ERASMUS UNIVERSITY ROTTERDAM
ERASMUS SCHOOL OF ECONOMICS
Bachelor Thesis Economics & Business

The Impact of Corporate Layoffs on Firm Performance in the US: Evidence from the Tech Industry

Financial Economics

Author: Celine Wang
Student number: 573047
Thesis supervisor: dr. (Vadym) VV Volosovych
Second reader: dr. (Ruben) R. de Bliek
Finish date: 12/10/2023

The views stated in this thesis are those of the author and not necessarily those of the supervisor, second reader, Erasmus School of Economics or Erasmus University Rotterdam.

ABSTRACT

This study examines the impact of the layoffs on the stock- and corporate performance of the US publicly listed tech firms between 1 March 2022 – 28 February 2023. Using event study, regression analysis, and a Difference-in-Difference model, it explores the effects of layoffs on stock prices and corporate performance. The sample consists of 368 publicly listed companies. A selection of 55 of the included companies released layoffs announcements between 1 March 2022 and 28 February 2023. These companies have all been categorized as technology companies according to the NASDAQ index.

The findings indicate that layoff announcements were associated with positive cumulative abnormal returns, challenging the conventional belief of negative stock reactions to layoffs. The improved stock performance may be attributed to factors like overhiring, copycat behavior, and cost reduction. Regarding corporate performance, the analysis revealed a negative effect on Return on Equity (ROE) following layoffs, supporting the hypothesis that layoffs worsen corporate performance. Furthermore, the research found no significant difference in the impact of layoffs on corporate performance between the tech industry and the overall US market, rejecting the hypothesis that the tech sector's response differs significantly. In summary, this research sheds light on the complexities of layoffs' effects in the tech industry, offering insights into stock performance and corporate outcomes, while highlighting the need for further investigation into the observed positive stock reactions.

The findings suggest that the corporate layoffs in the US positively affected the stock performance, negatively affected the corporate performance, and the effect of the layoffs did not differ for the tech industry in comparison to layoffs in other industries.

Keywords: Layoffs, Tech Industry, Corporate Performance, Stock performance

JEL codes: G30, G14, J60

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CHAPTER 1 Introduction

"The Big Tech's pandemic bubble burst" said CNN Business on January 22nd, 2023 (Duffy, 2023). Dropping stock prices, a heightened price volatility and declining corporate performance; all signs that the phase of hypergrowth of the tech industry is officially over. Companies such as Apple and Microsoft saw record-high returns in recent years, especially during the COVID-19 pandemic. However, ultimately economic uncertainties and macroeconomic factors led to the "tech-bubble"-bursting, starting at the end of 2021 with tech stock prices dropping by more than 30% in 2022 (Movement, 2023). Along with this stagnation in firm performances, massive waves of layoffs could be observed in the tech industry, such as Meta cutting 10,000 of its employees in March 2023 (Isaac, 2023). By laying off thousands of employees, tech companies attempt to respond accordingly to macroeconomic conditions, cut costs and thereby improve stock and company performance. Both stock performance and the number of layoffs are significant indicators of the economic performance of a country, thus making them highly relevant in measuring a country's prosperity.

To understand the impact the post COVID-19 layoff-waves have on firm performances, literature can be consulted. First of all, layoffs can be split in two main categories, namely low demand layoffs and restructuring layoffs (Hahn & Reyes, 2004). The consensus backed by multiple papers, is that layoffs follow a period of poor operating and stock price performance (Hillier et al., 2007). Furthermore, stock prices also react negatively to the announcement of employee layoffs, as for investors layoffs often look like signs of financial distress, which causes a significant drop in stock prices after layoff announcements (Lee, 1998).

On the contrary, other literature suggests that the market reacts positively to restructuring-related layoffs on the announcement date (Hahn & Reyes, 2004). This is further supported by Chen at al. (2001) who claim that firms that have had layoffs have significantly higher profit margins and labor productivity than their industry peers, hence why it cannot be concluded that layoffs result in a worse financial position for the firm. Corporate focus namely increases after having layoffs which can be a sign of restructuring to improve the firm and profitability.

Moreover, for an accurate analysis it is also important to look at the nature of the layoff and whether the layoffs are a product of the (macro)economic environment, external pressure, long-and short-term gain, increasing productivity or other factors. Specific industry factors are also important as Elayan et al. (2003) find that there's a significant difference in the market reaction to layoff announcements per industry type.

The existing literature provides a strong foundation on the impact of layoffs on firm performance. The results from previous research, however, may be outdated due to the lack of research in the digital age. The rise of AI, the current high accessibility of (financial) information through social media and the internet, in addition to the higher participation of individual investors and speculators are factors that haven't been considered by previous research and this different context may affect the outcomes of the research. Furthermore, previous articles have mostly looked at the aggregate level while this paper will examine the tech industry specifically, which is a perspective that hasn't been widely shown before. With thousands of workers currently losing their jobs, it poses the relevant question whether these layoffs have a significant effect on stock prices and firm performance and what this effect is. This research is relevant as it could help companies better recognize if layoffs are an effective strategy of increasing productivity, cutting costs and improving stock performance.

Considering the existing literature and proposed research idea, the main research question of this paper will be:

"What is the effect of corporate layoffs that have occurred at US Firms in the technology sector in the post COVID-19 era (March 2022 – February 2023) on stock prices and corporate performance?"

To assess this research question, three different hypotheses have been formulated. A closer look will be taken at the effect of layoffs on the stock prices and the corporate performance. Moreover, it will be researched how this differs for the tech industry in comparison to other sectors in the US. The relevant outcome variables are stock market performance and corporate performance and will be mainly measured by the variables stock prices and Return on Equity (ROE). The unit of analysis is the number of layoffs which will be measured by the number of layoff announcements.

Two different frameworks will be used to determine the results. Firstly, the effect of layoffs on stock prices will be determined by using the event study methodology pioneered and expanded by Fama et. al (1969), Brown & Warner (1985) and MacKinlay (1997). Second, the effect of layoffs on corporate performance and the tech sector will be tested via a regression analysis and a Difference-in-Difference Model consequentially. This approach allows for the measurement of the impact of layoff announcements on corporate performance. It also facilitates a comparative analysis to assess how these layoffs have specifically affected the tech industry in contrast to other industries.

Concerning the data, the event of impact will be the layoff announcements. Different data sources will be consulted; for the data of the stock returns and the key financials used to determine corporate performance, a mix of the CRSP US Stock Database (Daily) and the CRSP/Compustat Merged Database (Quarterly) will be utilized. These databases consist of daily and monthly stock return data from over 32,000 listed US securities and financial report data respectively. Furthermore, the data on the layoffs will be obtained via the websites Layoffs.fyi and Layoffstracker.com which are trackers of layoffs, and they derive their data from news articles and company reports. This data will be complimented by data of the WARN Act, which is a US law that requires certain companies to give a notification before implementing mass layoffs, to protect workers.

The sample consists of 55 layoffs announcements of US public listed technology companies between 1 March 2022 and 28 February 2023.

My hypothesis is that the recent layoffs did have a significant, possibly negative impact on the stock prices and corporate performance, with a bigger impact on the tech industry than other sectors. The unique economic conditions of the post COVID-19 era and digitalization whilst having the highest number of layoffs in 2022 since the dot-com bubble (CBS News, 2023) have provided a different context in comparison to previous research, which could very well lead to different outcomes. Furthermore, since this research is only applicable to the US, it is important to acknowledge that labor regulations vary greatly across countries and can impact the extent to which companies can pursue layoffs and their effects on stock prices. Additionally, considering layoffs are still ongoing in the tech industry, difficult-to-control variables such as changing macroeconomic trends and economic uncertainty could lead to different implications for this research in the future, as well as limitations within the used models such as the Difference-in-Difference framework.

In this paper, firstly there will be a deeper dive into previous academic studies to determine the ongoing discussion regarding the effect of layoffs on stock and firm performance. Next, a framework regarding the hypotheses, data and methods will be formed, in the sections 3-5. Lastly the results will be analyzed, after which a conclusion and discussion will be made.

CHAPTER 2 Theoretical Framework

To take a deeper dive into why the post COVID-19 layoff announcement wave occurred and its effects, further literature will be consulted. Firstly, literature will be consulted to explain what layoffs are and why they take place. Potential discussion points that can occur during research will also be assessed. Secondly, a closer look of stock returns and corporate performance will be taken to clearly define what these terms mean. Third, a clear overview of existing literature will be presented to assess the current findings of the effect of layoffs on stock performance and overall corporate performance. These will be categorized by positive and negative findings. Finally, a closer look will be taken of the tech industry, and which effects this specific industry might have on the relationship between the stock performance and the firm's performance and efficiency.

2.1 Layoffs

Layoffs can be defined as "An occasion when a company stops employing someone, sometimes temporarily, because the company does not have enough money or enough work." (Cambridge Dictionary, 2023). On macroeconomic level this act can have impact on the domestic employment level, while on microeconomic level this act can have impact on labor costs, firm efficiency and internal structure and workload. While a single layoff has marginal effect on a firm, a large series of layoffs in a firm or across single can certainly have impact on the entire economy, for example in the form of the growth of GDP or the trust of consumers in the economy via the signifying effect of layoffs.

A company can have various reasons to decide to stop employing one or multiple employees. Firstly, employee cuts can happen when firms experience declining product demand which in turn also results in a decline in labor demand. Secondly, due to innovation, certain product- and/or service processes become outdated and are therefore no longer as profitable, which in turn causes lower demand of labor thus cuts of employees. The third reason is that firms' labor forces are being used inefficiently and therefore resources can be allocated to more effective purposes, which will lead to layoffs for restructuring purposes (Chen et al., 2001). Consequently, it is also important to note that these different reasons for layoffs can also have a strong impact on how the stock price responds to the layoff announcement and how the company will perform after these announcements have been made.

To further define layoff types, Kashefi and McKee (2002) define two types of layoffs: proactive and reactive layoffs. Proactive layoffs are layoffs that are done with a long-term strategy in mind where the firm is undertaking some type of restructuring to be more cost effective or more productive. These layoffs can also be described as restructuring layoffs. On the other hand, reactive layoffs will be implemented when operations are unprofitable, there is declining sales growth, an economic downturn and when labor costs are too high for the firm to afford. These layoffs are also known as low demand layoffs.

The reason the low demand layoffs are perceived to be worse for the firm in comparison to the restructuring layoff is that the market will perceive the layoff to be because of lack of resources and lack of turnover rate. The restructuring layoffs on the other hand signify a company's attempt to reduce overhead, costs or to restructure the firm to enhance the company's performance thus increasing the firm's value (Elayan et al., 1998).

In the case of the waves of layoff announcements after the COVID-19 pandemic, a multitude of reasons could be pointed out. First of all, macroeconomic factors that affected the entire economy such as an increased inflation and high energy prices due to the war in Ukraine have slowed down the growth of the global economy. Overall, the worsening economic conditions have contributed to companies having to let go of their employees (Gourinchas, 2023). Furthermore, with a low supply for labour, the cost of hiring and retaining skilled tech workers has been rising which has led to certain companies cutting costs by implementing layoffs.

Further implications that are tied directly to the technology industry will be discussed in a different section.

2.2 Layoff announcements and stock returns

Corporate press releases such as layoff announcements frequently have an effect on stock prices, with known cases of positive as well as negative returns. As information is being released to investors and the public, phenomena such as increased stock price volatility and shifted consumer-and investor trust can occur. This is because the information companies give out, signify and clarify how well a company is doing, and investors react (Neuhierl et al., 2013). The way stock prices react to layoffs announcements, can be explained via Efficient Market Theory (EMH). Efficient market theory is a fundamental theory that explains how financials markets are highly efficient in processing and reflecting all available information, resulting in asset prices that fully and accurately incorporate all known information (Fama et al., 1969).

In the case of layoff announcements, there has been relatively extensive research on the effect of layoffs on the firm's stock and overall corporate performance. There are mixed opinions on what this effect exactly entails as different studies have found different outcomes.

In existing literature, papers such as Hallock (1997), Chen et al. (2001) and Hillier et al. (2007) have found negative returns. Elayan et al. (1998) conclude that layoffs announcements generally lead to a negative market reaction, as investors interpret them as a sign that the company is in financial problems. The market reaction to layoffs also depends on the reason for the layoffs. Layoffs that are announced as a way to improve efficiency are met with a less negative market reaction than layoffs that are announced as a way to cut costs. Next to that, the market's response to layoff announcements will also vary significantly based on industry types. Firms that place a greater emphasis on human capital are more responsive to changes in their workforce and tend to be more negatively impacted by layoff announcements compared to companies that rely more on physical capital.

Hillier et al. (2007) also conclude that layoff announcements are followed by a negative stock reaction due to their signifying of poor financial conditions. The negative stock returns occurred for companies with poor financial results and where the market was unaware of the poor financial state the firm was in. A key take-away Hillier et al. (2007) found, is that there was not enough evidence to conclude that layoffs improved firms' operating performance.

Chen et al. (2001) observes a significant negative stock market response to layoff announcements and find a -1,2% average 2-day abnormal stock return. However, in the long-term, their findings reveal that layoffs are often preceded by a period of weak stock and operating performance, and subsequently, they observe improvements in both areas after the layoffs. They conclude that companies that implement layoffs overall do not harm themselves performance-wise. Next to this, they discovered that the primary motivation behind layoff announcements is reduction of labour costs in their research.

On the other hand, several papers also find positive stock returns upon layoff announcements. Examples are Marshall et al. (2012), Hahn and Reyes (2004) and Palmon et al. (1997). Marshall et al. (2012) put an emphasis on the market conditions as they found positive stock returns in response to layoffs in times of an economic upswing, while they found negative stock returns during times of financial crises. They suggest that market conditions outweigh firm-level explanations for layoffs in influencing investor reactions.

Kashefi and McKee (2002) focus on the type of layoff and conclude that proactive layoffs cause positive abnormal returns, while announcements of reactive layoffs will experience a negative abnormal return. These conclusions are also supported by Hahn and Reyes (2004) who find negative abnormal returns for low demand layoffs and positive abnormal returns for restructuring layoffs. Furthermore, in their research the layoff reason is the only significant factor that impacts market reaction. Industry and other firm-level factors do not have a significant impact.

Overall, it can be concluded that a majority of studies conclude a negative stock reaction upon layoff announcements, but with a few nuances depending on the reason for layoff, macroeconomic conditions and the amount of information available to investors, where the stock reaction will be positive.

2.3 Tech Industry specific factors

To determine why the tech industry specifically experienced a high number of layoffs in the period following the pandemic, we can have a closer look at the industry specific factors that have contributed to the massive layoffs.

First of all, the tech industry enjoyed hypergrowth in the years prior to and also during the pandemic. This higher-than-average growth led to a lot of tech companies becoming overly optimistic about the future and their growth potential. This optimism was reflected in the hiring behavior of tech companies, causing overhiring, However, the pandemic and macroeconomic conditions also caught up to the tech industry in 2022, causing strain on financial resources. The combination of the large cases of overhiring and high prices for labour, unfortunately meant layoffs for a lot of companies (Mayer, 2023).

Secondly, the nature of the industry has a lot of impact on companies' growth and sequentially their workers. The tech industry can be characterized by its volatile nature, with a rapid pace of innovation. While this innovation drives growth, it can also lead to job displacement as new technologies replace old ones, making certain roles or skill sets obsolete, also known as "creative destruction". The tech industry is constantly changing, and companies need to be able to adapt to these changes in order to survive. This can be a challenge, and it can lead to layoffs as companies restructure or re-evaluate their strategies to align with changing product demands and technologies. (Spencer & Kirchhoff, 2006). Furthermore, the tech sector itself is at the forefront of developing automation and AI technologies. As companies adopt these technologies internally, certain routine or repetitive jobs might be automated, leading to workforce reductions.

Third, companies also imitate each other by implementing so called "copycat layoffs". In these scenarios a spike in hiring or layoffs comes to exist because companies decide to hire more or lay off more simply because other firms are doing so. Through this phenomenon called 'social contagion', firms attempt to cut costs and streamline operations, since their competitors are doing the same. Research concludes firms even follow through with these "copycat layoffs" when from a strategic point of view, layoffs do not make sense for certain firms (Budros, 1997).

CHAPTER 3 Hypotheses

To define the research that will be conducted in this paper, several hypotheses will be formulated in order to create a framework to guide this study. These hypotheses will help answer the central research question as these hypotheses will all partially contribute to measure the effect of corporate layoffs that have occurred at US Firms in the technology sector in the post COVID-19 era (March 2022 – February 2023) on stock prices and corporate performance. The first hypothesis concerns the effect of the corporate layoffs in the tech industry on the stock performance of these companies. Based on the existing research the following hypothesis has been formulated:

H_1: *US Tech Companies affected by layoff announcements in the period March 2022-Feb 2023 have experienced a decrease in stock performance.*

This hypothesis is based on various results from previous research that suggests that layoffs generally have a negative effect on stock performance, such as Worrell et al. (1991) and Hillier et al. (2007). A decrease in stock performance will be defined as a negative stock return following layoffs. Literature implies that positive stock returns, as a result of layoffs, only appear when there are clear motives of restructuring and optimization behind the layoffs. Hypothesis 1 will be tested via the event study methodology, where abnormal and cumulative abnormal returns will be observed to conclude whether there is a significant effect of layoff announcements on stock performance (Brown & Warner, 1985). As the layoff announcements of the post-COVID era are mostly the results of overhiring, increasing labor costs and copycat behavior as described in the previous section, this aligns with the expectation of negative stock returns, thus a decrease in stock performance following the layoff announcements.

H_2: *US Tech Companies that have experienced layoffs will have a worsened corporate performance in the period following the layoffs, in comparison to companies that did not implement layoffs.*

Hypothesis 2 builds upon hypothesis 1 and aims to take a look at the longer-term corporate performance of the firm after layoffs are implemented. The hypothesis will be tested through observing a few key financials of the quarterly results of a company in the quarter after implementing layoffs and calculate if there are any significant changes. In this manner, it can be determined whether the layoffs have had any impact on the firm's performance. This will be done via regression analysis and the Difference-in-Difference framework. Studies such as Yliopisto (2016) and Saba (2023) have also used regression analysis to determine the effect of layoffs on corporate performance and have found slight negative effects on corporate performance after implementing layoffs. As it is not clear that the tech layoffs were implemented with restructuring in mind, hypothesis 2 will align with these previous conclusions and describe a negative effect.

H_3: The effect of the layoffs on corporate performance is different for the tech industry than the US market as a whole.

Hypothesis 3 is based on the fact that the tech industry possesses significantly different characteristics than other industries and therefore will react differently to layoffs than other firms. The research of Elayan et al. (1998) reveals that the response of the market on layoffs varies depending on the sector the company operates in and that a large role can be attributed to whether the firm is service-or manufacturing oriented. Companies that provide services tend to experience more pronounced negative impacts from layoff announcements compared to the manufacturing companies. In the case of the tech industry, both capital and labour are important. However, it can be argued that the human capital of the engineers and workers carry more value and therefore the tech industry is more service-focused. The market conditions for the tech industry and the services-oriented nature, therefore there is reason enough to suspect a different effect on the corporate performance.

CHAPTER 4 Data

4.1 Data sources and sample characteristics

Different data sources will be consulted; for the data of the stock returns and the key financials used to determine corporate performance, a mix of the CRSP US Securities Database (Daily) and the CRSP/Compustat Merged Fundamentals Database (Quarterly) will be utilized. These databases consist of daily and monthly stock return data from over 32,000 listed US securities and quarterly financial report data respectively. Variables such as daily stock return, market value, total assets etc. have been derived from these databases to form the base of the dataset that will be used.

Furthermore, the data on the layoffs will be obtained via the websites Layoffs.fyi and Layoffstracker.com which are trackers of layoffs, and they derive their data from news articles and company reports. This data will be complimented by data of the WARN Act, which is a US law that requires certain companies to give a notification before implementing mass layoffs, to protect workers.

Moreover, to be included in the sample, the companies in the sample also have to fulfill certain requirements. First, this sample only contains announcements with at least 1000 employees or 5% of staff cut, to make sure the included layoffs have a certain significance for the company and its results. Firms that have made another significant announcement on the days surrounding the layoff announcements will be omitted (Kohl, 1999). Next to that, to further ensure the layoffs are large enough, this sample only contains companies that have a market capitalization of at least $300 million.

The sample consists of 368 publicly listed companies in the United States. A selection of 55 of the included companies released layoffs announcements between 1 March 2022 and 28 February 2023. These companies have all been categorized as technology companies according to the NASDAQ index. For hypothesis 1, the 55 layoff tech companies will act as the sample and will be utilized in the event study that will be performed to measure stock performance. The other 279 US technology companies that did not experience layoffs will serve as a benchmark/control group and will be used for the Difference-in-Difference model in hypothesis 2. The full list of the layoff companies can be found in Appendix A.

In the DiD-framework, considering there is no single event of impact as every company separately handles each layoff announcement, a more streamlined and simplified version of the sample will be used to perform the regression analysis. The layoff companies will be limited to technology companies that implemented layoffs during Quarter 4 of 2022 (October – December 2022) or Quarter 1 of 2023 (January 2023 – March 2023), which results in a sample of 44 tech layoff companies. The data of of all other 11 tech companies that had layoffs in months other than Q4 2022 or Q1 2023 will be removed from the DiD-framework sample as these companies neither fit within the control or the treatment group.

Furthermore, the data can be identified as panel data, where available company data is collected from Quarter 1 of 2022 until Quarter 3 of 2023. Here, Q1 2022 acts as t=1, Q3 2022 is t=2, etc. until Q3 of 2023 that acts as t=7.

Q42022 and Q12023 have been chosen as period of treatment because Q42022 and Q12023 were characterized with a high number of layoffs in comparison with other quarters that had available data. It is important to note that the layoffs that happened in the month March of 2023, will be omitted from, as it falls out of the scope of this study. This is because this study focuses on the period March 2022 – February 2023. However, naturally the layoffs in January and February 2023 will be taken into account. With regard to the DiD-framework, the following three timeframes will used:

1. Pre-layoff Period: Q3 2022 (July – September 2022)
2. Layoff Period: Q4 2022 and Q1 2023 (October 2022 – March 2023)
3. Post-layoff Period: Q2 2023 (March – June 2023)

Lastly, for the data intended to use for the analysis of the third hypothesis, a sample of 34 non-technology companies that also dealt with layoffs will be added. These companies had layoffs that took place in Q42022 or Q12023. The sample will be representative of the market outside of the tech industry and includes companies from the finance industry, healthcare industry, telecommunications industry and consumer goods sector for example. The sample that will be used for this hypothesis consists of 78 companies; 34 non-technology layoff companies and 44 tech layoff companies to measure what effect the industry has on the effect on the corporate performance after layoffs.

4.2 Descriptive statistics

A few descriptive statistics have been generated to form a better understanding of the data and also to perform preliminary analyses on the data.

Table 1: Average Stock Returns March 2022 – Feb 2023

	S&P500	Average all tech companies
Mean	-0.0002	-0.0014
Standard Deviation	0.015	0.032
Minimum	-0.043	-0.079
Maximum	0.055	0.124
Number of observations (days)	251	251

Notes: Average stock returns for the market return (S&P500) and the stock returns for tech companies. Variables are in percentages (%), e.g. -0.0002 = 0.02%. 251 observations which equals to 251 days of stock returns.

In Table 1 you can see the average stock returns over the period March 2022 – February 2023 of the S&P500 and the cumulative average of all 55 tech companies. Both the tech sector stock return and the overall market return have been negative on average with a return of -0.0014 and -0.0002 respectively. As you can see the average stock return is lower for the tech companies than for the market proxy S&P500. This could possibly indicate a more negative stock return for tech companies in comparison to the market, but this will be tested in a further section. It can also be noted that the tech companies are more volatile as the standard deviation is bigger and also has a larger difference between the minimum and maximum return on stocks in comparison to the S&P500 index.

Table 2: Companies in Sample

Variables	Observations
Non-layoff tech companies (control group)	279
Tech layoff companies Q42022 & Q12023	44
Tech layoff companies non-Q42022 & Q2023	11
Non-tech layoff companies Q42022 & Q12023	34
Total	368

Notes: Categories of different companies within the sample.

In Table 2 you can find a short overview of the kind of companies in the sample. As can be seen from the table, the total of companies in the sample is 368 with a distinction between layoff and non-layoff companies. Furthermore, there is also a distinction between the 44 tech layoffs that happened in Q4 2022 and Q1 2023 that will be used for the regression versus the total of 55 tech layoff companies across March 2022 – February 2023 that will be used for the event study. Lastly, the final part of the sample consists of the 34 non-tech layoff companies that will be used for hypothesis 3. See Appendix A for a list of all layoff companies.

Table 3: Descriptive Statistics

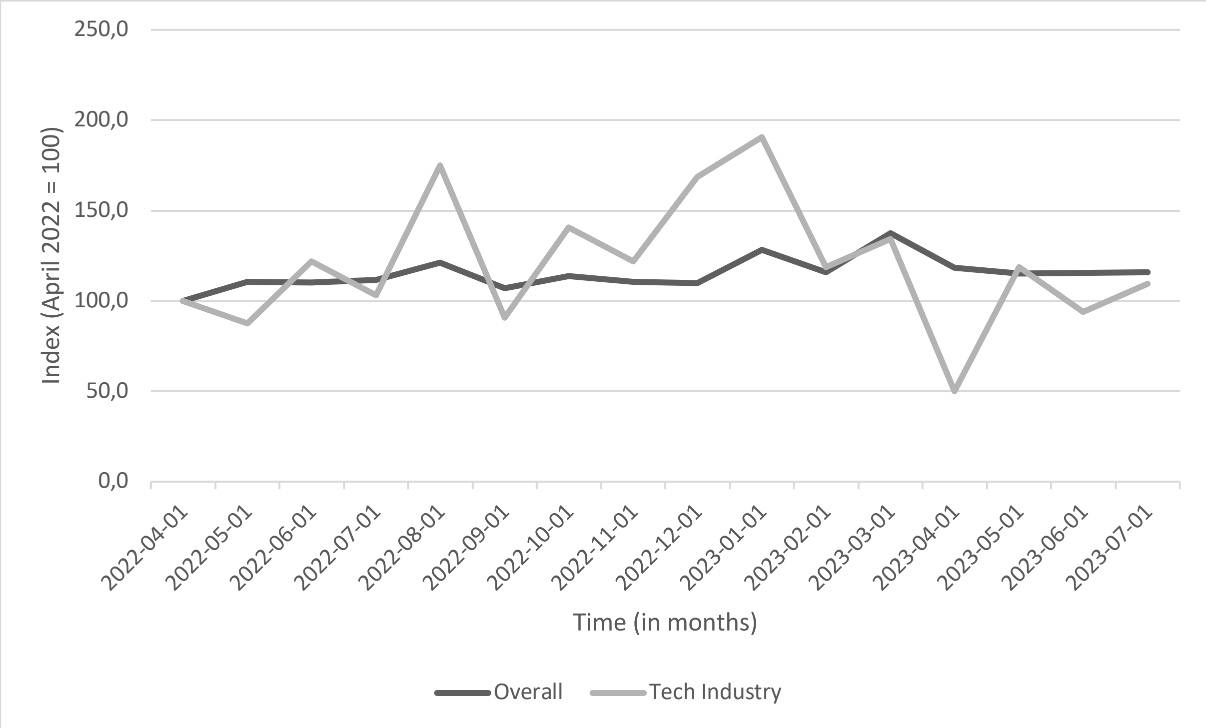
Variables	**Pre- Layoffs (t=-1)**	**During Layoffs (t=0)**	**Post- Layoffs (t=1)**	**Dif. Δ t-stat**	**Dif. Δ p-value**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
ROE	0.010	0.019	-0.015	0.520	0.604
	(0.387)	(0.478)	(2.095)		
DE_RATIO	0.616	0.523	2.153	-1.133	0.258
	(9.246)	(5.511)	(23.931)		
Net Income	-0.457	-0.528	-0.111	-1.075	0.283
Margin	(4.301)	(6.878)	(0.806)		
SALES	1388.328	1494.097	1368.142	0.275	0.784
	(5618.948)	(7007.074)	(5781.536)		
MKT_VALUE	20787.930	21324.81	25396.85	-0.396	0.692
	(126090.5)	(120077.6)	(152489.1)		
CASH	795.122	828.220	830.981	-0.247	0.805
	(2057.013)	(2130.244)	(2095.893)		
Number of observations	334	333	332		

Notes: Variables are in $ or in ratios (0-1). Sample of 334 US publicly listed tech companies, key financials. The table shows the mean of the various variables and between the parentheses are the standard deviations. The fo

In Table 3 the descriptive statistics can be found of company financials in the quarter leading up to (t=-1), quarter of (t=0) and quarter after (t=1) the layoff announcements within the companies. When comparing the different metrics, it can be seen that ROE, Sales and DE ratio have all decreased upon the layoff announcements. However, it is also important to note that the Market Value, Cash did see an increase. A t-test was also performed where the H_0 was tested whether or not the mean of the variables ROE, Debt to Equity ratio etc. are significantly different from each other during the 'During Layoff' and 'Post-Layoff'-period. The t-statistics and p-values displayed in column 4 and 5, but all p-values are insignificant, which means there is not enough evidence to support that the mean of the variables as listed above have changed significantly since the layoff in comparison to before the layoff.

Figure 1

Layoffs and Discharges in Tech vs. Overall



Notes. April 2022 serves as index baseline where April 2022 = 100. Time is in months and in this figure the number of layoffs across all sectors are being compared to the number within the tech/information industry.

Lastly, to give a better understanding of the position of tech layoffs within the full layoff landscape within the US, Figure 1 shows a graph of the number of tech layoff versus the number of layoffs overall between April 2022 and July 2023. Here April 2022 serves as baseline with the index of 100. The trend for number of layoffs for all industries seems to be more stable in comparison to the tech company trend. Overall, the number of tech layoffs seems to be fairly even until July 2022 where a higher level of layoffs was seen in the tech industry in comparison to layoffs overall. This trend of significantly higher numbers of tech layoffs continues into the end of 2022. For example, in December 2022 tech layoffs surged by 65.5%, in contrast to the 26% increase observed for layoffs across all sectors. The graph is derived from the U.S. Bureau of Labor Statistics via FRED. The table that was used to produce this graph can be found in Appendix B.

CHAPTER 5 Methodology

5.1 Hypothesis 1: Event Study Methodology

First of all, the methodology that will be used to test hypothesis 1 is the event study methodology by Brown & Warner (1985). The event study methodology has been widely applied to investigate how stock prices react to various corporate events, policy changes, and economic occurrences and will also be used for the layoff announcements. The event study methodology follows a certain framework that will start off with the identification of the layoff announcements as event of impact and sample selection that has been done in Chapter 4. Continuing with analysis, with regards to the event study methodology an event window tracking the stock prices 20 days prior to and 20 days after the announcement will be set to measure the effects of layoff announcements on the outcome variables, in which the layoff announcement will be t = 0 (Kasefi and McKee, 2002). This way, average returns per day in the window can be calculated. Smaller event windows such as [-5,0] will be conducted next to the primary window of [-20,20] to investigate different perspectives of the impact of the layoff announcements.

To benchmark the actual returns, the expected market return during the event window can be estimated via the OLS Market Model and the difference between the actual and market returns will give the abnormal returns (AR) and cumulative abnormal return (CAR) (Marshall et al., 2012). Firstly, after extracting stock data, the daily stock returns can be calculated as follows:

$$(1)\ \ Daily\ Stock\ Return\ (\%) = \frac{(Closing\ price\ of\ today - Closing\ price\ of\ yesterday)}{Closing\ price\ of\ yesterday}$$

Then, the expected market returns can be estimated via the following formula as demonstrated by MacKinlay (1997). In this formula $E(R_{it}|\, X_t)$ represents the expected return of stock i at time t, α is the intercept that stands for the stock's expected return when Rm is 0 or when there is no systemic risk (β). β stands for the systematic risk of the asset, which means that it is a quantification of how much an asset's returns tend to move in relation to the market. Rm is the return on the market portfolio which is represented by the S&P500 in this case.

$$(2)\ \ E(R_{it}|\, X_t) = \alpha + \beta * Rm$$

The formula that will be used to calculate the ARs is as follows, where AR_{it} stands for the abnormal return, R_{it} is the actual return and $E(R_{it}|\, X_t)$ is the expected market return in the period t. (MacKinlay, 1997).

$$(3)\ \ AR_{it} = R_{it} - E(R_{it}|\, X_t)$$

Furthermore, formula 3 represents the Cumulative Abnormal Average Return (CAAR), or the sum of abnormal returns of layoff companies. This entails that the CAAR holds the cumulative effect of the layoff announcement on the average return of the layoff companies over period t. In short, the CAAR helps us understand how the average returns of the group of layoff companies change over time following the layoff announcement. For example, a negative CAAR would indicate that the companies in our sample experienced a negative abnormal return after the layoff announcement, on average. A positive CAAR would indicate the opposite and would show positive abnormal stock returns.

$$(4)\ CAAR_t = \sum_{t=1}^{T} AR_{it}$$

In the case of layoffs, it is also important to note that there is no single event of shock, as companies all implement their own layoffs. Therefore, it is necessary to take into account these different event dates and make sure each layoff and its subsequent effect on the company, will be considered. An event timeline can be made to align all the stock data per company, to make sure the event window is utilized correctly for all companies.

Lastly, the ARs and CARs can be analysed with statistical tests such as a t-test to determine whether the abnormal return is statistically significant, indicating the statistical impact of layoffs.

5.2 Hypothesis 2&3: Regression Analysis & Difference-in-Differences Model

Hypothesis 2

Hypothesis 2 will be tested by comparing the firm performances of tech companies that have had layoffs to the firm performances of tech companies that did not have layoffs, via OLS regression and a Difference-in-Difference Model. Analysing the changes in the quarterly results of the companies that had layoffs vs. the companies that did not, will help assess the impact of the layoffs on the corporate performance. The firm performance will be defined in variable ROE_{it} as the ROE is a good indicator and can capture the firm's profitability and efficiency in generating returns for their shareholders. The independent variable of interest will be $LAYOFF_{it}$.

Furthermore, several control variables will be added to the regression to address the issue of omitted variable bias (OVB). OLS Regression becomes unreliable when there is a strong correlation between an omitted variable and the included variable, making it essential to introduce control variables to mitigate the bias resulting from the omission of this influential variable. Only variables that are relevant in literature are included in the regression, aiming to prevent multicollinearity issues and the subsequent increase in standard errors. The goal is to ultimately attain a more precise estimator for our model. Therefore, in line with literature, the control variables Debt-to-Equity Ratio and Market Value have been introduced to the model (Saba, 2023).

To reiterate the sample, a smaller sample from the selection of layoff companies will be taken, which results in a sample of 44 layoff companies. All of these companies experienced layoffs in Quarter

4 of 2022 or Quarter 1 of 2023, which is between 1 October 2022 and 28 February 2023. Overall, this leads to the following regression:

$$(5)\ ROE_{it} = \beta_0 + \beta_1 * LAYOFF_{it} + \beta_2 * DE\_Ratio_t + \beta_3 * \ln\left(MKT\_Value_t\right) + \varepsilon_{it}$$

In this regression ROE_{it} is the dependent variable and this the Return on Equity will be used as a proxy for the corporate performance of a company. The overall performance of a firm will be captured by the variable ROE_{it} as the ROE is a useful tool to indicate how well a company is utilizing its equity capital to generate profits. Elayan et al. (1998) also describes the ROE as an efficient indicator of corporate performance, and they use this variable their research. The ROE is a metric between 0-100% and is calculated as follows:

$$(6)\ Return\ on\ Equity = \frac{Net\ Income}{Stockholders'Equity} * 100\%$$

To further elaborate on the model; β_0 represents the constant term, which is the point where the regression intercepts the y-axis.
$LAYOFF_{it}$ is a dummy variable that takes on the value 1 in the period/quarter that the layoffs were taking place, and the value 0 otherwise. β_1 shows how much the ROE changes depending on if there has been a layoff announcement in that period or not.

DE_Ratio_t is included as a control variable and DE Ratio stands for the Debt-to-Equity ratio. The DE ratio measures a firm's financial leverage by comparing its debt to shareholders' equity. A positive β_2 may suggest that higher leverage affects ROE negatively, as interest expenses can reduce profits (Yliopisto, 2016).

MKT_Value_t is another control variable and it represents a company's total market capitalization, reflecting its perceived value in the stock market. A positive coefficient β_3 may imply that higher market value is associated with higher ROE, indicating investor confidence. A log is added to this variable as it can improve interpretability as all other variables are expressed as ratio's or are dummy variables, while Market Value is in absolute numbers.

The error term ε_{it} captures the unexplained variation in the dependent variable (ROE) due to factors not included in the model. It is expected to have a mean of zero, and its variance represents the model's goodness of fit. A smaller variance indicates a better fit.

To add to the robustness of the model, a Difference-in-Difference (DiD) framework will be used; this model can be used to estimate the causal effect of the layoffs by comparing changes in outcomes over time between the corporate performance before and after the layoffs. Here, NASDAQ-listed companies in the technology sector that experienced layoffs will act as the ‘treatment group’, while the technology companies that did not experience layoffs will act as the ‘control group’. The treatment will be defined as the layoff announcements. Next to that, the financial results of the quarter before, during and after the layoffs will be gathered. After this, statistical tests will be conducted to determine whether the observed changes in corporate performance are statistically different between the layoff and non-layoff groups (Lechner, 2011).

The Difference-in-Difference Model (DiD) attempts to estimate the causal effect of a treatment, but heavily relies on assumptions to do so. A key assumption in DiD is that, in the absence of the treatment, the treatment and control groups would have followed similar trends over time. This is known as the "parallel trends" assumption. If this assumption holds, any deviation from parallel trends after the treatment can be attributed to the treatment itself. Using the DiD-framework could lead to improvements of the robustness by for example controlling for time-invariant differences or reducing selection bias. There are also limitations to the DiD-framework that will be elaborated on in Chapter 8 "Discussion". The regression that will be used can be seen in Formula 7:

$$(7)\ ROE_{it} = \beta_0 + \beta_1 * LAYOFF_{it} + \beta_1 * TREATMENT_{it} + \beta_3 * DE_{Ratio_t} + \beta_4 * \ln(MKT\_Value_t) + \varepsilon_{it}$$

Like mentioned before, $LAYOFF_{it}$ is a dummy variable that takes on the value 1 in the period that the layoffs were taking place, and the value 0 otherwise. $TREATMENT_{it}$ is the treatment variable and will take on the value 1 if the stock in question belongs to a company that has issued layoffs in the layoff period Q4 2022 or Q1 2023, and the value 0 if it did not implement layoffs. The control variables remain the same as the one used in the previous regression.

Hypothesis 3

Hypothesis 3 focuses on the effect the type of industry has on the corporate performance when a company issues layoffs. This is to assess whether or not the layoff wave of the tech industry differs from layoffs in other sectors. As previously discussed, the tech industry did have a higher-than-average amount of layoffs in the period April 2022 – July 2022 in comparison to layoffs overall (Figure 1). A sample of 44 tech layoff companies and 34 non-tech layoff companies, that all issued layoffs in Q4 2022 or Q1 2023, will be used in this sample. To measure the effect of the type of industry, a similar regression analysis as done for Hypothesis 2 will be used. The regression is as follows:

$$(8)\ ROE_{it} = \beta_0 + \beta_1 * LAYOFF_{it} + \beta_2 * INDUSTRY_t + \beta_3 * INTERACTION_t + \beta_4 * DE\_RATIO_t + \beta_5 * \ln(MKT\_Value_t) + \varepsilon_{it}$$

In this regression, ROE_{it} is the dependent variable as it is the proxy for corporate performance. The control variables remain the same as for the regression in Hypothesis 2. Furthermore, once again $LAYOFF_{it}$ is a binary variable that equals 1 during the period when layoffs occurred and 0 at all other times. A newly introduced variable is $INDUSTRY_t$ and $INDUSTRY_t$ is a dummy variable that takes on 0 if the company is not in the tech industry, and the value 1 if it is a tech company. It will not be possible to use a Difference-in-Difference analysis and treatment variable, as all companies in this sample have experienced a shock in the form of layoffs, as the treatment variable would then not show anything relevant. Lastly an interaction effect will be added, by using the variable $INTERACTION_t$ which can be calculated by multiplying $LAYOFF_{it}$ and $INDUSTRY_t$. This interaction term represents the interaction effect between layoff and industry, capturing whether the effect of a layoff on ROE is different for different industries.

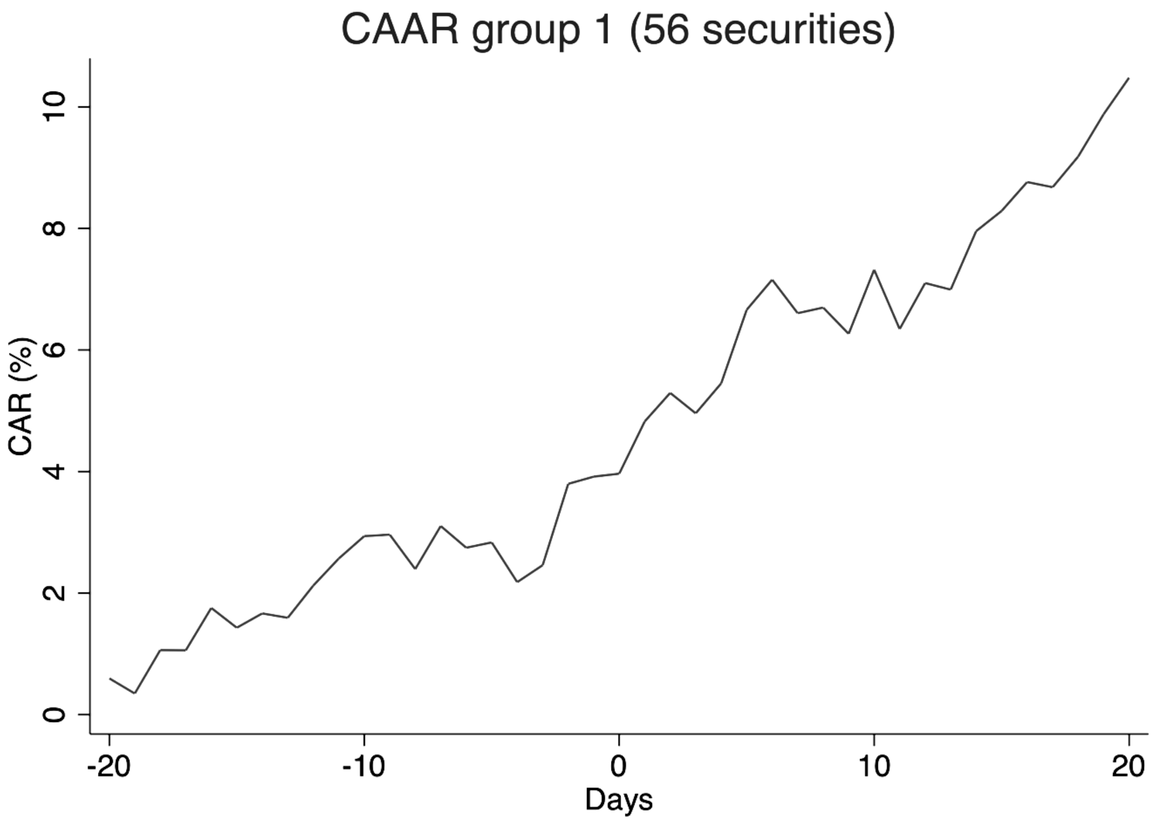
Depending on the sign and significance of the variable $INTERACTION_t$, we will be able to assess whether the type of industry has an effect on the corporate performance. A positive coefficient will be able to tell us that a tech company that has had layoffs, will have a more positive ROE than a non-tech company that has had layoffs. On the other hand, a negative coefficient will tell us that a tech company that has had layoffs, has a more negative ROE than a non-tech company with layoffs. Lastly, the evidence might be inconclusive if the results are not significant.

CHAPTER 6 Results

6.1 Hypothesis 1: Event Study Methodology

To answer the first hypothesis concerning the effect of layoffs on stock performance, an event study was used to perform analysis. This resulted in Figure 2, where the trend of the CAAR over the span of the event window (-20,20) is plotted. As is clear, there is a positive CAAR even before the event date that continues to grow more positive over the event window. After the event of impact (t=0) the CAAR continues to be positive, which indicates an on average positive abnormal return after the layoff announcements were made.

Figure 2: CAAR Graph Event Study



Notes: The graph shows the cumulative abnormal returns (CAARs) of a group of 56 securities in the days following a layoff announcement. The event window shown includes 20 prior to and 20 days after the layoff announcement. The CAAR is in percentages (%) and time is in days.

This can also be observed in Table 4 that showcases the average CAAR over different event windows. In the [-20,20] event window as displayed in the graph, a 0.61% cumulative abnormal return can be observed. This number however is not significant. Several other CAARs have been calculated and a wide range of returns have been estimated. However, CAAR [-30,30] estimates a 22.01% cumulative normal return that is significant with an α=0.01 This positive CAAR of 22.1% suggests that, on average, the stock returns of layoff companies during the event window were better than what would be expected based on the market return (S&P500). The same holds for CAAR [-10.10] and CAAR[-5.5] that have a significant CAAR of 5,6% and 4,27% respectively. It is important to note that although, not all CAARs are significant, it is remarkable that all CAARs are positive. This might suggest that US tech companies that have been affected by layoffs, experience an increase in stock performance following the layoffs. This means that the stock returns after the layoff announcements, are positive. Furthermore, in Appendix D a table can be found where the cumulative abnormal returns are calculated over the course of event window [-5,5].

Table 4: Average Stock Returns March 2022 – Feb 2023

Event Window	Mean averaged CAAR
CAAR [-20,20]	0.6093%
CAAR[-10,10]	5.5951%**
CAAR[-30,30]	22.0144%***
CAAR[-5,5]	4.2700%**
CAAR[-1,1]	0.9237%
CAAR[0,1]	0.7708%
Number of observations	55

Notes: Cumulative Average Abnormal Returns for several event windows for US tech companies.

6.2 Hypothesis 2&3: Regression Analysis and DiD-Model

Hypothesis 2

The second hypothesis focuses on the effect of layoffs on corporate performance. As mentioned earlier, a regression analysis alongside a Difference-in-Difference framework will be used to assess this effect. The data consists of panel data with random effects. This was determined by performing a Hausman test. The Hausman Test is used to determine which model (fixed effects or random effects) is more appropriate for a specific dataset by evaluating whether the estimated coefficients in the two models are consistent or differ systematically. The result of the Hausman test concluded that the difference in coefficients was not systematic and that the Hausman test was not significant. Not rejecting the null hypothesis implies that there is not a systematic difference between the fixed- and random effects estimators, and the random effects model is preferred. The following regressions were used for the results in Table 5.

$$(1)\ ROE_{it} = \beta_0 + \beta_1 * LAYOFF_{it} + \varepsilon_{it}$$

$$(2)\ ROE_{it} = \beta_0 + \beta_1 * LAYOFF_{it} + \beta_2 * DE\_Ratio_t + \beta_3 * \ln(MKT\_Value_t) + \varepsilon_{it}$$

$$(3)\ ROE_{it} = \beta_0 + \beta_1 * LAYOFF_{it} + \beta_1 * TREATMENT_{it} + \beta_3 * DE_{Ratio_t} + \beta_4 * \ln(MKT\_Value_t) + \varepsilon_{it}$$

Table 5: Regression Results Hypothesis 2

Independent Variables	Return on Equity (ROE) OLS (1)	Return on Equity (ROE) OLS (2)	Return on Equity (ROE) DiD (3)
LAYOFF	-0.079 (0.108)	-0.189** (0.093)	-0.058 (0.060)
DE RATIO		-0.061*** (0.002)	-0.061*** (0.002)
ln(MARKET VALUE)		0.033** (0.017)	0.034** (0.017)
TREATMENT			-0.155** (0.071)
Constant	-0.083 (0.099)	-0.221* (0.131)	-0.214* (0.130)
Number of companies	365	364	364
Number of observations	1874	1865	1865
$\boldsymbol{R^2}$	0.000	0.921	0.921

Notes: OLS regression. The sample consists of 334 firms from the United States that have data from five different quarters. Market Value is in $. Ratios are between 0-1. Standard errors are given between. *p < 0.10 **p < 0.05 ***p < 0.01.

In the following Table 5 the results from the regression analysis and DiD-model are shown. The estimates show that in the most basic regression model (1) where only $LAYOFF_{it}$ is used as independent variable, the layoff has a negative effect on the corporate performance (ROE). It shows a decrease in corporate performance of -0.079. The explanatory power of this model is however very small with a R^2 of 0.000 or 0%. The R^2 displayed is the Within R^2.

In the second OLS (2) model, the control variables have been added. The effect of $LAYOFF_{it}$ remains negative, but not only is the effect bigger in the expanded model, the effect of $LAYOFF_{it}$ has also turned significant with a p-value of 0.05. Furthermore, the control variable DE_RATIO_t has a negative impact on the ROE, as the coefficient of this variable is -0.061, with a significance that holds with an α of 1%. The control variable ln $(MARKETVALUE)_{it}$ is also significant and it adds a positive effect to ROE of 0.033. Furthermore the R^2 of this model is 0.921, which means 92,1% of the variation in the dependent can be explained by this model, which is relatively high.

In the third (3) model, the Difference-in-Difference framework is being applied and in this analysis the variable $TREATMENT_t$ is added. $TREATMENT_t$ means that the corporate performance of the tech firms that did not implement layoffs and the tech firms that did implement layoffs will be compared. As can be seen in Table 5 Model 3, the $LAYOFF_{it}$ variable is no longer significant. However, the $TREATMENT_t$ variable is now significant. The coefficient is -0.155, which means that if a tech company implemented layoffs, the corporate performance will be worse and have a ROE -0.155 lower than the tech companies that did not implement layoffs. Again, both DE_RATIO_t and $(ln * MARKETVALUE)_{it}$ are significant as control variables, where the effects are similar to the previous model with a negative effect of -0.061 for the Debt to Equity Ratio and a positive effect of 0.034 for the logged Market Value. Lastly, the R^2 which shows the amount of variation in the dependent variable that is being captured, is 0.921, which means this model is a fairly good fit for the data. A relatively high R^2 also means the model is effective at predicting the values of the dependent variable based on the independent variable, thus means that the model is a good predictor of the dependent variable.

Hypothesis 3

For hypothesis 3, a regression analysis was used to measure the effect of the type of industry on the impact of layoffs on corporate performance. In OLS Model (1) only the variable $INDUSTRY_t$ was used to single out the effect, but this result was not significant and had a R^2 of 0.000. The complete OLS Model (2) however also includes several control variables and adds the variable Layoff. Moreover, an interaction variable was added in the form of $INTERACTION_t$, which is calculated as follows: $INDUSTRY_t * LAYOFF_{it}$. The interaction variable measures the difference of the impact of layoffs between the tech and non-tech companies. The following regression was used for OLS Model (2):

$$(1)\ ROE_{it} = \beta_0 + \beta_1 * LAYOFF_{it} + \beta_2 * INDUSTRY_t + \beta_3 * INTERACTION_t + \beta_4 * DE\_RATIO_t + \beta_5 * \ln(MKT\_Value_t) + \varepsilon_{it}$$

Table 6: Regression Results Hypothesis 3

Independent Variables	**Return on Equity (ROE)**	**Return on Equity (ROE)**
	OLS (1)	**OLS (2)**
INDUSTRY	0.025 (0.081)	-0.048 (0.080)
LAYOFF		-0.052 (0.056)
INTERACTION		0.006 (0.083)
DE RATIO		-0.054** (0.024)
MARKET VALUE		0.019 (0.014)
Constant	-0.160*** (0.055)	-0.206* (0.102)
Number of companies	75	75

Number of observations	450	450
$\boldsymbol{R^2}$	0.000	0.315

Notes: OLS regression. The sample consists of 27 firms from the United States that have data from five different quarters, off of which 13 tech layoff companies and 14 non-tech layoff companies. Market Value is in $. Standard errors are given between. *p < 0.10 **p < 0.05 ***p < 0.01.

Based on Table 6, it can be concluded that industry does not have a significant effect on the corporate performance of a company when it has had layoffs, as the $INTERACTION_t$ variable is not statistically significant. This suggests that there is not sufficient evidence to point out a difference in the relationship between layoffs and the corporate performance for tech and non-tech companies. The variables $LAYOFF_{it}$ and $INDUSTRY_t$ are also insignificant, which means they do not provide enough evidence that they have a significant impact on corporate performance (ROE). The control variable DE_Ratio_t does have a significant impact against an α=0.01 and has a value of -0.054, which means when the Debt-to-Equity Ratio goes up, the Return of Equity decreases with -0.054. The logged Market Value does not have a significant impact in this regression. Lastly, the R^2 in the model is 0.315 which equals 31.5%, which is relatively low. This means this model captures and can explain 31,5% of the variation in the dependent variable in this regression, which indicates improvements can be made to the model. Overall, this regression shows that the type of industry does not have a significant impact on the corporate performance after layoffs, which means the effect of the layoffs on the tech industry does not differ from the layoffs in other sectors.

CHAPTER 7 Conclusion

This paper researches the effect of the corporate layoff wave on the stock- and corporate performance of the technology sector in the post COVID-19 era in the United States of America. The integral research question that was discussed in this paper was as follows:

"What is the effect of corporate layoffs that have occurred at US Firms in the technology sector in the post COVID-19 era (March 2022 – February 2023) on stock prices and corporate performance?"

This research was deducted by using an event study model to examine the stock performance of companies that experienced layoffs, by looking at abnormal returns and cumulative abnormal stock returns, while comparing the stock results to market returns. Furthermore, a regression analysis and Difference-in-Difference model were utilized to assess the corporate performance of the companies affected by the layoff wave. On top of that, an analysis was performed to estimate the effect of industry on the layoffs. The results found in this research will contribute to the evaluation whether layoffs are an effective strategy to restructure a company or cut costs and will also give us a better understanding how a layoff wave affects companies from a financial perspective. Furthermore, this paper highlights the technology industry specifically, which is a new perspective which can help the growing industry to understand the specific implications of layoffs for their sector and employees.
Around the central research question, three different hypotheses were formulated to determine several key components essential for answering the research question.

H_1: *US Tech Companies affected by layoff announcements in the period March 2022-Feb 2023 have experienced a decrease in stock performance.*

Concerning the first hypothesis, the results have shown that there was a positive cumulative abnormal return upon layoff announcement. This could imply that US tech companies facing layoffs tend to observe improved stock performance subsequent to the layoffs. In other words, it suggests that there are positive stock returns following the announcements of layoffs. This is interesting as the majority of previous literature have suggested a negative stock return upon layoff announcement. From this research alone, it cannot be concluded why this improved stock performance has occurred. However, based on previous research, it could be due to the overhiring and copycat-behaviour. Overhiring and high labour costs that were negatively impacting the firm's and therefore stock's performance, could have been a catalyst for the layoffs. The layoffs balanced the workforce out and therefore the stock's performance improved. Due to 'copycat-behaviour' and big tech corporations issuing layoffs, these phenomena could have muted the effect the layoffs had on stock performance as well. Investors may not have viewed the layoffs as a negative signal, given that a substantial portion of the industry appeared to be implementing layoffs as well. However, as a statistically significant reason for the improvement of stock performance could not be derived from this research, hypothesis 1 will be rejected.

H_2: US Tech Companies that have experienced layoffs will have a worsened corporate performance in the period following the layoffs, in comparison to companies that did not implement layoffs.

The second hypothesis looks at the longer-term corporate performance and the implications of layoffs on this corporate performance. Based on the regression analysis to calculate these results, the most basic and expanded regression models revealed a negative effect on corporate performance (ROE). In these models, ROE acted as the proxy for corporate performance and the dependent variable. The corporate performance showed a decrease of -0.079 and -0.189 respectively, with a relatively high explanatory R^2 of 92,1% for the expanded OLS model with control variables, which means a strong explanatory power.

In the Difference-in-Difference model, the $TREATMENT_t$variable was introduced to compare tech firms that implemented layoffs with those that did not. Interestingly, the variable $LAYOFF_{it}$ lost its significance. However, $TREATMENT_t$ became significant, with a coefficient of -0.155. This suggests that tech companies implementing layoffs experienced worse corporate performance, with ROE being 0.155 lower than tech companies that did not undergo layoffs. In summary, the analysis suggests that layoffs within the tech industry could potentially harm corporate performance, providing partial support for the hypothesis. Similar to the previous model, the R^2 of this model was 0.921, which means 92,1% of the variation in the dependent can be explained by this model, which is relatively high.

H_3: The effect of the layoffs on corporate performance is different for the tech industry than the US market as a whole.

Lastly, when looking at the difference between the effect of layoffs on corporate performance in the US tech industry versus the effect of layoffs on corporate performance for the US market as a whole, the results found the variable $INTERACTION_t$ to be statistically insignificant in explaining the variation in corporate performance when considering layoffs. This result suggests that, based on the data and statistical analysis performed, there is no significant difference in the impact of layoffs on corporate performance between the tech industry and the US market as a whole. In other words, the effect of layoffs on corporate performance appears to be relatively consistent across these two segments and is not different. All in all, there was no conclusive evidence found to accept the third hypothesis and will thus be rejected.

Overall, the results indicate that corporate layoffs in the US had a positive impact on stock performance, a negative impact on corporate performance, and this impact was consistent between the tech industry and other sectors.

CHAPTER 8 Discussion

8.1 Econometric Validity and Limitations

Concerning the validity and limitations in this study, several things can be pointed out. First of all, it is important to note that the Difference-in-Difference framework, although applicable, is of limited use in this research as the shock in this research is not entirely exogenous. This relates to the Parallel Trends assumption as it is crucial for the control and treatment groups to follow parallel trends as this assumption allows researchers to attribute differences in outcomes post-intervention to the shock itself. A layoff is not exogenous as it is a decision made by the company internally. Naturally, exogenous factors such as the macroeconomic conditions and regulations affect all companies, but it is more of a challenge to fulfil the Parallel Trends Assumption with layoffs as the intervention. In the future it could be advised to utilize a more advanced model to mitigate the risks involved with the DiD-framework.

Furthermore, as the period of time that was focused on during this research, is relatively recent, is it always possible that implications and effects have not revealed themselves yet, and therefore could not be included in this paper. It takes time for changes in variables such the ROE, Market Value etc. to appear and an improved or worsened Market Value for example may not have manifested itself yet after a single quarter. Therefore, it would be advisable to reconsider this research and data in the future and observe changes in the data.

Moreover, the included sample in this research is relatively small and only span over a single year. To enhance robustness and decrease chances of biases, unreliable estimators, and statistical errors, a bigger sample could be used over the span of multiples years, to better observe changes in stock and corporate performance.

8.2 Recommendations

As is expected in research, there are always improvements possible to expand the study. This paper was specifically focused on the effect of layoff announcements on stock-and corporate performance in the American technology industry. To provide a wider perspective, other countries than the US could be considered as well in this research. Since other countries, such as the Netherlands, have different laws and policies around employee rights and workforce reduction, it could add an interesting point of view to see the differences between countries. Other variables such as the role of AI could also be factored into a broadened model, if appropriate data is available. Lastly, more comprehensive research on layoffs with a closer look on micro-level, could be enlightening. This way, you could look more closely to why layoffs have occurred in certain firms and which type of workers get laid off the most often and why. Furthermore, a labour productivity and efficiency perspective could also be used as a measure of corporate performance opposed to the financial perspective only, to enhance the study.

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APPENDIX A Layoff Companies in Sample

#	Ticker Symbol	Company Name	Layoff Date	Notes
1	DM	Desktop Metal, Inc.	13/06/2022	Tech Layoff
2	COMP	Compass, Inc.	14/06/2022	Tech Layoff
3	PATH	UiPath Inc.	27/06/2022	Tech Layoff
4	APP	AppLovin Corporation	27/06/2022	Tech Layoff
5	HOOD	Robinhood Markets, Inc.	26/04/2022	Tech Layoff
6	NEWR	New Relic, Inc.	18/08/2022	Tech Layoff
7	SNAP	Snap Inc.	31/08/2022	Tech Layoff
8	GDRX	GoodRx Holdings, Inc.	31/08/2022	Tech Layoff
9	LPSN	LivePerson, Inc.	15/09/2022	Tech Layoff
10	DOCU	DocuSign, Inc.	28/09/2022	Tech Layoff
11	EGHT	8x8, Inc.	04/10/2022	Tech Layoff
12	RAMP	LiveRamp Holdings, Inc.	03/11/2022	Tech Layoff
13	VRNS	Varonis Systems, Inc.	06/11/2022	Tech Layoff
14	META	Meta Platforms, Inc.	09/11/2022	Tech Layoff
15	RNG	RingCentral, Inc.	09/11/2022	Tech Layoff
16	BLND	Blend Labs, Inc.	10/11/2022	Tech Layoff
17	ASAN	Asana, Inc.	15/11/2022	Tech Layoff
18	ESTC	Elastic N.V.	30/11/2022	Tech Layoff
19	ZUO	Zuora, Inc.	06/12/2022	Tech Layoff
20	BKKT	Bakkt Holdings, Inc.	08/12/2022	Tech Layoff
21	NRDY	Nerdy, Inc.	08/12/2022	Tech Layoff
22	DSP	Viant Technology Inc.	13/12/2022	Tech Layoff
23	BIGC	BigCommerce Holdings, Inc.	15/12/2022	Tech Layoff
24	MU	Micron Technology, Inc.	03/01/2023	Tech Layoff
25	CRM	Salesforce, Inc.	04/01/2023	Tech Layoff
26	VMEO	Vimeo, Inc.	04/01/2023	Tech Layoff
27	SOUN	SoundHound AI, Inc.	05/01/2023	Tech Layoff
28	INFA	Informatica Inc.	10/01/2023	Tech Layoff
29	DH	Definitive Healthcare Corp.	12/01/2023	Tech Layoff
30	LVOX	LiveVox Holdings, Inc.	17/01/2023	Tech Layoff
31	MSFT	Microsoft Corporation	18/01/2023	Tech Layoff
32	NCNO	nCino, Inc.	18/01/2023	Tech Layoff
33	MGNI	Magnite, Inc.	19/01/2023	Tech Layoff
34	LAW	CS Disco, Inc.	19/01/2023	Tech Layoff
35	GOOGL	Alphabet Inc.	20/01/2023	Tech Layoff
36	YEXT	Yext, Inc.	23/01/2023	Tech Layoff
37	PD	PagerDuty, Inc.	24/01/2023	Tech Layoff
38	IBM	International Business Machines Corporation	25/01/2023	Tech Layoff

39	LRCX	Lam Reserach Corporation	25/01/2023	Tech Layoff
40	CFLT	Confluent, Inc.	26/01/2023	Tech Layoff
41	NTAP	NetApp, Inc.	31/01/2023	Tech Layoff
42	HUBS	HubSpot, Inc.	31/01/2023	Tech Layoff
43	MTCH	Match Group, Inc.	01/02/2023	Tech Layoff
44	OKTA	Okta, Inc.	02/02/2023	Tech Layoff
45	DELL	Dell Technologies Inc.	06/02/2023	Tech Layoff
46	SCWX	SecureWorks Corp.	07/02/2023	Tech Layoff
47	ZM	Zoom Video Communications, Inc.	07/02/2023	Tech Layoff
48	GDDY	GoDaddy Inc.	08/02/2023	Tech Layoff
49	GTLB	GitLab Inc.	09/02/2023	Tech Layoff
50	TWLO	Twilio Inc.	13/02/2023	Tech Layoff
51	BLKB	Blackbaud, Inc.	14/02/2023	Tech Layoff
52	DOCN	DigitalOcean Holdings, Inc.	15/02/2023	Tech Layoff
53	MLNK	MeridianLink, Inc.	28/02/2023	Tech Layoff
54	EB	Eventbrite, Inc.	28/02/2023	Tech Layoff
55	BYND	Beyond Meat, Inc.	14/10/2022	Non-Tech Layoff
56	UPST	Upstart Holdings, Inc.	01/11/2022	Non-Tech Layoff
57	NSTG	NanoString Technologies Inc.	08/11/2022	Non-Tech Layoff
58	RDFN	Redfin Corporation	09/11/2022	Non-Tech Layoff
59	ILMN	Illumina, Inc.	14/11/2022	Non-Tech Layoff
60	CSCO	Cisco Systems, Inc.	16/11/2022	Non-Tech Layoff
61	AMZN	Amazon.com, Inc.	16/11/2022	Non-Tech Layoff
62	ROKU	Roku, Inc.	17/11/2022	Non-Tech Layoff
63	SYBX	Synlogic, Inc.	01/12/2022	Non-Tech Layoff
64	DOMA	Doma Holdings Inc.	06/12/2022	Non-Tech Layoff
65	BZFD	BuzzFeed, Inc.	06/12/2022	Non-Tech Layoff
66	APRN	Blue Apron Holdings, Inc.	08/12/2022	Non-Tech Layoff
67	EGIO	Edgio, Inc.	13/12/2022	Non-Tech Layoff
68	CVNA	Carvana Co.	18/12/2022	Non-Tech Layoff
69	BFLY	Butterfly Nework, Inc.	04/01/2023	Non-Tech Layoff
70	SFIX	Stitch Fix, Inc.	05/01/2023	Non-Tech Layoff
71	EDIT	Editas Medicine, Inc.	09/01/2023	Non-Tech Layoff
72	COIN	Coinbase Global, Inc.	10/01/2023	Non-Tech Layoff
73	LIFX	Life360, Inc.	12/01/2023	Non-Tech Layoff
74	TDOC	Teladoc Health, Inc.	18/01/2023	Non-Tech Layoff
75	VRM	Vroom, Inc.	18/01/2023	Non-Tech Layoff
76	ISPO	Inspirato Incorporated	18/01/2023	Non-Tech Layoff
77	W	Wayfair Inc.	20/01/2023	Non-Tech Layoff
78	CTV	Innovid Corp.	23/01/2023	Non-Tech Layoff
79	VCSA	Vacasa, Inc.	24/01/2023	Non-Tech Layoff
80	WISH	ContextLogic Inc.	31/01/2023	Non-Tech Layoff
81	PYPL	PayPal Holdings, Inc.	31/01/2023	Non-Tech Layoff

82	FREQ	Frequency Therapeutics, Inc.	01/02/2023	Non-Tech Layoff
83	GETR	Getaround, Inc.	02/02/2023	Non-Tech Layoff
84	OPRT	Opportun Financial Corporation	09/02/2023	Non-Tech Layoff
85	BARK	BARK, Inc.	09/02/2023	Non-Tech Layoff
86	UDMY	Udemy, Inc.	14/02/2023	Non-Tech Layoff
87	REAL	The RealReal, Inc.	16/02/2023	Non-Tech Layoff
88	EQRX	EQRx, Inc.	24/02/2023	Non-Tech Layoff

Note: All layoff companies in sample.

APPENDIX B Table Index Tech Layoffs vs. Overall

Observation Date	Overall	Tech Industry
2022-04-01	100,0	100,0
2022-05-01	110,4	87,5
2022-06-01	110,1	121,9
2022-07-01	111,5	103,1
2022-08-01	121,2	175,0
2022-09-01	107,0	90,6
2022-10-01	113,6	140,6
2022-11-01	110,7	121,9
2022-12-01	109,9	168,8
2023-01-01	128,1	190,6
2023-02-01	116,0	118,8
2023-03-01	137,5	134,4
2023-04-01	118,5	50,0
2023-05-01	115,2	118,8
2023-06-01	115,6	93,8
2023-07-01	115,9	109,4

Note: Index tech layoffs vs. overall layoffs. Baseline is April 2022 with index = 100.

APPENDIX C Table CAARs

t	CAAR (1)	Standard error (2)	t-stat (3)	p-VALUE (4)
-5	0,304%	0.024	0.13	0.899
-4	-0,951%	0.033	-0.29	0.777
-3	0,845%	0.042	0.20	0.842
-2	1,963%	0.036	0.54	0.591
-1	1,347%	0.027	0.50	0.618
0	1,911%	0.024	0.81	0.421
1	1,626%	0.025	0.65	0.521
2	0,312%	0.025	0.13	0.901
3	-0,765%	0.033	-0.23	0.820
4	3,997%	0.044	0.92	0.369
5	2,639%	0.034	0.78	0.445
N				

Notes: Cumulative Abnormal Average Return displayed in percentages per day in an event window of [-5,5]. Sample of 55 companies. The standard error, t-statistics and p-values are also displayed.

APPENDIX D REGRESSION RESULTS HYPOTHESIS 2 – SMALLER SAMPLE

Independent Variables	Return on Equity (ROE) OLS (1)	Return on Equity (ROE) OLS (2)	Return on Equity (ROE) DiD (3)
LAYOFF	-0.154***	-0.097*	0.011
	(0.060)	(0.057)	(0.062)
DE RATIO		-0.004	-0.004
		(0.006)	(0.006)
MARKET VALUE		0.000***	0.000***
		(0.000)	(0.000)
ROA		1.081*	0.951
		(0.569)	(0.599)
TREATMENT			-0.119**
			(0.053)
Constant	.0067352	0.002	0.006
	(.009175)	0.010	(0.010)
N	1701	1,692	1,692
R^2	0.0014	0.0295	0.0327

Notes: OLS regression. The sample consists of 334 firms from the United States that have data from five different quarters. Market Value is in $. Ratios are between 0-1. Standard errors are given between. *p < 0.10 **p < 0.05 ***p < 0.01.