Economic Trends and Tech Layoffs: Understanding the Economic Forces Reshaping the Tech Industry

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Github Repository

March 16, 2025

Abstract

This project work considers the correlation between layoff trends and macroeconomic indicators: GDP, interest rates, etc. Data was collected through web scraping, Open-Datasets(Kaggle), and the whole dataset of layoff information is from 2020 to 2025. Data for 2020-2022 was gathered through Kaggle. Data after 2022 was collected from Airtable's through data scraping. The FRED API captures the economic trends. Macroeconomic indicators formed the basis of the analysis. Our findings point to significant trends linking layoff rates to economic downturns and policy reforms, providing implications for the broad economic impact of employment trends. The study points out the central role of economic forces in shaping the stability of labor markets as well as the importance of evidence-based analysis in predicting workforce patterns.

Keywords: Layoff Trends, Economic Indicators, Data Scraping, GDP, Interest Rates, Workforce Analysis, Correlation Analysis

1 Introduction

The global economy is in its very own nature highly dynamic and from that point of view, substantially alter vital aspects of society such as job opportunities and retention. In particular, the technology industry has experienced very great upheaval through the years. For years it has been seen as an industry of stability, innovation, and constant growth, however recent trends show otherwise. In past few months, an unprecedented number of more than 51000 employees have been laid off by the bulk of big corporations, including Meta, Amazon, Microsoft, Google, and many others. This layoff wave is among the largest employment declines in industry history, and it forces basic questions about the economic and strategic forces driving these efforts.

The sheer quantity and regularity of such layoffs themselves reveal that they are not isolated incidents but are the culmination of a larger trend among the tech sector. Post-pandemic market adjustments, inflationary stress, rising interest rates, and shifting investment priorities have been among the reasons cited. A scenario, wherein job security, which used to be taken for granted inside a technology industry, now comes under greater scrutiny. This new context calls for an examination of the relationship between the economy and working patterns, especially in a sector that was thought to boost economic growth and technological innovation.

2 Motivation

Being international students seeking a career in technology, we've been seeking internships vigorously since last fall but never received interview invitations until now. This is firsthand evidence of how job hunting is hard in the current climate. Even if one gets employed, it's a terrifying thought to do business in the job market with the existing layoff trend. It is motivated by a desire to find and emphasize determinants of employment stability in the technology sector with the goal of providing information that would be useful to both job seekers and policymakers.

3 Literature Review

Some articles claim that the tech layoffs hinge on a plethora of reasons: from the economic condition and inflation to higher interest rates, over-hiring, and a normalization phase following the COVID-19 pandemic[1]. This is exacerbated by the rise of AI[2], which has taken out many traditional roles in tech, contributing to increasing unemployment in the IT sector. In 2024 alone, despite a strong labor market, the tech sector had massive layoffs, shedding over 225,000 tech workers[3]. This paradox of layoffs happening even when the economy is strong has been the center of attention of late.

4 Research Gap

A lot of recent news covers the rising tide of layoffs in high-tech industries. Reports cite inflation as well as rising interest rates and corrections in the post-pandemic market[4] as prime suspects for such layoffs. Little empirical research exists that has firmly established connections between layoff rates and the economic factors of GDP growth and interest rate variability over time. Even though there are press releases and some anecdotal references drawing a connection between recessions and workforce cutbacks([5], quite very few studies have thoroughly documented hiring behaviors in the tech sector in correspondence with these external factors.

Finding a solution to this gap may contribute to creating a more detailed view of challenges for new incoming job seekers in tech occupations, and the ones who are already there. Our project aims to seek answers to the following research questions.

5 Research Questions

1. What is the nature of correlation between macroeconomic indicators (GDP, interest rate) and layoff trends within the U.S. tech sector from 2020 to 2025?
2. In what way have external economic shocks (like those of the COVID-19 pandemic and the bursting of the 2022 tech bubble) led to fluctuations in layoff rates among other industries in general and tech in particular?

3. What role does a company's corporate financial health (funds raised, investment stage) play in influencing this decision regarding the number of layoffs and their scope?

4. Do major corporations target geographically centralized layoffs and if yes, to what extent does the nature of targeting differ between the various states?

5. What industries with the tech sector experienced the heaviest job losses, in comparison with the industry overall?

6 Methodology

6.1 Data Scraping

While scraping the data, we found ourself practicing a lot of trial and error methods. Records fetching from Airtable's dynamic content loading and virtualized scrolling turned out to be more difficult and time consuming than expected. Since Airtable provided no easy way to use a direct API, we opted for the use of Selenium WebDriver to navigate the page. The typical scrolling mechanisms did not pan out, so we had to try multiple manners before locking on the best course of action for doing so.

The **first way** we tried was to set the offset and **scroll stepwise** to fetch the data. Most of the time, though, the scrollbar would freeze for 20 to 30 iterations and jump suddenly to row 400, skipping many data rows. To work on this, we calculated the heights of rows and tried scrolling some fixed number of rows per iteration; however, that too did not solve the problem, since the scrollbar was still unpredictable. After that, we tried to **scroll in the parent container**, but only later we figured out that the Xpath we grabbed was not doing the scrolling thing actually. Next, we tried to scroll into view each row by using **"scrollIntoView" function in JavaScript**; while it did work to some extent, the page got refreshed eventually, and we lost all our progress as the page was reset to top. We also tried to select the last visible row and scroll it into view in order to **trigger lazy loading in Airtable**, but this technique wasn't able to consistently load more records. Another way to do this was that it mimicked mouse wheel scrolls by dispatching **JavaScript's WheelEvent**, which gives tremendous control over the incremental steps of scrolling, but produced a jittery result. The other method was to drag the scrollbar in small increments (10 pixels each iteration), but as scrolling occurred, the variable speed of scrolling changed erratically, leaving gaps in the data.

For debugging, we put in row counting and no-change detection, noting **.dataRow elements** to see whether new rows were loading. If no changes were detected for several iterations, we assumed we had reached the end of the dataset. While this approach finally verified the inconsistency in scrolling, it did not fix the issue. Accordingly, we tried to simulate presses of the **"ARROW-DOWN"** key as though doing manual scrolling, only to see that after a few iterations it stopped responding. Afterward, we tried out scrolling on the basis of **offsets with ActionChains** from Selenium, manually noting which rows were visible and estimating the number of iterations required. There, we noticed that with an increased depth of scrolling, the scrolling speed accelerated, skipping great spans of data. We then attempted to make the offset iterative, dynamically changing, with little effect to slow down the scrolling.

The **last method** adopted was to make the scroll movement, (0,1), ensuring minimal movement per iteration while increasing the iteration count, running over 1240 iterations.

So it retrieved six times the expected amount of data at first, hence the post-data extraction filtering for unique rows. This method allowed one to optimize the amount of data retrieved and avoid data misses. Overall, it involved a lot of **trial and error** with different scrolling methods in Airtable scraping. The combination of **dynamic content loading, unpredictable UI behaviors, and virtualized scrolling** made the task heavy going. The final method, involving fine-grained scrolling and removing duplication, worked best, showcasing the difficulties in scraping heavily dynamic web apps.

These datasets illustrate a historical layoff trend after augmenting our existing database scraped from Airtable with publicly available layoff data downloaded from Kaggle from 2020 and 2022. The combination of both sets of data gave us a continuum from 2020 to 2025, which we analyzed to include macroeconomic trends into our layoff analysis.

Through the API of **Federal Reserve Economic Data (FRED)**, which provides a combination of various U.S. economic indicators we tried to incorporate macro-economic data in our analysis. The aim was to grab economically relevant information that could help ascertain how tech layoffs varied over time with the relevant economic information. To access the FRED API, we had to set up an API key first, hence we used the fredapi library to request data. While we enjoyed the access to many economic indicators, finding the right datasets that would mesh well with our layoff data was a challenge.

One of the **initial hurdles** we faced while dealing with economic characteristics was to find which of them would come to be relevant to layoffs. The FRED API contains thousands of economic indicators that cover various industries and kinds of markets. Careful consideration and **back-and-forth analysis** involved manually sifting through these datasets. We had to be make sure that the actual indicators fit both statistically and made logical sense with respect to employment conditions in the tech space.

After manually reviewing various options, we focused on the following **key economic indicators**: Gross Domestic Product (GDP) Growth Rate, Unemployment Rate by State, Federal Funds Interest Rate, Inflation Rate (Consumer Price Index - CPI), Tech Industry Employment Levels, Labor Force Participation Rate.

Once we got clear on indicators, we made API requests for each economic attribute and constructed responses into a Pandas DataFrame. Economic data channels are usually expressed on either a monthly or quarterly basis, hence we ensured that the **timestamps were compatible** with the layoff data. The **missing values** from time series data were imputed via interpolations, ensuring continuity within the data. Another impediment was identifying the right names of the economic attributes within FRED API. The API codes each dataset quite specifically, and they are not always self-evident. Matching a dataset exactly with what we wanted on our end became a case of running round in a circle with **multiple API queries**, checking descriptions and doing test outputs. This took a whole lot of trial and error before finalizing Datasets.

6.2 Data Processing

Data processing was undertaken in an organized manner to unify and standardize the layoff data from Kaggle and Airtable, so as to enable consistent information for proper analysis. Both datasets were about layoffs but with different column names, formats, and structures that needed some cleaning before merging, and later exploration. There were some inconsistent column names that had to be standardized to facilitate the merging process. We made use of a column mapping to change all headers into the same name format. Once they had been renamed, we set the "Date" column to a standardized datetime format so that everything could be sorted and analyzed on chronological terms.

Before merging, each dataset was filtered in respect to years we needed. Also, missing values in the essential columns (Laid Off, Percentage) were dropped to keep the data accurate. Still, the level of funding with missing values was retained, given that the imputation of this would distort some sort of financial analyzation afterwards. The two datasets were cleaned and filtered, and the merging process into a single DataFrame was executed in such a way as to maintain column definitions while respecting the uniqueness of many records. The generated dataset was further sorted by date in a descending order to ensure that the most recent layoffs are appearing at the front.

6.3 Visualization

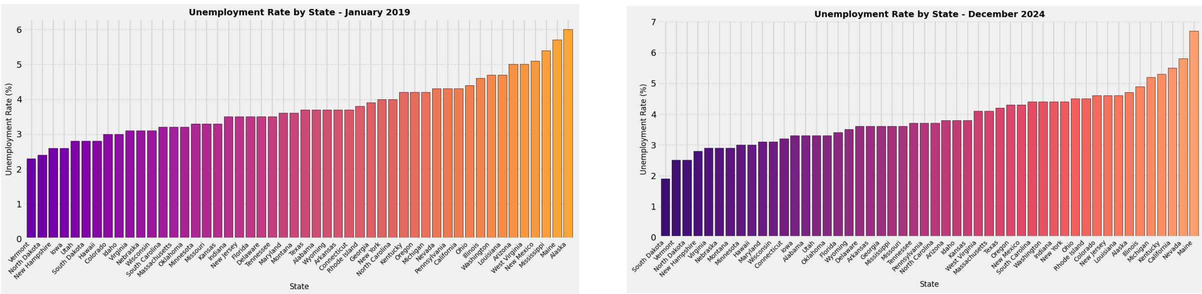

Figure 1: Unemployment rate comparison across all 50 states, January 2019 and December 2024.

The analytical presentation in Figure 1, displays how economic downturns have created job instability in distinct regions. The jump in unemployment of Statesthat includes Maine, Nevada, and California gives more credibility to the notion that such layoffs have some correlation with macroeconomic situations.

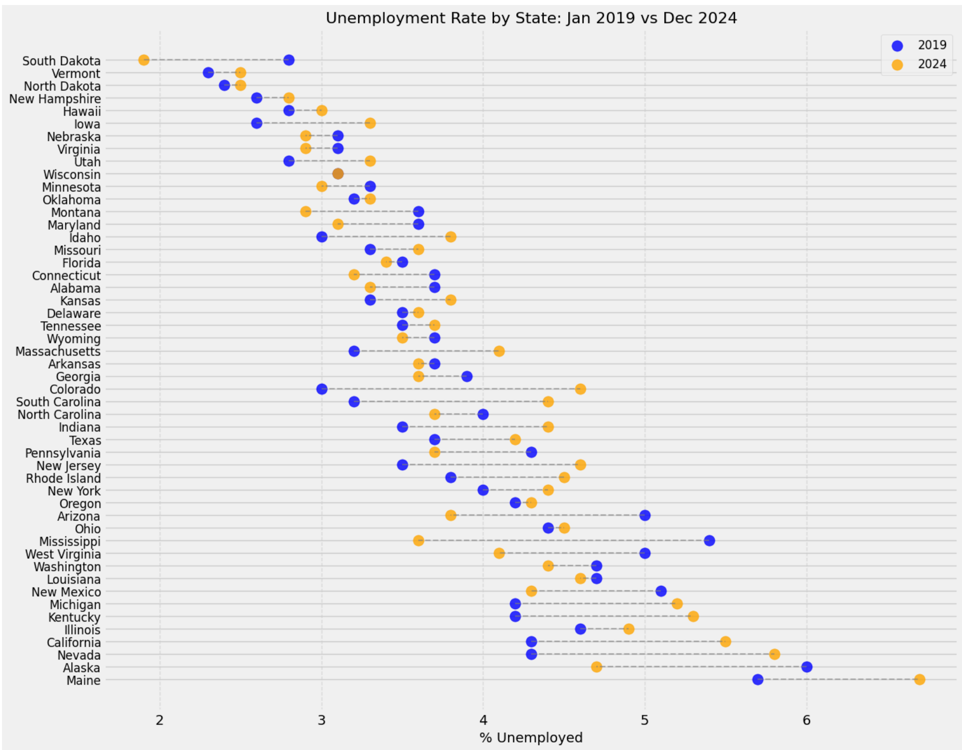

Figure 2: Comparison of dot plots highlighting state-wise unemployment trends over time.

The comparison of the dot plots in Figure 2 indeed highlights that most states experienced an increase in unemployment, with some having more resilience than others. This organization of the data confirms the hypothesis that economic turbulence resulted in a widely shared but often focused loss of jobs, particularly in states with prominent amounts of tech activities.

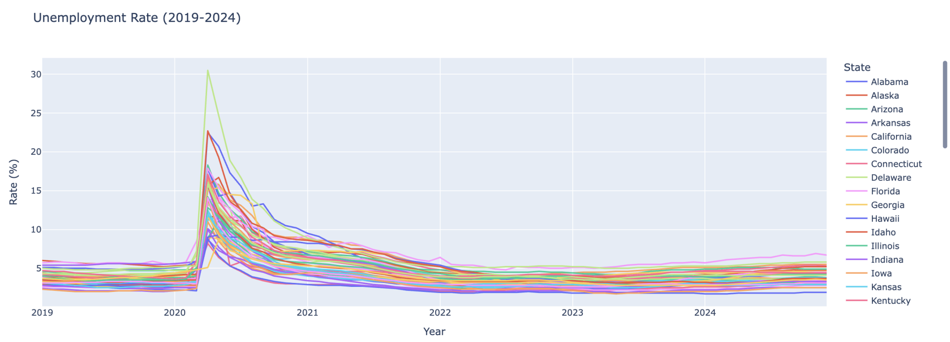

Figure 3: Time Series Analysis of Unemployment Rate from 2019 to 2024.

Figure 3 presents various changes during the COVID-19 shock, partial recovery, and subsequent increase in layoff announcements after the successive interest hikes and market corrections.The data indicates that certain states experience considerably more ups and downs, especially those with economies driven by technology, thus confirming a position of relative exposure for the sector to downturns in economic conditions. This visualization takes macro perspective, providing a link between national employment trends and the spurt of layoffs in the tech sector.

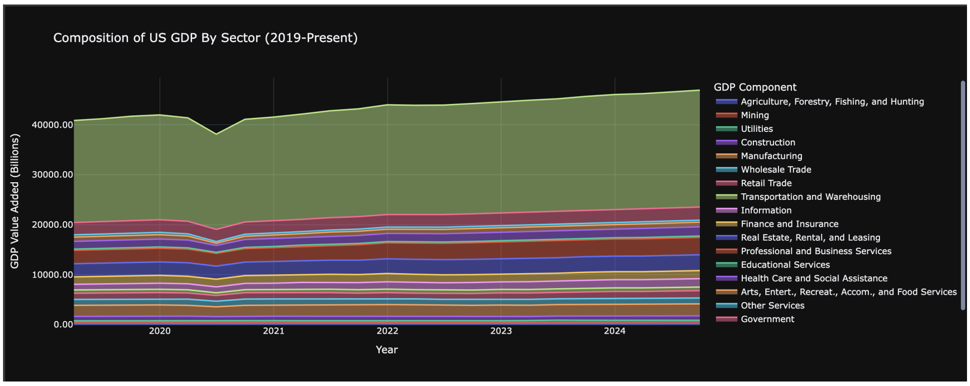

Figure 4: Comparision of US GDP by sector

To better understand economic trends, Figure 4 shows fluctuations in tech revenues compared to finance and healthcare, which were stable. This supports the idea that not every industry is affected equally by recessions, and layoffs preferentially occur in areas, like tech, that have enjoyed fast growth and are now under risk.

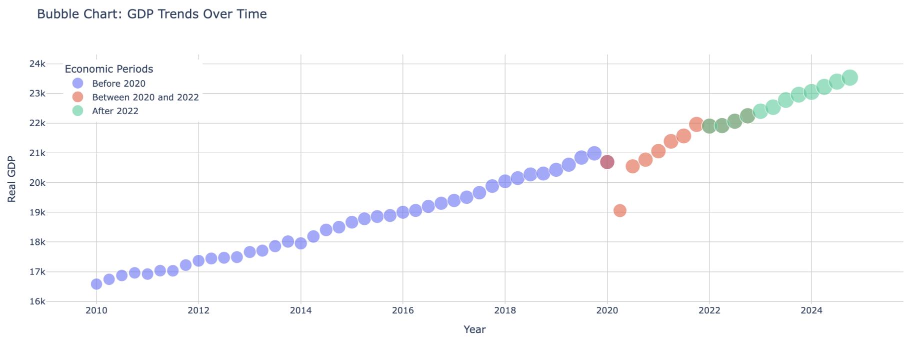

Figure 5: GDP trends through bubble chart

Figure 5 outlining GDP trends over time splits economic activity into three portions: pre-pandemic stability, COVID-19 recession and recovery, and lastly, post-2022 layoffs and tightening. Layoffs hence continued amidst GDP stabilization, indicating that GDP recovery does not equate to job security.

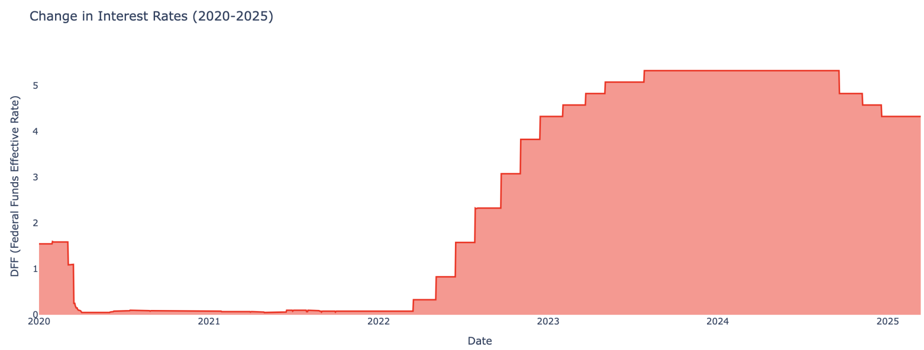

Figure 6: Change in Interest Rates over the years

The role interest rates will play in corporate hiring and cost-cutting decisions relates to the interest change visualization as we see in Figure 6. The steep raise in interest rates post-2022 coincides with layoffs peaking, supporting the assertion that the higher borrowing cost led to the reduced hiring rate and downsizing of the many. Overlay analysis of layoffs and interest rates further indicates a direct relationship between increasing interest rates and rising layoffs. The time-lag effect points to business responses to interest rate hikes in increments; they may choose to lay off employees only after the company has come under financial strain.

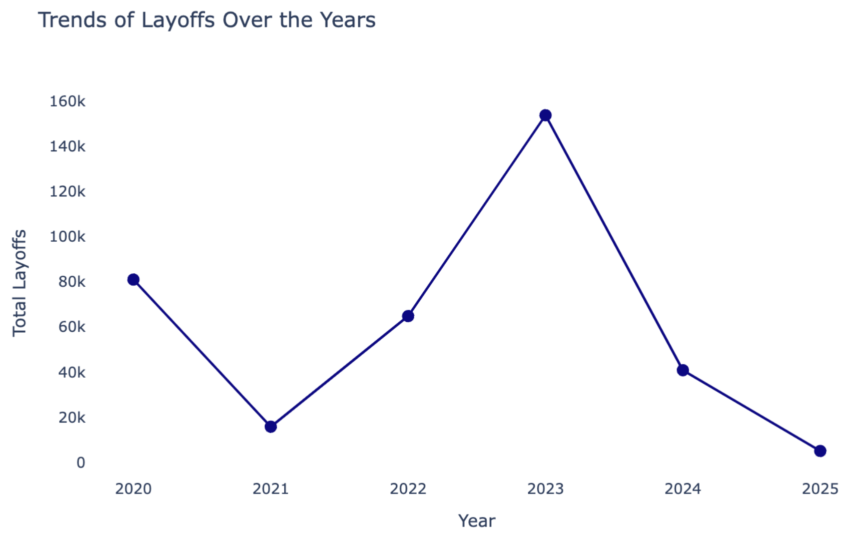

Figure 7: Trends in layoff

Figure 7 captured the spikes of layoff activities in 2020 (COVID-19) and 2023 (post-tech boom correction), with a minor decrease in 2024, remaining above pre-COVID levels. This visualization further depicts that layoffs in tech are not cyclical but structurally shifting; that is, companies are changing in response to the developing economic reality. The overall visualization set abides by best practices, strongly substantiating the claims with data-driven insights and is introductory to understddddddddanding how economic shifting influences layoff occurrences in the tech sector.

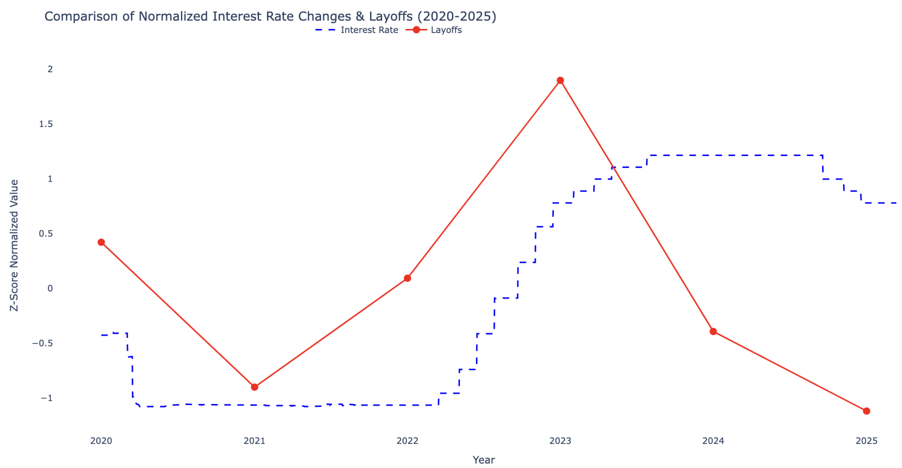

Figure 8: Interest Rate and Layoff Rate Analysis

Figure 8 illustrates the relationship between increasing interest rates and layoffs in the technology sector. In the period from 2020 to 2021, low rates enabled business growth but layoffs continued to be minimized. In 2021, there was a sharp increase in the rate of interest, which then caused mass layoffs that peaked out by the year 2023. In 2024 to 2025, although interest rates were high, layoffs declined; that is, the delayed reaction was probably cause companies take time to implement cost cutting. This confirms that high-interest rates do induce layoffs, but only with some delay because time is needed for the actual implementation of cost-defraying measures. The data visualization adequately provides support to the theoretical assumption that tremendous economic policies have an effect on the stability of jobs within technology.

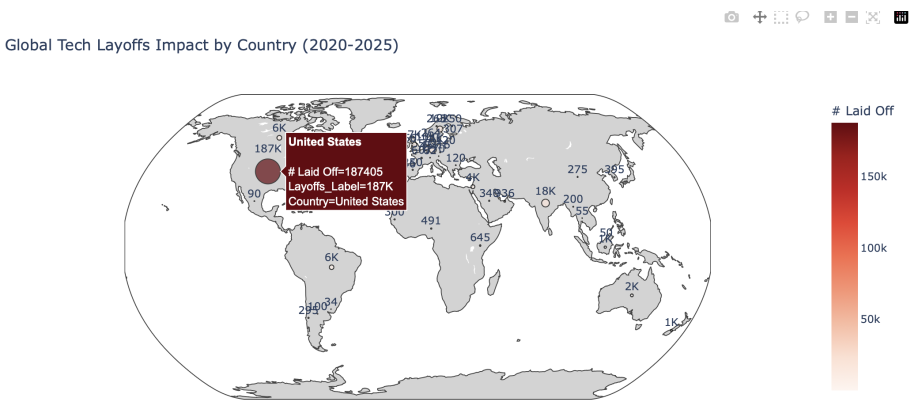

Figure 9: Global Tech Layoffs Impact by Country

Figure 9 illustrates the global distribution of tech redundancies from 2020 to 2025, with the United States being the most affected, with 187K redundancies. The rest of the regions, including Europe, Asia, and South America, have varying levels of redundancies since they are impacted by varying economic conditions and industry reliance. The heatmap is able to show these variations, giving insight into how workforce cuts have impacted the global tech sector.

7 Conclusion

Our findings determine the key economic drivers and structural shifts that are behind workforce reductions in tech. To give answers to the research questions we had at the start, these are some numbers based on the above findings:

- **Macroeconomic Impact:** The economic impacts of increased interest rates showed a high positive association with employment reductions, and GDP was of very small direct impact; raising the cost of lending was the primary reason for employment decreases, rather than economic slowdowns.

- **External Shocks:** COVID-19 (2020) invented initial layoffs in tech followed closely by a hiring boom from 2021–2022 and the following sharp contraction led by the 2022 tech bubble burst, forcing companies to lay off workers so they could get back into compliance with constraints posed on them financially.

- **Financial Health:** Startups and mid-stage companies witnessed a higher rate of layoffs due to an increased reliance on venture capital; large tech firms, on the other hand, made staffing cuts later on due to waning profitability. .

- **Geographic Trends:** Most layoffs occurred in the U.S. tech hubs of Silicon Valley, Seattle, and Austin; overseas, layoffs were low due to different funding structures and operational costs involved in the sectors.

- **Industry-Specific Impact:** High layoff numbers were reported in SaaS, fintech, and e-commerce; semiconductor, cloud computing, and cybersecurity industries did comparatively well and withstood the most impact.

References

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