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A VÉDELMI IPARI VÁLLALATOKRA AZ USA-BAN ÉS AZ
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THE ISRAEL-HAMAS WAR'S IMPACT ON THE AEROSPACE &
DEFENSE INDUSTRY IN THE UNITED STATES AND THE EU

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Abstract

This paper investigates the market response following the eruption of armed conflict between Hamas and Israel on October 7, 2023, within the Gaza Strip, with a specific focus on the defense sector. Employing the event study methodology, the research seeks to discern whether notable abnormal returns occurred among defense sector stocks during the period surrounding the conflict. The findings reveal that markets exhibited efficient trading behavior, notably manifesting significant positive abnormal returns, particularly on the day of the conflict. This study contributes to the existing literature by shedding light on market reactions to geopolitical events and deepening understanding regarding the repercussions of warfare on the performance of defense sector companies.

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1 Introduction

On October 7, 2023, armed groups operating in the Gaza Strip, led by the Palestinian Hamas leadership, launched an attack against Israel. International markets responded variably to the events. While the Israeli volatility index (VTA35) spiked practically at market opening, the American (VIX), European (VSTOXX), and Hong Kong (VHSI) volatility indices began to rise after news of the prolonged conflict emerged.

The outbreak of conflicts, in general, can cause an increase in uncertainty, as supply chains can be disrupted and energy price volatility can increase (Umar et al., 2022), the impact of which is difficult to predict. However, if we take Fama (1970) theory of efficient markets as a benchmark, we should assume positive and significant abnormal returns in our case, i.e. in the defence industry.

The reason is that the escalation of war creates a general feeling of negativity, panic, and fear, which makes countries and communities spend more on innovation, defense, and military industry. This leads to an increase in the overall defence budget, as happened, for example, in the EU in the year of the Russian-Ukrainian conflict, according to an EDA (2022) report. In addition, elevated military budgets could mean more orders for companies in the defence and defence-related sectors. On this assumption, I should detect a positive and significant return on the day of the event at the outbreak of war.

In my study, I apply the event study methodology and seek to answer the question of whether markets are trading considering the expected excess returns in the sector, which would be the case if we were to see significant and positive abnormal returns around the time of the event.

In this study I concluded that the markets were trading according to the efficient market theory on the day of the event, meaning that a significant positive return could be detected in the defence industry.

2 Literature review

The impact of wars (Nerlinger and Utz, 2022), armed conflicts, and terrorist activities (Arin et al., 2008) on asset prices has been the subject of numerous studies. These studies have shed light on the fact that events of the mentioned nature affect markets differently over various time horizons. Generally, price reactions are strongest in markets and industries directly affected by the attack (Brounen and Derwall, 2010).

When we look at the impact of the outbreak of a conflict on a particular sector, the literature is vast. The impact of the outbreak of war on the defence sector has been the

subject of numerous studies (Billingsley et al., 1987; McDonald et al., 1994; Shapiro et al., 1999; Leigh et al., 2003; Schneider and Tröger, 2004), which consistently found that, although the escalation of a war has a pseudo-negative impact on the stock market, as the confidence index falls, the returns of defence companies still react significantly positively to the news.

However, as Schneider and Tröger (2004) note, war events can affect the sector in different ways, for example, peace negotiations that end the war can lead to negative returns for companies in the sector.

Shapiro et al. (1999) article is also interesting in our case because the sample size used for the study is almost identical to the one used in this study. They found that the technical complexity of companies is positively related their abnormal returns.

3 Data and methodology

3.1 Data

The data used for the analysis was provided by the Eikon Refinitiv database, from which I first downloaded daily stock returns of companies corresponding to the Aerospace & Defence industry. These firms were not filtered by their current activity (alive or dead), as this would eliminate the “survivorship bias” identified by Brown et al. (1992). The sample exclusively contains stocks, with mutual funds and other products being excluded. To avoid the cross-listing effect that can cause bias in abnormal return estimates (Gu and Reed, 2013), I downloaded only the primary stock for each stock, excluding data from smaller markets. Furthermore, instead of using closing stock prices, I used the daily Total Return Index between 31/12/2021 and 31/10/2023, as this is an adjusted price index that reflects the impact of dividend payments on stock value when dividends are reinvested. I report all the non-natural values in dollars.

For cross-sectional analysis I used the monthly time series of Common Shares Outstanding, Unadjusted Price, and Research and Development Expenditures. I used the ICB subsector name (ICBSUN) for the industry classification. To get GEO codes, I used the country of domicile for the period between 01/01/2022 and 01/10/2023.

I worked with the statistical data analysis software R (version 4.4.0) to generate the results and for all calculations and data cleaning (RCoreTeam, 2024). More precisely I used the *erer*, *quantmod*, *tidyverse* and *tidyquant* packages to generate my results.

3.2 Data cleaning

Based on the above conditions, I initially downloaded the data of 620 companies. However, these are raw data, so filtering is necessary. It is essential for the application of the methodology that we have an adequate amount of data available for the examined companies both in the event window $[-10,10]$ and in the period preceding the event. Accordingly, a company can only be included in the sample if there is no missing data for all time points in the event window and if we have at least 120 observations in the estimation period.

During data cleaning, I tried to extract reliable and relevant data from the initial database containing 620 observations by applying various filters. Initially, we examined cases where there was an observation at the time of the event, so we received 595 observations. After that, 520 observations remained after filtering out missing observations (NA) for all data points.

Further refinement involved filtering based on the estimation window, leaving us with 233 valid observations. Finally, applying the event window-based filter, only 43 companies remained in the data set. To measure market performance, I observed the returns of the remaining 43 companies. The benchmark portfolio is a simple equally weighted portfolio, with the returns shown in Figure 1.

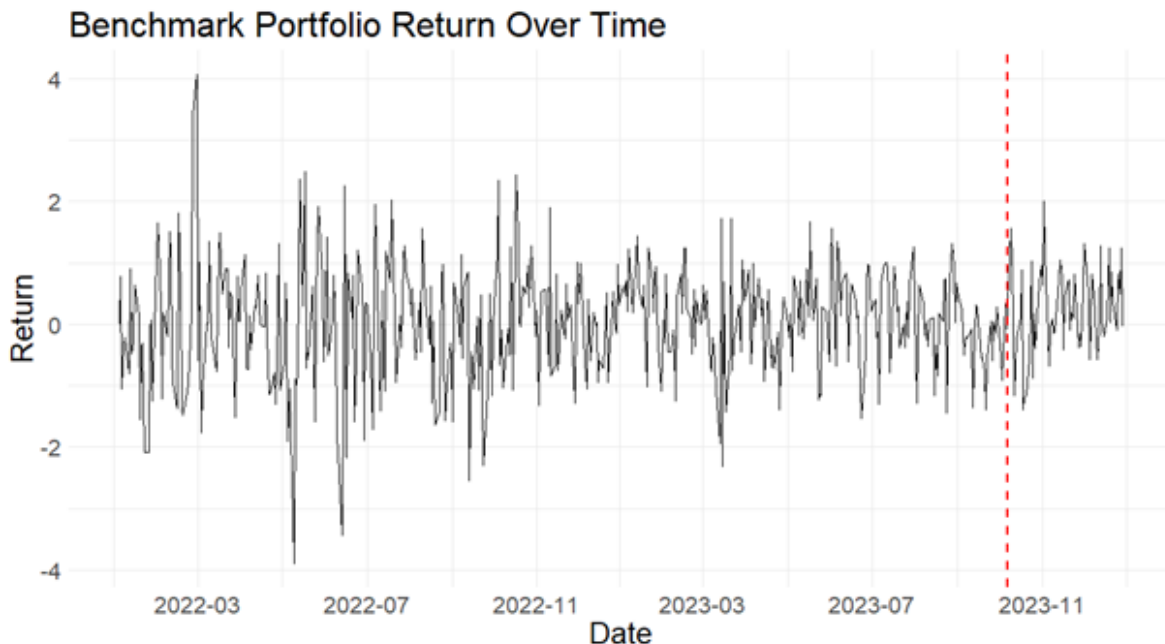


Figure 1: *Evolution of the benchmark portfolio over the estimation period and around the event. The event date (07/10/2024) is highlighted with a red dashed line.*

3.3 Event study methodology

To answer the research question mentioned earlier, I need to use the event study approach, which is best understood from the studies of Fama et al. (1969) and MacKinlay (1997). The main argument in favour of this methodology is its ability to examine the impact of a given event period on stock and asset prices.

In the first step, I specify the event window, which in our case is 21 days, starting 10 days before and ending 10 days after the event. According to MacKinlay (1997) this time period is long enough to analyse both the period before and after the event.

I then need to download the daily stock data of the selected companies and calculate each stock's daily percentage change. As pointed out in the paper by Fama et al. (1969), a stock's daily rate of return can be calculated by the natural logarithm of the stock price (Eq.1), which is also true for the market index used for the event study.

$$R_{it} = \log \left(\frac{P_t}{P_{t-1}} \right) \quad (1)$$

After this, the next step is to calculate the expected returns, which are calculated using the data in the estimation window. The length of the window can vary from study to study, usually ranging from 100 days to less than a year (MacKinlay, 1997; Armitage, 1995). In our case, the length of the window will be 240 days, from which the alpha and beta of the stock will be calculated. There are several ways to calculate normal or expected returns. Among these models, the market model, CAPM, the adjusted market model or French-Fama multi-factor models are the approaches well delineated, used and recommended in the international literature (Strong, 1992; MacKinlay, 1997; Brown and Warner, 1985; Fama and French, 1993). In my study, I will apply the market model among the above approaches.

Finally, I will compute the abnormal returns (AR), which are obtained by subtracting the expected returns. This gives me how the actual return deviates from the expected return in the event window.

I use parametric tests to examine the robustness of the results, which is essential to be able to state beyond any doubt whether it was the event that had a significant impact on the price of the asset. The range of parametric tests is quite wide, however, the most used test in the event study literature (Maneenop and Kotcharin, 2020; Pandey and Kumari, 2021) is the t-test (Brown and Warner, 1980), which will be used in this study.

3.4 The market model

The market model is one of the most used statistical models used in event studies to calculate α and β using OLS regression (MacKinlay, 1997). This model, like many other approaches, uses benchmark indices to calculate abnormal returns, in our case, it is an artificially created market index, generated from the returns of companies in the sector.

In my study, I will follow the methodological notations and formulas outlined in MacKinlay (1997). The market model is often chosen as the method for calculating expected and abnormal returns because of its simplicity and performance. This can be described by a simple single factor OLS regression formula

$$R_{it} = \alpha_i + \beta_i R_{mt} + \epsilon_{it} \quad (2)$$

$$\mathbb{E}(\epsilon_{it} = 0) \quad \text{var}(\epsilon_{it}) = \sigma_{\epsilon_{it}}^2 \quad (3)$$

where, α_i is the constant representing the initial point of fit of the security within the estimation window, β_i is the market model coefficient indicating how sensitive the stock return is to the market index return, R_{it} and R_{mt} are the return of the security and the benchmark index, respectively.

In the next step, I calculate the abnormal returns based on the residual and the estimated parameters by subtracting the estimated parameters from the actual observed market returns using the following formula:

$$AR_{it} = R_{it} - \alpha_i - \beta_i R_{mt} \quad (4)$$

where, AR_{it} is the abnormal return on security i at time t . According to MacKinlay (1997), abnormal returns, as a function of market returns, will be normally distributed. Furthermore, since the above formula is intended to calculate the abnormal returns of firm i alone, an aggregate formula is needed that includes the results of all the firms in the sample:

$$AAR_t = \frac{1}{N} \sum_{i=1}^N AR_{it} \quad (5)$$

I calculate the average abnormal return using the above formula (AAR) for period t for all (N) pairs of firms-events. Using this, we can obtain time series specific cumulative

abnormal returns (CAR) using the following formula:

$$CAR(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_t \quad (6)$$

In order to aggregate returns by time and group, we need the Cumulative Average Abnormal Returns (CAAR), which is calculated using the following equation:

$$CAAR(t_1, t_2) = \frac{1}{N} \sum_{i=1}^N CAR_i(t_1, t_2) \quad (7)$$

3.5 Tests for statistical significance

To call our results statistically significant, we need to conduct tests. Testing the regressions helps us to determine how different the model estimates are from the null hypothesis, and thus to judge whether they are statistically significant or not.

These tests can be divided into 2 groups, parametric and non-parametric tests. Parametric tests assume that the returns of the individual companies in the sample follow a normal distribution, while non-parametric tests do not (Serra, 2004). However, since non-parametric tests are most often used because of their simplicity, I will also do so in my study.

H1: $AAR \neq 0$ and $H0 : AAR = 0$

H1: $CAAR \neq 0$ and $H0 : CAAR = 0$

The null hypothesis (H0) examines whether stocks influenced by a particular event will show neither Average Abnormal Returns nor Cumulative Average Abnormal Returns. Conversely, the alternative hypothesis (H1) explores whether these stocks will exhibit either positive or negative Average Abnormal Returns or Cumulative Average Abnormal Returns.

In this context, abnormal returns for each security are adjusted by dividing them by the standard deviation calculated during their estimation period:

$$t_{AAR} = \frac{AAR_t}{S_{(AAR_t)}} \quad (8)$$

where, $S_{(AAR_t)}$ is an estimate of standard deviation of the average abnormal returns $\sigma(AAR_t)$. Then, standard deviation is estimated as:

$$S_{(AAR)} = \sqrt{\sum_{t=1}^{T_0} \frac{AAR_t^2}{T_0 - 1}} \quad (9)$$

where, T_0 is the number of days in the estimation window.

Then, I estimate, t-statistic for CAARs by dividing CAARs with standard deviation:

$$t_{\text{CAAR}} = \frac{\text{CAAR}_t}{\sqrt{T \cdot S_{(\text{AAR}_t)}}} \quad (10)$$

If statistical tests indicate that the t-statistic is greater than or equal to a critical value, then the null hypothesis (H_0) will be rejected. This rejection implies that the Average Abnormal Returns (AARs) or Cumulative Average Abnormal Returns (CAARs) will be deemed statistically significant.

4 Results and limitations

In this chapter, I present the results of my abnormal returns calculations. Table 1 shows the AR values of the commented companies on the event day (09/10/2023) and on the 10th day before the event day (09/10/2023), selected by industry group and region, based on GEO code. For the cumulative AARs I chose an event window of $[-10,10]$, meaning that I calculated this much lag and lead per event day. By group, the second row indicates the corresponding test statistic with the null hypothesis that the corresponding $\text{AR} = 0$.

I wanted to limit my analysis mainly to companies from 3 continents, but due to missing data (e.g. no trading in China for more than a week around the event day due to the Mid-Autumn Festival and China’s National Day), excluding Asia, I only examined the trading of companies registered in countries in Europe and America, which can be precisely identified by country code, separately. Based on the data points checked manually, it can be said that they represent almost half and half of the sample.

A study by Zhang et al. (2022) examined how firms respond to the geopolitical risk index (GPR index) and found that the defense sector also follows the index’s rise. My results are in line with this finding, as there was a significant positive abnormal return for defense sector companies on the day of the escalation of the war, the day of the event ($\text{AAR}[0]$), when, as presented in the second figure, the GPR index spiked.

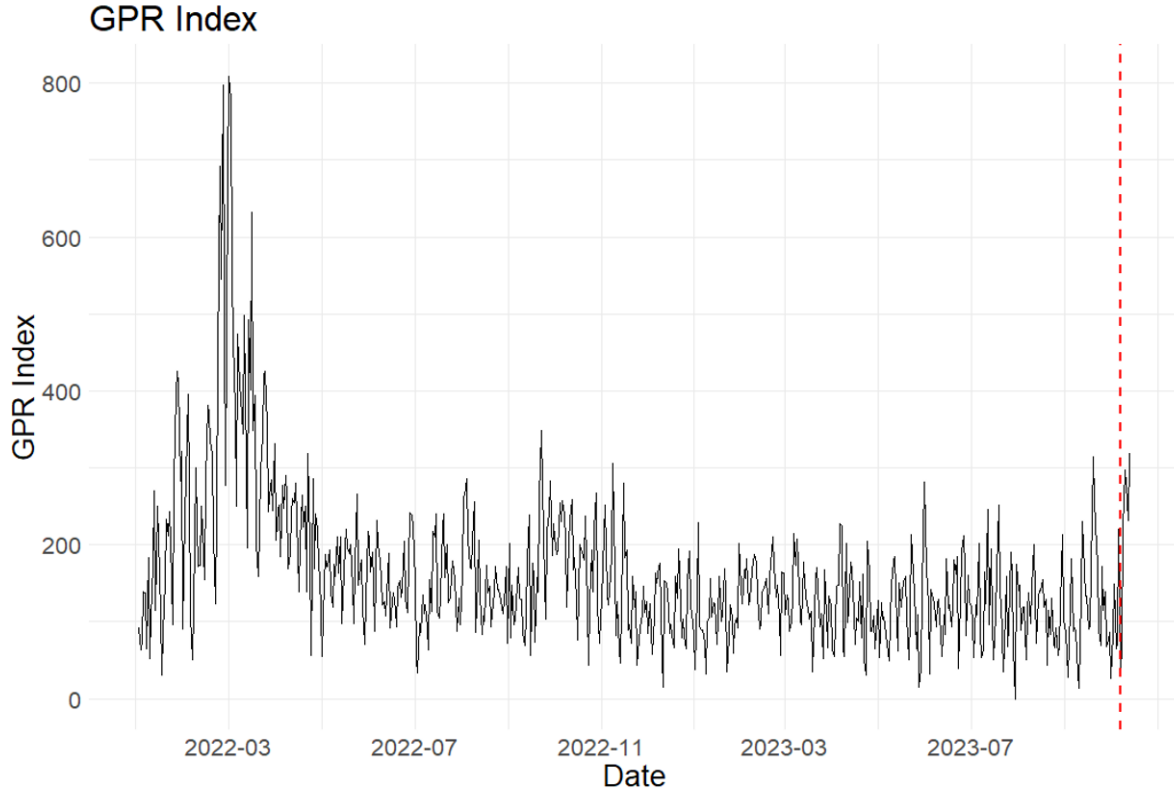


Figure 2: *Evolution of the GPR index over the estimation period and around the event. The event date (07/10/2024) is highlighted with a red dashed line.*

Moreover, there is a significant result within the event window $[-10,10]$ This outcome can be attributed to a negative event due to disequilibrium information flows and an increase in uncertainty may even have a longer-term impact on asset prices. In addition, it is interesting to note that while there is no significant change in returns in the EU markets, there is for companies listed in the US, a common result (Schmutz et al. (2020); Khanthavit (2020); Nerlinger and Utz (2022)).

Table 1: Aggregated Abnormal Returns

This table showcases the aggregated AR (Abnormal Returns) values for grouped entities. Columns represent the aggregated abnormal returns (AAR) for the event day (09/10/2023) and the preceding 10 days, along with cumulative AAR values over the event window of $[-10, 10]$. Within the table, every second row presents the t -test statistic value for hypothesis testing, where the null hypothesis (H_0) posits that the AR is equal to zero. Bold emphasis highlights AR values significantly different from zero.

	Type	AAR[-10]	AAR[0]	CAAR[-10,10]
<i>Industry group</i>				
Aerospace	AR	1.16	-0.34	-0.78
	t -stat.	(2.01)	(-0.50)	(-0.23)
Defense	AR	-0.24	3.19	5.76
	t -stat.	(-0.40)	(4.15)	(3.13)
<i>Region</i>				
America	AR	0.85	1.34	3.93
	t -stat.	(1.40)	(1.96)	(1.26)
Europe	AR	-0.07	1.26	-0.59
	t -stat.	(-0.15)	(1.28)	(-0.40)

The second table shows the AARs during the event window, separated by industry and region. We observe that around the event day, significant abnormal returns are observed in the defense sector for several days after the event day. This is in line with the observation of Shapiro et al. (1999), which can be explained by the difficulty for markets to price in uncertainty after the event day.

Furthermore, let us assume that the outbreak of war was not predicted by any variable or factor, as it was reported in the press as an unexpected event. In this case, it might be interesting to examine what other factors could have played a role in the significant positive returns observed in US markets before the day of the event, which could have been caused by investors with extra information about the outbreak of war if that the above scenario did not occur.

Table 2: Aggregated Abnormal Returns in the event window separated by industry and region

The table shows the evolution of the AARs in the event window $[-10, 10]$, grouped by industry group and region. Each second column describes the test statistics associated with the values.

t	Industry group				Region			
	Aerospace (n = 32)		Defense (n = 28)		America (n = 38)		Europe (n = 22)	
	AAR	t-stat	AAR	t-stat	AAR	t-stat	AAR	t-stat
-10	1.16	2.01	-0.24	-0.40	0.85	1.40	-0.07	-0.15
-9	-0.43	-1.26	0.02	0.07	-0.59	-1.91	0.42	1.14
-8	0.21	0.49	0.39	0.63	0.29	0.54	0.31	0.74
-7	-0.55	-0.94	-0.95	-1.40	-0.95	-1.60	-0.37	-0.58
-6	-0.25	-0.51	-0.36	-1.06	0.07	0.18	-0.94	-2.45
-5	0.01	0.01	-0.67	-2.60	-0.08	-0.21	-0.70	-2.61
-4	-0.14	-0.47	0.03	0.07	0.18	0.63	-0.49	-0.97
-3	0.58	1.48	0.40	0.66	1.31	2.95	-0.92	-2.24
-2	-0.17	-0.31	-0.06	-0.41	0.02	0.03	-0.35	-1.48
-1	0.65	1.03	0.75	1.88	1.49	3.02	-0.67	-1.36
0	-0.34	-0.50	3.19	4.15	1.34	1.96	1.26	1.28
1	-0.80	-1.53	-0.56	-1.86	-1.37	-3.38	0.49	1.30
2	0.69	1.70	0.74	2.71	0.75	2.03	0.66	2.58
3	-1.59	-1.99	-0.22	-0.61	-1.78	-2.71	0.49	1.25
4	-0.34	-1.02	1.33	1.50	0.94	1.42	-0.42	-0.89
5	-0.10	-0.19	0.36	1.17	0.31	0.65	-0.22	-0.94
6	0.45	1.00	0.55	0.74	0.85	1.43	-0.11	-0.22
7	-0.74	-0.56	0.51	2.16	-0.15	-0.13	-0.17	-0.47
8	-0.29	-0.53	-0.83	-2.58	-0.37	-0.81	-0.84	-1.98
9	-0.19	-0.64	0.54	1.97	0.15	0.58	0.15	0.42
10	1.39	2.88	0.83	0.99	0.68	1.66	1.90	1.82

Of course, the results above do not give a complete picture of the effect of the explanatory variables. However, as expected, the abnormal returns on the day of the event are significantly explained by the defence sector. This explanatory power remains even when the effect on CARs around the day of the event (CAR $[-1,1]$) is considered, which decays over time, as shown in Table 5 and 6. Hence, my results for the defence sector can be considered robust.

However, it is interesting to note that neither the location of the companies nor the amount spent on research and development explained the abnormal returns on any time horizon, whereas as a rational investor it may be worth investing in military companies that innovate and develop before and at the outbreak of war, as the new technology can provide a competitive and combat advantage (Blasko (2013)). This result is not in line with Shapiro et al. (1999) finding, might be explained by the different sample selection.

Table 3: Results of linear regression (AR[0])

*Results of linear regressions ran on event-date abnormal returns. The coefficients of the different explanatory variables and the corresponding test statistics are shown in the rows. The results were obtained by running three differential models. In the first, only industry is included as an explanatory variable. In the second, only geo-code-based segregation. In the third, the above two and the research development expenditure. Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1*

	Dependent variable: AR[0]		
	(1)	(2)	(3)
Defense	4.87*** (4.71)		5.014*** (4.83)
America		-1.28 (-0.99)	0.92 (0.86)
R&D spendings			0.00 (1.65)
Constant	-0.28 (0.70)	2.6 (3.19)**	-1.50 (-1.43)
Observations	43	43	43
R ²	0.35	0.33	0.40
Adjusted R ²	0.34	0.00	0.35

This study has several limitations that warrant acknowledgement. Firstly, it overlooks the potential impacts of firm-specific events occurring within the event window, which could significantly influence the returns of individual firms. Secondly, the sample exclusively consists of returns from defense companies sourced from Datastream. This narrow selection might not fully capture the broader landscape of firms influenced by defense spending. Thirdly, there is a possibility that other defense-dependent entities, beyond those included in the study, such as suppliers to major defense firms, could have been overlooked. Consequently, the findings may only be reliably generalized to the analysed firms, potentially limiting the broader applicability of the results.

Additionally, based on this study’s results, further in-depth analysis is needed to incorporate other possible explanatory variables into the model. Although there is a significant sectoral result, other variables did not significantly affect on abnormal returns either on the day of the event or at other time horizons. In view of the above, the analysis can be complemented by a detailed examination of additional factors for a more complete understanding.

Table 4: Results of linear regression CAR([-1,1])

*Results of linear regression where the dependent variable is the [-1,1] CARs. The coefficients of the different explanatory variables and the corresponding test statistics are shown in the rows. The results were obtained by running three differential models. In the first, only industry is included as an explanatory variable. In the second, only geo-code-based segregation. In the third, the above two and the research development expenditure. Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1*

	Dependent variable: CAR[-1,1]		
	(1)	(2)	(3)
Defense	4.59*** (3.67)		4.82*** (3.86)
Europe		1.02 (0.73)	-0.86 (-0.69)
R&D spendings			0.00 (1.60)
Constant	-1.44 (-1.69)	0.23 (0.26)	-2.49 (-2.34)*
Observation	61	61	61
R ²	0.19	0.01	0.22
Adjusted R ²	0.17	0.01	0.19

5 Conclusion

The study, based on the results of the international literature, sought to answer the question of whether a significant positive abnormal return could be observed at the time of the outbreak of the Israel-Hamas conflict.

To investigate this problem, I used the event study approach and found that the main conclusion of the studies that examined the response of defense sector firms to the outbreak of wars does not differ from the main conclusion of this paper, as there is a positive and significant abnormal return on the day of the event in the defense sector. However, the effect is not significant either before the event or during the event window, suggesting that markets reacted promptly to the conflict.

The fact that the impact in the EU is not significant may be because this conflict has less impact on European companies that are already heavily involved in the Russian-Ukrainian conflict. Furthermore, the finding that, unlike Shapiro and colleagues, R&D spending has no significant influence on abnormal returns on the day of the event may be explained by reasons of inadequate data quality or simply that this variable really does not have explanatory power in this case.

As further research, it may be worth investigating whether, in this case, a peace negotiation, once the war is over, will have a negative impact on defence industry firms, as in the case of the Gulf War peace negotiation in Schneider and Tröger (2004).

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Appendices

Table 5: Results of linear regression (CAR[-3,3])

Results of linear regression where the dependent variable is the [-3,3] CARs. The coefficients of the different explanatory variables and the corresponding test statistics are shown in the rows. The results were obtained by running three differential models. In the first, only industry is included as an explanatory variable. In the second, only geo-code-based segregation. In the third, the above two and the research development expenditure.

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1*

	Dependent variable: CAR[-3,3]		
	(1)	(2)	(3)
Defense	6.83* (2.31)		7.27* (2.43)
Europe		3.63 (1.17)	3.34 (1.11)
R&D spendings			0.00 (0.91)
Constant	-2.15 (-1.02)	-0.16 (-0.08)	-4.63 (-1.72).
Observation	54	54	54
R ²	0.09	0.02	0.13
Adjusted R ²	0.08	0.01	0.08

Table 6: Results of linear regression (CAR[-5,5])

Results of linear regression where the dependent variable is the [-5,5] CARs. The coefficients of the different explanatory variables and the corresponding test statistics are shown in the rows. The results were obtained by running three differential models. In the first, only industry is included as an explanatory variable. In the second, only geo-code-based segregation. In the third, the above two and the research development expenditure.

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

	Dependent variable: CAR[-5,5]		
	(1)	(2)	(3)
Defense	8.93*		9.45*
	(2.48)		(2.58)
Europe		2.12	1.90
		(0.55)	(0.61)
R&D spendings			0.00
			(0.83)
Constant	-3.66*	0.19	-5.57
	(-1.41)	(0.07)	(-1.67)
Observation	51	51	51
R ²	0.11	0.01	0.13
Adjusted R ²	0.90	-0.01	0.07

Table 7: Results of linear regression (CAR[-10,10])

Results of linear regression where the dependent variable is the [-10,10] CARs. The coefficients of the different explanatory variables and the corresponding test statistics are shown in the rows. The results were obtained by running three differential models. In the first, only industry is included as an explanatory variable. In the second, only geo-code-based segregation. In the third, the above two and the research development expenditure.

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

	Dependent variable: CAR[-10,10]		
	(1)	(2)	(3)
Defense	3.93		3.31
	(1.11)		(0.93)
Europe		-6.17.	5.84
		(-1.74)	(1.61)
R&D spendings			0.00
			(0.17)
Constant	1.15	5.51*	-2.28
	(0.47)	(2.48)	(-0.64)
Observations	43	43	43
R ²	0.03	0.07	0.09
Adjusted R ²	0.01	0.04	0.02