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# **Overreaction or Opportunity? An Event Study of Defense Sector Stocks Responding to Geopolitical Shocks**

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Generative AI tools (e.g., ChatGPT, Copilot) were used to assist in coding, data analysis, and/or refining the language of this thesis. Appendix F of this thesis provides a detailed account of the use of Generative AI tools during the development of this thesis. By submitting this thesis I declare that I am fully responsible for the accuracy and completeness of its content.

## **Abstract**

This study aims to examine whether defense sector stocks overreact to geopolitical shocks, specifically focussing on the Russia-Ukraine war and the Israel-Gaza conflict. The research uses an event study methodology to calculate the Cumulative Average Abnormal Returns (CAAR) over multiple pre- and post-event windows across three models. Consistent for both events and all three models, defense sector stocks show a steady increase in CAAR over the one-year post-event period. This pattern contradicts the overreaction hypothesis, which would predict an initial spike followed by a correction. To compare the findings for the defense sector, a control group of non-defense stocks is taken into consideration. For non-defense stocks, the results suggest that their cumulative average abnormal returns do not consistently deviate significantly from zero over time. The research concludes that defense sector stocks show drift over the one year post-event period, rather than a short term overreaction. Although the study is limited to a one year post-event horizon, the findings offer valuable insights into investor reactions to geopolitical shocks across defense and non-defense sector equities.

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## 1 Introduction

In the first half of 2025, the declaration of World War III was threatened twice. The newly elected president of the United States of America, Donald Trump, shut down all military aid to Ukraine in February. Since the start of the invasion, the United States have been a key resource in giving Ukraine a fighting chance to withhold Russia from entering Ukraine territory. The declaration by Donald Trump to stop all aid provided by the US was a global shock, which was likewise reflected in the global equity markets. Late June 2025 president Trump initiated an attack on Iran by bombing their key nuclear facilities. Threatening world peace twice within a time span of 6 months.

Geopolitical shocks have historically been a primary source of market disruptions, influencing both the global economy and investors sentiment. In recent years the frequency and intensity of geopolitical conflicts have increased, marked by the outbreak of the Russia-Ukraine war in February 2022 and the Israel-Gaza conflict in October 2023. These events have thrust financial markets into a state of volatility, where geopolitical shocks often trigger negative market reactions (Leahy et al., 2023). However there have been papers suggesting a potential hedge against geopolitical conflicts, insinuating the geopolitical shock can be beneficial for specific sectors in the equity market (Covachev & Fazakas, 2025; Guidolin & Ferrara, 2010). The defense sector in particular, which is typically influenced by government defense contracts and national security concerns, may not follow typical patterns of market reaction seen in other sectors. Investors shift their attention to the defense sector when the threat of geopolitical instability emerges. Much of the existing literature however, focussed on the overall market reaction during war declarations (Boubaker et al., 2022; Gaio et al., 2022; Yousaf et al., 2022).

Increased interest in the defense sector during times of geopolitical uncertainty may be more driven by the news, and less by the fundamental value of a stock like traditional economics might suggest (Fama, 1970). Do investors react primarily based on news or is all information priced in immediately when information becomes public, like Fama (1970) and the Efficient Market Hypothesis (EMH) suggests? Previous literature has found that investors are sensitive to influential news, often grabbing investors their attention and possibly acting without taking the firms fundamentals into consideration (Barber & Odean, 2008; Huynh & Smith, 2017). The essence of behavioural finance suggests that investors do not always act rationally, but are often influenced by emotional and psychological biases.

De Bondt & Thaler (1985) were the first to introduce the concept of over/under reaction, with their work in 1985. Over/under reaction indicates that investors react either too much so that the price is valued higher than the stock's fundamental value, or that investors do not react sufficiently, indicating that the

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price stays below the fundamental value in the short-run. The most frequently used method to research over/under reaction is through calculating the Abnormal Return (AR) and Cumulative Abnormal Return (CAR) of a stock. AR represents the amount that a stock performs higher/lower than the expected return of the stock. When a stock is over/under valued in the short run, it is expected that the stock will correct itself in the long run towards the fundamental value, what the stock is worth intrinsically. While it is interesting to measure the effect of geopolitical shocks on the equity market, previous research has touched on this topic in the past (Boubaker et al., 2022, 2023; Boungou & Yatie, 2022; Ijaz et al., 2025; Pandey et al., 2024). Likewise, the effect of geopolitical shocks on the defense sector has been examined by previous literature (Covachev & Fazakas, 2025). Previous literature has not yet examined the investor behaviour within the defense sector reacting to geopolitical shocks. Investor behaviour will be tested considering both the start of the Russia-Ukraine conflict and the start of the Israel-Gaza conflict. The research conducted in this paper attempts to go beyond existing literature, by aiming to answer the following question: *To what extent do defense sector stocks exhibit signs of investor overreaction following geopolitical shocks, and how does this compare to non-defense sector stocks?*

The research question will be answered through an event study framework. To test for potential overreaction by investors, the Cumulative Average Abnormal Return (CAAR) will be calculated over multiple event windows. The event windows gradually increase in length, by examining CAAR over the event windows a decrease or increase in CAAR can explain investor reactions to the two events. The abnormal return is calculated using three different models, well established in event study literature. To confirm an overreaction in the short-run followed by a correction in the long-run, CAAR should be increasing in the short-run event windows and decreasing over the long-run. The findings suggest however that throughout the one year post-event window, CAAR for defense sector stocks gradually increases for both events, thus implying a drift rather than a correction. Non-defense sector stocks do not show a significant difference from zero in CAAR over the post-event windows.

The thesis is structured as follows. First an overview of existing literature is presented, out of which the hypothesis will be formed. Following the hypothesis the methodological approach is outlined, with a detailed description of how the research is conducted. Next the data is described and results will be interpreted. Lastly, a discussion and conclusion will summarise the results and will involve suggestions for future research expanding on this paper. The concluding chapters include the reference list and the appendix.

## 2 Literature Review

### 2.1 *Information and Price Reactions in Financial Markets*

When economic theories were first introduced, models were built assuming rational behaviour by investors. There was no ambiguity in the market, and no room for arbitrage. Fama (1970) introduced the Efficient Market Hypothesis (EMH), assuming that all public information was priced into assets immediately. EMH suggests it is impossible to create exceeding returns compared to the market average in the long run. According to Fama (1970), stocks are valued at their fundamental value immediately after news is public, pricing in all information instantly.

A growing body of empirical evidence however challenged the findings of Fama (1970). Phenomena like post-earnings announcement drift, momentum effects and price reversals suggest that markets are not entirely efficient. Additionally, EMH suggests that investors are all rational and have homogenous goals in the financial markets. Fama (1970) fails to account for individual psychological differences between investors. In reaction to these limitations theories have evolved and take into account potential biases and investor psychology (Barber & Odean, 2008; De Bondt & Thaler, 1985; Kahneman & Tversky, 1979).

When geopolitical stability diminishes, particularly in cases leading to military conflicts, rational behaviour is often not enough to explain the movements in financial markets. While traditional models might attribute volatility to risk premiums, they do not fully explain why certain sectors react disproportionately to black swan events. Moreover, traditional models fail to explain corrections or momentum that might occur during periods of geopolitical shocks.

### 2.2 *Stock Market Reactions to War and Geopolitical Shocks*

Geopolitical events have a strong impact globally. Often multiple countries are involved, and the safety of neighbour countries is compromised. In recent years there have been numerous cases where geopolitical shocks or war outbreaks occurred, and research has shown that these geopolitical shocks have a negative effect on the stock market (Boubaker et al., 2022; Gaio et al., 2022; Leahy et al., 2023; Yousaf et al., 2022). On February 24<sup>th</sup> 2022, Russia declared war to Ukraine and invaded their lands. This event led to a global geopolitical shock. The war between Russia and Ukraine, is the largest political shock in the past decade. Previous research has found that the declaration of war by Russia had a significant negative effect on the stock market, generally in the short run (Ahmed et al., 2022; Boubaker et al., 2022, 2023; Gaio et al., 2022; Martins et al., 2023; Meng & Yu, 2023; Yousaf et al., 2022).

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Another geopolitical shock has taken place since the declaration of war by Russia, which is the conflict between Israel and Hamas, starting on October 7th 2023. This conflict has received comparatively less academic attention, likely due to its more recent emergence. Nonetheless, it had a substantial global impact, still relevant at the time of writing in June 2025. The effect is also reflected in movements within the financial markets (Bhattacharjee et al., 2024; Ijaz et al., 2025; Pandey, 2024). Research published by Pandey et al. (2024) investigated how variations in national happiness levels influenced financial market reactions to the Israel-Hamas conflict. Through an event study the authors found that stock indices from happier nations are generally more resilient to this geopolitical shock. Cui & Maghyereh (2024) examined whether the Israeli-Palestinian conflict intensified volatility spillovers, the authors found a strong effect on the spillovers among oil, natural gas, gold and the Palestine and Israel stock market. Pandey (2024) analysed the effect of the conflict on currency exchange rates, and the effect on the stock market across different geographic regions. The reaction of the Israel-Hamas conflict has not been examined yet on defense sector stocks, this research will aim to provide an answer to this undiscovered territory. While both events examined in this paper are geopolitical shocks of large impact globally, differences like the geographic location of the events and the scale of the shock might impact investor reactions. The geographic location of the Russia-Ukraine event had a positive impact on European defense stocks, according to Covachev & Fazakas (2025). Examining the events separately and examining potential differences will contribute to existing literature, as this has not yet been attempted by previous research.

Previous research has examined the effect of global events, both violent and non-violent, and the effect on the equity market (Bradford & Robison, 1997; Gu et al., 2021; Guidolin & Ferrara, 2010). Most studies find a negative relation between the geopolitical uncertainty and equity markets, however some argue that there are positive effects on the financial market that blossom from war (Guidolin & Ferrara, 2010).

Almost exclusively, studies examining the effect of geopolitical uncertainty focus on the effect of the global equity market. There are a limited amount of studies that are focussed on specific sectors. Most papers that focussed on a specific sector examined the effect of the Russian invasion on the financial industry (Boubaker et al., 2023; Martins et al., 2023). Both studies find that the financial industry was hit more severe than the average stock market, in the short run. Additionally, the European financial sector has been hit the hardest of all regions (Boubaker et al., 2023). Covachev & Fazakas (2025) examined the effect of the Russia-Ukraine war and the Wagner group coup on the European defense industry. Their results stated that on the day of the invasion, there was a high abnormal return. The Wagner group coup conversely had a negative effect on the defense stocks. These findings suggest that the defense industry could act as a hedge against geopolitical shocks (Covachev & Fazakas, 2025).

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### 2.3 *Explaining Irrational Market Reactions*

The relationship between geopolitical shocks and the equity market has been established by previous research (Bradford & Robison, 1997; Gu et al., 2021; Guidolin & Ferrara, 2010). Does the financial market immediately price in the event within seconds, consistent with the Efficient Market Hypothesis (Fama, 1970)? It is true that in this day and age markets react to news and events within seconds, yet the investors often trade on news sentiment, not on fundamental value. Thus, public information is not always immediately priced in, and stocks are often over/under valued. So why do investors not act rational? Why does arbitrage continue to exist in financial markets? This is where behavioural finance is introduced.

Investors are sensitive to news and events, especially news and events that has strong sentiment (Barber & Odean, 2008; Huynh & Smith, 2017; Tetlock, 2007). These strong reactions to news and events can lead to behavioural biases, deviating from the efficient market hypothesis. The first to introduce over/under reaction were De Bondt & Thaler (1985), the authors suggested that investors overweight recent information. This overreaction can lead to prices being higher than their fair value in the short run, this is corrected for in the long run when prices return back to their fundamental value. Daniel et al. (1998) expanded on the topic and introduced both overconfidence and biased self-attribution as explanations for over/under reactions in financial markets. Overconfidence can lead investors to believe that their information is superior, while self-attribution bias underreacts to public information that might be contrary to their beliefs. Abbas et al. (2009) confirmed the overconfidence bias and the self-attribution bias in their paper, while adding that overconfidence is observed more aggressively in a bull market.

News is able to be spread more rapidly across our population than ever before, online news articles are available for the public, and can be easily shared through social media. Attention-grabbing news can have a significant effect on investor behaviour in financial markets. For example, Fischer (2012) found that in the drug industry, investors systematically underreact to earnings announcements. While news leads to an overreaction in the stock market. Earnings announcements, that can contain information that gives insight on a company's fundamental value, thus has less influence on investors investment decisions than flashing news, grabbing their attention. A potential reason for this could be that investors might not understand the detailed content of earnings announcements, while news articles are understood by the general public. These findings suggest that investors do not always react rational towards a potential change in the fair value of a company, when after an overreaction a correction will take place in the long run.

Tetlock (2007) found that high pessimism in the media predicts a downward trend in the equity market, and that extreme values for pessimism (high or low) have a positive effect on the trading volume of a stock. Huynh & Smith (2017) examined the news tone, and the strength of the news, trying to understand which type of news cause momentum effects and underreaction. Huynh & Smith (2017) find that higher attention to news keeps investors reacting to the news for an extended period of time. Additionally, investors underreact more to high attention positive news, rather than low-attention or negative news. While this study will employ event study methodology to analyse the reaction on the defense sector investors, it is equally important to understand why investors over/under react to news. Because news spreads information of the events within seconds, investors are likely to respond rapidly in the stock market.

#### *2.4 Event Studies as a Tool to Capture Investor Behaviour*

Previous studies have examined the war between Russia and Ukraine through an event study framework. Boubaker et al. (2022) and Bounou & Yatie (2022) looked at the impact on global stock market returns, providing the first empirical evidence for a negative relationship between the Russo-Ukrainian war and stock market indices. However, these papers limit their research to the effect on the financial market, and fail to take into account investor behaviour.

Several studies have researched investor behaviour to earnings announcements, which can be considered pseudo-events. Fischer (2012) finds an underreaction to earnings announcements. Berkman & McKenzie (2012) find that institutional investors do react to earnings announcements by firms. X. Huang et al. (2014) investigate the different tone used by management, and find that a positive tone leads to an overreaction of the stock, led by a negative delayed reaction in the following quarters.

A more recent paper that examines investor behaviour based on event studies is authored by Thu Quang (2024), investigating investor reactions to black swan events in the Vietnam stock market. Findings conclude that investors overreact to domestic black swan events, however investors underreact to international black swan events, including the Russia-Ukraine war.

#### *2.5 Research Gap and Contribution*

Geopolitical shocks and increased geopolitical uncertainty often leads to a significant negative reaction in the equity market (Boubaker et al., 2022; Bounou & Yatie, 2022; Ijaz et al., 2025). Some specific sectors, like the financial industry, are hit harder than the average financial markets (Boubaker et al., 2023). Yet there are sectors that might act as a hedge to geopolitical shocks, the defense sector specifically (Covachev

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& Fazakas, 2025). Investors seek safety in the stock market and prepare for potential geopolitical instability, thus acting as a hedge against geopolitical shocks.

Event studies are used to measure the reaction by investors to black swan events, literature as of today has not yet examined the potential presence of over/under reactions on geopolitical shocks on the long run. While Covachev & Fazakas (2025) have found results of the European defense industry sector reacts positively to the Russian invasion in the short-run, the authors fail to search for potential over/under reactions by investors. Additionally, most event studies on geopolitical risk are attributed to the Russo-Ukrainian war. This research will take into account both the war between Russia-Ukraine and the Israel-Gaza war. As the effect of geopolitical shocks on the global equity market has been examined in the past, this paper aims to focus primarily on the defense sector. While additionally controlling for non-defense stocks to compare potential differences.

Building on the findings of previous literature, research in the past has proposed that investors, are likely to overreact to high impact news and events (Daniel et al., 1998; De Bondt & Thaler, 1985; Fischer, 2012; Thu Quang, 2024). Past literature has also shown that geopolitical shocks often negatively affect the equity market (Bhattacharjee et al., 2024; Boubaker et al., 2022; Bradford & Robison, 1997). Covachev & Fazakas (2025) found that defense stocks can act as a potential hedge against geopolitical shocks due to investors speculating a potential escalation of the events. Combining the knowledge and findings of the forementioned literature, the following hypotheses can be formed:

- *H1: Defense sector stocks exhibit an upwards overreaction to geopolitical shocks in the short-run, followed by a correction downwards towards the fundamental value in the long-run.*
- *H2: Non-defense sector stocks exhibit an initial significant negative reaction to geopolitical shocks, with the weaker performance persisting while the geopolitical instability is unresolved.*

Due to the significant investor sentiment that geopolitical shocks create, it is expected that investors do overreact to the Russia-Ukraine war and the Israel-Hamas conflict (Daniel et al., 1998; De Bondt & Thaler, 1985). Defense sector stocks are expected to experience positive abnormal returns in the short run, in line with Covachev & Fazakas (2025). This will likely manifest in short-term overpricing, which is expected to be followed by a long-term correction as the market re-adjusts.

Previous literature has examined the effect of geopolitical shocks on several sectors, although almost exclusively the short term reaction to the event. Boubaker et al. (2023) and Martins et al. (2023) found a negative reaction in the financial sector as a reaction to the shock. The global equity market also responded negatively in the short run (Boubaker et al., 2022; Yousaf et al., 2022). While less academic papers are focussed on the long-term effect, an article from MSCI confirms that the global equity market took a hit

the year following the Russian invasion (Leahy et al., 2023). Therefore it is expected that the non-defense stocks are negatively impacted during times of geopolitical instability.

### 3 Methodology

#### 3.1 Research Design and Event Study Framework

This study aims to investigate investor reactions to major geopolitical shocks. Specifically the outbreak of the war between Russia and Ukraine (February 24th 2022), and the start of the war between Israel and Gaza (October 7th 2023). Due to October 7<sup>th</sup> occurring on a Saturday, the event date used for estimating investor behaviour is October 9<sup>th</sup> instead. To measure this effect, this paper will conduct an event study. Event studies consist of an estimation window, pre-event windows, the event, and a post event windows. The estimation window is used to estimate abnormal returns based on a period that is not influenced by the two events. For this research the estimation window is one year and ranges from January 1<sup>st</sup> 2021 until December 31<sup>st</sup> 2021. This study utilizes multiple lengths of event windows in order to observe investor behaviour over longer periods of time. Below the event windows are illustrated, negative numbers represent the amount of days before the event and positive numbers represent the amount of days after the event.

- *Pre-event windows:* [-10, -1] & [-3, -1]
- *Event:* [0, 0]
- *Short-run event windows:* [0, +3] & [0, +10]
- *Medium-run event window:* [0, +30] & [0, +90]
- *Long-run event window:* [0, +180] & [0, +365]

This design enables the analysis of immediate market reactions as well as post-event drift or potential overreaction. The longest post-event window is capped at 365 days after the event, to avoid overlap between the two events. Classical studies on investor overreaction demonstrate that return reversals and drift can persist over multiple years (Bernard & Thomas, 1989; De Bondt & Thaler, 1985; Jegadeesh & Titman, 1993). Still, the long-horizon studies are not without issues. Kothari & Warner (1997) stress that multi year event studies could be vulnerable to model misspecification or inflated variance. Therefore this paper uses a balanced design to capture the immediate reaction to the shocks, while still trying to capture potential overreaction or drift over the one year period post-event.

Both abnormal returns and cumulative abnormal returns will be calculated using daily stock return data, and through these findings it can interpret whether the cumulative abnormal return will return to the

mean in the long term, or show momentum by becoming greater over time. With the help of CAR across the event windows for defense stocks and non-defense stocks, the hypotheses stated in section 2.5 can be tested. This study follows the general methodology on event studies provided by MacKinlay (1997), who provided the golden standard framework for all future event studies. Previous studies have used both abnormal returns and cumulative abnormal returns to examine investor reactions to events (Boubaker et al., 2022, 2023; Fischer, 2012; Gunaratne & Yonesawa, 1997; Pevzner et al., 2015). This paper aims to use a similar methodology, while implementing numerous models that have proven to add value to estimating expected return of a stock.

### 3.2 *Models to Estimate Expected Returns*

Three different models will be used to estimate both AR and CAR over the event windows, this approach allows for robustness checks across the models. The CAPM-model was one of the first models allowing to calculate expected returns, but is too simplified in modern day (Fama & French, 2015). Therefore, additional models will aim to add explanatory power to estimating the expected return. All three models will be calculated using an OLS regression.

The CAPM-model is the simplest model applied in this study, it aims to estimate the expected return for individual stocks, using the market return and a risk free return. Below the CAPM-model is illustrated:

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \epsilon_{it}$$

- $R_{it}$  = Return of stock i at time t
- $R_{mt}$  = Return of the market at time t
- $R_{ft}$  = Risk-free return at time t
- $\epsilon_{it}$  = Error term of stock i at time t

To estimate the expected return of a stock the CAPM-model uses only one factor, market return subtracted by the risk free return (MacKinlay, 1997). Returns that are only predicted by a single factor are often not great at estimating with accuracy, due to the lack of control variables. This is where multifactor models are introduced. Multifactor models try to increase the explanatory power by adding factors to the model. There have been numerous studies on potential factors that provide added value to estimating expected returns. Possibly the most well known are the 4-factor model (Carhart, 1997; Fama & French, 1993), and the 6-factor model (Carhart, 1997; Fama & French, 2015). Fama & French their findings are well

recognized among financial economics, this research will therefore additionally use these two multifactor models to estimate the expected return. Furthermore, Carhart (1997) contributed to the models by introducing the momentum factor, which is originally not included in the models by Fama & French (1993, 2015). Therefore this research will add momentum to the Fama & French models, following the approach by previous papers utilizing event studies (Covachev & Fazakas, 2025; Yue et al., 2020).

*The 4-Factor Model:*

$$R_{it} - R_{ft} = \alpha_i + \beta_m(R_{mt} - R_{ft}) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t + \beta_{MOM} \cdot MOM_t + \epsilon_{it}$$

*The 6-Factor Model:*

$$R_{it} - R_{ft} = \alpha_i + \beta_m(R_{mt} - R_{ft}) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t + \beta_{RMW} \cdot RMW_t + \beta_{CMA} \cdot CMA_t + \beta_{MOM} \cdot MOM_t + \epsilon_{it}$$

- $R_{it}$  = Return of stock i at time t
- $R_{ft}$  = Risk-free return at time t
- $\alpha_i$  = Intercept (alpha) for stock i
- $R_{mt}$  = Return of the market at time t
- $SMB_t$  = Small Minus Big (size factor) at time t
- $HML_t$  = High Minus Low (value factor) at time t
- $RMW_t$  = Robust Minus Weak (profitability factor) at time t
- $CMA_t$  = Conservative Minus Aggressive (investment factor) at time t
- $MOM_t$  = Momentum factor at time t
- $\epsilon_{it}$  = Error term for stock i at time t

Fama & French (2015) add a size factor to account for the size of the firm, reflecting a risk premium for smaller firms. The value factor accounts for book to market ratio, where high value stocks are awarded higher return. The profitability factor consists of robust profitability minus weak profitability, where higher profitability increases expected return. The investment factor attributes higher expected return to more conservative investments, rather than aggressive. Lastly, the momentum factor takes into account

performance of the previous period, where well-performing stocks increase expected return according to Carhart (1997).

When the expected return is calculated for the individual stocks, it is possible to calculate the abnormal return for the individual stocks. The formula for AR is shown below:

$$AR_{it} = R_{it} - \hat{R}_{it}$$

- $AR_{it}$  = Abnormal return of stock i at time t
- $R_{it}$  = Actual return of stock i at time t
- $\hat{R}_{it}$  = Expected return of stock i at time t, estimated by the CAPM-model, 4-factor model or the 6-factor model

To test whether investors under/over react to an event, the cumulative abnormal return is calculated (MacKinlay, 1997). When CAR is decreasing in the long-run relative to the short-run, it is suggested that investors overreacted to the event, due to returns reverting back to the mean (Daniel et al., 1998; De Bondt & Thaler, 1985; Huynh & Smith, 2017). An increase in CAR would suggest that there is drift, as the stock maintains momentum over the long-term. The CAR formula consists of the following:

$$CAR_i = \sum_{t=T_1}^{T_2} AR_{it}$$

- $CAR_i$  = Cumulative abnormal return for stock i
- $\sum_{t=T_1}^{T_2} AR_{it}$  = Sum of abnormal returns over event window from  $T_1$  to  $T_2$ .

CAR will be calculated for all stocks independently and over the multiple event windows, to test for potential over/underreaction for stocks on an individual level. The results however will be interpreted by comparing two groups: defense sector stocks and non-defense sector stocks. Additionally, the results of the two events will be compared to test for potential differences in investor reaction. Comparing the results between two geopolitical shocks will add to existing literature, as previous literature has yet to examine these two events with regards to over/under reaction in the market.

While AR calculates the abnormal return for one moment in time, the CAR sums the abnormal returns over the total event windows as defined above. The cumulative average abnormal return will be utilized

to answer the research question. CAAR will be calculated for the defense sector stocks and the non-defense sector stocks:

$$CAAR = \left(\frac{1}{N}\right) * \sum_{i=1}^N CAR_i$$

- $CAAR$  = Cumulative average abnormal return
- $N$  = Number of stocks in the sample
- $CAR_i$  = Cumulative abnormal return for stock  $i$

CAAR will give a simple, easy to understand overview to see the difference in CAR for both test groups. The results will provide insights whether defense stocks and non-defense stocks move differently in times of geopolitical uncertainty, in line with Boubaker et al. (2023); Covachev & Fazakas (2025) and Guidolin & Ferrara (2010). To test whether the CAAR values are significantly different from 0, a Wilcoxon Signed-Rank test is used (Wilcoxon, 1945). This non-parametric test tests the null hypothesis whether the median CAR for the two groups is equal to zero. The test is applied separately to each group within each event window, for both events. The test is performed on an individual firm level (CAR), however by calculating the median CAR the results are presented for the defense sector and non-defense sector groups.

Additionally, a Mann-Whitney U Test will be performed to compare the differences between the two groups of stocks (Mann & Whitney, 1947). The Mann-Whitney U Test aims to compare two different groups, similar to the Two-Sample T-Test. However, due to the relatively small sample of stocks that are used for this research, the Mann-Whitney U Test is used as a non-parametric alternative. The goal of the Mann-Whitney U Test is to provide potential insights and test whether there is a significant difference in CAAR between the two test groups, the test will be conducted for both events. The null hypothesis tests whether the distributions of the two independent groups are equal, indicating no difference between the two groups. If the P-value for the Mann-Whitney U Test is below 0.05, it suggests that there is a significant difference between the two groups examined.

To further examine whether the defense sector exhibit significantly different cumulative abnormal return patterns compared to the other sectors during the one year event window, a panel regression model with random effects was employed. The model specification is shown below.

$$CAR_{it} = \beta_0 + \beta_1 * D_i + \beta_2 * T_t + \beta_3 * (D_i * T_t) + u_i + \varepsilon_{it}$$

- $CAR_{it}$  = Cumulative abnormal return for firm i at time t, provided by the 6-factor model
- $D_i$  = Dummy variable equal to 1 if firm i is in the defense sector, 0 otherwise
- $T_t$  = Time (in days) relative to the event
- $D_i * T_t$  = Interaction term to capture differential time trends for defense firms
- $u_i$  = Firm-specific random effect
- $\varepsilon_{it}$  = Error term for firm i at time t

This specification allows for testing not only the sectoral difference in CAR, but also whether defense sector firms experience a different trajectory over time compared to non-defense firms through an interaction effect.  $\beta_1$  represents the average difference in CAR between defense and non-defense firms. The interaction term  $\beta_3$  tests whether defense firms react differently to geopolitical shocks over time relative to the non-defense stocks. To estimate the panel regression model, CAR is provided by the Fama-French 6-factor model. This model is selected as it controls for various variables and exhibits the highest explanatory power across the three models.

The model accounts for unobserved heterogeneity across firms by assuming that firm-specific effects are uncorrelated with the explanatory variables, in this case the sector of the firms. The random effects specification was validated through a Hausman Test, of which the results can be found in Appendix E Table 20. The Hausman Test failed to reject the null hypothesis, implying that the random effects estimator is consistent and efficient. To further confirm whether the random effects model adds value to the findings, a Breusch-Pagan Test is performed. The Breusch-Pagan Test when applied to a random effects model tests whether the results show significant effects relative to a standard OLS regression. Findings of the Breusch-Pagan Test for both event regressions can be found in Appendix E table 21. Both tests in table 21 rejected the null hypothesis, concluding that the random effects model shows significant effects relative to a standard OLS regression.

Finally, the research will compare the effects across the two events. To statistically test the difference in findings for both events, a Wilcoxon Signed-Rank Test is conducted (Wilcoxon, 1945). Again, due to the relatively small sample of stocks the non-parametric version of the Paired T-test is used. The Wilcoxon Signed-Rank Test is used in this case due to the similar sample of stocks for both events. The null hypothesis for the Wilcoxon Signed-Rank Test suggests that the median of the differences between paired observations is zero.

### 3.3 Data Collection

This study focuses on a sample of 20 defense sector stocks and 17 non-defense sector stocks. The 20 defense stocks are chosen due to their presence in the Van Eck Defense ETF (VanEck, 2023), this tracker consists of the largest companies present in the defense sector and will provide a great mix of global firms within the sector. The defense sector stocks part of the Van Eck Defense ETF are filtered based on if the firm is operating in developed world countries. To facilitate a clear comparison between defense and non-defense sectors, a sample of originally 20 non-defense firms was selected to match the sample size of defense firms. Companies were randomly drawn from a pool of publicly traded non-defense firms to avoid introducing selection bias. Later 3 firms were excluded due to inconsistency in the data. The list of companies together with the sector and country allocation can be found in Appendix A Table 8.

The stock return data, ranging from 2021 up until 2024, is provided by LSEG. The return data is daily and is displayed in percentage change. Daily data is preferred due to the event windows being constructed with daily data. Additionally, the market return and the risk free rate is provided by the Fama-French library, which includes daily data of market return and risk free rate for the developed world (French & Fama, 2025). For the control variables provided by Fama & French (1993, 2015), the daily values are provided in the Fama and French Data Library (French & Fama, 2025).

The dates that will be investigated are the 24th of February 2022, and the 9th of October 2023, which represent the dates of the Russian invasion and the Israel-Gaza conflict, respectively. The 9th of October is treated as the start of the Israel-Gaza conflict, as the actual date (7th of October) was not a trading day. The event windows will be divided into pre-event windows ( $[-10, -1]$  &  $[-3, -1]$ ), window of the events themselves  $[0, 0]$ , short-run post-event windows ( $[0, +3]$  &  $[0, +10]$ ), medium-run post-event window ( $[0, +30]$  &  $[0, +90]$ ) and long-run event windows ( $[0, +180]$ ,  $[0, +365]$ ).

## 4 Results

### 4.1 *Descriptive Statistics and Data Overview*

Before proceeding to interpret the results, this section provides a structured overview of the data characteristics used for the event study. The dataset contains returns of firms operating across multiple different sectors and countries, with a heavy focus on the defense sector. Additionally, it includes the Fama-French 5 factors (market access return, SMB, HML, RMW, CMA) and momentum (MOM), these variables are used to create the regression models which are used to calculate the expected returns through alpha and beta (Carhart, 1997; Fama & French, 1993, 2015).

The data spans from January 1<sup>st</sup> 2021 up until the 31<sup>st</sup> of December 2024. The two event dates that are used for this event study are the Russian invasion of Ukraine on February 24<sup>th</sup> 2022, and the Israel-Hamas conflict on October 9<sup>th</sup> 2023. The time span chosen allows the use of 2021 as the estimation window, a window prior to both events to estimate the abnormal return, without influence of either event. Additionally the dataset allows the post-event window to reach 365 days for both events.

The initial data inspection involves verifying completeness of data per firm, this is done by checking the amount of data points for the firm return data. Table 9 in Appendix A shows the amount of data points present for each firm's return over the chosen time span. Firms with fewer than 950 observations over the four-year period were excluded from the dataset to ensure data completeness and avoid distortions in the event window and CAR calculations caused by missing values. Table 10 in Appendix A provides the amount of firms per sector, where the defense sector is indicated as its own sector and is not taken into account in the industrials sector.

Table 1 below summarizes the descriptive statistics of the key variables that are used to conduct the event study. The table provides descriptives of the stock returns and the 5 Fama-French factors plus momentum factor. Both the return variable and the Fama-French control variables are in decimals. Return is used as the dependent variable and has a mean of 0.0009, close to 0. One thing to note is the high kurtosis for the return variable, this indicates heavy tails and thus often more outliers for the variable. As this is daily return data this is to be expected. Standard deviation for the return variable is high relative to the other variables, valued at 0.0208, more detailed return statistics are provided below.

The market factor ranges from -0.0367 to 0.0503, and has a standard deviation of 0.0091. The other Fama-French factors show distributions close to 0, at first glance seeming steady over the 4 years, while

the momentum factor does have a relatively large minimum-maximum value, ranging from -0.0469 to 0.0211.

**Table 1: Descriptive Statistics of Main Variables**

Variable	Mean	SD	Min	Max	Skew	Kurtosis
<b>Return</b>	0.0009	0.0208	-0.2734	0.4257	0.7890	21.714
<b>Market Return</b>	0.0002	0.0091	-0.0367	0.0503	-0.0685	2.0323
<b>SMB</b>	-0.0003	0.0042	-0.0136	0.0225	0.2903	1.0356
<b>HML</b>	0.0003	0.0067	-0.0251	0.0290	0.0768	1.2950
<b>RMW</b>	0.0001	0.0034	-0.0106	0.0151	0.0440	0.4590
<b>CMA</b>	0.0002	0.0047	-0.0186	0.0159	-0.0713	1.0534
<b>MOM</b>	0.0002	0.0072	-0.0469	0.0211	-0.8256	3.5760
<b>Risk-Free Return</b>	0.0001	0.0001	0.0000	0.0002	-0.2516	-1.8398

Note: Table 1 provides descriptive statistics for the main variables used in the analysis. Values include the mean, standard deviation (SD), minimum and maximum, skewness, and kurtosis.

Table 2 presents summary statistics for the returns per sector. The number of observations is highest by a large margin for the defense sector, as 20 of the 37 stocks in the data set are active in the defense sector. The standard deviation is second highest for the defense sector, closely behind the consumer discretionary sector. A high standard deviation indicates higher volatility for these sectors and therefore it can be interpreted as more risky. The mean daily returns across all sectors are relatively modest. However, we do see the highest maximum return is in the defense sector, with a 42.6% return in a day.

**Table 2: Summary Statistics Return per Sector**

Sector	Observations	Mean Return	SD Return	Min Return	Max Return	Median Return
<b>Defense</b>	19913	0.0010	0.0227	-0.2730	0.4260	0.0009
<b>IT</b>	3984	0.0009	0.0180	-0.1560	0.0974	0.0009
<b>Financials</b>	3984	0.0007	0.0136	-0.0839	0.1360	0.0010
<b>Consumer Discretionary</b>	2987	0.0006	0.0285	-0.1440	0.2140	0.0000
<b>Consumer Staples</b>	2977	0.0001	0.0123	-0.0758	0.0944	0.0001
<b>Energy</b>	997	0.0013	0.0177	-0.0792	0.0607	0.0008
<b>Healthcare</b>	974	0.0012	0.0198	-0.2070	0.1730	0.0008
<b>Industrials</b>	997	0.0009	0.0165	-0.0528	0.0837	0.0012

Note: Table 2 summarizes daily return statistics by sector, including the number of observations, mean, median, standard deviation (SD), minimum and maximum daily return.

To test for correlation between variables, the return variable is split into individual company returns. The single firm returns are checked for correlation together with the Fama-French variables. Due to a high number of correlations, the table has been filtered on correlations higher than 0.5 or lower than -0.5. Additionally, an extra column has been added to indicate whether firms are in the same industry. Table 11 in Appendix B shows the full list of correlations higher than 0.5 or lower than -0.5. The same industry column illustrates that 17 out of 22 correlations between firms higher than 0.5 or lower than -0.5, occurred for firms in the same industry. It is expected however that firms in the same industry can lead to high correlation in returns.

Skewness of individual firm returns is checked and visualized in Figure 3 Appendix B. Skewness measures the asymmetry of the distribution of the return data. Skewness of zero would imply that there is a perfect symmetrical distribution of returns. When skewness is higher than 1 or lower than -1, it is coloured red in Figure 3. The figure illustrates that the firms with a positive skewness higher than 1, are all defense sector stocks. However, similarly the two firms with skewness lower than 1 are also stocks active in the defense sector. All other firms do not show signs of high skewness of returns.

To ensure the reliability of the CAAR estimates, only days with at least 15 firms reporting in each group were included (15 of 17 for non-defense and 15 of 20 for defense). When firm observations per day are too low, it creates potential outliers in the CAAR calculations which can heavily influence the CAAR over time. In appendix B, Table 12 displays the days with the least amount of observations for the defense sector stocks and non-defense sector stocks across both events.

After carefully inspecting the data, the results for the different regression models to estimate the expected returns can be interpreted. The regressions are calculated using OLS. Table 3 below represents the summary statistics of the different models, divided into defense stocks and non-defense stocks. The models estimates the expected return for the stocks by adding the alpha and beta's. The expected return can be subtracted from the actual return to achieve the abnormal return per firm. The parameters to calculate the expected returns is calculated over 2021, to be independent from both event windows. The average alpha, beta and R-squared per sector for the three models is shown in Table 3.

Among all three models we see an outperformance for non-defense stocks, while the defense stocks underperform slightly. Using the 6-factor model the difference is smallest, where non-defense stocks outperform with an alpha of 0.0007 and defense stocks underperform by -0.0001. The market beta shows a relatively similar value across all models and for the two groups. The negative SMB beta suggest that the non-defense stocks act like large-cap stocks, while the defense stocks their positive beta suggests the stocks act more in line with small cap firms. This is in line with suggestions by Fama & French (1993, 2015),

as the non-defense stocks consists of large companies with some of the highest market caps currently. Defense stocks are thus suggested to be relatively smaller compared to these global large cap stocks. HML measures the high book-to-market versus low book-to-market. In the 4-factor model both groups of firms are in line with high value orientation, which would be expected knowing the nature of large cap giants and defense sector stocks. However the 6-factor model changed the direction for defense sector stocks to be more in line with low book-to market firms. The momentum beta is negative for defense sector stocks and positive for non-defense stocks. A positive momentum beta suggests the group benefits from recent winners (Carhart, 1997), defense sector stocks act as contrarians in the data set. A negative beta could suggest to be in line with the first hypothesis, where it is expected that defense stocks might revert back to the mean after positive returns. The 6-factor model includes two additional factors, the RMW beta suggest that defense sector stocks act as firms with lower profitability due to the negative beta of -0.76. Non-defense stocks act as highly profitable firms with a positive RMW beta. The reaction is in line with what Fama & French (2015) suggest, as the large cap non-defense stocks are among the most profitable companies in the world. It is therefore expected that the non-defense group would have a higher RMW beta. Lastly CMA is positive for both groups, with a higher beta of 0.5885 for defense sector stocks. Both betas suggest that the firms act as conservative firms with lower growth. Fama & French (2015) imply that firms that invest conservatively earn higher returns than firms that invest aggressively, therefore the beta might imply that defense sector stocks invest more conservative.

Lastly, the R-squared is shown in the last column, as expected the R-squared increases when additional factors are added as control variables. Generally across all three models the model explains non-defense sector returns better, one possible explanation for this is that non-defense sector stocks are more diversified. The 6-factor model explains 36.32% of the firm returns for non-defense stocks, while only explaining 22.24% for the defense stock returns.

**Table 3: Summary Statistics for the Three Models**

Model	Alpha	Beta MKT	Beta SMB	Beta HML	Beta RMW	Beta CMA	Beta MOM	R <sup>2</sup>
CAPM - Defense	-0.0003	0.8533						0.1053
CAPM - Non-Defense	0.0008	0.8680						0.1711
4-Factor - Defense	-0.0004	0.9352	0.3484	0.3417			-0.0605	0.2011
4-Factor - Non-Defense	0.0007	0.8302	-0.3699	0.0450			0.0823	0.3405
6-Factor - Defense	-0.0001	0.8845	0.0774	-0.0383	-0.7600	0.5885	-0.1170	0.2224
6-Factor - Non-Defense	0.0007	0.8326	-0.3652	0.0372	0.0082	0.0164	0.0833	0.3632

Note: Table 3 presents the summary statistics for the CAPM, 4-Factor, and 6-Factor regression models applied to defense and non-defense sector portfolios. Values include alpha and factor betas on the market (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA), and momentum (MOM) factors, where applicable.

After constructing the regression models to provide estimates for calculating the abnormal return, the three regressions were tested for heteroskedasticity and normality. To test for heteroskedasticity a Breusch-Pagan test was performed across the three models. The Breusch-Pagan test is executed per firm to provide a mean P-value per sector, provided in Table 13 Appendix C. When the P-value is lower than 0.05 the Breusch-Pagan test suggests presence of heteroskedasticity for the groups. A handful of firms on the individual level show signs of heteroskedasticity. On the sector level the energy and industrial sectors show signs of heteroskedasticity, suggesting that the variance of errors is not constant. Heteroskedasticity is not problematic for interpreting the results in this research however, as the regressions are solely used to calculate the expected return of a firm. Testing whether alpha or the beta's are significant is of no importance. Nevertheless, heteroskedasticity on the individual firm level might influence tests conducted on CAR when using the values from the regressions. This problem is accounted for by solely using non-parametric tests due to the data structure.

Table 14 in Appendix C presents the results for the Shapiro-Wilk test, testing for normality on individual firm level to construct the mean P-value on the sector level. If the P-value is lower than 0.05 the Shapiro-Wilk test suggests that the results for a firm are not normally distributed. The energy and financial sector suggest normality as the P-value is higher than 0.05 across the three models. All other sectors show signs of non-normality, with mean P-values lower than 0.05. Similar to heteroskedasticity, the presence of non-normality is not problematic for this research, as the regressions are solely used to calculate the expected return of a firm. Yet, it might influence statistical test on CAR when using results from the regressions. Non-parametric tests that are used for this research do not assume a specific distributions, and therefore do not assume homoskedasticity or normality.

## 4.2 Evidence from the First Event

With the alpha, betas, and actual returns of the companies, the abnormal return is calculated. The abnormal returns are used to calculate the cumulative abnormal returns over the different event windows, specified in chapter 3. Table 4 below gives the cumulative average abnormal return for the defense sector stocks and non-defense sector stocks, the findings show whether the set of stocks behave differently across the multiple event windows. The first hypothesis can be tested by analysing whether the defense sector stock have a (higher) abnormal return in the earlier event windows which decreases over longer time periods. Table 4 visualizes CAAR for the first event, the war between Russia and Ukraine.

**Table 4: CAAR over the Multiple Event Windows, for Defense Sector Stocks and Non-Defense Sector Stocks during the Russia-Ukraine Conflict**

Event Window	CAPM-Model	CAPM-Model	4-factor Model	4-factor Model	6-factor Model	6-factor Model
	- Defense	- Non-Defense	- Defense	- Non-Defense	- Defense	- Non-Defense
[-10, -1]	0.0145	-0.0073	0.0096	-0.0055	0.0094	-0.0058
[-3, -1]	0.0121	0.0010	0.0097	0.0020	0.0093	0.0020
[0, 0]	0.0652***	-0.0093	0.0743***	-0.0110	0.0704***	-0.0109
[0, 3]	0.0664***	-0.0021	0.0753***	-0.0038	0.0733***	-0.0037
[0, 10]	0.2422***	-0.0107	0.2512***	-0.0138	0.2503***	-0.0143
[0, 30]	0.2993***	0.0045	0.3157***	-0.0031	0.3007***	-0.0033
[0, 90]	0.3422***	-0.047*	0.3355***	-0.0565*	0.2852***	-0.0572*
[0, 180]	0.4350***	-0.0170	0.4610***	-0.0190	0.4172***	-0.0193
[0, 365]	0.5358***	-0.1292*	0.5474***	-0.1199	0.4443***	-0.1201

Note: Table 4 presents the cumulative average abnormal returns for defense and non-defense sector stocks across various event windows surrounding the start of the Russia-Ukraine war. The values are based on three models: the CAPM, 4-factor model, and 6-factor model. CAARs are reported separately for defense and non-defense sectors to illustrate differences in market reactions over time. CAAR values are tested for statistical significance using the Wilcoxon Signed-Rank Test. Significance levels: \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.05$ .

For all three models, findings are showing only slightly different results. Across all models the two pre-event windows suggest a slightly positive CAAR in the defense sector. Moving forward across the post-event windows the defense sector CAAR increases gradually when transitioning from short-run to long-run, again consistent across all three models. CAAR is generally lower for the 6-factor model compared to the CAPM-model and 4-factor model. To test whether the findings for the defense sector stocks are significantly different from 0, a Wilcoxon Signed-Rank test is performed. The findings of the Wilcoxon Signed-Rank test can be found in Table 15 Appendix D. The two pre-event windows are insignificant across all three models due to their P-value being higher than 0.05, suggesting that there is no significant CAR in

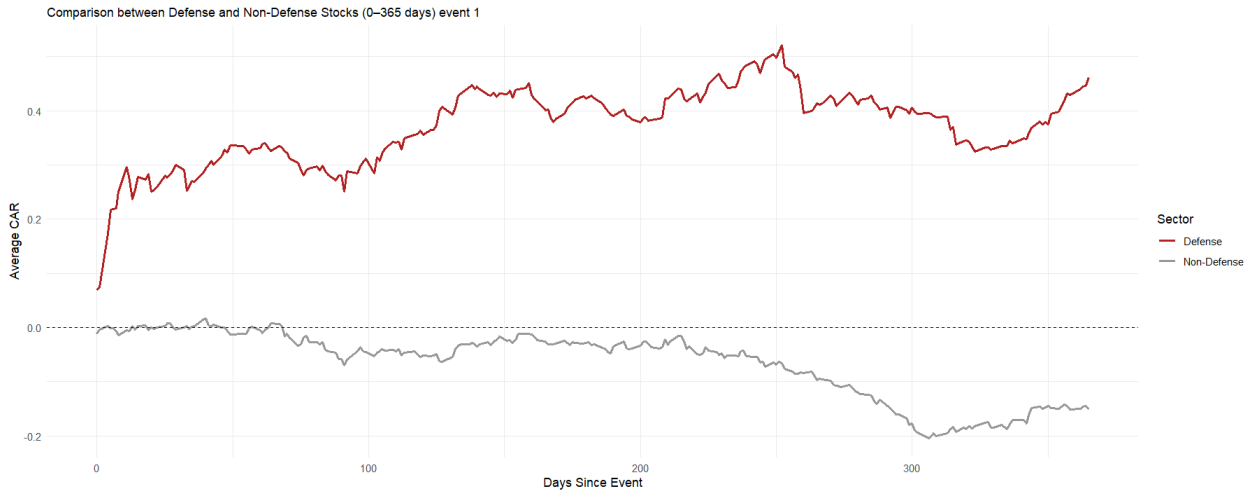
the pre-event windows. All post event windows however have P-values below the 0.05 threshold. Findings from Table 15 suggest that the CAAR values found in the post-event windows are all significantly different from 0. The two pre-event windows implying that CAR is zero before the start of the event, strengthens the evidence of the defense sector reacting significantly to the event. Therefore we can conclude that H1 is rejected for the first event, as defense sector CAAR gradually increases over the one year period following the event. Contrary to the anticipated overreaction in the short run followed by a correction downwards in the long-run (Daniel et al., 1998; De Bondt & Thaler, 1985).

Figure 1 visualizes the 6-factor model post-event CAAR over a one year period for the defense sector stocks, identified by the red line. The graph shows a sharp increase in the first days after the event, gradually increasing over time. Around the 250 day mark there is a decreasing trend in CAAR, however this recovers after the 325 day mark. Figure 1 additionally shows a similar increase around the 325 days mark for non-defense stocks.

In all 3 models, the non-defense stocks observe a gradual downward trend in CAAR. The 6-factor model illustrates a CAAR of -0.1201 in the [0, 365] post event window. The findings clearly show differences in performance of the two groups, at first glance confirming that defense sector stocks react significantly different to geopolitical shocks compared to the non-defense sectors. Table 15 in Appendix D shows the results for the Wilcoxon Signed-Rank test for non-defense stocks, only one event window has a P-value lower than 0.05 across the three models for the first event study. The 3-month post-event window is significant across all three models, while the 1-year post event window is significant only for the CAPM-model. All other event windows are insignificant, implying that the majority of findings for non-defense CAAR values are not significantly different from zero. Findings from Table 4 and Table 15 reject H2 for the first event, as no significant deviation from zero can be found in CAAR for non-defense stocks across the post-event windows.

The one year post-event window CAAR for the 6-factor model is depicted in Figure 1, identified by the grey line. The graph visualizes the gradual decrease over the year. Similar to the defense sector CAAR, the line recovers slightly in the later stage of the year.

**Figure 1: Post-Event CAAR over Time for Defense and Non-Defense Stocks for the Russia-Ukraine Conflict**



Note: Figure 1 illustrates the cumulative average abnormal returns of defense and non-defense sector stocks during the Russia–Ukraine conflict. CAAR is based on the Fama-French 6-Factor model results presented in Table 4.

To empirically test whether CAAR for defense and non-defense sector stocks significantly differ, a Mann-Whitney U Test is used to compare the results. Table 16 can be found in Appendix D and represents the P-values for all 3 models, per event window. The P-value can signal whether the results between the two groups are significantly different from each other, or whether there is no difference to observe. For the two pre-event windows ( $[-10, -1]$  &  $[-3, -1]$ ), the P-value is higher than 0.05 across all three models. However all post-event windows have a P-value of 0, indicating that in all post-event windows CAAR values significantly differ between the two test groups.

While the Wilcoxon Signed-Rank Test indicates mostly no statistically significant change in the non-defense sector, a robustness check using a panel regression provides further insight into sectoral CAR differences. Table 5 presents the results of the random effects regression model applied to the first event. CAR represents the dependent variable, while a defense sector dummy, time measured in days, and an interaction term between the dummy variable and time are the predictors. The model yields an R-squared of 0.1023 and adjusted R-squared of 0.1020, suggesting that around 10.2% of the variation in CAR is explained by the model.

The intercept represents the baseline CAR for non-defense firms at time zero, the insignificant intercept (P-value = 0.6706) indicates that non-defense stocks did not exhibit abnormal returns at the start of the event window. The defense dummy is positive and statistically significant, with the coefficient valued at 0.2776, implying a significant outperformance relative to the non-defense group. Time is estimated in days

following the event, and has a negative estimate of -0.0004 while being significant. The estimate suggests non-defense stocks experienced a gradual decline in CAR over the event window, this is in line with the findings of Table 4. Most notably the interaction between the defense dummy and time is positive and significant, with an estimate of 0.0008. The coefficient implies that the outperformance by defense stocks increased by 0.08% per day relative to non-defense sectors. The results from Table 5 reinforce the findings in Table 4, where the defense sector exhibits a gradual increase in CAR post-start of the event.

**Table 5: Random Effects Model Regression Russia-Ukraine Event**

R-squared: 0.1023				
Adjusted R-squared: 0.1020				
Term	Estimate	Std. Error	Statistic	P-value
Intercept	0.0225	0.0530	0.4253	0.6706
Defense Dummy	0.2776***	0.0721	3.8527	0.0001
Time	-0.0004***	0.0000	-23.1821	0.0000
Defense * Time	0.0008***	0.0000	31.9135	0.0000

*Note: Table 5 represents the results for the random effects panel regression model, examining the relationship between cumulative abnormal returns and a sector dummy, during the Russia-Ukraine conflict. The model includes a defense sector dummy, a time variable (days since the event), and an interaction term between the dummy variable and time. Statistical significance is denoted as follows: \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.05$ .*

Findings represented in Table 4 and Table 5 confirm that defense sector stocks do react positively to the start of the war between Russia and Ukraine. The results are significant according to the findings in Table 15. Across all models CAAR increased for the defense sector while the event windows gradually shifted from short-run to long-run. Therefore the first hypothesis, suggesting that defense sector CAAR increases in the short-run but decreases in the long-run, is rejected with regards to the first event. H2 is similarly rejected due to findings in Table 15 that fail to prove that CAAR values for non-defense stocks are significantly different from zero. The second event will conduct a similar analysis on the start of the Israel-Gaza conflict.

### 4.3 Evidence from the Second Event

Following the results from the first event, the results on the Israel-Gaza conflict can be found in Table 6 below. The CAPM model, 4-factor model and the 6-factor model are shown in Table 6 and are split between non-defense and defense sector stocks. All 3 models are consistent in their findings, and no significant change is present when comparing the results of the three models.

**Table 6: CAAR over the Multiple Event Windows, for Defense Sector Stocks and Non-Defense Sector Stocks during the Israël-Gaza Conflict**

Event Window	CAPM-Model	CAPM-Model	4-Factor Model	4-Factor Model	6-Factor Model	6-Factor Model
	- Defense	- Non-Defense	- Defense	- Non-Defense	- Defense	- Non-Defense
[-10, -1]	-0.0112	-0.0043	0.0036	-0.0105	-0.0026	-0.0105
[-3, -1]	-0.0050	-0.0042	-0.0032	-0.0060	-0.0026	-0.0060
[0, 0]	0.0487***	-0.0048	0.0479***	-0.0053	0.0506***	-0.0053
[0, 3]	0.0630***	0.0082	0.0647***	0.0049	0.0747***	0.0050
[0, 10]	0.0706***	-0.0076	0.0704***	-0.0119	0.0733***	-0.0120
[0, 30]	0.0553**	-0.0228	0.0658**	-0.0274	0.0601**	-0.0274
[0, 90]	0.0141	-0.0737*	0.0012	-0.0637*	-0.0068	-0.0633*
[0, 180]	0.1795***	-0.1037	0.1915***	-0.1154	0.1962**	-0.1143
[0, 365]	0.2940***	-0.2215*	0.3427***	-0.2296*	0.2962***	-0.2284*

Note: Table 6 presents the cumulative average abnormal returns for defense and non-defense sector stocks across various event windows surrounding the Israel-Gaza conflict. Each row represents a different event window, while columns correspond to results from the CAPM, 4-factor, and 6-factor models. The CAARs are presented separately for defense and non-defense stocks to highlight sector-specific responses over time. CAAR values are tested for statistical significance using the Wilcoxon Signed-Rank Test. Significance levels: \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.05$ .

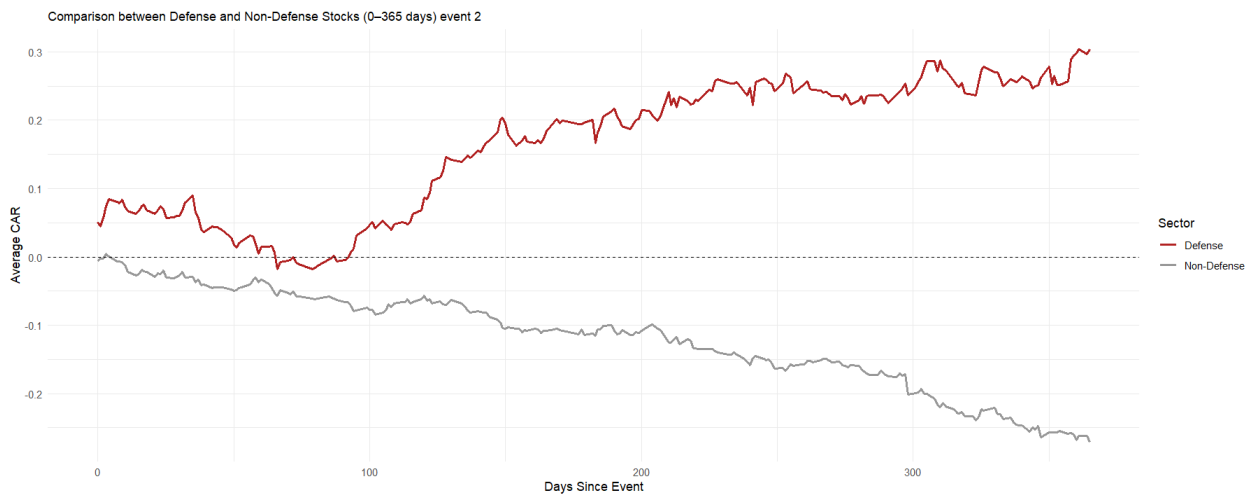
Both pre-event windows provide a slightly negative CAAR for defense sector stocks and non-defense sector stocks. The day of the event had a strong positive reaction on the defense sector CAAR. The 6-factor model shows defense sector CAAR hovering between 0.05 and 0.07 in the first month after the event, while dropping below 0 in the 3 month post-event window. However, in the two long-run event windows CAAR increased significantly, ending with a positive CAAR of 0.2962. The CAPM-model and the 4-factor model are more optimistic across the board, not falling below 0 in any of the post-event windows. Table 17 in appendix D represents the Wilcoxon Signed-Rank test for the second event, to test the significance of the findings represented in Table 6 above. Both pre-event windows are insignificant, consistent with the findings of the first event. The other event windows are significant across all models, except for the 3-month post-event window, which is insignificant for the three models. Table 6 shows a strong decrease in defense sector CAAR for the [0, 90] event window, increasing strongly again for the longer post-event windows. The Wilcoxon Signed-Rank test confirms that the findings for the 3-month post event window is insignificant. Interpreting the findings of Table 6 and Table 17 rejects the first hypothesis, as CAAR does not correct downwards in the long-run following the event.

Figure 2 below visualizes the 6-factor model defense sector CAAR across the 1-year post-event window, identified by the red line. The figure shows a dip around the 90 day mark, as discussed in the paragraph above. However over the course of a year the sector strongly recovered with a consistent upward trend for the remainder of the year.

Generally across all post-event windows the non-defense sector stocks had a significantly lower CAAR than the defense sector stocks, implying that there is outperformance by defense sector stocks. The 6-factor model one-year post-event window gives a CAAR of -0.2284 for non-defense sector stocks. The findings of the 6-factor model are in between the findings for the CAPM-model and the 4-factor model. The significance of the findings for non-defense sector CAAR are shown in Table 17 Appendix D. Contrary to the findings of the defense sector stocks, the 90-day post-event window significant across all models. Apart from the 90-day and 365-day post-event windows, other windows are insignificant. While there is partial evidence of persistent underperformance for non-defense stocks, there is not enough evidence for accepting H2. The second hypothesis is therefore partially supported by the findings in Table 6 and Table 17.

Figure 2 provides a visual representation of the non-defense CAAR over time, post start of the Israël-Gaza conflict, identified by the grey line. The figure shows a gradual decline over the course of a year, moving in opposite directions of the defense sector.

**Figure 2: Post-Event CAAR over Time for Defense and Non-Defense Stocks for the Israel-Gaza Conflict**



*Note: Figure 2 illustrates the cumulative average abnormal returns of defense and non-defense sector stocks during the Israel-Gaza conflict. CAAR is based on the Fama-French 6-factor model results from Table 6.*

To test whether there is a significant difference between the two groups, the Mann-Whitney U Test is applied. The findings of the Mann-Whitney U Test can be found in Appendix D Table 18. A P-value lower than 0.05 implies that the values between the two groups for a given event window significantly differs. For both pre-event windows ([-10, -1] & [-3, -1]) no significant difference is found between the two groups, this is consistent with the findings of the first event. For the [0, 90] event window similarly no significant

difference can be found between defense and non-defense sector stocks CAAR, this is consistent among all 3 models. All other post-event windows and the event day itself observe a significant difference when comparing the two groups. The results in Table 6 above confirm the higher CAAR for defense sector stocks.

A robustness check is performed by regressing CAR over time, controlling for a defense sector dummy and an interaction term between the dummy variable and time. Table 7 presents the results of the random effects panel regression model for the second event. The R-squared and adjusted R-squared is 0.3373 and 0.3371, respectively. Compared to the first event the model explains almost twice as much of the variation in CAR.

The intercept, which reflects the baseline CAR for non-defense stocks at the time of the event, is statistically insignificant (P-value = 1). Likewise, the defense dummy is also statistically insignificant (P-value = 0.7927), suggesting that neither defense stocks or non-defense stocks at time zero showed abnormal returns. The time variable is statistically significant, showing a negative coefficient of -0.0007. The coefficient for time only suggests non-defense stocks CAR decreases over the one year post-event window. Lastly, the interaction effect is statistically significant and has a positive estimate of 0.0014. Findings suggest that while no abnormal return is found at the time of the event, CAR increases over time for the defense sector. Table 7 illustrates similar results to the CAAR estimates in Table 6, with the exception that the defense sector does not show a significant abnormal return at the time of the event for the regression results.

**Table 7: Random Effects Model Regression Israel-Gaza Event**

R-squared: 0.3373				
Adjusted R-squared: 0.3371				
Term	Estimate	Std. Error	Statistic	P-value
Intercept	-0.0000	0.0447	-0.0001	1.0000
Defense Dummy	0.0160	0.0608	0.2628	0.7927
Time	-0.0007***	0.0000	-40.0387	0.0000
Defense * Time	0.0014***	0.0000	65.5024	0.0000

*Note: Table 7 represents the results for the random effects panel regression model, examining the relationship between cumulative abnormal returns and a sector dummy during the Israel-Gaza conflict. The model includes a defense sector dummy, a time variable (days since the event), and an interaction term between the dummy variable and time. Statistical significance is denoted as follows: \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.05$ .*

The results for the Israel-Gaza conflict are not in line with the first hypothesis, and only partially in line with H2. As the findings show a gradual increase in CAAR over time for defense sector stocks instead of an over-reaction in the short run. Non-defense sector CAAR managed to show significant difference from zero in only two post-event windows. The gradual increase in CAAR could imply a drift, potentially caused by

underreaction where investors failed to immediately price in the effect of the geopolitical shock (Daniel et al., 1998; De Bondt & Thaler, 1985). CAAR estimations presented in Table 6 and the random effects panel regression presented in Table 7 confirm the findings.

#### 4.4 *Cross-Event Differences*

Section 4.2 and section 4.3 discuss the results for both the Russia-Ukraine event and the Israël-Gaza event. The findings have a similar trend for both events, defense sector stocks over a one year post-event window gradually increase in CAAR. These findings are not in line with H1, stating that investors overreact to events in the short run, with a correction occurring in the long-run (Daniel et al., 1998; De Bondt & Thaler, 1985). The gradual increase in CAAR shows the outperformance of defense sector stocks in times of geopolitical uncertainty. The findings are strengthened by the decreasing CAAR of non-defense sector stocks over the same time period, however the findings are not consistently significant. This section will test whether the trend in CAAR for both groups differ significantly across the two events.

To empirically test whether there is a difference in findings between the two events, a Wilcoxon Signed-Rank Test is conducted. The results of the test can be found in Appendix D Table 19, where the P-values of the test are documented for all 3 models, per event window. The pre-event windows and up until three days post-events, all illustrate a P-value higher than 0.05 by a large margin across the three models. All post-event windows that follow however, have P-values significantly lower than 0.05. Therefore concluding that for longer time horizons, findings are significantly different from one another across all three models. Despite the similar trend for both groups of stocks, the start of the Russia-Ukraine war had a stronger positive effect on the defense sector equities. For non-defense sector stocks the start of the Israel-Gaza conflict led to a stronger negative reaction over the course of a year.

## 5 Discussion and Conclusion

### 5.1 Discussion

The results of this study suggest a strong positive reaction to geopolitical shocks in the defense sector. Non-defense sector CAAR did not prove to be consistently different from zero, across post-event windows. Both the CAAR analysis and the random effects panel regression indicate a significant divergence in CARs between defense and non-defense stocks. Nevertheless, it is important to consider the methodological limitations underlying these findings.

First, it needs to be taken into consideration that the abnormal returns are calculated through regression data covering solely the year 2021. This might pose a potential limitation, due to the relative short pre-event estimation window. Relying on stock returns of one particular year could reflect unrealistic over longer time horizons. This in turn might have influence on CAR values observed during the event windows, reflecting structural differences rather than the effect of both events. Estimating expected return by relying on stock returns over 2021 could affect the findings of this study. However, an estimation window of a year prior to the event is known in event study methodology (MacKinlay, 1997).

The sample size, while balanced among the two groups, remains relatively small compared to other studies. Defense sector stocks examined were 20 in total for this research, while non-defense stocks counted 17 firms due to some stocks being eliminated from the research due to inconsistent data. The data set was sufficient in comparing the two groups, however the sample is too small to compare on a sector level. The main focus of this paper is to observe the investor behaviour on defense sector stocks, which was successful with the data used for the research. Still, future research could expand on the topic by increasing the number of firms and potentially provide insights on the sector level. To achieve this, a larger sample of stocks per sector is necessary. Findings would contribute significantly to understanding the dynamic between individual sectors and geopolitical instability.

Third, the geographical scope of this research is limited to developed countries, due to the limited data for the Fama-French factors. While the focus of this study ensures data quality and comparability for developed countries, it will be interesting to expand towards emerging markets effects moving forward.

The main limitation of this paper lies in the limited length of long-run post-event windows. The maximum length of post-event windows for this study was one year post-event. There are previous papers with extended time horizons that only find significant findings between 1 and 3 years post-event (De Bondt & Thaler, 1985; Jegadeesh & Titman, 1993). Unfortunately for this study it was no possibility to extend the

post-event windows over one year, due to overlap of the two events and due to data availability for the Israël-Gaza conflict. Extending the observation window for future research could therefore reveal delayed market corrections after a one year horizon.

Furthermore, while this research conducts the event study with multiple well-established models, it must be acknowledged that the returns observed in the defense and non-defense sectors might be influenced by various exogeneous factors unrelated to the events examined in this paper. Kothari & Warner (1997) warn for the possible inaccuracy when interpreting long-run event windows. The Fama-French factors were included to mitigate exogeneous exposure, yet complete isolation for event studies is not possible in an open market context.

Lastly, while this study aims to observe investor reaction to the start of geopolitical shocks, both events are still active as of the time of writing in June 2025. The event being concluded or not within the examined time frame might have influence on the findings of the research. In this case neither event is concluded and over the course of a year the defense sector responds exclusively positive. However, future research could additionally examine the reaction when the events are fully resolved. It will be interesting to observe whether the event concluding has significant influence on the defense sector.

## 5.2 Conclusion

This paper aims to answer the following research question: *To what extent do defense sector stocks exhibit signs of investor overreaction following geopolitical shocks, and how does this compare to non-defense sector stocks?* To answer the research question, an event study was conducted to calculate the cumulative abnormal return over multiple event windows. A short-run increase in CAR followed by a long-run decrease in CAR would imply an initial overreaction by investors (Covachev & Fazakas, 2025; Daniel et al., 1998; De Bondt & Thaler, 1985). The expected return, which is used to calculate the abnormal return, was calculated with the help of three different models: the CAPM-model, the 4-factor model and the 6-factor model. Across all three models, CAR for defense sector stocks increased over the course of one year post-event. The findings were consistent for both events analysed, therefore rejecting the first hypothesis: Defense sector stocks exhibit an upwards overreaction to geopolitical shocks in the short-run, followed by a correction downwards towards the fundamental value in the long-run.

In addition to defense sector stocks, a control group was added with firms from diversified sectors and regions. The control group over the course of one year post-events had a gradual decrease in CAAR, contrary to the findings for defense sector stocks. The findings could not be consistently confirmed by the Wilcoxon-Signed Rank test however, which failed to prove that the CAAR values for the non-defense stocks

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were significantly different from zero. The results rejected the second hypothesis for the first event, and only partially supported findings of the second event. Therefore not providing enough evidence to accept the second hypothesis: Non-defense sector stocks exhibit an initial significant negative reaction to geopolitical shocks, with the weaker performance persisting while the geopolitical instability is unresolved (Boubaker et al., 2022; Leahy et al., 2023; Yousaf et al., 2022).

Daniel et al. (1998) introduced drift to public signals, which might apply to the cases examined in this paper. Rather than CAAR decreasing in the one year period after the event, CAAR kept on increasing. There are a number of reasons why CAAR could increase over time instead of decrease. The one year post-event window could prove to be too short to find significant overreaction, where multiyear post-event windows could add to the findings of this research (De Bondt & Thaler, 1985; Jegadeesh & Titman, 1993). The findings could suggest that not all information of the event is taken into account in the short-run and investors need time to process the information, causing drift (Daniel et al., 1998; Fischer, 2012; Thu Quang, 2024). The more likely is the possibility that demand increases for defense sector firms, improving their revenue and profitability and driving up stock prices due to a better forecast for future earnings.

In summary, this study provides empirical evidence that defense sector stocks behave differently reacting to geopolitical shocks compared to other sectors. Rather than exhibiting an overreaction in the short-run followed by a reversion to the mean, the findings suggest that defense sector CAAR steadily increases in the year following the two geopolitical shocks. The findings suggest that investors might view defense sector stocks as long-term beneficiaries in times of uncertainty on a geopolitical level. While the current findings are limited to a one year post-event time frame, they offer meaningful insights in how financial markets might respond to geopolitical events. Future research can expand on the findings by increasing the time horizon for post-event analysis. Additionally future studies can dive deeper into reactions to shocks on individual sector level. Ultimately, this paper aims to contribute to the understanding of investor reactions to geopolitical shocks. While also helping to develop the understanding of the relationship between geopolitical events, and equities in both the defense sector and non-defense sector stocks.

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## 7 Appendix

### 7.1 Appendix A – Firm Characteristics

*Table 8: List of firms including country and sector*

Company Name	Country	Sector
AeroVironment	USA	Aerospace & Defense
BWX Technologies	USA	Aerospace & Defense
Babcock International	UK	Aerospace & Defense
Booz Allen Hamilton	USA	Aerospace & Defense
CACI International	USA	Aerospace & Defense
Curtiss-Wright	USA	Aerospace & Defense
Dassault Aviation	France	Aerospace & Defense
Hensoldt	Germany	Aerospace & Defense
Huntington Ingalls Industries	USA	Aerospace & Defense
KBR	USA	Aerospace & Defense
Leonardo DRS	USA	Aerospace & Defense
Leonardo SpA	Italy	Aerospace & Defense
Mercury Systems	USA	Aerospace & Defense
Moog	USA	Aerospace & Defense
Palantir Technologies	USA	Aerospace & Defense
Parsons	USA	Aerospace & Defense
QinetiQ Group	UK	Aerospace & Defense
Saab	Sweden	Aerospace & Defense
Science Applications International	USA	Aerospace & Defense
Thales	France	Aerospace & Defense
Amazon	USA	Consumer Discretionary
Tesla	USA	Consumer Discretionary
Volkswagen	Germany	Consumer Discretionary
L'Oréal	France	Consumer Staples
Nestlé	Switzerland	Consumer Staples
Unilever	UK	Consumer Staples
Exxon Mobil	USA	Energy
Allianz	Germany	Financials
HSBC	UK	Financials
JPMorgan	USA	Financials
Royal Bank of Canada	Canada	Financials
Novo Nordisk	Denmark	Healthcare
Schneider Electric	France	Industrials
ASML	Netherlands	Information Technology
Apple	USA	Information Technology
Microsoft	USA	Information Technology

<b>SAP</b>	Germany	Information Technology
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*Note: This table lists the companies included in the analysis, along with their country and sector classification.*

**Table 9: Observations per Firm**

<b>Company name</b>	<b>Number of observations</b>
<b>Novo Nordisk</b>	974
<b>Saab</b>	980
<b>Nestlé</b>	983
<b>Leonardo SpA</b>	991
<b>Allianz</b>	993
<b>Hensoldt</b>	993
<b>SAP</b>	993
<b>Volkswagen</b>	993
<b>ASML</b>	997
<b>AeroVironment</b>	997
<b>Amazon</b>	997
<b>Apple</b>	997
<b>BWX Technologies</b>	997
<b>Babcock International</b>	997
<b>Booz Allen Hamilton</b>	997
<b>CACI International</b>	997
<b>Curtiss-Wright</b>	997
<b>Dassault Aviation</b>	997
<b>Exxon Mobil</b>	997
<b>HSBC</b>	997
<b>Huntington Ingalls Industries</b>	997
<b>JPMorgan</b>	997
<b>KBR</b>	997
<b>L'Oréal</b>	997
<b>Leonardo DRS</b>	997
<b>Mercury Systems</b>	997
<b>Microsoft</b>	997
<b>Moog</b>	997
<b>Palantir Technologies</b>	997
<b>Parsons</b>	997
<b>QinetiQ Group</b>	997
<b>Royal Bank of Canada</b>	997
<b>Schneider Electric</b>	997
<b>Science Applications International</b>	997
<b>Tesla</b>	997
<b>Thales</b>	997
<b>Unilever</b>	997

*Note: This table presents the number of daily return observations available for each firm included in the study.*

**Table 10: Number of Firms per Sector**

---

<b>Sector</b>	<b>Number of Firms</b>
<b>Defense</b>	20
<b>IT</b>	4
<b>Financials</b>	4
<b>Consumer Discretionary</b>	3
<b>Consumer Staples</b>	3
<b>Energy</b>	1
<b>Healthcare</b>	1
<b>Industrials</b>	1

---

*Note: Table 10 represents the number of firms per sector*

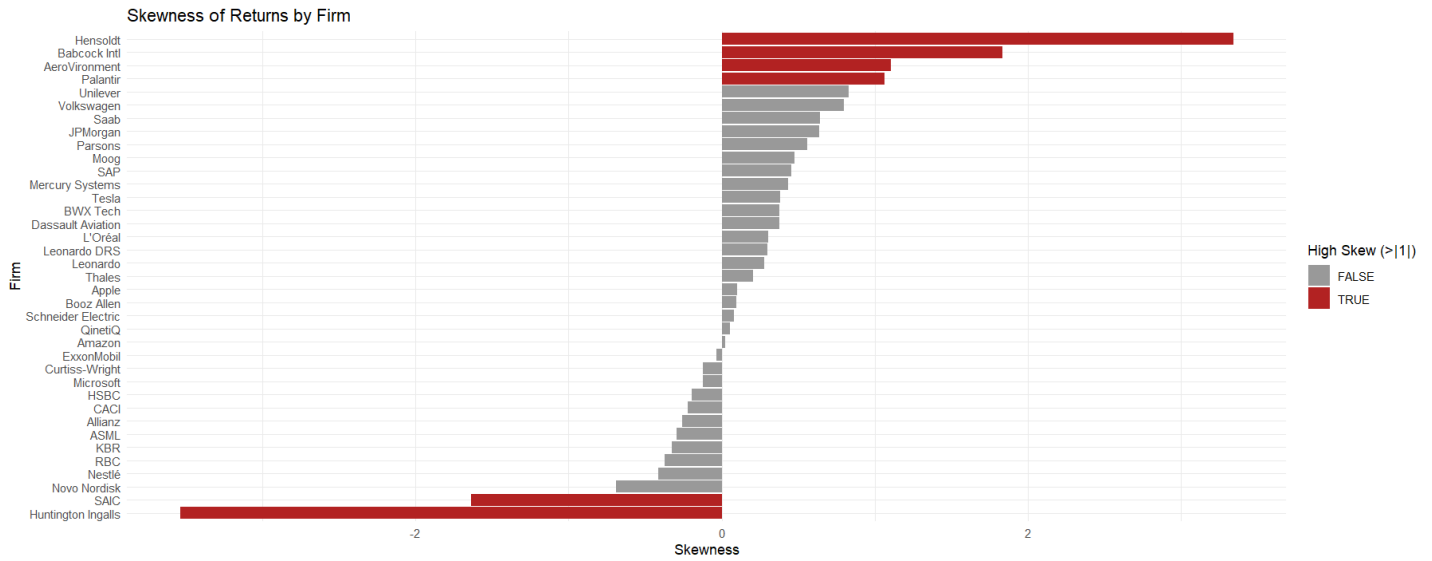
## 7.2 Appendix B – Descriptive Statistics

**Table 11 : Pairwise Correlations Including Same Sector Column**

Variable 1	Variable 2	Correlation	Same Sector
Schneider Electric	L'Oréal	0.5269	No
Allianz	HSBC	0.5076	Yes
Science Applications International	Booz Allen Hamilton	0.6094	Yes
CACI International	Booz Allen Hamilton	0.6572	Yes
Schneider Electric	SAP	0.5506	No
ASML	SAP	0.5592	Yes
CACI International	Science Applications International	0.6851	Yes
Curtiss-Wright	Moog	0.6126	Yes
Royal Bank of Canada	JPMorgan	0.5357	Yes
ASML	Schneider Electric	0.6018	No
Microsoft	Amazon	0.6569	No
Apple	Microsoft	0.6623	Yes
Hensoldt	Thales	0.5061	Yes
Leonardo SpA	Thales	0.6099	Yes
Dassault Aviation	Thales	0.6729	Yes
Saab	Thales	0.5114	Yes
Leonardo SpA	Hensoldt	0.5347	Yes
Curtiss-Wright	BWX Technologies	0.5326	Yes
Curtiss-Wright	KBR	0.5423	Yes
Dassault Aviation	Leonardo SpA	0.5461	Yes
Saab	Leonardo SpA	0.5307	Yes
Amazon	Apple	0.5351	No
cma	mkt	-0.5091	N/A
cma	hml	0.7826	N/A
mkt	Royal Bank of Canada	0.5246	N/A
mkt	Schneider Electric	0.5365	N/A
mkt	Microsoft	0.5704	N/A
mkt	Amazon	0.5635	N/A
mkt	ASML	0.5554	N/A
mkt	Apple	0.5749	N/A
smb	Microsoft	-0.5431	N/A
hml	Microsoft	-0.5468	N/A
Amazon	cma	-0.5838	N/A

*Note: This table reports pairwise correlation coefficients between selected firms and variables, along with an indicator of whether the firms operate within the same sector.*

**Figure 3: Skewness of Returns by Firm**



Note: This figure displays the skewness of daily stock returns for each firm in the sample. Positive values indicate right-skewed distributions, while negative values indicate left-skewness. Bars highlighted in red denote firms with high skewness

**Table 12: Top 10 days with Least Observations for Both Events**

Day #	Event 1 Day (Defense)*	Event 1 Obs (Defense)**	Event 1 Day (Non-Defense)	Event 1 Obs (Non-Defense)	Event 2 Day (Defense)	Event 2 Obs (Defense)	Event 2 Day (Non-Defense)	Event 2 Obs (Non-Defense)
1	91	19	91	15	213	19	213	15
2	102	19	102	15	241	19	224	15
3	120	19	49	16	256	19	85	16
4	172	19	78	16	311	19	171	16
5	316	19	92	16	0	20	214	16
6	0	20	158	16	1	20	240	16
7	1	20	0	17	2	20	297	16
8	4	20	1	17	3	20	0	17
9	5	20	4	17	4	20	1	17
10	6	20	5	17	7	20	2	17

Note: This table lists the ten event days with the fewest available return observations for both defense and non-defense firms across Event 1 and Event 2. Event days are measured as the number of days since the event date.

### 7.3 Appendix C – OLS Model Diagnostics

**Table 13: Breusch-Pagan Test P-Values per Model and Sector**

Sector	CAPM-Model Mean P-Value	4-Factor Model Mean P-Value	6-Factor Model Mean P-Value	Firm Count
Defense	0.4499	0.4536	0.4705	20
IT	0.3978	0.2524	0.2546	4
Financials	0.3268	0.3654	0.4489	4
Consumer Discretionary	0.5795	0.7398	0.7184	3
Consumer Staples	0.6612	0.5921	0.6646	3
Energy	0.0438	0.0110	0.0195	1
Healthcare	0.0704	0.4000	0.5128	1
Industrials	0.0012	0.0022	0.0113	1

*Note: Table 13 reports the mean p-values from Breusch-Pagan tests across three models: CAPM, 4-Factor, and 6-Factor by sector. The firm count indicates the number of firms per sector included in the test.*

**Table 14: Shapiro-Wilk Test P-Values per Model**

Sector	CAPM- Model Mean P-Value	4-Factor Model Mean P-Value	6-Factor Model Mean P-Value	Firm Count
Defense	0.0382	0.0035	0.0057	20
IT	0.0115	0.0000	0.0009	4
Financials	0.2063	0.1302	0.2715	4
Consumer Discretionary	0.0000	0.0000	0.0000	3
Consumer Staples	0.0072	0.0008	0.0005	3
Energy	0.1174	0.4293	0.3048	1
Healthcare	0.0000	0.0000	0.0000	1
Industrials	0.0005	0.0005	0.0005	1

*Note: This table presents the mean p-values from Shapiro-Wilk tests across the CAPM, 4-Factor, and 6-Factor models by sector. The firm count indicates the number of firms per sector included in the test.*

## 7.4 Appendix D – CAAR Significance Tests

**Table 15: Wilcoxon-Signed Rank Test P-Values for the Russia-Ukraine Conflict**

Sector	Event Window	CAPM P-value	4-Factor P-value	6-Factor P-value
Defense	[-10, -1]	0.0897	0.0973	0.0897
Defense	[-3, -1]	0.1650	0.3118	0.3300
Defense	[0, 0]	0.0000	0.0000	0.0000
Defense	[0, 3]	0.0000	0.0000	0.0000
Defense	[0, 10]	0.0000	0.0000	0.0000
Defense	[0, 30]	0.0000	0.0000	0.0000
Defense	[0, 90]	0.0000	0.0000	0.0003
Defense	[0, 180]	0.0000	0.0000	0.0000
Defense	[0, 365]	0.0000	0.0000	0.0006
Non-Defense	[-10, -1]	0.0714	0.3778	0.2435
Non-Defense	[-3, -1]	0.5477	0.2842	0.2633
Non-Defense	[0, 0]	0.2247	0.2247	0.1901
Non-Defense	[0, 3]	0.7467	0.5477	0.4874
Non-Defense	[0, 10]	0.7467	0.5477	0.5171
Non-Defense	[0, 30]	0.8536	0.7467	0.7119
Non-Defense	[0, 90]	0.0232	0.0395	0.0448
Non-Defense	[0, 180]	0.5791	0.4874	0.3778
Non-Defense	[0, 365]	0.0150	0.0797	0.1454

Note: Table 15 represents the mean P-value for the Wilcoxon-Signed Rank test for the first event. P-value is indicated per event window for defense stocks and non-defense stocks.

**Table 16: Mann-Whitney U Test P-Values for the Russia-Ukraine Conflict**

Event Window	CAPM model P-values	4-Factor model P-values	6-Factor model P-values
[-10, 1]	0.0330	0.1326	0.0851
[-3, 1]	0.3261	0.6623	0.6843
[0, 0]	0.0000	0.0000	0.0000
[0, 3]	0.0000	0.0000	0.0000
[0, 10]	0.0000	0.0000	0.0000
[0, 30]	0.0000	0.0000	0.0000
[0, 90]	0.0000	0.0000	0.0000
[0, 180]	0.0000	0.0000	0.0000
[0, 365]	0.0000	0.0000	0.0000

Note: Table 16 displays the P-value for the Mann-Whitney U Test, comparing CAAR between defense sector and non-defense sector stocks. Table 16 applies to the Russia-Ukraine event. Results are shown for the CAPM, 4-Factor and 6-Factor models.

**Table 17: Wilcoxon-Signed Rank Test P-Values for the Israel-Gaza Conflict**

Sector	Event Window	CAPM P-Value	4-Factor P-Value	6-Factor P-Value
Defense	[-10, -1]	0.0759	0.5706	0.6215
Defense	[-3, -1]	0.1429	0.2024	0.2611
Defense	[0, 0]	0.0000	0.0000	0.0000
Defense	[0, 3]	0.0000	0.0000	0.0000
Defense	[0, 10]	0.0000	0.0000	0.0000
Defense	[0, 30]	0.0073	0.0042	0.0056
Defense	[0, 90]	0.4749	0.9854	0.7841
Defense	[0, 180]	0.0007	0.0006	0.0012
Defense	[0, 365]	0.0010	0.0002	0.0003
Non-Defense	[-10, -1]	0.8900	0.2069	0.1202
Non-Defense	[-3, -1]	0.9265	0.4038	0.5171
Non-Defense	[0, 0]	0.1089	0.1089	0.1454
Non-Defense	[0, 3]	0.3060	0.9632	0.8900
Non-Defense	[0, 10]	0.7819	0.4586	0.4307
Non-Defense	[0, 30]	0.3289	0.1594	0.1901
Non-Defense	[0, 90]	0.0174	0.0202	0.0348
Non-Defense	[0, 180]	0.1202	0.0984	0.0887
Non-Defense	[0, 365]	0.0150	0.0174	0.0150

Note: Table 15 represents the mean P-value for the Wilcoxon-Signed Rank test for the second event. P-value is indicated per event window for defense stocks and non-defense stocks.

**Table 18: Mann-Whitney U Test P-Values for the Israel-Gaza Conflict**

Event Window	CAPM-model P-values	4-factor model P-values	6-factor model P-values
[-10, 1]	0.3569	0.1675	0.4417
[-3, 1]	0.4599	0.9880	0.9161
[0, 0]	0.0000	0.0000	0.0000
[0, 3]	0.0000	0.0000	0.0000
[0, 10]	0.0000	0.0000	0.0000
[0, 30]	0.0016	0.0004	0.0004
[0, 90]	0.0184	0.1174	0.2317
[0, 180]	0.0005	0.0003	0.0002
[0, 365]	0.0000	0.0000	0.0000

Note: Table 18 displays the P-value for the Mann-Whitney U Test, comparing CAAR between defense sector and non-defense sector stocks. Table 16 applies to the Israel-Gaza event. Results are shown for the CAPM, 4-Factor and 6-Factor models.

**Table 19: Wilcoxon Signed-Rank Test Comparing the Two Events for All Three Models**

Event Window	CAPM-model P-values	4-factor model P-values	6-factor model P-values
[-10, 1]	0.1448	0.2077	0.1175
[-3, 1]	0.0774	0.0298	0.0439
[0, 0]	0.4735	0.1491	0.1917
[0, 3]	0.6872	0.6872	0.5209
[0, 10]	0.0002	0.0001	0.0002
[0, 30]	0.0000	0.0000	0.0000
[0, 90]	0.0001	0.0001	0.0020
[0, 180]	0.0007	0.0005	0.0007
[0, 365]	0.0004	0.0004	0.0013

Note: This table presents p-values from Wilcoxon Signed-Rank tests comparing cumulative average abnormal returns across the two geopolitical events for each event window. Results are reported for the CAPM, 4-Factor, and 6-Factor models.

## 7.5 Appendix E – Random Effects Model Significance Tests

**Table 20: Panel Regression Hausman Test Results**

Event	Test Statistic	Degrees of Freedom	P-Value
1	0.0000	2	1.0000
2	0.0399	2	0.9802

Note: Table 20 presents the results of the Hausman Tests for the panel regression models. The test is performed for both regression models to empirically test whether to use the random or fixed effects model

**Table 21: Breusch-Pagan Test for the Random Effects Panel Regression**

Event	Chi-squared	Degrees of Freedom	P-value
1	617607	1	0.0000
2	585358	1	0.0000

Note: This table reports Breusch-Pagan Test results for random effects regression models. The table shows results for the first and second even as denoted in the first column.

## 7.6 Appendix F – AI Statement of Purpose

### Statement of purpose

This appendix provides a detailed description of the use of generative AI tools during the development and writing of the research proposal. The tools were used for refinement of language, ensuring clarity and precision in the presentation of the findings. Additionally the AI tool was used to insert the list of stocks efficiently with ticker, region and sector. All outputs generated were critically evaluated and, where necessary modified by myself to align with the objectives of this research. Outputs were never used without evaluating the precision and relevance.

### Tools used

- ChatGPT (GPT-4o)

### Scope of Use

#### *Writing and grammar refinement*

- Tool: ChatGPT (GPT-4o)
- Purpose: The generative AI tool was used to check for spelling, and to give rewrite suggestions where necessary.
- My role: The AI-generated suggestions were critically reviewed by myself before choosing to apply the suggestions to the research proposal. This was done whenever generative AI tools were used throughout the writing of the research proposal.
- My reflection: The AI tool was helpful when checking for grammar mistakes.
- Applied throughout the whole thesis.

#### *Data visualization*

- Tool: ChatGPT (GPT-4o)
- Purpose: The generative AI tool was used to transfer values from R into Word tables.
- My role: Providing the values to be used for the tables, additionally checking the accuracy of the data that was provided by the AI model.
- My reflection: Using the AI tool for inserting data from R into Word tables saved myself from work of manually adding the tables and prevent formatting issues when exporting from R. The information in the tables was checked by myself before adding it to the thesis.

- Applied in sections: 3.2, 3.3, 4.1, 4.2, 4.3 for tables: 4, 5, 6, 7, 8, 9, 13, 14, 15, 16, 17, 18

#### *Coding and Data Analysis*

- Tool: ChatGPT (GPT-4o)
- Purpose: The generative AI tool was used to help creating and fine tuning the R-script where necessary, helping with errors when they occurred and explaining codes.
- My role: Providing the problem I was running into and sending the code I have for the AI tool to analyse it and find the potential problem. If the problem was solved by a recommendation this code was checked and implemented into the R script.
- My reflection: Using the AI tool for optimizing the R code was helpful when running into problems or wanting to implement extra information into the thesis.
- Applied to the R script.

#### Complete log of AI Interaction

##### ***Writing and grammar refinement***

1.

*Query to ChatGPT (GPT-4o):* Can you provide a rewrite suggestion where necessary in this part of the introduction: In recent years the frequency and intensity of geopolitical conflicts have increased, with the Russia-Ukraine war commencing in February 2022, and the Israel-Gaza conflict beginning in October 2023. Financial markets have been thrust into a state of volatility, where geopolitical shocks often make financial market react negatively.

*Output from ChatGPT (GPT-4o):* Certainly! Here's a revised version of that passage with grammar, clarity, and flow improved:

Original: In recent years the frequency and intensity of geopolitical conflicts have increased, with the Russia-Ukraine war commencing in February 2022, and the Israel-Gaza conflict beginning in October 2023. Financial markets have been thrust into a state of volatility, where geopolitical shocks often make financial market react negatively.

Revised: In recent years, the frequency and intensity of geopolitical conflicts have increased, marked by the outbreak of the Russia-Ukraine war in February 2022 and the Israel-Gaza conflict in October 2023. These events have thrust financial markets into a state of heightened volatility, with geopolitical shocks often triggering negative market reactions.

*How it was used:* After carefully checking whether the context of the text was not affected, I decided to choose the revised sentence provided. Used in the introduction.

2.

Query to ChatGPT (GPT-4o): Can you revise this sentence: The essence of behavioral finance suggests that investors do not always act rationally, but also by emotional and psychological biases.

Output from ChatGPT (GPT-4o): Certainly. Here's a clearer and more grammatically refined version of that sentence:

Revised:

The essence of behavioral finance suggests that investors do not always act rationally, but are often influenced by emotional and psychological biases.

Let me know if you'd prefer an even more academic or concise version.

*How it was used:* The sentence was used after making sure it did not change the context of the sentence. Used in the introduction.

3.

Query to ChatGPT (GPT-4o): Can you find an alternative way to phrase the following: Another geopolitical shock has taken place since the Russia-Ukraine war, which is the conflict between Israel and Hamas, starting on October 7 2023. The latter conflict has been less examined by research, possibly due to the event being more recent. Nevertheless, the Israel-Hamas conflict brought global impact when announced, also shown in the financial markets

Output from ChatGPT (GPT-4o): Certainly! Here's a smoother and more academic alternative to that passage: Following the Russia-Ukraine war, another significant geopolitical shock occurred with the outbreak of the Israel-Hamas conflict on October 7, 2023. This conflict has received comparatively less academic attention, likely due to its more recent emergence. Nonetheless, it had a substantial global impact, which was also reflected in movements within the financial markets.

*How it was used:* Part of the revised version was used due to the better flow of the sentence. Used 2.2 of the literature review.

4.

Query to ChatGPT (GPT-4o): Can you find a better way to phrase the following: While this study will utilize event study methodology to analyse the reaction on the defense sector investors, it is important to understand how investors possibly over/under react to news. This is because news spreads information of the events globally within seconds, to which investors will react in the stock market.

---

*Output from ChatGPT (GPT-4o):* Certainly! Here's a more polished and academically appropriate version of your sentence: While this study employs event study methodology to analyze investor reactions within the defense sector, it is equally important to consider the potential for investor over- or underreaction to news. Given that news disseminates information about geopolitical events globally within seconds, investors are likely to respond rapidly in the stock market—often in ways that may not fully reflect underlying fundamentals.

*How it was used:* Part of the revision was used to get a better structured sentence. Used in section 2.3 of the literature review.

5.

*Query to ChatGPT (GPT-4o):* Can you give a rewrite suggestion: Through both the Mann-Whitney U Test and the Wilcoxon Signed-Rank Test it is possible to not only examine the investors reaction on geopolitical events, but conduct robustness checks by examining the difference between defense sector stocks and non-defense sector stocks while also examining the difference between the two events

*Output from ChatGPT (GPT-4o):* Certainly! Here's a clearer and more academically structured revision: The Mann-Whitney U Test and the Wilcoxon Signed-Rank Test allow for a comprehensive analysis of investor reactions to geopolitical events. These tests not only facilitate robustness checks by comparing defense and non-defense sector stocks but also enable an examination of potential differences in investor responses between the two geopolitical events.

*How it was used:* Part of the revision was used for better construction of the sentences. Used in section 3.2 of the methodology.

6.

*Query to ChatGPT (GPT-4o):* Please rewrite the following: Firms with less than 950 observations over the time span of 4 years were removed from the dataset, due to missing observations, which might affect the accuracy of the event windows and the CAR calculations.

*Output from ChatGPT:* Sure, here's a cleaner and more academic version of that sentence: Firms with fewer than 950 observations over the four-year period were excluded from the dataset to ensure data completeness and avoid distortions in the event window and CAR calculations caused by missing values. Let me know if you'd like a more technical or more accessible version as well.

*How it was used:* The sentence was used for a better flow in results section 4.1.

7.

*Query to ChatGPT (GPT-4o):* While both the cumulative average abnormal returns across multiple event windows and the sector-level panel regression imply a significant divergence in CAR comparing defense and non-defense sector stocks, it is important to assess the methodological boundaries within which the results are obtained. rewrite this the sentence is too long

*Output from ChatGPT:* You're right — the sentence is a bit long and dense. Here's a clearer and more concise rewrite: While both the CAAR analysis and the sector-level panel regression indicate a significant divergence in CARs between defense and non-defense stocks, it is important to consider the methodological limitations underlying these findings. Let me know if you'd like a slightly more formal or more technical version depending on your section.

*How it was used:* After checking whether it fits the paragraph the feedback was taken into consideration when reframing the sentence.

### **Data visualization**

8.

*Query to ChatGPT (GPT-4o):* Estimate Std. Error z-value Pr(>|z|) (Intercept) 0.0225351394 5.298273e-02 0.4253299 6.705962e-01 defense\_dummy 0.2776421916 7.206410e-02 3.8527114 1.168170e-04 days\_diff\_event1 -0.0004225783 1.822865e-05 -23.1820955 6.902104e-119 defense\_dummy:days\_diff\_event1 0.0007910907 2.478856e-05 31.9135371 1.732817e-223 provide this info in a table please with values always rounded to 4 decimals

*Output from ChatGPT:* Here is the tidy Word table with your regression results for Event 1, with values rounded to 4 decimals: Download Regression Results Table – Event 1

Let me know if you'd like to generate a similar table for Event 2 or combine both in one document.

*How it was used:* The table was used to import into Word, after carefully checking the data and reformatting the table to match the style of the document. Used for Table 5 section 4.2.

9.

*Query to ChatGPT (GPT-4o):* sector mean\_p1 mean\_p2 mean\_p3 count 1 IT 0.397842222 0.25235714 0.25458818 4 2 consumer\_dis 0.579525248 0.73984432 0.71838219 3 3 consumer\_staples 0.661166822 0.59212431 0.66456273 3 4 defense 0.449879082 0.45360062 0.47054141 20 5 energy 0.043771179 0.01098435 0.01945441 1 6 financials 0.326789020 0.36536525 0.44885706 4 7 healthcare 0.070434276 0.39999953 0.51283577 1 8 industrials 0.001196911 0.00224544 0.01127248 1 can you know provide a

tidy word table rounded decimals to 4, even if 0, and provide tidy names for columns and rows, similar to previously

*Output from ChatGPT:* Here is the tidy Word table with Breusch-Pagan test results per sector, rounded to 4 decimals and with clear column labels:

Download Breusch-Pagan Test by Sector Table

Let me know if you'd like the same format for the Shapiro-Wilk test or another summary.

*How it was used:* The table was used to import into Word, after carefully checking the data and reformatting the table to match the style of the document. Used for Table 14 Appendix C

10.

*Query to ChatGPT (GPT-4o):* Now I have this table for defense stocks, I want you to make a table in word, with an event column, event window shown as [0,0] etc. and CAPM-model P-value, 4-Factor model P-value and 6-factor model P-value, can you do that? event window sector n\_firms p\_1 p\_2 p\_3 1 1 0\_0 Defense 20 1.335144e-05 5.722046e-06 5.722046e-06 2 1 0\_10 Defense 20 1.907349e-06 1.907349e-06 1.907349e-06 3 1 0\_180 Defense 20 1.907349e-06 3.814697e-06 1.907349e-05 4 1 0\_3 Defense 20 9.536743e-06 9.536743e-06 9.536743e-06 5 1 0\_30 Defense 20 1.907349e-06 1.907349e-06 1.907349e-06 6 1 0\_365 Defense 20 5.722046e-06 5.722046e-06 5.855560e-04 7 1 0\_90 Defense 20 1.907349e-06 3.814697e-06 2.613068e-04 8 1 pre10\_1 Defense 20 8.969498e-02 9.730721e-02 8.969498e-02 9 1 pre3\_1 Defense 20 1.649570e-01 3.117943e-01 3.299828e-01 10 2 0\_0 Defense 20 1.907349e-06 1.907349e-06 1.907349e-06 11 2 0\_10 Defense 20 3.814697e-06 9.536743e-06 5.722046e-06 12 2 0\_180 Defense 20 7.076263e-04 5.855560e-04 1.209259e-03 13 2 0\_3 Defense 20 1.907349e-06 1.907349e-06 1.907349e-06 14 2 0\_30 Defense 20 7.295609e-03 4.220963e-03 5.580902e-03 15 2 0\_365 Defense 20 1.016617e-03 1.678467e-04 2.613068e-04 16 2 0\_90 Defense 20 4.749050e-01 9.854355e-01 7.841263e-01 17 2 pre10\_1 Defense 20 7.585144e-02 5.705967e-01 6.215134e-01 18 2 pre3\_1 Defense 20 1.429062e-01 2.024498e-01 2.610989e-01

*Output from ChatGPT:* Here is the Word document with the Wilcoxon Signed-Rank test results for defense stocks, neatly formatted and rounded to 4 decimals:

Download Wilcoxon\_Defense\_Results.docx

*How it was used:* The table was used to import into Word, after carefully checking the data and reformatting the table to match the style of the document. Used for Table 15 and 17 in Appendix D

11.

*Query to ChatGPT (GPT-4o):* event window sector n\_firms p\_1 p\_2 p\_3 1 1 0\_0 Non-Defense 17 0.22468567 0.22468567 0.19009399 2 1 0\_10 Non-Defense 17 0.74665833 0.54766846 0.51708984 3 1 0\_180 Non-Defense 17 0.57905579 0.48738098 0.37782288 4 1 0\_3 Non-Defense 17 0.74665833 0.54766846 0.48738098 5 1 0\_30 Non-Defense 17 0.85363770 0.74665833 0.71189880 6 1 0\_365 Non-Defense 17 0.01499939 0.07968140 0.14543152 7 1 0\_90 Non-Defense 17 0.02322388 0.03953552 0.04476929 8 1 pre10\_1 Non-Defense 17 0.07141113 0.37782288 0.24349976 9 1 pre3\_1 Non-Defense 17 0.54766846 0.28416443 0.26332092 10 2 0\_0 Non-Defense 17 0.10888672 0.10888672 0.14543152 11 2 0\_10 Non-Defense 17 0.78190613 0.45857239 0.43067932 12 2 0\_180 Non-Defense 17 0.12020874 0.09837341 0.08865356 13 2 0\_3 Non-Defense 17 0.30604553 0.96322632 0.88996887 14 2 0\_30 Non-Defense 17 0.32894897 0.15937805 0.19009399 15 2 0\_365 Non-Defense 17 0.01499939 0.01742554 0.01499939 16 2 0\_90 Non-Defense 17 0.01742554 0.02015686 0.03479004 17 2 pre10\_1 Non-Defense 17 0.88996887 0.20689392 0.12020874 18 2 pre3\_1 Non-Defense 17 0.92651367 0.40376282 0.51708984  
now exactly the same for these non-defense stocks please

*Output from ChatGPT:* The Word document with Wilcoxon test results for non-defense stocks is ready.

You can download it here:

Download Wilcoxon\_Non\_Defense\_Results.docx

*How it was used:* The table was used to import into Word, after carefully checking the data and reformatting the table to match the style of the document. Applied to Table 13 and 17 in Appendix D.

12.

*Query to ChatGPT (GPT-4o):* 1 [-10, 1] 0.0330 0.1326 0.0851 2 [-3, 1] 0.3261 0.6623 0.6843 3 [0, 0] 0.0000 0.0000 0.0000 4 [0, 10] 0.0000 0.0000 0.0000 5 [0, 180] 0.0000 0.0000 0.0000 6 [0, 30] 0.0000 0.0000 0.0000 7 [0, 365] 0.0000 0.0000 0.0000 8 [0, 3] 0.0000 0.0000 0.0000 9 [0, 90] 0.0000 0.0000 0.0000 please  
insert these values in a table in word, however please put them in order of the event windows

*Output from ChatGPT:* Your Word table with the p-values for Event 1 across different models and event windows is ready:

Download Event1\_Model\_Pvalues.docx

*How it was used:* The table was used to import into Word, after carefully checking the data and reformatting the table to match the style of the document. Applied to Table 16 Appendix D for the Mann Whitney U Test.

13.

*Query to ChatGPT (GPT-4o):* 1 [-10, 1] 0.3569 0.1675 0.4417 2 [-3, 1] 0.4599 0.9880 0.9161 3 [0, 0] 0.0000  
0.0000 0.0000 4 [0, 10] 0.0000 0.0000 0.0000 5 [0, 180] 0.0005 0.0003 0.0002 6 [0, 30] 0.0016 0.0004  
0.0004 7 [0, 365] 0.0000 0.0000 0.0000 8 [0, 3] 0.0000 0.0000 0.0000 9 [0, 90] 0.0184 0.1174 0.2317 Please

insert these values in a table in word, however please put them in order of the event windows

*Output from ChatGPT:* Here is your Word table with the p-values for Event 2, now correctly ordered by event window:

Download Event2\_Model\_Pvalues.docx

*How it was used:* The table was used to import into Word, after carefully checking the data and reformatting the table to match the style of the document. Applied to Table 18 Appendix D for the Mann Whitney U Test.

14.

*Query to ChatGPT (GPT-4o):* 1 Regression 1 FALSE -0.007324506 0.001018025 -0.009278666 -0.002136931  
-0.01069265 0.004456547 -0.04700921 -0.01700411 -0.1292337 NA NA NA NA NA NA NA NA NA NA NA  
NA NA NA NA NA NA NA 2 Regression 1 TRUE 0.014541672 0.012145085 0.065202690 0.066437749  
0.24217516 0.299321540 0.34224995 0.43498102 0.5357834 NA NA NA NA NA NA NA NA NA NA NA  
NA NA NA NA NA NA 3 Regression 2 FALSE NA NA NA NA NA NA NA NA NA NA -0.005535245 0.002032907 -  
0.01097714 -0.003759846 -0.01383717 -0.00312554 -0.05647392 -0.01903592 -0.1199091 NA NA NA NA  
NA NA NA NA NA 4 Regression 2 TRUE NA NA NA NA NA NA NA NA NA NA 0.009575287 0.009691562  
0.07429312 0.075347699 0.25115223 0.31568251 0.33549276 0.46097079 0.5474207 NA NA NA NA NA  
NA NA NA NA 5 Regression 3 FALSE NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA -  
0.005820052 0.002016682 -0.01091761 -0.003742867 -0.01431655 -0.00327755 -0.05721124 -  
0.01928963 -0.1201175 6 Regression 3 TRUE NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA  
NA 0.009419266 0.009263537 0.07043324 0.073253010 0.25034651 0.30069517 0.28516638 0.41718867  
0.4442501 Please insert these values of CAAR into a table for the first event. Merge the three regressions per event window.

*Output from ChatGPT:* The CAAR summary table for Event 1 (covering all three regressions and both groups) has been formatted and exported:

Download CAAR\_Event1\_Summary.docx

Let me know if you want the same for Event 2 or prefer a visual chart comparison.

*How it was used:* The table was used to import into Word, after carefully checking the data and reformatting the table to match the style of the document. Used for Table 4 in section 4.2.

15.

*Query to ChatGPT (GPT-4o):* regression is\_defense car\_pre10\_1\_e2 car\_pre3\_1\_e2 car\_0\_0\_e2 car\_0\_3\_e2 car\_0\_10\_e2 car\_0\_30\_e2 car\_0\_90\_e2 car\_0\_180\_e2 car\_0\_365\_e2 car2\_pre10\_1\_e2 car2\_pre3\_1\_e2 car2\_0\_0\_e2 car2\_0\_3\_e2 car2\_0\_10\_e2 car2\_0\_30\_e2 car2\_0\_90\_e2 car2\_0\_180\_e2 car2\_0\_365\_e2 car3\_pre10\_1\_e2 car3\_pre3\_1\_e2 car3\_0\_0\_e2 car3\_0\_3\_e2 car3\_0\_10\_e2 car3\_0\_30\_e2 car3\_0\_90\_e2 car3\_0\_180\_e2 car3\_0\_365\_e2 1 Regression 1 FALSE -0.004343337 -0.004206838 -0.004833632 0.008224815 -0.007639752 -0.02275535 -0.07374212 -0.1037148 -0.2214919 NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA 2 Regression 1 TRUE -0.011183725 -0.005043960 0.048655828 0.063048977 0.070597186 0.05526008 0.01413218 0.1795274 0.2940000 NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA 3 Regression 2 FALSE NA NA NA NA NA NA NA NA NA -0.010525936 -0.006037517 -0.005331258 0.004943642 -0.01192957 -0.02739460 -0.063674736 -0.1153878 -0.2295642 NA NA NA NA NA NA NA NA NA NA 4 Regression 2 TRUE NA NA NA NA NA NA NA NA NA 0.003624372 -0.003242119 0.047927787 0.064730203 0.07041246 0.06579392 0.001209029 0.1915164 0.3427235 NA NA NA NA NA NA NA NA NA NA 5 Regression 3 FALSE NA NA NA NA NA NA NA NA NA -0.010491239 -0.005984879 -0.005333797 0.00499153 -0.01195475 -0.02742286 -0.063273172 -0.1142776 -0.2283613 6 Regression 3 TRUE NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA NA -0.002604893 -0.002637055 0.050586382 0.07468740 0.07334886 0.06009674 -0.006754606 0.1962471 0.2962175. Please make a similar table for event 2, merging the results for the different regressions per event window.

*Output from ChatGPT:* Here is the transposed CAAR summary table for Event 2, with each column showing one regression and group combination:

Download CAAR\_Event2\_Summary\_Transposed.docx

*How it was used:* The table was used to import into Word, after carefully checking the data and reformatting the table to match the style of the document. Used for Table 6 section 4.3.

16.

*Query to ChatGPT (GPT-4o):* Novo Nordisk Saab Nestlé Leonardo SpA Allianz Hensoldt SAP Volkswagen ASML AeroVironment Amazon Apple BWX Technologies Babcock International Booz Allen Hamilton CACI International Curtiss-Wright Dassault Aviation Exxon Mobil HSBC Huntington Ingalls Industries JPMorgan

KBR L'Oréal Leonardo DRS Mercury Systems Microsoft Moog Palantir Technologies Parsons QinetiQ Group Royal Bank of Canada Schneider Electric Science Applications International Tesla Thales Unilever this same list of companies, can you make a table with the names in the first column, the country in the second column, and the sector in the third column. Order the companies on alphabetically on the SECTOR column

*Output from ChatGPT:* The Word table with company names, countries, and sectors—sorted alphabetically by sector—is ready. You can download it here:

Download Company\_Sector\_Sorted.docx

*How it was used:* The table was used to import into Word, after carefully checking the data and reformatting the table to match the style of the document.

17.

*Query to ChatGPT (GPT-4o):* 1 ASML 997 2 AeroVironment 997 3 Allianz 993 4 Amazon 997 5 Apple 997 6 BWX\_Technologies 997 7 Babcock\_International 997 8 Booz\_Allen\_Hamilton 997 9 CACI\_International 997 10 Curtiss-Wright 997 11 Dassault\_Aviation 997 12 Exxon\_Mobil 997 13 HSBC 997 14 Hensoldt 993 15 Huntington\_Ingalls\_Industries 997 16 JPMorgan 997 17 KBR 997 18 L'Oréal 997 19 Leonardo\_DRS 997 20 Leonardo\_SpA 991 21 Mercury\_Systems 997 22 Microsoft 997 23 Moog 997 24 Nestlé 983 25 Novo\_Nordisk 974 26 Palantir\_Technologies 997 27 Parsons 997 28 QinetiQ\_Group 997 29 Royal\_Bank\_of\_Canada 997 30 SAP 993 31 Saab 980 32 Schneider\_Electric 997 33 Science\_Applications\_International 997 34 Tesla 997 35 Thales 997 36 Unilever 997 37 Volkswagen 993

for this list of companies, can you make a word table, with the firm names deleting the \_, the rightc column is number of observations

*Output from ChatGPT:* The Word table with cleaned company names and their number of observations is ready. You can download it here:

Download Company\_Observations\_Table.docx

*How it was used:* The table was used to import into Word, after carefully checking the data and reformatting the table to match the style of the document. Applied to Table 9 Appendix A.

18. .

*Query to ChatGPT (GPT-4o):* sector mean\_p1 mean\_p2 mean\_p3 count 1 IT 0.397842222 0.25235714 0.25458818 4 2 consumer\_dis 0.579525248 0.73984432 0.71838219 3 3 consumer\_staples 0.661166822 0.59212431 0.66456273 3 4 defense 0.449879082 0.45360062 0.47054141 20 5 energy 0.043771179 0.01098435 0.01945441 1 6 financials 0.326789020 0.36536525 0.44885706 4 7 healthcare 0.070434276

0.39999953 0.51283577 1 8 industrials 0.001196911 0.00224544 0.01127248 1 can you know provide a tidy word table rounded decimals to 4, even if 0, and provide tidy names for columns and rows, similar to previously

*Output from ChatGPT:* Here is the tidy Word table with Breusch-Pagan test results per sector, rounded to 4 decimals and with clear column labels:

Download Breusch-Pagan Test by Sector Table

Let me know if you'd like the same format for the Shapiro-Wilk test or another summary

*How it was used:* The table was used for section Appendix C Table 13, after carefully checking the data.

19.

*Query to ChatGPT (GPT-4o):* sector

mean\_p1 mean\_p2 mean\_p3 count 1

IT 1.148087e-02 4.915428e-05 9.191229e-04

4 2

consumer\_dis 1.395514e-05 2.153369e-07 2.745894e-07

3 3

consumer\_staples 7.230283e-03 8.413596e-04 4.815689e-04

3 4

Defense 3.815820e-02 3.543345e-03 5.657634e-03

20 5

Energy 1.173709e-01 4.293156e-01 3.048420e-01

1 6

Financials 2.063173e-01 1.302497e-01 2.715037e-01

4 7

Healthcare 2.154463e-11 3.274800e-12 3.680156e-12

1 8

Industrials 4.601031e-04 4.701262e-04 4.519344e-04

1 now make a similar word table for shapiro test, round every value to 4 decimals and give the same tidy names

*Output from ChatGPT:* Here is the tidy Word table with Shapiro-Wilk test results per sector, rounded to 4 decimals and with clean column headers:

Download Shapiro-Wilk Test by Sector Table

Let me know if you'd like to add interpretation or include this in an appendix section.

*How it was used:* The table was used after carefully checking the data, applied to Table 14 for section Appendix C.

20.

*Query to ChatGPT (GPT-4o):* term estimate std.error statistic p.value 1 (Intercept) 0.0233549043 5.314373e-02 0.4394668 6.603233e-01 2 defense\_dummy 0.2656164846 7.228277e-02 3.6746862 2.381419e-04 3 days\_diff\_event1 -0.0005230981 1.946035e-05 -26.8801956 3.743467e-159 4 defense\_dummy:days\_diff\_event1 0.0009158757 2.653909e-05 34.5104363 5.594102e-261, changed the event window slightly to 0, 365, thus need to insert new tables, please make a word table rounding to 4 decimals for all values.

*Output from ChatGPT:* Here is your Word document with the regression results for Event 1, rounded to 4 decimals and formatted in a clean table:

Download Table 5 – Random Model Regression Event 1 (0 to +365)

Let me know if you'd like a version for Event 2 as well.

*How it was used:* The table was inserted to section 4.2 Table 5, after carefully checking the correctness of the data.

21.

*Query to ChatGPT (GPT-4o):* term estimate std.error statistic p.value 1 (Intercept) -2.469106e-06 4.470030e-02 -5.523690e-05 0.9999559 2 defense\_dummy 1.597595e-02 6.079872e-02 2.627678e-01 0.7927295 3 days\_diff\_event2 -6.521283e-04 1.628743e-05 -4.003874e+01 0.0000000 4 defense\_dummy:days\_diff\_event2 1.445789e-03 2.207231e-05 6.550239e+01 0.0000000 similar for table two, word table with rounded by 4 decimals

*Output from ChatGPT:* Here is the Word document for Table 7 – Random Effects Regression for Event 2 (0 to +365), with all values rounded to 4 decimals:

Download Table 7 – Event 2 Regression

Let me know if you'd like a combined version with both tables in one document

*How it was used:* The table was inserted to section 4.3 Table 7, after carefully checking the correctness of the data.

## Coding and Data Analysis

22.

*Query to ChatGPT (GPT-4o):* Lets do per sector, can you rewrite the following code keeping everything else similar, so that instead of dummy it is shown per sector? ### Combining bp-tests for all 3 AR regressions # Rename p-value columns for clarity bptest\_reg1 <- bptest\_reg1 %>% rename(p\_1 = bptest\_p) bptest\_reg2 <- bptest\_reg2 %>% rename(p\_2 = bptest\_p) bptest\_reg3 <- bptest\_reg3 %>% rename(p\_3 = bptest\_p) # Merge all Breusch-Pagan test results by firm name bptest\_all <- bptest\_reg1 %>% full\_join(bptest\_reg2, by = "firm") %>% full\_join(bptest\_reg3, by = "firm") # Join with firm\_info to bring in is\_defense dummy bptest\_all <- bptest\_all %>% left\_join(firm\_info %>% select(firm, is\_defense), by = "firm") # Group by defense status and summarise p-values bptest\_grouped <- bptest\_all %>% group\_by(is\_defense) %>% summarise( mean\_p1 = mean(p\_1, na.rm = TRUE), mean\_p2 = mean(p\_2, na.rm = TRUE), mean\_p3 = mean(p\_3, na.rm = TRUE), count = n() ) %>% mutate( sector = case\_when( is\_defense == "YES" ~ "Defense", is\_defense == "NO" ~ "Non-Defense" ) ) %>% select(sector, everything(), -is\_defense)

*Output from ChatGPT:* Sure, Mats — here's the rewritten code to summarize the Breusch-Pagan test per sector instead of per dummy. Everything else (structure, column renaming, merging) is preserved:

---

8 Updated R Code — per sector

r

KopiërenBewerken

```
# Rename p-value columns for clarity
bptest_reg1 <- bptest_reg1 %>% rename(p_1 = bptest_p)
bptest_reg2 <- bptest_reg2 %>% rename(p_2 = bptest_p)
bptest_reg3 <- bptest_reg3 %>% rename(p_3 = bptest_p)
# Merge all Breusch-Pagan test results by firm name
bptest_all <- bptest_reg1 %>%
  full_join(bptest_reg2, by = "firm") %>%
  full_join(bptest_reg3, by = "firm")
# Join with firm_info to bring in sector
bptest_all <- bptest_all %>%
  left_join(firm_info %>% select(firm, sector), by = "firm")
# Group by sector and summarise p-values
```

---

```

bptest_grouped <- bptest_all %>%
  group_by(sector) %>%
  summarise(
    mean_p1 = mean(p_1, na.rm = TRUE),
    mean_p2 = mean(p_2, na.rm = TRUE),
    mean_p3 = mean(p_3, na.rm = TRUE),
    count = n()
  ) %>%
  arrange(sector) # optional: alphabetic sort

```

---

## 9 Output:

sector	mean_p1	mean_p2	mean_p3	count
Consumer Staples ...	...	...	...	...
Energy	...	...	...	...
Industrials	...	...	...	...

Let me know if you'd like to generate a Word table or plot these values to show model stability across sectors.

*How it was used:* The R code was used after carefully checking if the goal was achieved. The code transformed the Breusch-Pagan test to sector results rather than on dummy level. Applied to Table 13 section Appendix C

23.

*Query to ChatGPT (GPT-4o):* ### Combining Shapiro test for all regressions

```

# Rename p-value columns
normality_reg1 <- normality_reg1 %>% rename(p_1 = shapiro_p)
normality_reg2 <- normality_reg2 %>% rename(p_2 = shapiro_p)
normality_reg3 <- normality_reg3 %>% rename(p_3 = shapiro_p)
# Merge all three Shapiro results by 'firm'
normality_all <- normality_reg1 %>%
  full_join(normality_reg2, by = "firm") %>%
  full_join(normality_reg3, by = "firm")

```

---

```

# Add defense sector info
normality_all <- normality_all %>%
  left_join(firm_info %>% select(firm, is_defense), by = "firm")
# Normalize labels (optional, but clean)
normality_all <- normality_all %>%
  mutate(sector = case_when(
    is_defense == "YES" ~ "Defense",
    is_defense == "NO" ~ "Non-Defense",
    TRUE ~ "Unknown"
  ))
# Group by sector and summarise
normality_grouped <- normality_all %>%
  group_by(sector) %>%
  summarise(
    mean_p1 = mean(p_1, na.rm = TRUE),
    mean_p2 = mean(p_2, na.rm = TRUE),
    mean_p3 = mean(p_3, na.rm = TRUE),
    count = n()
  )
) now for the shapiro test, please provide exact same code but grouping per sector not dummy

```

*Output from ChatGPT:* Sure Mats — here's the adjusted version of your Shapiro-Wilk test combination code, now grouped per sector instead of the dummy (is\_defense). Everything else stays the same:

---

## 10 Updated R Code — Grouping by sector

```

r
KopiërenBewerken
# Rename p-value columns
normality_reg1 <- normality_reg1 %>% rename(p_1 = shapiro_p)
normality_reg2 <- normality_reg2 %>% rename(p_2 = shapiro_p)
normality_reg3 <- normality_reg3 %>% rename(p_3 = shapiro_p)
# Merge all three Shapiro results by 'firm'
normality_all <- normality_reg1 %>%
  full_join(normality_reg2, by = "firm") %>%

```

---

```

full_join(normality_reg3, by = "firm")
# Add sector info from firm_info
normality_all <- normality_all %>%
  left_join(firm_info %>% select(firm, sector), by = "firm")
# Group by actual sector (e.g., IT, Financials, etc.)
normality_grouped <- normality_all %>%
  group_by(sector) %>%
  summarise(
    mean_p1 = mean(p_1, na.rm = TRUE),
    mean_p2 = mean(p_2, na.rm = TRUE),
    mean_p3 = mean(p_3, na.rm = TRUE),
    count = n()
  ) %>%
  arrange(sector)

```

---

This will now give you Shapiro-Wilk test results per industry sector, matching how you did it for the Breusch-Pagan test.

Let me know if you want to convert the results into a Word table or visualize them!

*How it was used:* The code was used to transform the Shapiro-Wilk results into sector level rather than dummy. First the code was carefully checked. Applied to table 14 Appendix C

24.

*Query to ChatGPT (GPT-4o):* ## Regression panel data event 2

```

# Add sector info and filter event 2
ar_all_e2 <- data_reg3 %>%
  select(firm, sector, days_diff_event2, ar) %>%
  filter(!is.na(days_diff_event2)) %>%
  filter(days_diff_event2 >= -10, days_diff_event2 <= 365)
# Compute daily CARs per firm
ar_all_e2 <- ar_all_e2 %>%
  arrange(firm, days_diff_event2) %>%
  group_by(firm) %>%

```

---

```

mutate(car = cumsum(ar)) %>%
ungroup()
# Set factor levels and reference category
ar_all_e2 <- ar_all_e2 %>%
  mutate(sector = factor(sector)) %>%
  mutate(sector = relevel(sector, ref = "defense"))
# Make days_diff_event2 numeric
ar_all_e2 <- ar_all_e2 %>%
  mutate(days_diff_event2 = as.integer(as.character(days_diff_event2)))
ar_all_e2$sector <- as.factor(ar_all_e2$sector)
ar_all_e2$firm <- as.factor(ar_all_e2$firm)
# Declare panel structure
pdata_e2 <- pdata.frame(ar_all_e2, index = c("firm", "days_diff_event2"))
pdata_e2$days_diff_event2 <- as.numeric(as.character(pdata_e2$days_diff_event2))
# Fixed and Random effects model
fe_model_e2 <- plm(car ~ sector + days_diff_event2, data = pdata_e2, model = "within")
re_model_e2 <- plm(car ~ sector + days_diff_event2, data = pdata_e2, model = "random")
# Hausman test for model selection
phtest(fe_model_e2, re_model_e2)
# Summarise the regression
summary_re_e2 <- summary(re_model_e2)
summary_re_e2$coefficients
summary_re_e2$fstatistic
summary_re_e2$r.squared
# Tidy model
re_model_e2 <- broom::tidy(re_model_e2) can you adjust this code so it also gives the interaction and
defense dummy, everything else exactly the same

```

*Output from ChatGPT:* Sure! Here's the adjusted code where we add an interaction term between sector and days\_diff\_event2 and include the defense\_dummy just as we did in your Event 1 model. The rest of the code structure remains the same.

11 Updated Code:

r

Kopiëren

```
## Regression panel data event 2
# Add sector info and filter event 2
ar_all_e2 <- data_reg3 %>%
  select(firm, sector, days_diff_event2, ar) %>%
  filter(!is.na(days_diff_event2)) %>%
  filter(days_diff_event2 >= -10, days_diff_event2 <= 365)
# Compute daily CARs per firm
ar_all_e2 <- ar_all_e2 %>%
  arrange(firm, days_diff_event2) %>%
  group_by(firm) %>%
  mutate(car = cumsum(ar)) %>% # cumulative abnormal return
  ungroup()
# Set factor levels and reference category
ar_all_e2 <- ar_all_e2 %>%
  mutate(sector = factor(sector)) %>%
  mutate(sector = relevel(sector, ref = "defense"))
# Create a dummy variable for Defense and Non-Defense
ar_all_e2 <- ar_all_e2 %>%
  mutate(defense_dummy = ifelse(sector == "defense", 1, 0))
# Make days_diff_event2 numeric
ar_all_e2 <- ar_all_e2 %>%
  mutate(days_diff_event2 = as.integer(as.character(days_diff_event2)))
ar_all_e2$sector <- as.factor(ar_all_e2$sector)
ar_all_e2$firm <- as.factor(ar_all_e2$firm)
# Declare panel structure
pdata_e2 <- pdata.frame(ar_all_e2, index = c("firm", "days_diff_event2"))
pdata_e2$days_diff_event2 <- as.numeric(as.character(pdata_e2$days_diff_event2))
# Fixed and Random effects model with interaction term and defense dummy
fe_model_e2 <- plm(car ~ defense_dummy * days_diff_event2, data = pdata_e2, model = "within")
re_model_e2 <- plm(car ~ defense_dummy * days_diff_event2, data = pdata_e2, model = "random")
# Hausman test for model selection
```

```

phtest(fe_model_e2, re_model_e2)
# Summarise the regression
summary_re_e2 <- summary(re_model_e2)
summary_re_e2$coefficients
summary_re_e2$statistic
summary_re_e2$r.squared
# Tidy the random effects model (including defense dummy and interaction term)
re_model_e2_tidy <- broom::tidy(re_model_e2, conf.int = TRUE)
# Display the tidy model
re_model_e2_tidy

```

Let me know if you need help interpreting the results or further customizations!

*How it was used:* The code was used to include an interaction variable to the regression model. Applied to Table 7 section 4.3.

25.

```

Query to ChatGPT (GPT-4o): ## Make the plot be CAR over time for 365 days E1 # Filter for Defense
firms, Event 1, and days 0 to 365 car_defense_365_e1 <- data_reg3 %>% filter(sector == "defense",
days_diff_event1 >= 0, days_diff_event1 <= 365) %>% arrange(firm, days_diff_event1) %>%
group_by(firm) %>% mutate(car = cumsum(ar)) %>% # Step 2: Compute cumulative AR (CAR) per firm
ungroup() %>% group_by(days_diff_event1) %>% summarise(avg_car = mean(car, na.rm = TRUE),
.groups = "drop") # Plot CAR for defense stocks 365 days E1 ggplot(car_defense_365_e1, aes(x =
days_diff_event1, y = avg_car)) + geom_line(color = "firebrick", linewidth = 1) + geom_hline(yintercept =
0, linetype = "dashed", color = "gray60") + labs(title = "Average Cumulative Abnormal Return (CAR) for
Defense Stocks", subtitle = "Event 1, 365 days", x = "Days Since Event", y = "Average CAR") +
theme_minimal() # How many firms contribute to CAR day defense stocks E1 data_reg3 %>% filter(sector
== "defense", days_diff_event1 >= 0, days_diff_event1 <= 365) %>% group_by(days_diff_event1) %>%
summarise(n_firms = n_distinct(firm)) %>% arrange(n_firms) %>% print(n = Inf) # How many firms
contribute to CAR per day non-defense stocks E1 data_reg3 %>% filter(sector != "defense",
days_diff_event1 >= 0, days_diff_event1 <= 365) %>% group_by(days_diff_event1) %>%
summarise(n_firms = n_distinct(firm)) %>% arrange(n_firms) %>% print(n = Inf) # How many firms
contribute to CAR day defense stocks E2 data_reg3 %>% filter(sector == "defense", days_diff_event2 >=
0, days_diff_event2 <= 365) %>% group_by(days_diff_event2) %>% summarise(n_firms =

```

```

n_distinct(firm)) %>% arrange(n_firms) %>% print(n = Inf) # How many firms contribute to CAR per day
non-defense stocks E2 data_reg3 %>% filter(sector != "defense", days_diff_event2 >= 0,
days_diff_event2 <= 365) %>% group_by(days_diff_event2) %>% summarise(n_firms = n_distinct(firm))
%>% arrange(n_firms) %>% print(n = Inf) ## Plot CAR over time for non-defense sector stocks 365 days
E1 # Filter for non-defense firms, Event 1, and days 0 to 365 car_nondf_365_e1 <- data_reg3 %>%
filter(sector != "defense", days_diff_event1 >= 0, days_diff_event1 <= 365) %>% arrange(firm,
days_diff_event1) %>% group_by(firm) %>% mutate(car = cumsum(ar)) %>% # Cumulative AR per firm
ungroup() %>% group_by(days_diff_event1) %>% summarise(avg_car = mean(car, na.rm = TRUE),
.groups = "drop") # Plot CAR for non-defense stocks ggplot(car_nondf_365_e1, aes(x = days_diff_event1,
y = avg_car)) + geom_line(color = "firebrick", linewidth = 1) + geom_hline(yintercept = 0, linetype =
"dashed", color = "gray60") + labs(title = "Average Cumulative Abnormal Return (CAR) for Non-Defense
Stocks", subtitle = "Event 1, 365 days", x = "Days Since Event", y = "Average CAR") + theme_minimal() ##
Plot CAR over time for defense sector stocks E2 # Filter for defense firms, Event 2, and days 0 to 365
car_defense_365_e2 <- data_reg3 %>% filter(sector == "defense", days_diff_event2 >= 0,
days_diff_event2 <= 365) %>% arrange(firm, days_diff_event2) %>% group_by(firm) %>% mutate(car =
cumsum(ar)) %>% # Cumulative AR per firm ungroup() %>% group_by(days_diff_event2) %>%
summarise(avg_car = mean(car, na.rm = TRUE), .groups = "drop") # Plot CAR for defense stocks
ggplot(car_defense_365_e2, aes(x = days_diff_event2, y = avg_car)) + geom_line(color = "firebrick",
linewidth = 1) + geom_hline(yintercept = 0, linetype = "dashed", color = "gray60") + labs(title = "Average
Cumulative Abnormal Return (CAR) for Defense Stocks", subtitle = "Event 2, 365 days", x = "Days Since
Event", y = "Average CAR") + theme_minimal() ## Plot CAR over time for non-defense sector stocks E2 #
Filter for non-defense firms, Event 2, and days 0 to 365 car_nondf_365_e2 <- data_reg3 %>%
filter(sector != "defense", days_diff_event2 >= 0, days_diff_event2 <= 365) %>% arrange(firm,
days_diff_event2) %>% group_by(firm) %>% mutate(car = cumsum(ar)) %>% # Cumulative AR per firm
ungroup() %>% group_by(days_diff_event2) %>% summarise(avg_car = mean(car, na.rm = TRUE),
.groups = "drop") # Plot CAR for non-defense stocks ggplot(car_nondf_365_e2, aes(x = days_diff_event2,
y = avg_car)) + geom_line(color = "firebrick", linewidth = 1) + geom_hline(yintercept = 0, linetype =
"dashed", color = "gray60") + labs(title = "Average Cumulative Abnormal Return (CAR) for Non-Defense
Stocks", subtitle = "Event 2, 365 days", x = "Days Since Event", y = "Average CAR") + theme_minimal()

```

So chat I have these commands for the 4 figures i ran to get CAR over time for event 1 and 2, and for defense and non-defense. Now what I want is to create 2 figures total, one for the first event with one

line for defense stocks and one line for non-defense stocks. then repeat the same for the second event.

We will start with the first. Can you help me create this?

*Output from ChatGPT:* Yes, let's start with Event 1 and combine both defense and non-defense stocks into one single figure with two lines.

We'll first prepare the two datasets (as you've already done), and then combine them into one before plotting. Here's how to do it step by step:

---

## 12 Step 1: Combine CAR data for Event 1

r

Kopieren

# Prepare defense data

```
car_defense_e1 <- data_reg3 %>%
  filter(sector == "defense",
         days_diff_event1 >= 0,
         days_diff_event1 <= 365) %>%
  arrange(firm, days_diff_event1) %>%
  group_by(firm) %>%
  mutate(car = cumsum(ar)) %>%
  ungroup() %>%
  group_by(days_diff_event1) %>%
  summarise(avg_car = mean(car, na.rm = TRUE),
            sector = "Defense",
            .groups = "drop")
```

# Prepare non-defense data

```
car_nondf_e1 <- data_reg3 %>%
  filter(sector != "defense",
         days_diff_event1 >= 0,
         days_diff_event1 <= 365) %>%
  arrange(firm, days_diff_event1) %>%
  group_by(firm) %>%
  mutate(car = cumsum(ar)) %>%
```

```
ungroup() %>%
group_by(days_diff_event1) %>%
summarise(avg_car = mean(car, na.rm = TRUE),
          sector = "Non-Defense",
          .groups = "drop")
# Combine into one dataframe
car_combined_e1 <- bind_rows(car_defense_e1, car_nondf_e1)
```

---

### 13 Step 2: Plot both lines in one figure

r

Kopiëren

```
# Plot combined CAR for Event 1
```

```
ggplot(car_combined_e1, aes(x = days_diff_event1, y = avg_car, color = sector)) +
  geom_line(linewidth = 1) +
  geom_hline(yintercept = 0, linetype = "dashed", color = "gray60") +
  labs(title = "Average Cumulative Abnormal Return (CAR) – Event 1",
       subtitle = "Comparison between Defense and Non-Defense Stocks (0–365 days)",
       x = "Days Since Event",
       y = "Average CAR",
       color = "Sector") +
  theme_minimal()
```

---

Let me know if you want to:

- use different colors
- smooth the lines
- add confidence intervals (if available)
- or export the figure

When you're ready, we'll do the same for Event 2.

*How it was used:* Used to combine the two lines for the first event shown in Figure 1 section 4.2.

26.

```

Query to ChatGPT (GPT-4o): ## Make the plot be CAR over time for 365 days E1 # Filter for Defense
firms, Event 1, and days 0 to 365 car_defense_365_e1 <- data_reg3 %>% filter(sector == "defense",
days_diff_event1 >= 0, days_diff_event1 <= 365) %>% arrange(firm, days_diff_event1) %>%
group_by(firm) %>% mutate(car = cumsum(ar)) %>% # Step 2: Compute cumulative AR (CAR) per firm
ungroup() %>% group_by(days_diff_event1) %>% summarise(avg_car = mean(car, na.rm = TRUE),
.groups = "drop") # Plot CAR for defense stocks 365 days E1 ggplot(car_defense_365_e1, aes(x =
days_diff_event1, y = avg_car)) + geom_line(color = "firebrick", linewidth = 1) + geom_hline(yintercept =
0, linetype = "dashed", color = "gray60") + labs(title = "Average Cumulative Abnormal Return (CAR) for
Defense Stocks", subtitle = "Event 1, 365 days", x = "Days Since Event", y = "Average CAR") +
theme_minimal() # How many firms contribute to CAR day defense stocks E1 data_reg3 %>% filter(sector
== "defense", days_diff_event1 >= 0, days_diff_event1 <= 365) %>% group_by(days_diff_event1) %>%
summarise(n_firms = n_distinct(firm)) %>% arrange(n_firms) %>% print(n = Inf) # How many firms
contribute to CAR per day non-defense stocks E1 data_reg3 %>% filter(sector != "defense",
days_diff_event1 >= 0, days_diff_event1 <= 365) %>% group_by(days_diff_event1) %>%
summarise(n_firms = n_distinct(firm)) %>% arrange(n_firms) %>% print(n = Inf) # How many firms
contribute to CAR day defense stocks E2 data_reg3 %>% filter(sector == "defense", days_diff_event2 >=
0, days_diff_event2 <= 365) %>% group_by(days_diff_event2) %>% summarise(n_firms =
n_distinct(firm)) %>% arrange(n_firms) %>% print(n = Inf) # How many firms contribute to CAR per day
non-defense stocks E2 data_reg3 %>% filter(sector != "defense", days_diff_event2 >= 0,
days_diff_event2 <= 365) %>% group_by(days_diff_event2) %>% summarise(n_firms = n_distinct(firm))
%>% arrange(n_firms) %>% print(n = Inf) ## Plot CAR over time for non-defense sector stocks 365 days
E1 # Filter for non-defense firms, Event 1, and days 0 to 365 car_nondf_365_e1 <- data_reg3 %>%
filter(sector != "defense", days_diff_event1 >= 0, days_diff_event1 <= 365) %>% arrange(firm,
days_diff_event1) %>% group_by(firm) %>% mutate(car = cumsum(ar)) %>% # Cumulative AR per firm
ungroup() %>% group_by(days_diff_event1) %>% summarise(avg_car = mean(car, na.rm = TRUE),
.groups = "drop") # Plot CAR for non-defense stocks ggplot(car_nondf_365_e1, aes(x = days_diff_event1,
y = avg_car)) + geom_line(color = "firebrick", linewidth = 1) + geom_hline(yintercept = 0, linetype =
"dashed", color = "gray60") + labs(title = "Average Cumulative Abnormal Return (CAR) for Non-Defense
Stocks", subtitle = "Event 1, 365 days", x = "Days Since Event", y = "Average CAR") + theme_minimal() ##
Combining defense and non-defense car for first event car_combined_365_e1 <-
bind_rows(car_defense_365_e1, car_nondf_365_e1) # Plot combined CAR for Event 1
ggplot(car_combined_365_e1, aes(x = days_diff_event1, y = avg_car, color = sector)) +

```

```
geom_line(linewidth = 1) + geom_hline(yintercept = 0, linetype = "dashed", color = "gray60") + labs(title = "Average Cumulative Abnormal Return (CAR) – Event 1", subtitle = "Comparison between Defense and Non-Defense Stocks (0–365 days)", x = "Days Since Event", y = "Average CAR", color = "Sector") + theme_minimal()
```

so i have this now, and the sector problem when trying it with `car_combined_365_e1`. Can you find the problem and fix the `car_combined_365_e1` including the sector?

*Output from ChatGPT:* Yes, I see the issue: in your current code for creating `car_defense_365_e1` and `car_nondf_365_e1`, you did not add a sector column before combining them with `bind_rows()`. So when plotting, the `color = sector` aesthetic fails because `sector` doesn't exist in the combined dataframe.

Let me give you the exact fixed version of your pipeline.

14 Step-by-step fix: add sector column before combining

15 Step 1: Recreate `car_defense_365_e1` with sector column

r

Kopieren

```
car_defense_365_e1 <- data_reg3 %>%
  filter(sector == "defense",
         days_diff_event1 >= 0,
         days_diff_event1 <= 365) %>%
  arrange(firm, days_diff_event1) %>%
  group_by(firm) %>%
  mutate(car = cumsum(ar)) %>%
  ungroup() %>%
  group_by(days_diff_event1) %>%
  summarise(avg_car = mean(car, na.rm = TRUE), .groups = "drop") %>%
  mutate(sector = "Defense")
```

16 Step 2: Recreate `car_nondf_365_e1` with sector column

r

Kopieren

```
car_nondf_365_e1 <- data_reg3 %>%
  filter(sector != "defense",
         days_diff_event1 >= 0,
         days_diff_event1 <= 365) %>%
```

```
arrange(firm, days_diff_event1) %>%
group_by(firm) %>%
mutate(car = cumsum(ar)) %>%
ungroup() %>%
group_by(days_diff_event1) %>%
summarise(avg_car = mean(car, na.rm = TRUE), .groups = "drop") %>%
mutate(sector = "Non-Defense")
```

17 Step 3: Combine both into one dataframe

r

Kopiëren

```
car_combined_365_e1 <- bind_rows(car_defense_365_e1, car_nondf_365_e1)
```

---

18 Step 4: Plot combined CAR over 365 days for Event 1

r

Kopiëren

```
ggplot(car_combined_365_e1, aes(x = days_diff_event1, y = avg_car, color = sector)) +
  geom_line(linewidth = 1) +
  geom_hline(yintercept = 0, linetype = "dashed", color = "gray60") +
  labs(title = "Average Cumulative Abnormal Return (CAR) – Event 1",
       subtitle = "Comparison between Defense and Non-Defense Stocks (0–365 days)",
       x = "Days Since Event",
       y = "Average CAR",
       color = "Sector") +
  theme_minimal()
```

---

Let me know if you'd like to:

- do the same for Event 2
- include firm counts per day as an annotation or tooltip
- overlay confidence intervals (if you have variance data)
- or export the figure to file (PDF/PNG)

*How it was used:* Used to combine the two lines for the first event shown in Figure 1 section 4.2.

---

27.

*Query to ChatGPT (GPT-4o):* ## Combining defense and non-defense car for first event

```
car_combined_365_e1 <- bind_rows(car_defense_365_e1, car_nondf_365_e1) # Plot combined CAR for
Event 1 ggplot(car_combined_365_e1, aes(x = days_diff_event1, y = avg_car, color = sector)) +
geom_line(linewidth = 1) + geom_hline(yintercept = 0, linetype = "dashed", color = "gray60") +
scale_color_manual(values = c("Defense" = "firebrick", "Non-Defense" = "steelblue")) + labs(title =
"Cumulative Average Abnormal Return (CAAR) – Event 1", subtitle = "Comparison between Defense and
Non-Defense Stocks (0–365 days)", x = "Days Since Event", y = "Average CAR", color = "Sector") +
theme_minimal()
```

now please copy this exactly for the second event, changing e1 to e2

*Output from ChatGPT:* Perfect, here's the exact copy for Event 2, with all e1 references updated to e2 and the colors, titles, and labels preserved:

---

r

Kopiëren

## Combining defense and non-defense CAR for second event

```
car_defense_365_e2 <- data_reg3 %>%
  filter(sector == "defense",
         days_diff_event2 >= 0,
         days_diff_event2 <= 365) %>%
  arrange(firm, days_diff_event2) %>%
  group_by(firm) %>%
  mutate(car = cumsum(ar)) %>%
  ungroup() %>%
  group_by(days_diff_event2) %>%
  summarise(avg_car = mean(car, na.rm = TRUE), .groups = "drop") %>%
  mutate(sector = "Defense")
car_nondf_365_e2 <- data_reg3 %>%
  filter(sector != "defense",
         days_diff_event2 >= 0,
         days_diff_event2 <= 365) %>%
  arrange(firm, days_diff_event2) %>%
  group_by(firm) %>%
```

---

```

mutate(car = cumsum(ar)) %>%
ungroup() %>%
group_by(days_diff_event2) %>%
summarise(avg_car = mean(car, na.rm = TRUE), .groups = "drop") %>%
mutate(sector = "Non-Defense")
car_combined_365_e2 <- bind_rows(car_defense_365_e2, car_nondf_365_e2)
# Plot combined CAR for Event 2
ggplot(car_combined_365_e2, aes(x = days_diff_event2, y = avg_car, color = sector)) +
  geom_line(linewidth = 1) +
  geom_hline(yintercept = 0, linetype = "dashed", color = "gray60") +
  scale_color_manual(values = c("Defense" = "firebrick", "Non-Defense" = "steelblue")) +
  labs(title = "Cumulative Average Abnormal Return (CAAR) – Event 2",
       subtitle = "Comparison between Defense and Non-Defense Stocks (0–365 days)",
       x = "Days Since Event",
       y = "Average CAR",
       color = "Sector") +
  theme_minimal()

```

Let me know if you want to:

- export these plots to files (ggsave)
- facet both events in a single figure
- or calculate statistical differences between the two CAAR lines.

*How it was used:* Used to combine non-defense and defense CAAR over time for the second event. Used in Figure 2 section 4.3.

28.

```

Query to ChatGPT (GPT-4o): > ar_all_e1 <- ar_all_e1 %>% + mutate(days_diff_event1 =
as.integer(as.character(days_diff_event1))) > str(ar_all_e1$days_diff_event1) int [1:9533] -10 -9 -8 -7 -6 -
2 -1 0 1 4 ... > pdata <- pdata.frame(ar_all_e1, index = c("firm", "days_diff_event1")) > View(pdata) >
str(pdata$days_diff_event1) Factor w/ 258 levels "-10","-9","-8",...: 1 2 3 4 5 6 7 8 9 10 ... - attr(*,
"names")= chr [1:9533] "AeroVironment--10" "AeroVironment--9" "AeroVironment--8" "AeroVironment-
7" ... - attr(*, "index")=Classes 'pindex' and 'data.frame': 9533 obs. of 2 variables: ..$ firm : Factor w/ 37

```

levels "AeroVironment",...: 1 1 1 1 1 1 1 1 1 1 ... ..\$ days\_diff\_event1: Factor w/ 258 levels "-10","-9","-8",...: 1 2 3 4 5 6 7 8 9 10 ... Im getting an error with regards to the amount of factors for days\_diff\_event1, how can we solve this?

*Output from ChatGPT:* Thanks for the update, Mats. To force days\_diff\_event1 to stay numeric, you'll need to convert the index after creating the panel structure. Here's a reliable workaround:

---

19 Final Fix: Force days\_diff\_event1 to stay numeric

r

KopierenBewerken

# Step 1: Clean before pdata.frame

```
ar_all_e1 <- ar_all_e1 %>%
```

```
  mutate(days_diff_event1 = as.integer(as.character(days_diff_event1)))
```

# Step 2: Declare panel structure

```
pdata <- pdata.frame(ar_all_e1, index = c("firm", "days_diff_event1"))
```

# Step 3: Force numeric again inside pdata

```
pdata$days_diff_event1 <- as.numeric(as.character(pdata$days_diff_event1))
```

# Confirm structure

```
str(pdata$days_diff_event1)
```

---

20 Now try the model again:

r

KopierenBewerken

```
re_model <- plm(car ~ sector + days_diff_event1, data = pdata, model = "random")
```

```
summary(re_model)
```

---

Let me know if this finally runs — this trick bypasses the automatic factor conversion inside `pdata.frame()`. Once it works, we can run the Hausman test as well.

*How it was used:* The R-code was checked and resolved the error. Therefore the code was used in the R-script.

29.

*Query to ChatGPT (GPT-4o):* `ar_all_e1 <- data_reg3 %>% select(firm, sector, days_diff_event1, ar) %>% filter(!is.na(days_diff_event1)) # Compute daily CARs per firm`  
`ar_all_e1 <- ar_all_e1 %>% arrange(firm,`

```

days_diff_event1) %>% group_by(firm) %>% mutate(car = cumsum(ar)) %>% # cumulative abnormal
return ungroup() ar_all_e1 <- ar_all_e1 %>% mutate(sector = relevel(sector, ref = "defense")) #
Regression e1 CAR and sectors ar_all_e1 <- ar_all_e1 %>% mutate(sector = factor(sector))
car_sector_lm_e1 <- lm(car ~ sector, data = ar_all_e1) tidy(car_sector_lm_e1) %>% arrange(p.value) #
Tidy the table for event 1 car_sector_lm_e1 <- tidy(car_sector_lm_e1) %>%
mutate(across(where(is.numeric), ~ round(.x, 4))) i want this code to only take into account the event
window used for CAAR as well, so 0 up until 365. Can you help with that

```

*Output from ChatGPT:* Yes — to make sure your regression only includes data from the event window 0 to +365, you'll want to filter `ar_all_e1` on `days_diff_event1` before computing the CARs. Here's how you can adjust your code:

```

r
KopierenBewerken
library(dplyr)
library(broom)
# Filter for the relevant event window: -10 to 365
ar_all_e1 <- data_reg3 %>%
  select(firm, sector, days_diff_event1, ar) %>%
  filter(!is.na(days_diff_event1)) %>%
  filter(days_diff_event1 >= -10, days_diff_event1 <= 365)
# Compute cumulative abnormal return (CAR) per firm
ar_all_e1 <- ar_all_e1 %>%
  arrange(firm, days_diff_event1) %>%
  group_by(firm) %>%
  mutate(car = cumsum(ar)) %>%
  ungroup()
# Ensure correct reference level for sector factor
ar_all_e1 <- ar_all_e1 %>%
  mutate(sector = factor(sector),
         sector = relevel(sector, ref = "defense"))
# Run regression: CAR ~ sector
car_sector_lm_e1 <- lm(car ~ sector, data = ar_all_e1)
# Tidy and round results

```

```
car_sector_lm_e1 <- tidy(car_sector_lm_e1) %>%  
  mutate(across(where(is.numeric), ~ round(., 4))) %>%  
  arrange(p.value)  
car_sector_lm_e1
```

## 21 Summary of Change:

The key line added is:

```
r
```

KopiërenBewerken

```
filter(days_diff_event1 >= -10, days_diff_event1 <= 365)
```

This ensures that only the days within your event window are used to build the cumulative CAR used in the regression. Let me know if you also want to restrict it to a different end date (like 10 or 30), or if you'd prefer to take the final CAR at day 365 per firm rather than cumulative over all days.

*How it was used:* The code was used to calculate CAR only over the one year post-event period. This was used for the random effects panel regression.