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What makes the 2022 tech layoffs different?
An Event Study Analysis on the stock market reaction.

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I. Introduction

The year 2022 is considered a rather turbulent period in the stock market, especially in the last quarter. Just look at the economic and energy crisis concerning the whole world: the war, rising inflation, and prices of oil, gas, and electricity. This means a heavy burden not only on households but also on large companies. Attenuating the negative effects of the crisis and cutting their expenses, several companies decided to perform massive layoffs. This refers to large-scale job cuts, often as a cost-cutting measure or in response to financial difficulties. The consequences of these layoffs can be significant and far-reaching. Firstly, the individuals who lose their jobs may face financial hardship and difficulty finding new employment. Layoffs can also have a negative impact on the morale and productivity of remaining employees who may feel anxious about job security and resentful towards their employers. From a corporate perspective, layoffs can have both short-term and long-term consequences. While they may reduce costs in the short-term, they can also result in decreased productivity, loss of institutional knowledge, and damage to the company's reputation.

The announcement of layoffs can also cause a company's stock price to decrease as investors may see it as a negative signal about the company's financial health and prospects. This can also lead to a loss of confidence in the company among consumers and other stakeholders, which can have long-term effects on the company's brand reputation and customer loyalty. Our first hypothesis is connected to these statements, that is, *there is a negative abnormal return in the stock market of that company that has announced a large-scale layoff.* We think that such information has a negative impact as it means a warning for stockholders. It may cause a massive sale of shares and therefore a fall in stock price.

Additionally, layoffs can have a broader impact on the economy by reducing consumer spending and creating a ripple effect throughout supply chains and related industries. If multiple companies in a particular industry are all implementing massive layoffs around the same time, it can lead to a broader economic downturn and even a recession. This is because the reduction in jobs and consumer spending can create a cycle of decreased demand, reduced production, and further layoffs across multiple sectors of the economy. So, we find it important to differentiate our research in diverse sectors: IT and non-IT sectors.
Massive corporate layoffs can occur in both IT and non-IT sectors, and the consequences can differ between the two. In the IT sector, layoffs may be driven by factors such as changes in

technology, shifts in consumer demand, or changes in the competitive landscape. For example, if a company's primary product or service becomes obsolete or is no longer in demand, it may need to cut jobs to stay financially viable. Similarly, if a competitor gains a significant advantage in the marketplace, a company may need to make strategic cuts to remain competitive. In the non-IT sector, layoffs may be driven by factors such as changes in consumer demand, economic downturns, or shifts in regulatory policy. For example, if a company operates in an industry that is particularly sensitive to changes in the economy, it may need to lay off workers during periods of economic downturn to remain financially viable. Regardless of the sector, massive corporate layoffs can have significant consequences for the individuals who lose their jobs, the remaining employees, the company's brand reputation, and the broader economy. According to this, our second hypothesis is that *there is no statistically significant difference between the abnormal return of the companies of the IT and non-IT sectors.* The base of our hypothesis is given by the assumption that a negative announcement has the same effect on stock market prices, and it does not matter in which sector the company is. The two raised hypotheses are independent of one another.

Our research paper is written within the confines of the Conference of Scientific Students' Associations[1]. According to the choice of subject, we are going to analyse the effects of layoff announcements, as mentioned above. The structure of the research is the following: first, we review the previous literature and studies on this topic and show how they are related to the current research area and whether they are relevant in 2022. Then we describe the data and explain the statistical analytical methods. After this, the results are presented, and we try to highlight the potential limitations. The paper ends with our conclusion.

[1] Tudományos Diákköri Konferencia – TDK

II. Literature review

1. Traditionally accepted views about layoff announcements

There is a large number of existing studies that examine the effects of corporate layoff announcements. Some of the common findings in the previous studies include a statistically significant negative impact on stock prices following layoff announcements. Factors such as the size and scope of the layoffs, the financial health of the company, and the broader economic conditions can all influence the magnitude of the stock price response. The strategic rationale behind the layoffs – such as cost-cutting measures or operational restructuring – may also affect how the market interprets the news and reacts accordingly. It's important to note that there may be variations in the findings across different studies and contexts and further research is often needed to fully understand the complex relationship between layoffs and stock prices. Therefore, we attempt to examine the existing studies thoroughly and with our research, make a contribution to this field.

A layoff announcement can elicit a negative stock price reaction when it is driven by a reaction to the firm's poor financial conditions. (Hillier, Marshall, McColgan, & Werema, 2007) The UK-listed companies' financial performance was studied during layoffs and it was found that poor operating and stock price performance, increased gearing, and threats from external markets precede layoffs. However, layoffs also lead to increased employee productivity and corporate focus.

Several studies highlighted the importance of differentiating between layoffs regarding their size and their expected duration. Similar to Hillier's findings, according to Worrel and co-authors' study, investors reacted negatively to announcements attributable to financial reasons. Negative preannouncement reactions occurred when negative hints about firms preceded announcements, and announcements of large or permanent layoffs elicited stronger negative responses than other announcements. (Worrell, Davidson III, & Sharma, 1991)

Another paper examines the connection between layoffs, executive pay, and stock prices. (Hallock, 1998) Firms that announce layoffs in the previous year pay their CEOs more and give their CEOs larger percentage raises than firms which do not have at least one layoff announcement in the previous year. However, the likelihood of announcing a layoff varies dramatically along other dimensions – for example, firm size. In addition, Hallock revealed that there is a small negative share price reaction to layoff announcements.

Permanent layoffs are largely the result of long-term changes in firms, whereas temporary layoffs represent an alternative to inventory accumulation (Saffer, 1983). In our study, we are specifically shifting the focus to layoffs with greater magnitude.

Another effect that is generally taken into account when examining the market reaction to layoffs is the leakage effect. Worrell et al. (1991) examined whether the stock market reacted

differently to layoff announcements given that there was any kind of information leakage or prior indication that a firm was planning to lay off its employees. They found, however, that there was weak evidence that in such cases there would be a significant difference in market response.
In contrast to the previously reviewed studies that mainly show negative effects, prior research also proves a positive stock price response, supposing special circumstances, such as restructuring (Cusatis, Miles, & Woolridge, 1993).

2. Studies regarding sectoral distribution and economic factors

In more recent studies researchers showed that the impact of mass layoff announcements on stock prices may also depend on the industry or sector in which the company operates. For example, in industries with high labour costs or cyclical downturns, mass layoffs may be seen as a necessary cost-cutting measure to weather economic challenges, and their impact on stock prices may be mitigated.
Such economic and industry-specific factors should be taken into consideration when drawing conclusions from layoffs. For instance, one layoff event study highlighted that although in some cases their results reflected the anticipated effects described by the traditionally accepted views, in their case they examined negative abnormal returns while investigating the effects of proactive layoff announcements in the renewable energy sector (Kunert, Schiereck, & Welkoborsky, 2017). This result questions the generality of the classical view that proactive restructuring announcements yield positive abnormal returns.
Furthermore, as demonstrated by another study, the stock price reaction to layoffs changed significantly between 1970 and 1999 (Farber & Hallock, 2009). A trend has been observed, where the distribution of stock market reactions became less negative to layoffs over time. This observation further justifies the relevance of our study, as our results may confirm or differ from this trend.
There is also a branch of event studies that examines the intra-industrial effects of layoffs. The purpose of these studies is to underline the importance of broader industrial implications of the layoff announcements of given corporations. An example of this could be the study of Goins and Gruca (2008), where they examined the contagion and the competitive effects of layoffs in the US oil and gas industry from 1989 to 1996. Even though their results showed negative abnormal returns for both competitors and other industry members, they also pointed out a limitation of the study, notably that it lacks the ability to generalize the results as only one industry has been observed. Thus, implying that studying other industries is required.

In addition to the previously mentioned factors, another aspect to consider when analysing the returns is the market regime. During a bear market, layoffs are expected to cause negative abnormal returns, while during a bull market, it occurs just the opposite of it (Marshall, McColgan, & McLeish, 2012). Bear markets refer to periods like the 2008 global financial crisis, or the 1960-70s in the US. Nevertheless, a recent study analysing layoffs in the US during the COVID-19 pandemic showed no abnormal returns, nor positive, nor negative, only changes in the stocks' trading volume and volatility (Floros, Psillaki, & Karpouzis, 2021). Therefore, it accentuates the importance of interpreting the results in context. This also implies not only market shocks but other relevant public corporate announcements as well since their proximity to the layoff announcement influences its effects (Farber & Hallock, 2009).

To summarise the literature's standpoint on the effects of layoff announcements, there are traditionally accepted views and there are more recent studies that emphasize the need to include industry characteristics and economic circumstances in the analyses. We will take into consideration both aspects during our research. And since the late 2022's tech layoffs have not yet been analysed, we attempt to supplement that gap in the existing literature.

III. Materials and Methods

3. Data

To obtain data on firms that recently announced layoffs, we used a Bloomberg article that summarized the largest corporate layoffs in 2022 (De Avila, 2022). Even though it listed the companies that either announced or were planning on layoffs, it did not explicitly mention the date of the announcement for each layoff. Thus, we utilized another database, namely Crunchbase News (Vedantam, 2022), where additional information about the layoffs where aggregated, including the announcement date and the newspaper where it was first announced. As for the stock prices, we downloaded the chosen companies' stock price data from the last 5 years from the Bloomberg terminal. When it came to choosing companies, we faced a limitation. Since we are solely focusing on firms that announced mass layoffs in 2022, we could only select from a small number of corporations. In total, we acquired stock information for 14 listed companies among which half of them were tech companies. Nevertheless, we decided to eliminate 4 of them for various reasons. Warner Bros lacked sufficient stock price data as it was listed in early 2022, whereas for Hewlett Packard we could not find one specific date of the announcement. Likewise, General Motors later confirmed that eventually they would restrain from layoffs despite corporate hardships and would rather consider cautious hiring (Lareau, 2022). Moreover, we decided not to include Twitter in our analysis hence the company went through a significant corporate restructuring following its acquisition by Elon Musk in late October 2022 (Zhan, 2022). Consequently, its inclusion in our analysis would have introduced substantial bias. This reduction left a study group of 10 corporate announcements with an equal share of tech and non-tech companies. We summarized it in **Table 1**.

Table 1 *Examined Companies*

Company	Sector	Date of Layoff Announcement	Layoff size
Microsoft	Software & Tech Services	Oct 17, 2022	<1,000 (<1%)
Snap	Internet Media & Services	August 31, 2022	1280 (20%)
Netflix	Internet Media & Services	September 14, 2022	300 (3%)
Peloton	Sporting Goods	October 6, 2022	500 (12%)
Lyft	Internet Media & Services	November 3, 2022	700 (13%)
Redfin	Real Estate	November 9, 2022	862 (13%)
Meta	Internet Media & Services	November 9, 2022	11,000 (13%)
Disney	Entertainment Content	November 11, 2022	7,000 (3.6%)
Amazon	Software & Tech Services	November 14, 2022	10,000 (3%)
Carvana	Automotive Retailers	November 18, 2022	1,500 (8%)

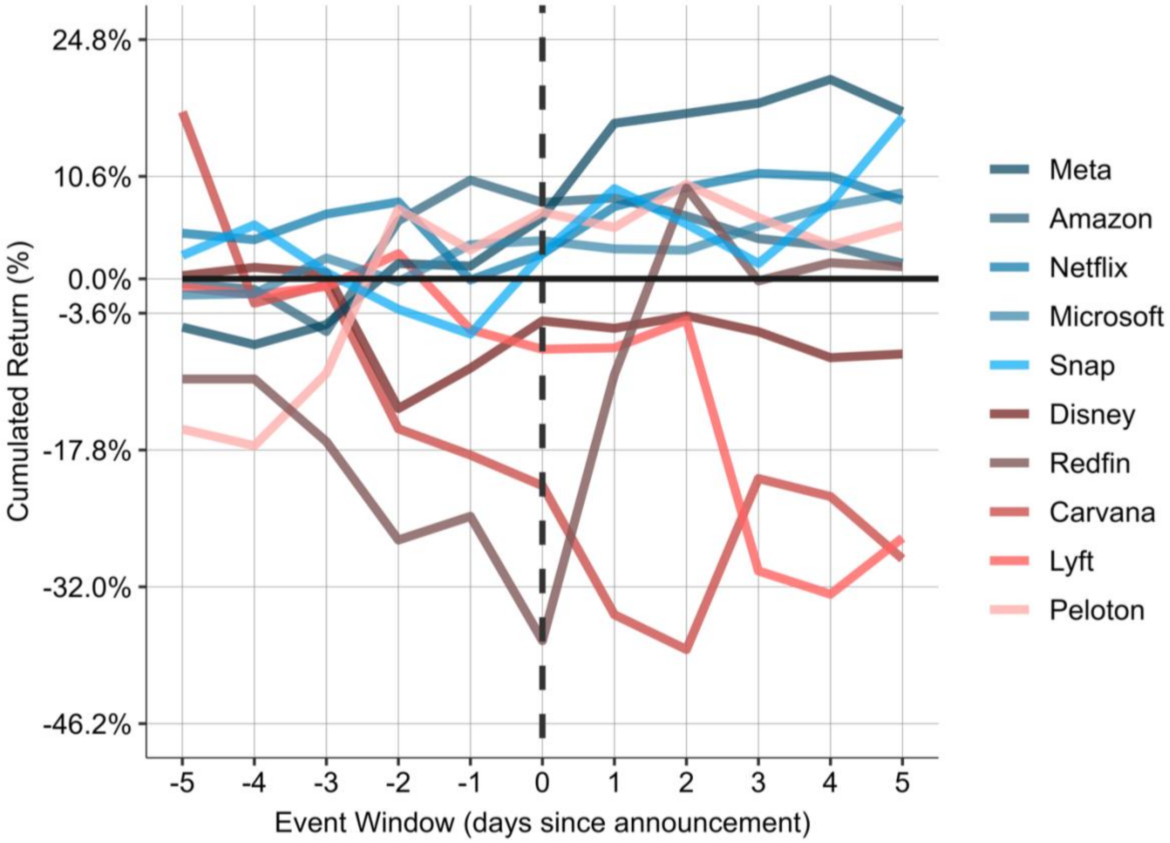
With regards to the market index data, we decided to apply the Standard and Poor's S&P 500 and the S&P 500 Information Technology indices in our analysis, where the latter one comprises those companies included in the S&P 500 that are classified as members of the GICS® information technology sector. We accessed the USD price return for the aforementioned indices via the Bloomberg Terminal. **Table 2** contains our categorizations.

Table 2 *Examined Firms and the related Market Portfolios*

Market Portfolio	**S&P 500**	**S&P500IT**
Firm	Carvana	Amazon
	Disney	Meta
	Lyft	Microsoft
	Peloton	Netflix
	Redfin	Snap

In **Figure 1** we can observe the change in the cumulative returns of the observed companies around the day of their layoff announcement date. The blue-shaded colours represent the companies that belong to the IT sector, while the red-shaded colours represent the companies in the non-IT sectors. We can notice that the cumulated returns of the IT companies (blue-shaded lines) follow a very similar pattern. Before the announcements, they mostly seem to vary around 0% cumulated return, in certain cases even increasing slightly, and after the announcements, they either do not change or increase. As for the companies belonging to non-IT sectors, the change in cumulated return in the sample is not so unison. Some companies stock returns increased, whilst others decreased sharply after the layoff announcement. These might suggest that we should expect similar results after performing the event study analysis.
Although this gives us some great visual insight into what data we are working with, simply by knowing the cumulated returns around the announcement dates we are not provided sufficient information to test the hypotheses of the current study. These are just momentary changes in return, and they do not reflect or quantify any abnormality in the stocks' returns. To examine true abnormalities, we need to conduct an event analysis.

Figure 1 *Cumulative Returns of Observed Companies*



4. Methodology

The methodology for answering our research questions is event analysis. In the description of the methodology, we build on the studies of MacKinlay (1997), and Binder (1998), as well as Rácz and Huszár (2019), which comprehensively review the analysis procedure. Based on these, we present the event analysis procedure and the most important methodological details from the point of view of our research. In the methodological description, we follow the notations of MacKinlay (1997).

In finance, the examined question is what kind of stock exchange rate change can be experienced because of some economic event in the case of certain securities. To put it more precisely: we are looking for the answer to whether an abnormal return can be observed as a result of the given event. In all cases, the first step is to define the event to be investigated and the associated event window, the period observed around the event. This is followed by the selection of the sample based on various selection criteria (described in the Data section). Next, it is necessary to determine how to measure abnormal returns. This is expressed by the following equation:

Equation 1 *Abnormal Return*

$$AR_{i\tau} = R_{i\tau} - E(R_{i\tau}|X_\tau)$$

where $AR_{i\tau}$, $R_{i\tau}$, and $E(R_{i\tau}|X_\tau)$ are the abnormal, actual, and expected returns respectively for firm *i* and for period τ. X_τ is the conditioning information for the expected (or normal) return model (Khotari & Warner, 2007).

1. *Expected returns*

During the calculation of the expected returns, we assume that the returns used for modelling follow a normal distribution, as well as being independent in time and having the same distribution. According to MacKinlay (1997), the use of two models is typical for most event analyses: the constant expected value model and the market model. The constant expected value model is often considered a naïve approach in the literature, as it does not distinguish between the effects of company-specific and market-specific information on stock prices (Corrado, 2011). For this reason, it can be difficult to determine whether the observed abnormal returns are caused by the event under study or whether they are caused by market fluctuations.

A more sophisticated solution is offered by the market model, which, similar to the CAPM model (Capital Asset Pricing Model; (Sharpe, 1964); (Lintner, 1965)), includes the relationship between the return of the securities and the market portfolio, thus reducing the variance of the abnormal return, and specifies the quantification of the impact of the event (MacKinlay, 1997) (Corrado, 2011):

Equation 2 *Market Model's Return*

$$R_{i\tau} = \alpha_i - \beta_i \cdot R_{m\tau} + \varepsilon_{i\tau}$$
$$\varepsilon_{i\tau} \sim N\left(0, \sigma_{\varepsilon_i}^2\right)$$

where R_{it} and R_{mt} are the returns of the *i*-th share and the market portfolio in period *t*, α_i and β_i are the parameters to be estimated from the regression model. The coefficient β_i shows the sensitivity of the *i*-th share to the market portfolio, α_i is the fitting parameter, and ε_{it} is the error term of the security observed in period *t*. We assume that the error term has zero expected value and follows a normal distribution with variance $\sigma_{\varepsilon_i}^2$.

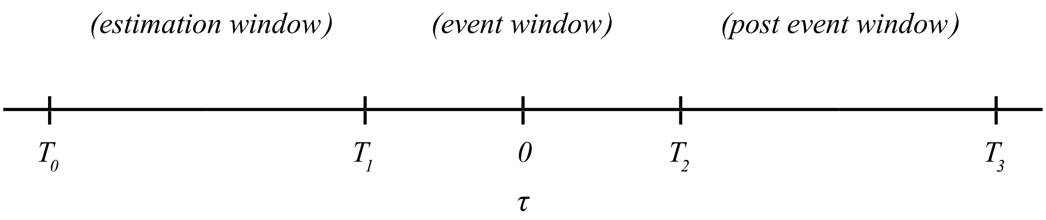
Our applied modelling logic assumes that the regression coefficients are constant in both the estimation period and the event window. (Binder, 1998) The real beta of a share may change over time, but looking at a short time horizon, it is unlikely that significant changes will occur in the risk profiles. In the case of large samples, however, the bias is close to zero, so the market model is an efficient way of estimating returns (Binder, 1998), and the effect of introducing additional factors is negligible (MacKinlay, 1997). As a conclusion of all this, in this paper, we use the market model to calculate normal returns.

2. *Event and Estimation windows*

The choice of the length of the event window and estimation window is somewhat arbitrary, which was basically determined based on the experience of previous research. Our investigated topic can be considered to have a short time horizon among event analyses, so a relatively short event window is a suitable choice for testing hypotheses. In the case of an event window shorter than one year, the analysis works quite reliably, and much fewer methodological problems arise during it (Khotari & Warner, 2007). In our case, in addition to the date of the event, at least the following trading day must be part of the event window so that announcements at the end of the trading day or after the close of the stock market are also taken into account since abnormal returns will necessarily occur on the following day as well. Generally, in practice, an interval of a few weeks is usual, which is symmetrical to the date of the event (MacKinlay, 1997). The shorter the event window, the less likely it is to have a distorting effect from other events affecting companies (Rao & Sreejith, 2014) It is important to note that if the event window is too long compared to the estimation period, it can significantly bias the test statistic if the estimated abnormal returns are correlated. In our case, therefore, we calculate the regression coefficients from a period no longer than 120 days used by MacKinlay (1997). The temporal separation of the two windows is also important. If we also used the return data of the event window for the regression model, we would get an incorrect parameter estimate, because it would already include the noise resulting from the announcement. (Boehmer, 1991)

Considering the above, we can formally describe the timeline of the event analysis as follows. The index of returns is τ, and the stages of the analysis are as follows. $\tau = 0$ is the date of the event, $T_{0+1} \leq \tau \leq T_1$, the estimation window, and $T_{1+1} \leq \tau \leq T_2$ is the event window. Then $L_1 = T_1 – T_0$ is the estimation window, and $L_2 = T_2 – T_1$ is the length of the event window. It is also possible to define a post-event window described by $T_{2+1} \leq \tau \leq T_3$ and length $L_3 = T_3 – T_2$, but this is not necessary for our research questions.

Figure 2 *Visualisation of Estimation-, Event- and Post-Event Window*



3. *Abnormal returns*

Since we model the expected return as a linear function of the return of the market portfolio, we can use equations (**Equation 1**) and (**Equation 2**) to write down the definition of the abnormal return used in the paper more precisely:

Equation 1 Abnormal Return

$$AR_{i\tau} = R_{i\tau} - E(R_{i\tau}|X_\tau)$$

where $T_{1+1} \leq \tau \leq T_2$, so τ denotes an event window period. The length of the periods used for parameter estimation and around the event was also determined, so we can start building the regression model. The parameters are estimated using the method of least squares (OLS). Based on (**Equation 2**), we know the expected return calculated during modelling, so by substituting this into equation (**Equation 1**), the abnormal returns around the event can be calculated as follows:

Equation 3 *Abnormal Returns around the Event*

$$AR_{i\tau} = R_{i\tau} - \left(\widehat{\alpha_\iota} + \widehat{\beta_\iota} R_{m\tau}\right)$$

where $AR_{i\tau}$ is the abnormal return of the *i*-th share, $R_{i\tau}$ and $R_{m\tau}$ are the returns of the *i*-th share and the market portfolio, respectively, in period τ. $\widehat{\beta_\iota}$ is the estimated regression coefficient expressing the sensitivity to the market yield, and $\widehat{\alpha_\iota}$ is the parameter helping the fit. To be able to draw statistically and economically relevant conclusions regarding the research questions, it is necessary to aggregate the abnormal returns. This can happen along the elements of the pattern as well as the dimension of time. The average abnormal return in period τ is the calculated arithmetic average from the data of the group's elements. This is described by **Equation 4**.

Equation 4 *Average Abnormal Return*

$$\overline{AR_{\tau}} = \sum_{i=1}^{N} \frac{AR_{i\tau}}{N}$$

If we want to test the surprise effect of a layoff announcement and the market efficiency, then we have to analyse a period longer than the interval, including the day of the event and the following trading day. Based on other empirical results, we can rightly assume that due to the emerging surprise, a short-term momentum effect can be observed in the stock exchange rates. In order to be able to test this assumption, it is necessary to aggregate the abnormal returns in time within the event window. Let's consider a period enclosed by τ_1 and τ_2, for which $T_1 < \tau_1 \leq \tau_2 \leq T_2$ is satisfied. Then let the cumulative abnormal return (CAR) of the *i*-th stock be observed in this interval.

Equation 5 *5Cumulative Abnormal Return*

$$CAR_i(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau}$$

By performing the same procedure on the sample and the groups formed from it, we obtain the cumulative average abnormal returns for any (τ_1, τ_2) interval of the event window. It is calculated on individual elements, utilised **Equation 4**, and will be used later during showing our results.

Equation 6 *Average Cumulative Abnormal Return*

$$\overline{CAR}(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} \overline{AR_{\tau}}$$

With this, we reviewed the main points of the applied methodology. We proceed in the same way in the case of the second hypothesis, but there we also examine whether the results obtained from the two samples differ significantly from each other, whether their cumulative average abnormal returns follow a distribution with the same expected value and variance.

IV. Results and Discussion

1. Event study results

After showing the data we worked with and the methodology we used for our research, we present the initial results. Our first task was to specify the size of the event window. We did this in two ways. First, we relied on other studies. Most of them claimed that the 5-day long event window is optimal so, we stick to that. In a later section, we work with different event windows – among other parameters – for examining whether our results and tests are robust.

The $\overline{AR}$ and $\overline{CAR}$ results – containing all firms on a 5-day long event window – are summarized in **Table 3**. Consistent with our previous findings we use event windows of 5 days for our plots. So, the results from **Table 3** are more understandable and expressive if they are illustrated. In **Figure 3**, we present the average cumulative abnormal returns for all observed stocks. These results are significant at a 10% confidence level. The event day (0) and the days before and after that are displayed on the horizontal axis while the average CARs are displayed on the vertical axis in percentage terms. As for the description, the average CAR slightly decreases at first but after the announcement, it begins to soar for a couple of days. For this, we state that there is a rather positive abnormal return in the stock market of companies which has announced massive layoffs, thus *we reject our first hypothesis*.

To test our second hypothesis, we split the firms by sectors: IT and non-IT. We did that because we assumed no difference between the returns of different sectors' stock prices, and we wanted to prove it. The $\overline{AR}$ and $\overline{CAR}$ results – containing IT and non-IT firms separately on a 5-day long event window – are summarized in **Table 4**. Same way that we did before, in **Error! Reference source not found.**, we showed the average cumulative abnormal returns of the IT and non-IT stocks simultaneously. Even if we just look at this figure, we can see a considerable distinction. The abnormal return of IT stocks follows a monotone growth, even before the announcement. After it, it increases more steeply. Moreover, it always stays positive. In the case of non-IT stocks, it is not as unambiguous anymore. Before the announcement, it mainly decreases and after that, it starts to grow – still in the negative range. Another fact that we can see is the confidence interval is different in magnitude. That is because of the different variances of the samples. It is expected that sample firms from more than one industry will have greater variance (MacKinlay, 1997).

Table 3 *Results for estimated average AR and CAR for all stocks*

Event Window (-5, +5)	$\overline{AR}$ %	$\overline{CAR}$ %
-5	0.861%	0.861%
-4	0.306%	1.167%
-3	-1.69%	-0.523%
-2	0.097%	-0.426%
-1	-1.006%	-1.432%
0	-0.129%	-1.562%
1	2.137%	0.576%
2	2.701%	3.277%
3	2.538%	5.815%
4	-1.859%	3.957%
5	0.458%	4.415%
Standard Error:	(±0.047%)	(±0.52%)

Note: the $\overline{CAR}$ results are plotted in **Figure 3**.

Figure 3 *Average Cumulative Abnormal Returns in the event period (All observed stocks)*

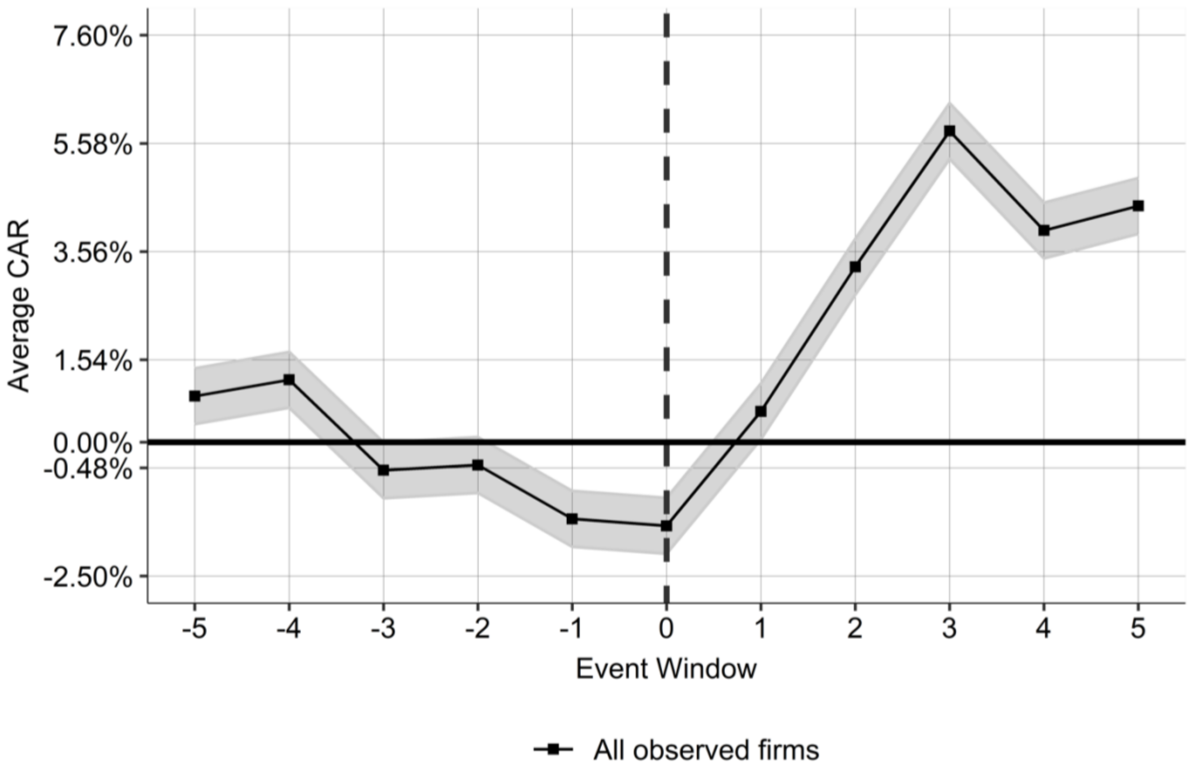
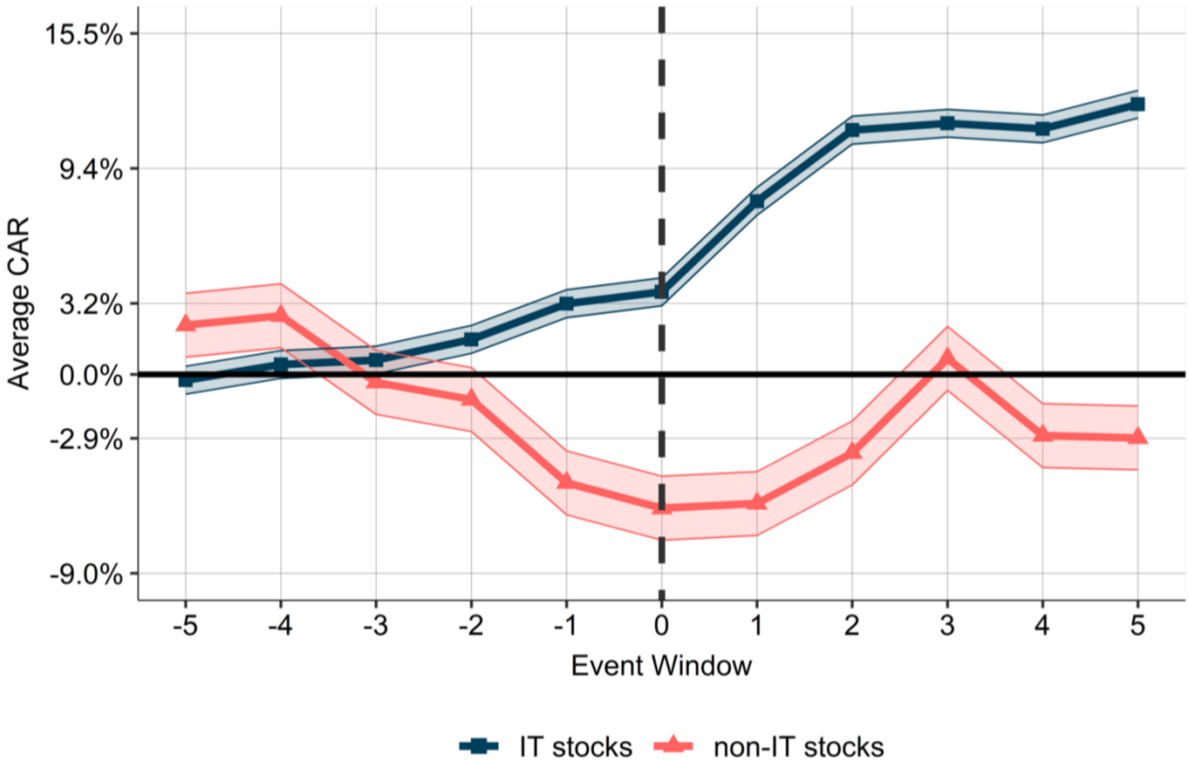


Table 4 *Results for estimated average AR and CAR for IT and non-IT stocks*

Event Window (-5, +5)	IT stocks $\overline{AR}$ %	IT stocks $\overline{CAR}$ %	non-IT stocks $\overline{AR}$ %	non-IT stocks $\overline{CAR}$ %
-5	-0.30%	-0.30%	2.20%	2.20%
-4	0.70%	0.50%	0.40%	2.70%
-3	0.20%	0.70%	-3.00%	-0.40%
-2	0.90%	1.60%	-0.80%	-1.10%
-1	1.60%	3.20%	-3.80%	-4.90%
0	0.50%	3.80%	-1.20%	-6.10%
1	4.10%	7.90%	0.20%	-5.90%
2	3.20%	11.10%	2.30%	-3.60%
3	0.30%	11.40%	4.30%	0.70%
4	-0.30%	11.20%	-3.50%	-2.80%
5	1.10%	12.30%	-0.10%	-2.90%
Standard Error:	(±0.06%)	(±0.63%)	(±0.13%)	(±1.45%)

Note: the $\overline{CAR}$ results for IT and non-IT stocks are plotted in **Figure 4**.

Figure 4 *Average Cumulative Abnormal Returns in the event period (IT and non-IT stocks)*



We then conducted a t-test with two samples. The value of the said t-test was 4.443 with a p-value of 0.00033. According to the results, we can reject the null hypothesis of having no difference between the abnormal return of the companies of the IT and non-IT sectors. There is a statistically significant difference, thus *we reject our second hypothesis.*

2. Robustness testing

Robustness testing, in general, is a process of evaluating the stability and reliability of a statistical model or method under different conditions and assumptions. In the context of an event study for stock exchange and (abnormal) returns, it can help to ensure that the results of the study are not sensitive to the particular choices made in the study design or to the specific assumptions made in the analysis. The goal of robustness testing is to ensure that our results of the event study are not overly dependent on any choices or assumptions and that they can be replicated and verified by other researchers. By performing robustness testing, we can have greater confidence in the validity and reliability of our findings.

For example, in an event study of stock returns, a robustness test may involve examining the results using different estimation windows, event windows, or benchmark portfolios to evaluate the sensitivity of the findings to these choices. It may also involve examining the results under different market conditions or using different statistical techniques to assess the stability of the findings. In our study, we choose three different methods to test our model's robustness:

1. By changing the event window size

To conduct a robustness test using different event windows, we analyse the impact of the event on abnormal returns using different periods around the event. In practice, we examined the same tests with different parameters. The estimation window was left unchanged – 60 days. However, compared to the original 5-day long event window, we used shorter (namely 1, 2, and 3-days long) and longer (namely 10, 15, and 20-days long) event windows during our tests. Consistently, we conducted the robustness test for all observed stocks, and even for IT and non-IT stocks. The results are summarised in **Table 5**.

For all observed firms' stock, the results are unambiguous. If the event window is larger than 5 days, the CAR significantly deviate from zero. This means that there is a negative cumulative abnormal return – inferred from the sign of t-statistics. If the event window is small than 5 days, conversely, the CAR does not deviate significantly from zero. It could mean, that the information does not affect the stock price in such a short interval.

If we examine the IT and non-IT stocks separately, we can draw different conclusions. Firstly, the IT stocks. In this case, it is slightly difficult to interpret the results. If the event window size is 1, 10, or 15, the CAR does not deviate significantly from zero. This may seem random, but a possible explanation is that in the case of the too small, or too large event window, the announcements do not have an influence on stock prices. For non-IT stocks conversely, the CAR values significantly deviate from zero for every event window size. This differentiates the IT and non-IT stock prices.

Table 5 *Results for Robustness Test with different Event Windows*

	All observed stocks		
Event Window (T_1, T_2)	$\overline{CAR}$ %	*t-statistic*	*p-value*
(-1,+1)	2.1%	-0.794	0.511
(-2,+2)	5.0%	0.616	0.571
(-3,+3)	7.5%	-0.322	0.759
(-5,+5)	6.0%	1.93	0.082*
(-10,+10)	4.3%	-10.274	0.000***
(-15,+15)	1.5%	-9.076	0.000***
(-20,+20)	4.6%	-9.882	0.000***
	IT stocks		
Event Window (T_1, T_2)	$\overline{CAR}$ %	*t-statistic*	*p-value*
(-1,+1)	4.0%	2.108	0.170
(-2,+2)	7.3%	2.709	0.054*
(-3,+3)	7.6%	3.047	0.023**
(-5,+5)	8.5%	3.777	0.004***
(-10,+10)	8.8%	0.338	0.739
(-15,+15)	11.6%	1.274	0.212
(-20,+20)	13.5%	5.393	0.000***
	non-IT stocks		
Event Window (T_1, T_2)	$\overline{CAR}$ %	*t-statistic*	*p-value*
(-1,+1)	0.2%	-12.644	0.006***
(-2,+2)	2.9%	-4.209	0.014**
(-3,+3)	7.0%	-5.226	0.002***
(-5,+5)	3.2%	-2.152	0.057*
(-10,+10)	-0.3%	-10.162	0.000***
(-15,+15)	-7.6%	-7.148	0.000***
(-20,+20)	-4.5%	-10.197	0.000***

Note: the deviation is statistically significant at a 10% level ('·'), at 5% level ('*'), at 1% level ('**'), at 0.1% level ('***').

2. By changing the estimation window size

A robustness test using different estimation windows involves testing the stability of the results of our statistical model when using different periods of data to estimate the model parameters. This involves dividing the sample period into multiple estimation windows of different lengths and estimating the parameters of the event study model separately for each window. Similarly to the previous part, we divided the robustness testing for all observed stock, then IT and non-IT socks. The unchanged parameter now is the 5-day-long event window, while the estimation window is different for every test. These include 30, (the original) 60, 90, 120 and 240 days.

Table 6 *Results for Robustness Test with different Estimation Windows*

Estimation Window (T_0, T_1)	Time period length (days)	$\overline{CAR}$ %	*t-statistic*	*p-value*
All observed stocks				
(-35,-5)	30	8.00%	3.964	0.003***
(-65,-5)	60	6.00%	1.93	0.082*
(-95,-5)	90	5.10%	0.595	0.565
(-125,-5)	120	4.90%	0.645	0.533
(-245,-5)	240	5.10%	1.222	0.25
IT stocks				
Estimation Window (T_0, T_1)	Time period length (days)	$\overline{CAR}$ %	*t-statistic*	*p-value*
(-35,-5)	30	10.7%	4.336	0.001***
(-65,-5)	60	8.5%	3.777	0.004***
(-95,-5)	90	8.5%	3.743	0.004***
(-125,-5)	120	8.7%	3.745	0.004***
(-245,-5)	240	8.3%	3.747	0.004***
non-IT stocks				
Estimation Window (T_0, T_1)	Time period length (days)	$\overline{CAR}$ %	*t-statistic*	*p-value*
(-35,-5)	30	4.8%	1.068	0.311
(-65,-5)	60	3.2%	-2.152	0.057*
(-95,-5)	90	1.5%	-3.512	0.006***
(-125,-5)	120	1.0%	-3.662	0.004***
(-245,-5)	240	1.8%	-3.033	0.013**

Note: the deviation is statistically significant at a 10% level ('·'), at 5% level ('*'), at 1% level ('**'), at 0.1% level ('***').

The robustness test results are summarised in **Table**. For all observed stocks, we have unfavourable results. The CARs significantly deviate from zero for only the 30- and 60-day-long estimation window. When we divided the test for IT and non-It, the results are much improved. For almost every estimation window, the cumulative abnormal returns significantly deviate from zero and based on the sign of their t-statistics, their trend is also identical to the ones in their group.

3. *By checking the industry effect*

The purpose of this segment is to confirm whether the empirical findings of the observed abnormal returns in the event study results section contained solely company-specific information or information regarding the industry as well. The relevance of this question is that understanding the scope of the effect would greatly influence the interpretation of the results. Another piece of evidence that suggests the relevance of examining the industry effect is the fact that the observed announcements mainly occurred not only in the last quarter of 2022 but in some cases even in the same month. The proximity of the announcement dates could indicate that in that period, there could have been an event that affected the entire industries of the observed stocks. In addition, there have been several event studies that emphasized the relevance of intra-industry effects in certain industries like the banking industry (Larry & René, 1992). Therefore, it is supporting the relevance of the examination of intra-industry effects in our case as well.

To ascertain such an effect, we decided to take another sample of corporations, which did not have layoffs in the inspected period. We selected three industry competitors' stock returns for each firm in our original sample. For determining the other industry members, we relied on the Bloomberg Industry Classification Standard (BICS) and the Bloomberg Classification System (BCLASS) whose purpose is to organize legal entities and securities into consistent peer groups according to specific activities and risk categories. We consider it to be a reliable classification system given that it is based on other industry classifications from official institutions and national statistics agencies such as NAICs, NACE and UK SIC (Bloomberg Professional Services, 2023).

As for the filtering process, we first selected companies from the sector which was considered the primary sector of the observed company. The reason for narrowing down only to the primary sector was that in our case there are companies that are present in multiple sectors, therefore it would have included competitors that were not as similar in activity and magnitude to our original company. Then we ordered the companies by industry revenue. As a second-level filter, we filtered to companies whose primary operation also fell into the same classification. As the next step, we randomly selected 3 industry competitors that were in the same industry revenue range as our observed company.

As a final step, before selecting the industry competitor for our sample we verified whether they complied with two additional criteria. Firstly, the competitor should not have had a layoff in the last quarter of 2022. This is a fundamental criterion since the purpose of this analysis is to see whether the layoff announcements of certain companies had an effect on its competitors, thus mitigating bias. Secondly, we ensured that the security we chose was listed on a US stock exchange, to avoid selecting equity from a foreign country that could have potentially introduced some bias via region-specific effects.

After conducting the selection process, we continued working with the companies shown in **Table 7** Examined Companies and their Competitors. We performed the same event study analysis on the industry competitors as described in the Methodology section of this study. We even used the same window sizes in order to facilitate the comparison. The only adjustment we made was that we assigned the announcement date of the observed company to its industry competitors.

Table 7 *Examined Companies and their Competitors*

	Non-IT sectors		
	Competitor 1	*Competitor 2*	*Competitor 3*
Carvana	Autonation Inc.	CRMT	Vroom Inc
Disney	Paramount Global	AMCX	Comcast
Lyft	Uber Technologies	Opendoor	Doordash
Peloton	Brunswick Corp	Topgolf Callaway	Visa Outdoor
Redfin	CBRE Group Inc	Compass Inc	Exp World Holding
	IT sector		
	Competitor 1	*Competitor 2*	*Competitor 3*
Amazon	Alibaba	Ebay	Etsy
Meta	Weibo Corp	Pinterest	Joyy Inc
Microsoft	Oracle Corp	Kingsoft	Snowflake Inc
Netflix	Spotify Technologies	Sirius XM Holding	Phoenix New Media Ltd.
Snap	Yelp Inc	Paltalk	Nextdoor Holding

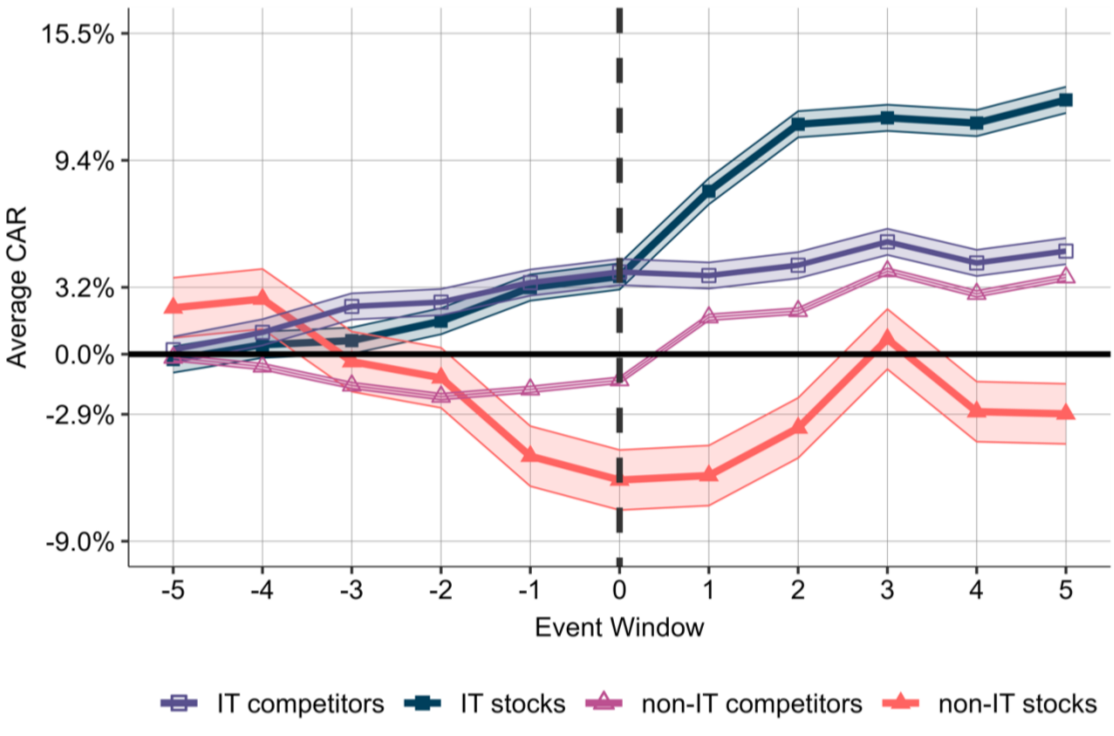
From the results of the event study including the industry competitors, we can suspect that the abnormal returns of our sample and the industry competitors differ (see the results in Appendix). The results are visualized in **Figure 5**, which displays the results discussed in the Event study results complemented by the average CAR values of the industry competitors.

Even if we just take a visual inspection of the non-IT stocks' and their industry competitors' average CAR, we can see that the two differ from each other. We conducted a two-sample t-test, which confirmed that at the 5% significance level, we can reject the null hypothesis of the test, therefore we can state that the means of the two samples statistically differ from each other (p-value = 0.0338). Furthermore, it seems that during the event period, the non-IT competitors' abnormal returns did not deviate much from the 0% average CAR, suggesting that the non-IT competitors' stocks followed their regular path. We can quantitatively confirm this statement after conducting a one-sample t-test, where we could not reject – at none of the conventional significance levels (1%, 5%, 10%) – the null hypothesis that it does not differ significantly from 0% (p-value = 0.36523).

As for the IT sector, there is a clear visual distinction between the observed IT companies and their competitors following the event date. The cumulative abnormal returns of the IT companies that had layoffs started to increase after the announcement dates whereas their competitors' abnormal returns seem to not increase in tandem with them and continue their path. With a two-sample t-test on the period after the event, we can confirm this difference, since we can reject the null hypothesis at a significance level of 5% that the means of the two samples are equal (p-value = 0.01099). From this, we can conclude that the layoff announcements of the given IT companies do not seem to have influenced the abnormal returns of their direct competitors. This means that our empirical findings, presented in the Event study results section, are likely to be company-specific effects as opposed to an effect caused by an industry trend.

Figure 5 *Average Cumulative Abnormal Returns in the event period*

(IT and non-IT stocks and their industry competitors)



3. Effects before and after the event

Previously, we had been focusing on the effects of the layoff announcements directly before and after the announcements in a short period of time. Nevertheless, drawing conclusions only based on the results in a relatively short event period can give us misleading interpretations since complex economic events may have completely different effects in the long run. Therefore, even if shorter event windows are typically used to observe a particular event, looking at longer windows is critical to understand complex economic events (Oler, Harrison, & Allen, 2008).

When examining the pre-event effects, we expect the average cumulative abnormal return to vary around 0%, assuming that there is no preliminary information leakage effect and/or any other abnormal effect. Our second assumption is that in the post-event window, the results will be consistent with our previous findings, meaning that after the immediate momentum effects of the layoff announcements the returns would level off and follow a newly determined path.

We used an event window of (-15,+3) for observing the pre-event effects and an event window of (-3,+15) for observing the post-event effects. The length of the event window was determined by two factors. Firstly, with respect to the economic turbulence of 2022, we did not want to choose an event window size that was too big, considering that it might have introduced some noise in our analysis. Secondly, when choosing the last day of the event period (T_2) for the post-event analysis, we faced a technical limitation, due to the fact that at the time of conducting this study, there was no available data for the returns of the observed stocks.

1. Before the event

After conducting the event study on the pre-event window as previously explained, we can observe that our initial assumptions about the pre-event effects might partially be true (see in Appendix). With the assistance of **Figure 6**, we can visualize the results better, where the x-axis shows the trading days in the event window relative to the announcement dates, and the y-axis shows the average cumulative abnormal returns for all observed stocks in percentage.

Figure 6 *Average CAR in the event period*

(All observed stocks Rw = 60, Ew = 15-3)

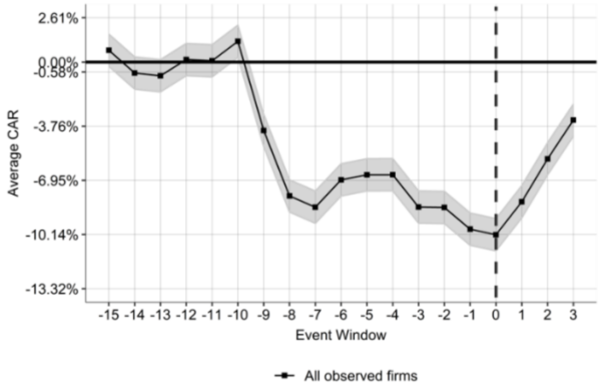
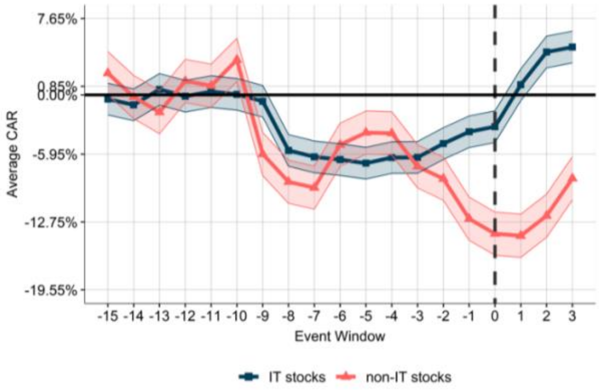


Figure 7 *Average CAR in the event period*

(IT and non-IT stocks Rw = 60, Ew = 15-3)



Note: *Rw* denotes Regression (Estimation) window, while *Ew* denotes Event window

Firstly, we can see that from 15 trading days before the announcements up until approximately 10 trading days before the announcements the average cumulative abnormal returns varied around 0%, as we expected it. However, from 10 trading days prior to the event, the average CAR sharply drops and then levels off. After the event, the average CAR starts climbing, just as our previous findings show in the Event study results section.

A possible explanation for the sharp decrease in average CAR in the event period of (-10, -7) could be the influence of another impactful event. Such noise was anticipated given that the last quarter of 2022 is considered to be a rather turbulent period in the stock market, as we previously explained it. After extensive, research we found that a possible event with such an impact on stock prices could have been the FOMC announcement of November 2nd (Federal Reserve, 2023). Given that most of the announcements of our examined companies occurred in mid- and early November this assumption seems reasonable. Furthermore, as can be learned from previous studies, the Fed's Monetary Policy's surprise effect has a significant impact on US and foreign asset prices. (Rosa, 2011) Additionally, the negative directionality of the $\overline{CAR}$ values between the trading day -10 and -7 could be explained by the fact that the FOMC announcement was a negative surprise effect as the market was expecting the ease of macroeconomic conditions. And as detailed in the 2010 study of Kurov, a negative surprise effect can cause negative abnormal returns (Kurov, 2010). Therefore, they seem like compelling evidence for the assumption that the FOMC decision had an effect on abnormal returns in that period.

In **Figure 7**, the pre-event effects of the announcements broken down by the IT and non-IT sectors are illustrated. We can see that the two sectors seem to have behaved similarly before the event. The only striking difference before the event seems to be only between the 7th and 3rd trading day prior to the event. The IT sector's abnormal returns level off after the sharp decrease presumably caused by the FOMC decision, whilst the non-IT sectors' abnormal returns increase for a short period of time and then continue decreasing. If we assume that the dip in average CAR was partially owing to the unexpected negative FOMC decision in November, then a possible reason behind this phenomenon could be the fact that different industries react to monetary policy differently (Ganley & Salmon, 1997). And since our non-IT group consists of companies that operate in distinct industries, a difference in reaction can be expected. At the same time, the levelling-off of the IT sector's abnormal returns could be explained by the fact that it represents companies from the same sector, thus it is expected that they react uniformly to such monetary decisions.

2. *After the event*

When performing the event study analysis on the post-event period, we found that after the immediate reactions of the observed stocks, the average cumulative abnormal returns seem to level off and show no signs of significant deviations in the period of (+4, +12). This could translate to the fact that the shock caused by the announcements put the stocks on a new path. However, as presented in **Figure 8**, after the 13th trading day following the announcement date other effects start to kick in.

Figure 8 *Average CAR in the event period*

(All observed stocks Rw = 60, Ew = 3-15)

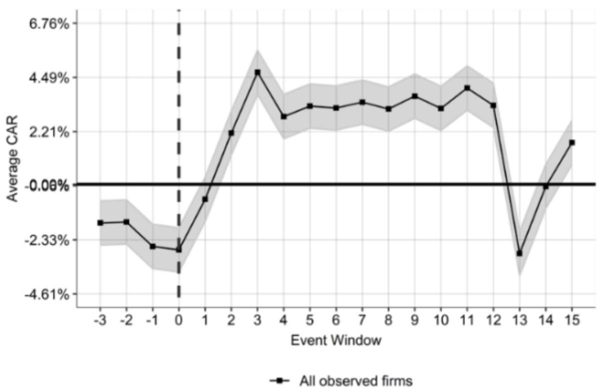
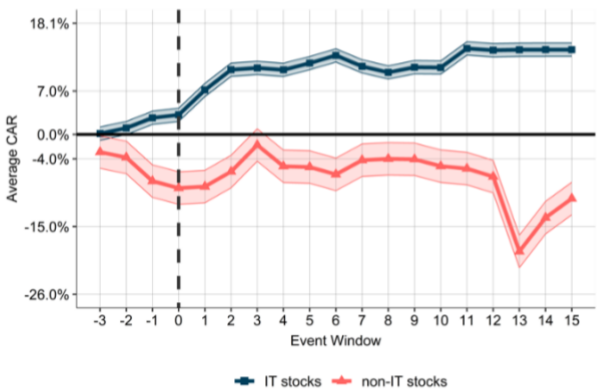


Figure 9 *Average CAR in the event period*

(IT and non-IT stocks Rw = 60, Ew = 3-15)



Note: *Rw* denotes Regression (Estimation) window, while *Ew* denotes Event window

In **Figure 9,** we can visually confirm that the dip seen in **Figure 8** is caused by a sharp decline in the non-IT sectors' average cumulative abnormal returns. After examining the non-IT group, we found that it could have mainly been caused by Carvana. Carvana is an automotive retailer company whose stock has been performing poorly in 2022 as there had been several negative news about the company in that period. And 13 days after their layoff announcement, another such negative news spread pessimism on Wall Street about the company, because of the downgrade of the stock's forecast by an analyst (Turner, 2022).

This phenomenon proves that after several days other non-layoff related events can influence the abnormal returns of a company. However, due to the relatively small size of our sample, we cannot firmly state this. Furthermore, to analyse the truly long-term effects of these layoff announcements it is necessary to extend the event window and examine the effects when the layoffs were carried out, nonetheless at the time of making this study there was no sufficient return data available.

V. Conclusion and Future Works

The year 2022 witnessed turbulence in the stock market, with global economic and energy crises impacting even large companies. Many of these companies responded by implementing massive layoffs as a cost-cutting measure. The consequences of these layoffs can be significant. From an investor’s perspective, the announcement of layoffs can be seen as a negative signal about the company’s financial health and prospects, leading to a decrease in stock price and a loss of confidence among consumers and stakeholders. Thus, in this study, we examined the stock market reaction to the large-scale layoff announcements of 2022 with the help of the event study methodology.

Event study methodology is a statistical technique used in empirical research to analyse the impact of a specific event on financial markets, focusing on the effects of an announcement on stock prices. In our case, it involves analysing the stock market performance of companies that have announced large-scale layoffs. The methodology includes collecting stock price data for the companies before and after the announcement of layoffs, and then analysing the abnormal returns (i.e., the difference between actual returns and expected returns) during the event window (i.e., the period surrounding the announcement). By comparing the actual returns during the event window with the expected returns, we can assess whether there is a statistically significant impact of the layoff announcement on the stock market performance of the companies. This methodology can help provide empirical evidence on the potential negative impact of layoffs on stock prices, as hypothesized in our thesis.

In our first hypothesis we expected that overall, there would be negative abnormal returns after the announcements given the negative economic circumstances of 2022. Nevertheless, we rejected this hypothesis because we found that there were positive abnormal returns after applying the event study analysis. An explanation for this result could be the case of IT companies. At the start of the COVID-19 pandemic in 2020, many tech companies’ profitability started to increase significantly due to the increase in demand for online services. To keep up the supply with the increasing demand, these companies initiated a massive hiring process. However, after the decline in infection rates and the reopening of several countries, the demand dropped and consequently the price of IT stocks. Thus, it makes sense that the market reacted positively to the layoffs since in this case, they had a restructuring and cost-efficiency enhancing purpose. Furthermore, we rejected our second hypothesis as well because we found a statistically significant difference between the abnormal returns of the IT and the non-IT sectors. We observed that there were mainly negative abnormal returns for non-IT stocks, even if we could see some increase after the announcements. Still, the wide confidence interval and the fact that not every non-IT company were part of the S&P500 index suggest that we cannot be entirely sure about the negativity of abnormal returns.

Robustness testing is an important step in our research. It means conducting additional analyses and tests to check the reliability and stability of the research findings and to ensure that the results are not dependent on specific assumptions or conditions. We used three different methods to test our model's robustness: changing the event window size, changing the estimation window size, and checking the industry effect.

Finally, we examined the potential pre- and post-event effects of these layoffs, in order to deepen our understanding of their effects. When examining pre-event effects with an asymmetric event window we found no clear evidence of effects prior to the announcement dates, given that the last quarter of 2022 was a rather turbulent period and any abnormality in the returns could have been caused by other major events. As for the post-event effects, we found that approximately 3 to 5 trading days after the announcements the abnormal returns lost momentum and levelled off, thus showing little sign of possible additional effects after the announcements.

Although we found that in this particular case, the layoff announcements generally showed positive abnormal returns, especially in the IT sector where primarily "white-collar" workers had been laid off, we recommend further research on whether this effect can be generalized to all "white-collar" layoffs. Likewise, we also suggest the examination of the potential correlation between the size of the layoffs and the magnitude of abnormal returns, considering that it would also expand our understanding of the findings of this study.

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VII. Appendix

Table 8 *Results for estimated average AR and CAR for all stocks (Pre-Event)*

Event Window (-15, +3)	$\overline{AR}$ %	$\overline{CAR}$ %
-15	0.696%	0.696%
-14	-1.337%	-0.641%
-13	-0.164%	-0.805%
-12	0.956%	0.151%
-11	-0.072%	0.078%
-10	1.145%	1.223%
-9	-5.243%	-4.020%
-8	-3.848%	-7.869%
-7	-0.663%	-8.532%
-6	1.609%	-6.923%
-5	0.295%	-6.627%
-4	0.004%	-6.623%
-3	-1.897%	-8.521%
-2	-0.025%	-8.545%
-1	-1.277%	-9.822%
0	-0.331%	-10.153%
1	1.942%	-8.211%
2	2.519%	-5.692%
3	2.285%	-3.407%
Standard Error:	(±0.05%)	(±0.95%)

__Table 9__ Results for estimated average AR and CAR for IT and non-IT stocks (Pre-Event)

Event Window (-15, +3)	IT stocks		non-IT stocks	
	$\overline{AR}$ %	$\overline{CAR}$ %	$\overline{AR}$ %	$\overline{CAR}$ %
-15	-0.426%	-0.426%	2.177%	2.177%
-14	-0.578%	-1.004%	-2.394%	-0.216%
-13	1.55%	0.545%	-1.516%	-1.733%
-12	-0.685%	-0.139%	3.125%	1.392%
-11	0.46%	0.321%	-0.485%	0.907%
-10	-0.271%	0.05%	2.602%	3.509%
-9	-0.694%	-0.645%	-9.447%	-5.938%
-8	-4.927%	-5.572%	-2.782%	-8.72%
-7	-0.642%	-6.213%	-0.58%	-9.3%
-6	-0.277%	-6.49%	4.293%	-5.007%
-5	-0.363%	-6.853%	1.223%	-3.784%
-4	0.564%	-6.289%	-0.067%	-3.851%
-3	0.021%	-6.268%	-3.319%	-7.17%
-2	1.377%	-4.891%	-1.241%	-8.411%
-1	1.189%	-3.702%	-4.009%	-12.42%
0	0.511%	-3.19%	-1.499%	-13.919%
1	4.206%	1.016%	-0.209%	-14.128%
2	3.276%	4.292%	2.009%	-12.119%
3	0.498%	4.79%	3.744%	-8.375%
Standard Error:	(±0.084%)	(±1.59%)	(±0.114%)	(±2.16%)

Table 10 *Results for estimated average AR and CAR for all stocks (Post-Event)*

Event Window (-3, +15)	$\overline{AR}$ %	$\overline{CAR}$ %
-3	-1.625%	-1.625%
-2	0.038%	-1.587%
-1	-1.025%	-2.612%
0	-0.145%	-2.757%
1	2.125%	-0.632%
2	2.786%	2.154%
3	2.549%	4.704%
4	-1.863%	2.84%
5	0.444%	3.284%
6	-0.08%	3.204%
7	0.243%	3.447%
8	-0.285%	3.162%
9	0.538%	3.7%
10	-0.515%	3.186%
11	0.857%	4.043%
12	-0.73%	3.313%
13	-6.222%	-2.909%
14	2.815%	-0.094%
15	1.847%	1.753%
Standard Error:	(±0.05%)	(±0.93%)

Table 11 *Results for estimated average AR and CAR for IT and non-IT stocks (Post-Event)*

Event Window (-3, +15)	IT stocks		non-IT stocks	
	$\overline{AR}$ %	$\overline{CAR}$ %	$\overline{AR}$ %	$\overline{CAR}$ %
-3	0.133%	0.133%	-2.876%	-2.876%
-2	0.908%	1.041%	-0.864%	-3.741%
-1	1.661%	2.702%	-3.853%	-7.593%
0	0.484%	3.186%	-1.129%	-8.722%
1	4.039%	7.225%	0.242%	-8.48%
2	3.298%	10.523%	2.434%	-6.046%
3	0.288%	10.81%	4.329%	-1.718%
4	-0.307%	10.504%	-3.471%	-5.188%
5	1.093%	11.597%	-0.119%	-5.307%
6	1.256%	12.853%	-1.196%	-6.503%
7	-1.781%	11.073%	2.31%	-4.193%
8	-0.985%	10.087%	0.211%	-3.982%
9	0.84%	10.928%	-0.069%	-4.052%
10	-0.048%	10.88%	-1.116%	-5.168%
11	3.101%	13.981%	-0.392%	-5.559%
12	-0.29%	13.691%	-1.303%	-6.862%
13	0.076%	13.767%	-12.173%	-19.035%
14	0.023%	13.79%	5.493%	-13.542%
15	-0.011%	13.779%	3.112%	-10.43%
Standard Error:	(±0.057%)	(±1.08%)	(±0.14%)	(±2.64%)

Table 12 *Results for estimated average AR and CAR for IT and non-IT stocks (Examined Companies and their Competitors)*

IT sector stocks				
	observed		*competitors*	
Event Window (-3, +15)	$\overline{AR}$ %	$\overline{CAR}$ %	$\overline{AR}$ %	$\overline{CAR}$ %
-5	-0.258%	-0.258%	0.214%	0.214%
-4	0.713%	0.455%	0.842%	1.056%
-3	0.2%	0.655%	1.251%	2.307%
-2	0.939%	1.594%	0.209%	2.515%
-1	1.623%	3.217%	0.942%	3.457%
0	0.538%	3.755%	0.513%	3.971%
1	4.117%	7.872%	-0.172%	3.799%
2	3.233%	11.105%	0.498%	4.297%
3	0.311%	11.416%	1.13%	5.428%
4	-0.253%	11.163%	-1.02%	4.408%
5	1.118%	12.281%	0.572%	4.98%
Standard Error:	(±0.057%)	(±0.632%)	(±0.177%)	(±1.942%)

Non-IT sector stocks				
	observed		*competitors*	
Event Window (-3, +15)	$\overline{AR}$ %	$\overline{CAR}$ %	$\overline{AR}$ %	$\overline{CAR}$ %
-5	2.241%	2.241%	-0.171%	-0.171%
-4	0.425%	2.666%	-0.426%	-0.597%
-3	-3.023%	-0.358%	-0.915%	-1.512%
-2	-0.781%	-1.139%	-0.541%	-2.053%
-1	-3.787%	-4.925%	0.352%	-1.702%
0	-1.152%	-6.078%	0.444%	-1.257%
1	0.215%	-5.862%	3.038%	1.781%
2	2.3%	-3.563%	0.304%	2.085%
3	4.291%	0.729%	1.924%	4.009%
4	-3.504%	-2.776%	-1.093%	2.916%
5	-0.107%	-2.882%	0.794%	3.71%
Standard Error:	(±0.132%)	(±1.451%)	(±0.013%)	(±0.148%)