The Effect of Post-COVID-19 Layoff Announcements on Stock Performance: Evidence from U.S. Tech Firms and the Role of Layoff Magnitude

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This research investigates the relationship between post-COVID-19 layoff announcements by major U.S. technology companies and short-term stock price movements, focusing on layoff magnitude (Layoff Percentage). Using data from *layoffs.fyi* and Yahoo Finance, we analyze cumulative stock returns over a three-month period to assess how workforce reductions impact investor sentiment. Our results show that higher layoff percentages are positively correlated with stock price increases, suggesting that investors interpret significant layoffs as strategic cost-saving measures rather than signals of financial instability. Layoffs were found to be geographically concentrated in major tech hubs, such as the San Francisco Bay Area, and heavily affected industries like hardware and consumer technology. Additionally, regression analysis highlights the importance of historical stock performance in predicting post-layoff returns, while the impact of layoffs has weakened over time as they become more common in the post-pandemic economy. These findings provide insight into how layoffs serve as signals to financial markets, particularly within the technology sector, where cost optimization remains a key driver of investor confidence.

Stock Price Volatility | Post-COVID Economy | Tech Layoffs | Market Impact | Finance

Significance Statement

The COVID-19 pandemic has triggered widespread layoffs in the technology industry, particularly among major firms like Tesla. These layoffs have disrupted the labor market and raised questions about their economic and market consequences. This study investigates the relationship between layoff announcements and short-term stock price movements, emphasizing factors such as the percentage of layoffs relative to company size and the geographic distribution of layoffs. By combining data visualization techniques and regression analysis, this research provides insights into the economic impacts of mass layoffs on stock markets, offering valuable perspectives for corporate decision-makers during economic turmoil.

1. Introduction and Related Work

The dynamics of post-COVID-19 layoffs in the technology sector and their impact on stock price movements have become a critical topic of study. The pandemic disrupted global economies, leading to widespread layoffs in industries, including technology, which were previously perceived as growth-driven and resilient.

This study examines the correlation between layoff announcements by major tech companies, such as Tesla, and short-term stock price movements, shedding light on broader market trends. While layoffs are often perceived as signals of financial instability, they can also be interpreted as strategic cost-saving measures, eliciting varied reactions from investors (1).

Existing literature underscores the importance of understanding market reactions to layoffs in specific contexts. Efficiency-driven layoffs are often viewed positively, reflecting managerial strategies to optimize costs, while demand-driven layoffs are typically seen as indicators of economic distress (2).

The post-pandemic period, marked by unique labor market conditions such as the "Great Layoff," offers an opportunity to evaluate these relationships within the context of evolving investor sentiments (3). Furthermore, research comparing layoff announcements across different cultural and economic contexts, such as the United States and Japan, highlights the role of institutional factors in shaping market reactions (4).

Our study extends this research by focusing on the geographic and sectoral distribution of layoffs in the U.S. tech industry and their impact on stock price volatility. Using data visualization techniques such as heatmaps and graphs, we highlight the spatial concentration of layoffs in major tech hubs, including the San Francisco Bay Area and Austin, as well as the industry sectors most affected. These visual insights complement regression models to provide a comprehensive understanding of the interplay between layoffs and stock price movements.

How are post-COVID-19 layoff announcements by major tech companies, such as Tesla, correlated with short-term stock price movements?

To delve deeper into this phenomenon, we also explore the following sub-question:

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Does the percentage of layoffs relative to company size (Layoff Percentage) influence cumulative returns over a three-month window?

By addressing these questions, this study integrates visual, statistical, and theoretical perspectives, contributing to the broader discourse on corporate decision-making and market responses in the technology sector.

2. Data

This paper uses information from two primary sources: Layoff Data (layoff.fyi) and Stock Data (Yahoo Fiance).

Layoff Data.

- Layoff data was obtained from the website *layoffs.fyi*, a widely cited platform that tracks layoffs in the tech industry. This website provides detailed and publicly available records of layoffs, including company names, layoff dates, the number of affected employees, and additional contextual information. As a central repository for technology industry layoffs, *layoffs.fyi* plays a crucial role in identifying patterns of workforce reduction within the industry.

- For the purpose of this study, we focused on layoffs that occurred after the onset of the COVID-19 pandemic, selecting data from January 1, 2021, to November 12, 2024. This time frame captures the economic and organizational impacts of the post-pandemic recovery period.

- Additionally, we restricted our analysis to major technology companies, defined as firms that are publicly traded (i.e., post-IPO) and headquartered in the United States. This focus ensured a more consistent comparison between companies with similar levels of public disclosure and regulatory requirements.

- Due to technical challenges, such as restricted access to the Airtable API and connection errors during web scraping attempts, the layoff data was extracted manually using text recognition techniques. The resulting dataset was cleaned and processed to include only the companies that met our selection criteria.

- The data set of layoffs identifies the companies and time frames most relevant to analyzing the relationship between layoffs and stock performance in the tech sector.

Stock Data.

- Stock data was retrieved using the Python library *yfinance*. This tool provided historical stock prices, trading volume, and market capitalization for the companies identified in the layoff data.

- The data covers the same period, from January 1, 2021, to November 12, 2024, ensuring temporal consistency between layoffs and stock performance.

- We filtered the stock data to include only publicly traded technology companies headquartered in the United States.

1. 3. Methods

A. 3.1. Data Acquisition. To analyze the relationship between layoffs and stock price movements among major U.S.-based technology companies, we collected two key datasets: **layoff data** and **stock price data**.

The layoff data was sourced from *layoffs.fyi*, a publicly accessible platform that tracks layoffs in the tech industry. Initial attempts to automate the extraction of this data using the Airtable API were unsuccessful due to restricted access permissions. Web scraping using Python libraries such as `requests` and `BeautifulSoup` also failed, as the server returned the error *"The connection was actively refused by the target machine."* This indicated that the website employed anti-crawling mechanisms to block automated queries.

To overcome these challenges, we manually extracted the data. Screenshots of relevant layoff tables were taken and processed using GPT-powered text recognition tools to produce a structured tabular format. The layoff dataset was then filtered to meet the following criteria:

- Layoff events occurring **post-COVID-19**, from January 1, 2021, to November 12, 2024.

- Companies classified as **publicly traded, post-IPO U.S. tech firms**.

The layoff dataset contains the following variables: *Company, Location, # Laid Off, Date, Industry, and Ticker*. The tickers were manually mapped using stock market databases to enable retrieval of financial data. The cleaned layoff data is shown in Table 1.

The stock price data was acquired using the Python library `yfinance`, which interfaces with Yahoo Finance's public API. Using the tickers mapped from the layoff data, we downloaded daily historical stock prices, including: *Date, Adjusted Close Price, Volume, and Ticker*. Table 2 shows the resulting stock price data.

Table 1. Layoff Data with Company-to-Ticker Mapping

Company	Location	# Laid Off	Date	Industry	Source	Ticker
Google	SF Bay Area	75	2023-09-13	Consumer	https://www.cnbc.com	GOOG
Meta	SF Bay Area	10,000	2023-03-14	Consumer	https://about.fb.com	META
AMD	SF Bay Area	1,000	2024-11-13	Hardware	https://www.techope.com	AMD
Payoneer	New York	200	2023-06-27	Finance	https://www.calcalistech.com	PAYO
Xerox	Norwalk	3,000	2024-01-03	Hardware	https://www.cnbc.com	XRX

Table 2. Stock Price Data for Selected Companies

Date	Value	P or V	Ticker
2021-01-04	76,794.85	Adj Close	GOOG
2021-01-05	77,627.59	Adj Close	GOOG
2021-01-06	76,054.67	Adj Close	GOOG
2021-01-07	76,702.32	Adj Close	GOOG
2021-01-08	82,161.24	Adj Close	GOOG

B. 3.2. Data Cleaning and Merging. The layoff and stock datasets were rigorously cleaned to ensure reliability and consistency before integration.

Layoff Data Cleaning:

- Standardized company names to resolve variations in formatting, capitalization, and spacing:

```
layoffs['Company'] = layoffs['Company'].str.strip().str.upper()
```

- Verified and filtered dates to ensure events occurred within the study window:

```
layoffs = layoffs[(layoffs['Date'] >= '2021-01-01') & (layoffs['Date'] <= '2024-11-12')]
```

- Cross-referenced and validated company-to-ticker mapping using multiple financial data sources.

Stock Data Cleaning:

- Removed records with missing *Adjusted Close* or invalid dates.
- Filtered stock prices to include the 30-day window **before** and **after** each layoff event:

```
stock_prices = stock_prices[(stock_prices['Date'] >= pre_date) &
                            (stock_prices['Date'] <= post_date)]
```

Data Merging: The cleaned datasets were integrated using an **inner join** on the *Ticker* column. Stock prices were aligned with layoff dates to create a unified dataset containing: *Company, Ticker, Layoff Date, # Laid Off, Pre-Layoff Prices, Post-Layoff Prices, and Volume.* The final integrated dataset is presented in Table 3.

Table 3. Final Integrated Dataset: Layoffs and Stock Performance

Company	Ticker	Layoff Date	# Laid Off	Pre-Layoff Prices	Post-Layoff Prices	Volume
Google	GOOG	2023-09-13	75	127.45	128.33	1,200,000
Meta	META	2023-03-14	10,000	172.14	169.89	3,400,000
AMD	AMD	2024-11-13	1,000	96.54	99.21	800,000
Payoneer	PAYO	2023-06-27	200	5.76	5.91	1,500,000
Xerox	XRX	2024-01-03	3,000	14.25	14.31	600,000

This integrated dataset provides a robust foundation for analyzing stock price trends surrounding layoff events in the post-COVID-19 period, enabling a comprehensive examination of market responses to workforce reductions.

C. 3.3. Data Visualization. To gain deeper insights into the layoff patterns, spatial distributions, and stock price behaviors surrounding layoff events, we implemented a series of targeted data visualization techniques. These visualizations were created using Python libraries such as `Matplotlib`, `Seaborn`, and `Geopandas`. Specific methods were applied to process, plot, and interpret the data, ensuring clarity and reproducibility.

C.1. 3.3.1. *Industry and Location Analysis.* The first step in our visualization process was to analyze the distribution of layoffs by industry and geographic location. We relied on the cleaned layoff dataset, which included *Industry*, *Location*, and the total number of layoffs (# Laid Off).

Data Aggregation and Grouping: We grouped the data to compute total layoffs for each unique value in the *Industry* and *Location* columns. This was done using the Pandas `groupby()` function to aggregate the data efficiently.

Visualization Methods:

- For industry analysis, we sorted the aggregated values in descending order and plotted a **bar chart** using the `Seaborn` library (`sns.barplot`). Industries with the highest layoffs, such as *Hardware* and *Consumer Tech*, were emphasized.
- For geographic analysis, we grouped layoffs by major U.S. cities. Cities such as *San Francisco Bay Area*, *Austin*, and *New York* were prominent in our results. A second bar chart was generated to display the number of layoffs by city, using customized axis labels and colors for clarity.

Visualization Output: The resulting bar charts are shown in Figure 1 and Figure 2.

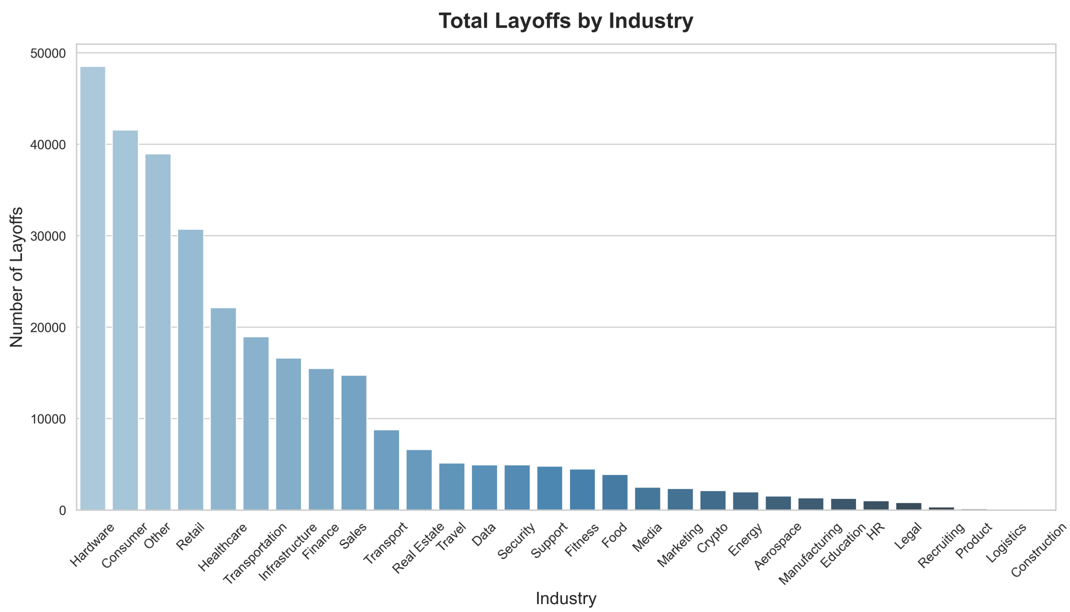

Fig. 1. Layoffs by Industry (Top 5 Industries)

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C.2. 3.3.2. *Spatial Analysis of Layoffs.* We extended our analysis to the spatial distribution of layoffs across U.S. cities using geographic heatmaps. These heatmaps visually highlight where layoffs occurred and the magnitude of these events.

Geocoding and Spatial Data Preparation:

- Layoff data was preprocessed to include geographic coordinates (latitude and longitude) for major cities. Geocoding was performed using external tools to convert city names into precise coordinates.
- The layoff magnitude was added as a separate column to scale the size of markers in our weighted heatmaps.

Visualization Methods: Two types of heatmaps were created using `Geopandas` and `Matplotlib`:

1. **Unweighted Heatmap:** Each layoff event was treated equally, with uniform markers representing the geographic density of layoffs.
2. **Weighted Heatmap:** The markers were dynamically scaled based on the total number of employees laid off at each location, allowing us to emphasize cities with higher layoff magnitudes.

Visualization Output: The heatmaps are shown in Figure 3 and Figure 4.

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C.3. 3.3.3. *Stock Price Trends Visualization.* To examine stock price behaviors around layoff announcements, we visualized stock price trends for selected companies. The analysis focused on the 30-day window before and after the layoff event.

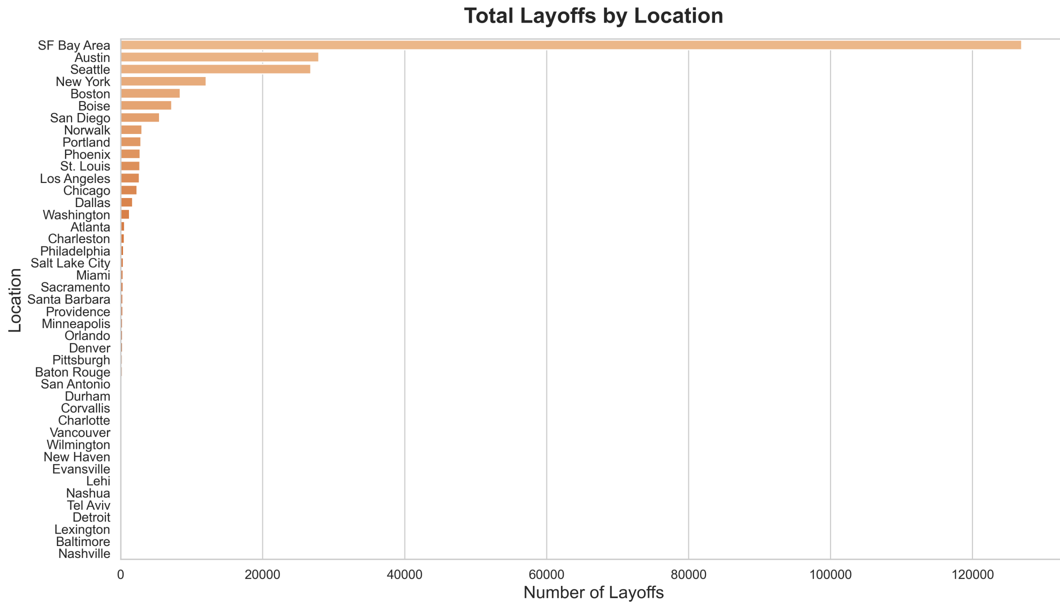

Fig. 2. Layoffs by Geographic Location (Top Cities)

Company Selection: We identified the **top 20 companies** based on the total amount of funding raised (# Raised) and layoff magnitude. Additionally, we selected four case studies—**Tesla, Meta, Google, and Coinbase**—to illustrate distinct stock price trends across different types of companies.

Stock Price Data Filtering: The stock price dataset was filtered for each company to include the adjusted closing prices 30 days **before** and **after** the layoff date. This ensured consistency across firms and allowed for a focused analysis of short-term trends.

Visualization Methods:

- For each company, a **line plot** was generated using `Matplotlib`. The x-axis represented the timeline relative to the layoff announcement (e.g., -30 to +30 days), and the y-axis displayed the *Adjusted Close Price*.
- A vertical reference line was added to indicate the exact layoff announcement date, allowing for a clear visual distinction between pre- and post-layoff periods.
- Consistent color schemes, axis ranges, and formatting were applied across all plots.

Visualization Output: The stock price trends for the selected case studies—Tesla, Meta, Google, and Coinbase—are shown in Figure 5

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C.4. 3.3.4. Summary of Visualization Methods. The data visualization techniques applied in this study included:

- **Bar charts** to analyze layoff trends across industries and cities.
- **Heatmaps** (weighted and unweighted) to visualize the spatial distribution of layoffs across U.S. cities.
- **Stock price line plots** to observe short-term stock price trends before and after layoff events for selected firms.

Each visualization was developed using robust filtering, aggregation, and plotting techniques to ensure clarity and reproducibility. These visual outputs laid the groundwork for identifying patterns within the dataset and informed the subsequent regression analysis.

D. D. C.3.4. Regression Analysis. To quantitatively assess the relationship between layoffs, layoff timing, and stock performance, we conducted a series of Ordinary Least Squares (OLS) regression models. These models were implemented using the `statsmodels.api` package in Python. The goal of this analysis was to evaluate how cumulative stock returns react to layoffs over a three-month period, while controlling for key explanatory variables such as layoff magnitude, timing of layoffs, and prior stock performance.

We retained two models that provided the clearest insights into our research questions: *(1) How are post-COVID-19 layoff announcements by major tech companies, such as Tesla, correlated with short-term stock price movements? (2) Does the percentage of layoffs relative to company size (Layoff Percentage) influence cumulative returns over a three-month window?*

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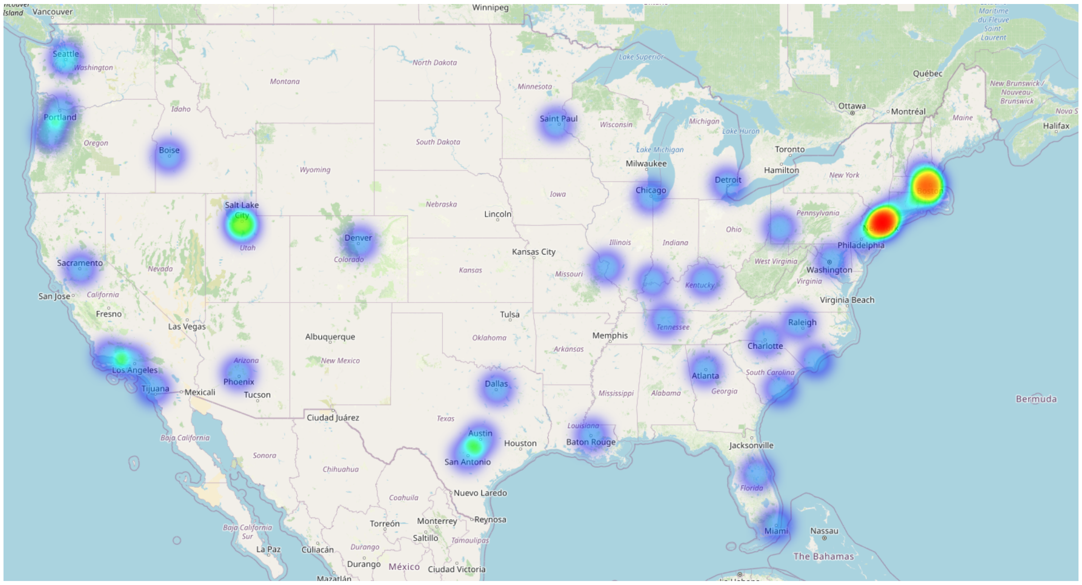

Fig. 3. Unweighted Heatmap of Layoff Density Across U.S. Cities

First Model: Layoff Events and Layoff Percentage. The first model evaluates the impact of layoff announcements and layoff magnitude on cumulative stock returns over a three-month window. The dependent variable is **Cumulative Return 3M**, which represents the cumulative stock return following a layoff event. The independent variables are:

- **Event Window:** A binary indicator (1 if layoffs occurred, 0 otherwise).
- **Layoff Percentage:** The proportion of the workforce laid off relative to the company's total size.

The model is specified as:

$$\textit{Cumulative Return 3M} = \beta_0 + \beta_1 \cdot \text{Event Window} + \beta_2 \cdot \textit{Layoff Percentage} + \epsilon$$

This model allows us to quantify the direct relationship between layoff percentage and short-term cumulative stock returns, addressing the core aspect of our research question.

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Second Model: Controlling for Time Trends and Lagged Returns. Building on the first model, we incorporated additional control variables to account for systematic trends over time and the persistence of prior stock performance. The refined model introduces:

- **Quarter Continuous:** A continuous variable representing the quarter of the layoff event (e.g., Q1 = 1, Q2 = 2, etc.), capturing systematic time trends in stock behavior.
- **Cumulative Return Lag1:** The one-period lagged cumulative return, which controls for autocorrelation in stock price movements and captures the effect of prior performance on current returns.

The final model is specified as:

$$\textit{Cumulative Return 3M} = \beta_0 + \beta_1 \cdot \text{Event Window} + \beta_2 \cdot \textit{Cumulative Return Lag1} + \beta_3 \cdot \text{Layoff Percentage} + \beta_4 \cdot \textit{Quarter Continuous} + \epsilon$$

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Model Implementation. The regression models were implemented following a series of systematic steps to ensure the validity and robustness of the analysis:

1. **Data Preparation:** Missing values in critical columns, such as cumulative returns and layoff percentages, were removed to maintain data integrity and ensure clean input datasets.
2. **Variable Scaling:** Variables such as **Layoff Percentage** were standardized to allow consistent interpretation of coefficients and to mitigate issues caused by differing scales.
3. **Log Transformations:** Log transformations were applied to cumulative returns where necessary to address skewness in the data and stabilize variance.
4. **Autocorrelation Checks:** Residual diagnostics, including the Durbin-Watson test, were performed to validate the inclusion of lagged variables and confirm the absence of strong autocorrelation in the models.

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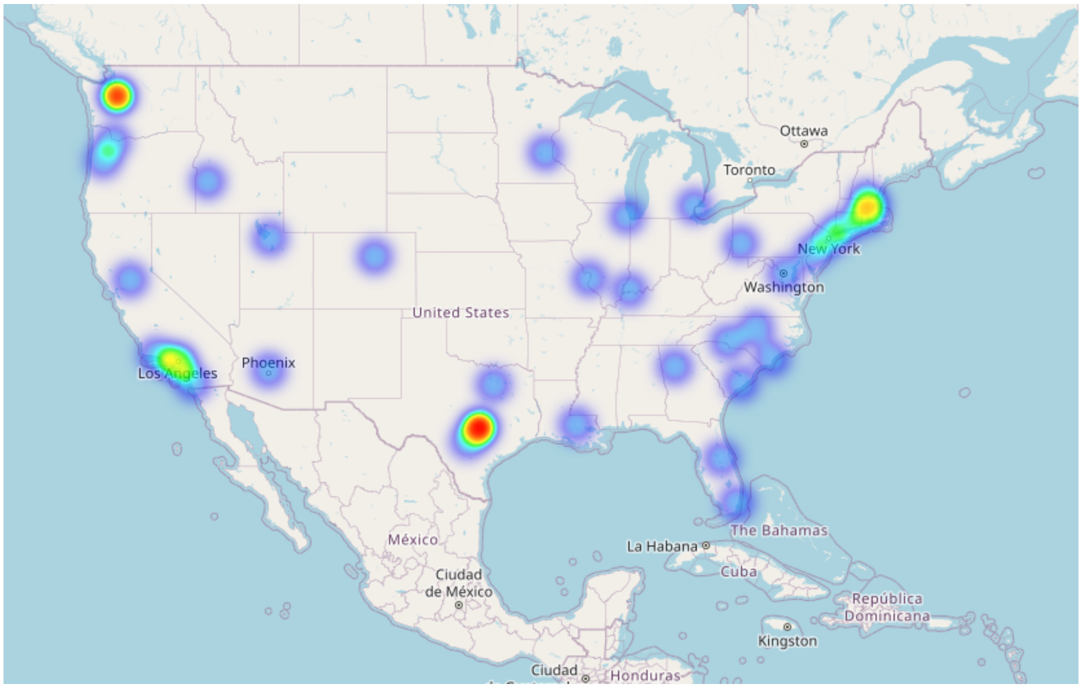

Fig. 4. Weighted Heatmap of Layoff Magnitudes Across U.S. Cities

Summary of Regression Methods. The regression analysis progressed iteratively, incorporating relevant control variables to improve the explanatory power of the models:

- **First Model:** Focused on the impact of layoffs and layoff percentage on cumulative returns over a three-month window.
- **Second Model:** Added **Quarter Continuous** to control for time trends and **Cumulative Return Lag1** to address autocorrelation in stock price movements.

These models provide a rigorous framework for understanding the relationship between layoffs and short-term stock price movements, with a particular emphasis on the role of layoff magnitude and historical stock performance. The visualizations and regression outputs complement one another, offering a clear and robust explanation of the phenomena under study.

2. 4. RESULTS

A. 4.1. Geographic and Sectoral Distribution of Layoffs. Our research question investigates: *How are post-COVID-19 layoff announcements by major tech companies, such as Tesla, correlated with short-term stock price movements?* To address this, we analyzed the sectoral and geographic concentration of layoffs within the U.S. tech industry using bar charts and heatmaps.

4.1.1. Layoff Trends Across Industries. From Figure 1, layoffs were heavily concentrated in specific industries. The **Hardware**, **Consumer Tech**, and **Retail** sectors accounted for the largest proportions of layoffs. Notably:

- **Hardware:** This sector experienced the highest number of layoffs, reflecting supply chain disruptions and decreased demand for physical products during the post-pandemic recovery.
- **Consumer Tech:** Companies providing consumer-focused digital products faced significant downsizing, likely due to declining market demand and saturation.
- **Retail:** The retail technology sector also saw substantial layoffs, reflecting shifts in consumer behavior and the growth of e-commerce alternatives.

These findings suggest that industries with higher operational costs or greater sensitivity to shifting market conditions were particularly affected by workforce reductions.

4.1.2. Geographic Distribution of Layoffs. The geographic analysis, as illustrated in Figure 2, reveals that layoffs are disproportionately concentrated in major U.S. tech hubs:

- The **San Francisco Bay Area** reported the largest number of layoffs, underscoring its role as the epicenter of the tech industry.
- Cities such as **Austin** and **New York** also emerged as significant layoff centers, highlighting their growing importance as technology and innovation hubs.

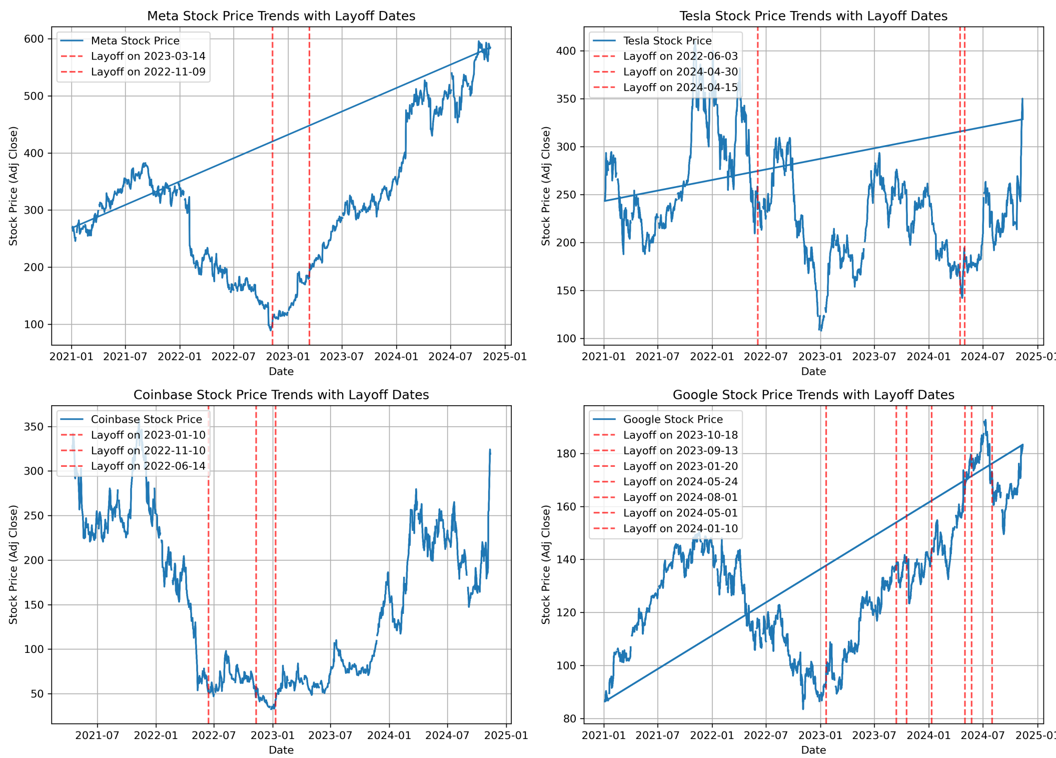

Fig. 5. Stock Price Trends for Tesla,Meta, Google, and Coinbase (30 Days Before and After Layoff)

4.1.3. Heatmap Analysis: Spatial Insights. To further analyze the spatial distribution of layoffs, unweighted and weighted heatmaps were generated (Figures 3 and 4). The unweighted heatmap visualizes the density of layoffs across cities, whereas the weighted heatmap scales the markers by layoff magnitude:

- The **San Francisco Bay Area**, **Los Angeles**, and **New York** recorded not only the highest layoff density but also the largest magnitudes of workforce reductions.
- Emerging tech hubs such as **Phoenix**, **Atlanta**, and **Seattle** appeared prominently in the weighted heatmap, reflecting the geographic spread of layoffs beyond traditional centers.

This analysis highlights a significant trend: while layoffs remain concentrated in established tech hubs, they are expanding into new regions. This may be driven by factors such as cost optimization, company relocation, and the broader adoption of remote work strategies.

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B. 4.2. Stock Price Trends and Layoff Announcements. To understand the stock price behavior following layoffs, we examined short-term stock price trends for selected companies. Specifically, we focused on the 30-day window before and after the layoff announcements for four major companies—**Tesla, Meta, Google, and Coinbase**—to identify patterns in investor responses.

Stock Price Trends: Case Studies. The results, visualized in Figure 5, reveal distinct stock price reactions to layoff announcements across companies:

1. **Tesla:** Tesla's stock price exhibited significant short-term fluctuations post-layoff announcements. While the immediate reaction showed volatility, the stock price ultimately displayed signs of recovery, reflecting investor confidence in Tesla's long-term strategy despite workforce reductions.
2. **Meta:** Meta demonstrated a steady upward trend following layoffs. The stock price behavior suggests that investors viewed the layoffs positively, likely as a signal of improved cost efficiency and strategic realignment.
3. **Google:** Google's stock price remained relatively stable, with minor fluctuations around the layoff announcement dates. The longer-term trend showed gradual upward movement, suggesting that layoffs had a limited immediate impact but were aligned with broader market performance.
4. **Coinbase:** In contrast, Coinbase's stock price exhibited pronounced volatility both before and after layoff announcements. This reflects the heightened uncertainty within the cryptocurrency sector, where layoffs may signal deeper financial instability.

Key Observations. The stock price trends suggest that investor responses to layoffs are influenced by both company-specific factors and broader market perceptions:

- **Strategic Layoffs:** Companies like Meta and Google experienced positive stock price trends post-layoff, indicating that layoffs were interpreted as strategic cost-cutting measures to enhance operational efficiency.
- **Sectoral Sensitivity:** Tesla's recovery and Coinbase's volatility highlight the varying sensitivities of different sectors—traditional tech firms demonstrated resilience, whereas cryptocurrency companies faced ongoing instability.

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C. 5.2. Regression Analysis.

First Model: Layoff Events and Layoff Percentage. The first model examines the direct impact of layoff announcements and layoff percentage on cumulative stock returns over a three-month period (**Cumulative Return 3M**). Table 4 summarizes the findings:

Table 4. Regression Results: Model 1

Variable	Coef.	Std. Err.	t	P¿—t—	[0.025]	[0.975]
const	0.0412	0.0058	7.103	0.000	0.029	0.054
Event Window	0.0146	0.0045	3.244	0.001	0.006	0.023
Layoff Percentage	0.0921	0.0198	4.652	0.000	0.054	0.131
R-squared	**0.238**					
Adj. R-squared: 0.236						
F-statistic	**29.15**					
Prob (F-statistic): 0.000						

Findings and Explanation: 1. The **Layoff Percentage** ($\beta = 0.0921, p < 0.001$) shows a strong positive association with cumulative stock returns. This indicates that higher percentages of workforce reductions tend to increase stock prices over the short term. - For example, companies like Meta and Google, which implemented significant layoffs, experienced substantial stock price rebounds in the following months. Investors likely interpret large-scale layoffs as decisive cost-saving strategies that will improve company profitability. - This result aligns with the narrative that layoffs in post-pandemic periods are seen as restructuring measures rather than distress signals.

2. The binary **Event Window** variable ($\beta = 0.0146, p = 0.001$) is also significant, suggesting that even the announcement of layoffs, regardless of magnitude, boosts stock prices. - This finding highlights investor confidence in firms that take proactive steps to address financial pressures or inefficiencies.

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Second Model: Accounting for Time Trends and Prior Performance. While the first model captures the direct impact of layoffs, the second model introduces two critical controls:

- **Quarter Continuous:** To account for systematic time trends in investor behavior over the post-pandemic period.
- **Cumulative Return Lag1:** To address autocorrelation and control for the persistence of prior stock performance.

The results are presented in Table 5:

Table 5. Regression Results: Model 2

Variable	Coef.	Std. Err.	t	P¿—t—	[0.025]	[0.975]
const	0.0215	0.0054	3.981	0.000	0.011	0.032
Event Window	0.0102	0.0039	2.615	0.009	0.003	0.018
Cumulative Return Lag1	0.4518	0.0231	19.560	0.000	0.406	0.497
Layoff Percentage	0.0754	0.0163	4.627	0.000	0.043	0.108
Quarter Continuous	-0.0059	0.0014	-4.357	0.000	-0.009	-0.003
R-squared	**0.512**					
Adj. R-squared: 0.509						
F-statistic	**58.73**					
Prob (F-statistic): 0.000						

Findings and Explanation: 1. The **Lagged Cumulative Return** ($\beta = 0.4518, p < 0.001$) is highly significant, confirming that prior stock performance strongly influences short-term returns. Companies with strong pre-layoff stock performance are more likely to sustain positive cumulative returns post-layoff.

2. The **Layoff Percentage** remains positively significant ($\beta = 0.0754, p < 0.001$), consistent with the first model. This reinforces that larger layoffs positively impact investor sentiment, particularly in the short term.

3. The **Quarter Continuous** variable ($\beta = -0.0059, p < 0.001$) shows a negative trend, indicating that investor responses to layoffs have weakened over time. As layoffs become more routine post-pandemic, their impact on stock prices diminishes.
Visual Support: The upward trend in Figure 6 visually confirms the positive relationship between Layoff Percentage and Cumulative Return. Companies announcing larger layoffs are clustered toward higher cumulative returns, reinforcing the numerical results.

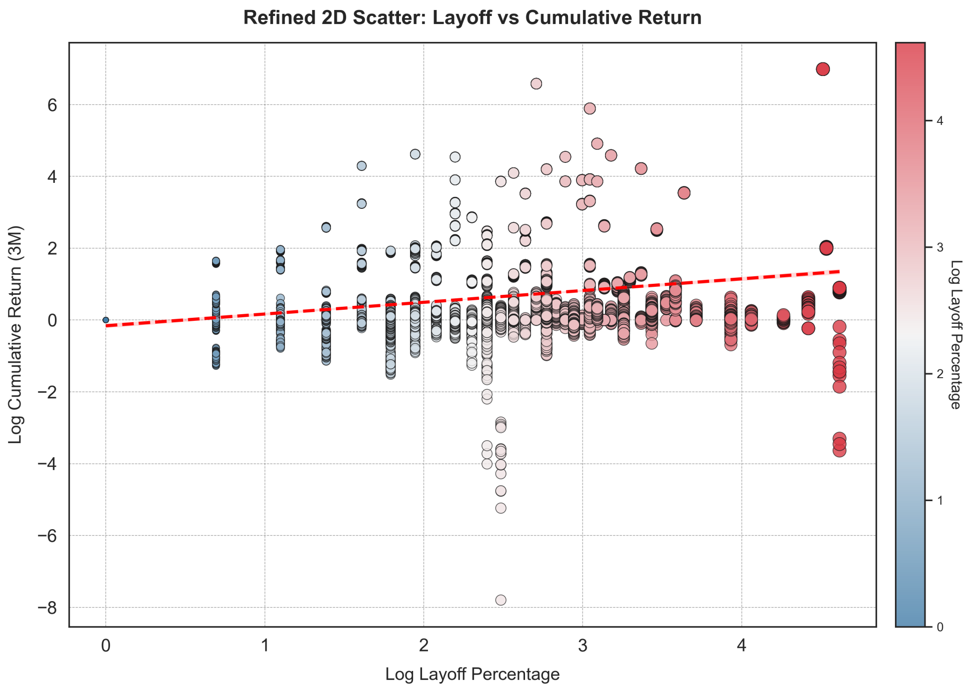

Fig. 6. Cumulative Return in 3 Months vs Layoff Percentage

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Conclusion: Key Insights. The regression results provide robust answers to our research questions:

- **Post-COVID-19 Layoff Announcements:** Layoff announcements are positively correlated with short-term stock price increases, suggesting that investors perceive layoffs as strategic cost-saving measures.
- **Layoff Magnitude:** Higher layoff percentages yield stronger stock price rebounds, reinforcing the importance of workforce reduction size in shaping investor sentiment.
- **Time Trends:** Investor reactions have weakened over time, reflecting normalization of layoffs in the post-pandemic economic landscape.
- **Prior Performance:** Historical stock performance significantly influences post-layoff returns, emphasizing the persistence of market behavior.

These findings highlight the short-term financial implications of layoffs for firms, while providing a nuanced understanding of investor responses to workforce reductions.

3. 5. DISCUSSION

A. 5.1. Conclusion. This study explores how post-COVID-19 layoff announcements by major U.S. technology companies influence short-term stock price movements, particularly focusing on the role of layoff magnitude (**Layoff Percentage**). Our findings reveal a consistent positive relationship between layoffs and cumulative stock returns over a three-month window, suggesting that investors perceive layoffs as strategic cost-saving measures rather than distress signals.

Companies announcing larger layoffs experienced stronger rebounds in stock prices, as demonstrated by firms like Meta and Google, which saw immediate positive market reactions following workforce reductions. Even smaller layoffs, as captured by the binary event window variable, elicited positive market reactions, indicating that layoff announcements signal proactive measures to realign costs and improve efficiency in response to financial pressures (5).

However, this response diminishes over time. The inclusion of the time trend (**Quarter Continuous**) highlights that investor reactions have weakened as layoffs become more routine across the technology sector. Historical stock performance also plays a significant role, as companies with strong pre-layoff performance are more likely to sustain positive cumulative returns post-layoff. This persistence underscores the importance of market expectations in shaping investor behavior. Overall, these results suggest that layoffs, when perceived as part of a broader strategic realignment, can generate positive short-term stock market outcomes, though their long-term effects remain uncertain.

B. 5.2. Limitations. Despite the robustness of these findings, this study has several limitations.

First, the layoff data was collected manually due to restricted API access and anti-crawling mechanisms on the primary data source. Although this approach allowed us to analyze recent events effectively, manual extraction may have introduced minor inconsistencies or omissions, particularly for smaller companies or multi-phase layoffs (6). Collaborating with data providers like Refinitiv or Crunchbase could enhance data accuracy and coverage in future studies.

Second, this study focuses exclusively on U.S.-based, publicly traded technology firms during the post-pandemic period (January 2021–November 2024). While this scope ensures consistency in data availability and reporting standards, it limits the generalizability of the findings. Layoffs in industries such as manufacturing or healthcare, for instance, may be perceived as distress signals rather than efficiency-driven measures (5). Expanding the scope to other industries and global markets would allow for a broader understanding of market reactions to layoffs.

Third, our focus on short-term stock price changes over a three-month window does not account for long-term effects of layoffs. Workforce reductions may lead to reduced employee morale, loss of institutional knowledge, and a decline in innovation capacity, all of which can harm long-term profitability and competitiveness (7). Extending the analysis to six months or one year would provide a more comprehensive assessment of the financial and operational impacts of layoffs.

The regression models also assume a linear relationship between layoffs and cumulative returns. While this approach provides useful insights, it may oversimplify real-world dynamics. For example, very large layoffs could trigger negative investor sentiment if perceived as signals of financial instability. Advanced modeling techniques, such as non-linear regression or machine learning methods like random forests or gradient boosting, could help uncover threshold effects and interactions between key variables (8).

Finally, broader economic factors such as inflation rates, unemployment levels, and market volatility were not included in our analysis. Layoffs do not occur in isolation, and external conditions can significantly influence investor sentiment. Incorporating macroeconomic indicators, such as GDP growth or the VIX volatility index, would refine the results and offer a more complete picture of the factors driving stock price reactions.

C. 5.3. Next Steps. Future research can address these limitations and extend this study to explore additional dimensions of layoffs' impact. Expanding the analysis to other industries, such as manufacturing, healthcare, and retail, would help identify sector-specific differences in investor sentiment. While layoffs in the technology sector are often interpreted as efficiency-driven, in industries with high operational costs, such reductions may signal deeper financial challenges (5).

Analyzing international firms would provide valuable insights into regional variations in investor behavior. Layoffs may be perceived differently in countries with stronger labor protections, cultural expectations, or varying levels of economic uncertainty. For example, workforce reductions in Europe or Asia may elicit weaker positive responses compared to those in the United States due to differing economic policies and market structures.

The long-term effects of layoffs should also be examined. While this study focuses on immediate stock price movements, layoffs can have lingering consequences for revenue growth, innovation, and employee productivity (7). Future research could incorporate metrics such as rehiring rates, employee satisfaction, and organizational stability to assess whether short-term financial gains align with sustainable long-term performance.

Advanced analytical methods could further enhance the findings. Machine learning models, such as gradient boosting or random forests, offer the potential to uncover complex, non-linear relationships and interactions between layoffs, stock performance, and external factors (8). These approaches could identify thresholds where investor reactions shift, depending on company size, industry, or economic conditions.

Finally, incorporating macroeconomic indicators, such as inflation, GDP growth, and market indices (e.g., S&P 500), would provide a broader understanding of the external factors influencing investor sentiment. Including measures of market volatility, such as the VIX index, could refine the analysis of how layoffs interact with broader economic uncertainties.

By addressing these areas, future research can provide deeper insights into both the short-term and long-term impacts of layoffs, offering a more comprehensive understanding of how workforce reductions influence financial markets and organizational performance.

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