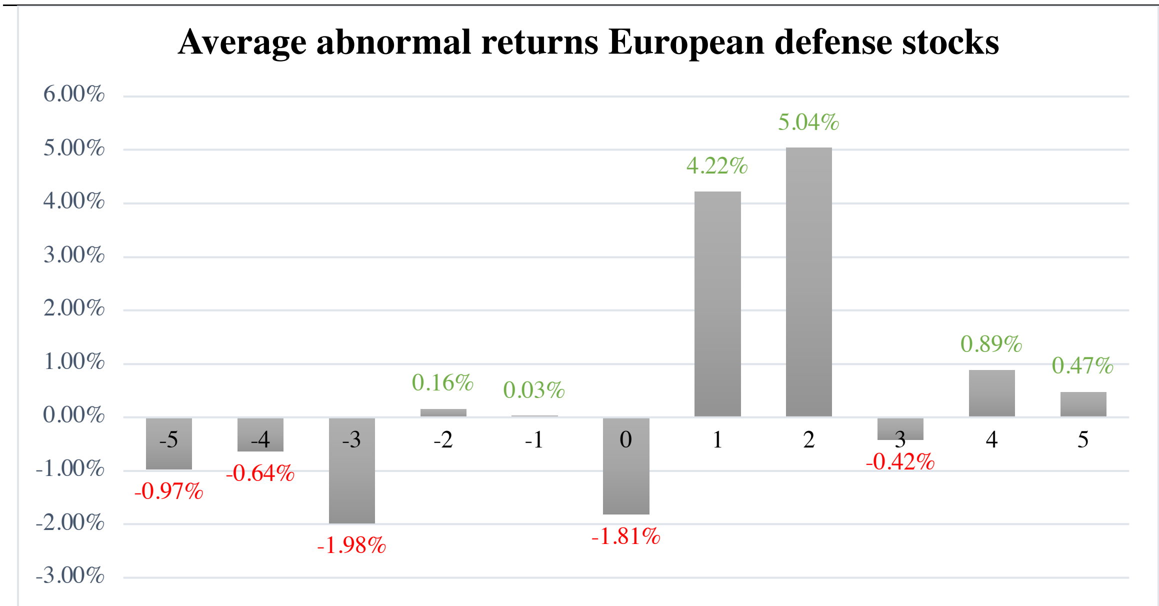

Figure 8: Average Abnormal Returns Chinese defense-related stocks during the event window (-5, + 5)

This diagram summarizes the average abnormal returns of the Chinese defense stocks during the event window. The constant mean model is used to calculate the average abnormal returns.

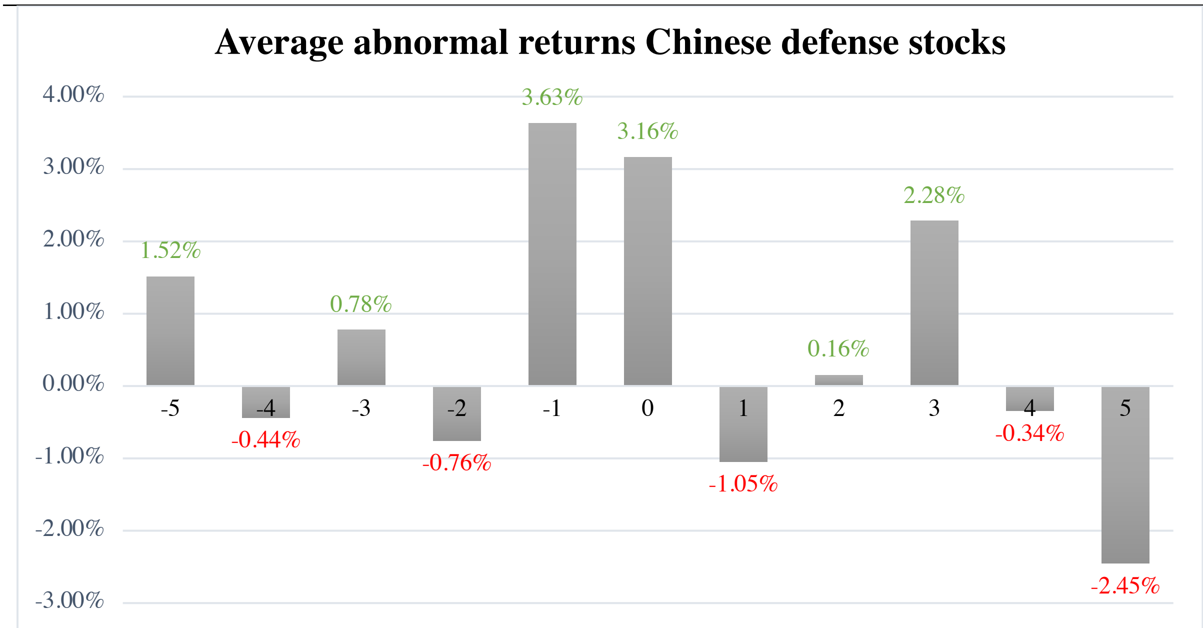

Table 40: Multivariate linear regression of the abnormal returns on the event date with dummy UN

Model specification: $AR_0 = \beta_0 + \beta 1*PE+\beta_2 *PB+\beta_3* MV+\beta_4 * DY + \beta_5*D + \beta_6 *DEP_{GAS} + \beta_7*UN$

Where PE is the price-earnings ratio, PB is the price-to-book ratio, MV is the market value, DY is the dividend yield, D is the distance in miles from Ukraine's capital Kiev, DEP_{GAS} is the dependence of a firm on Russian gas and UN is a dummy if a country is supporting Ukraine. The robust standard error, t-value, p-value and the 95% confidence interval of each coefficient is given in the table. The asterisks ***, **, * provide the level of significance. Furthermore, the mean and the standard deviation of the dependent variable are provided. Next to that the R^2, the adjusted-R^2, the F-test and the number of observations are given in the lower part of the table.

AR_0	Coef.	Robust St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
PE	0	.00001	0.21	.83295	-.00002	.00002	
PB	.00001	.00001	1.47	.1429	0	.00003	
MV	0	0	2.21	.02742	0	0	**
DY	-.00376	.00054	-6.94	0	-.00482	-.0027	***
D	.00002	0	21.29	0	.00002	.00002	***
DEP_{GAS}	.00208	.00351	0.59	.55377	-.00481	.00897	
UN	.02153	.00163	13.24	0	.01834	.02472	***
Constant	-.08746	.00351	-24.89	0	-.09435	-.08057	***

Mean dependent var	-0.02380	SD dependent var	0.03889
R-squared	0.39198	Number of obs	1830
Adjusted R-squared	0.38964	Prob > F	0.00000
F-test	130.11472		

**** p<.01, ** p<.05, * p<.1*

Table 41 A & B: Variance inflation factors of the defense-related stocks' multivariate regression

The Variance Inflator Factor (VIF) is used to check the presences of multicollinearity between independent variables in a regression. The VIF is based on the following formula:

$$VIF = \frac{1}{1 - {R_i}^2}$$

Where ${R_i}^2$ represents the unadjusted coefficient of determination for regressing the i[th] independent variable on the remaining ones. *D* is the distance in miles from Ukraine's capital Kiev, DEP_{GAS} is a dummy for the dependence of a country on Russian gas, *S* is a dummy for military support to Ukraine, *DEFB* is the defense budget of a country relative to its GDP, *DY* is the dividend yield and *MV* is the market value.

Table 41A: Variance inflation factor

	VIF	1/VIF
DEP_{GAS}	62.292	.016
D	47.345	.021
S	11.744	.085
DEFB	11.523	.087
MV	1.087	.92
DY	1.039	.962
Mean VIF	22.505	.

Table 41B: Variance inflation factor without D_{GAS}

	VIF	1/VIF
DEFB	10.222	.098
D	8.385	.119
S	5.539	.181
MV	1.049	.954
DY	1.018	.982
Mean VIF	5.242	.