The Ripple Effect: Unraveling the Intricate Relationship Between Tech Sector Layoffs and Consumer Spending Patterns in the San Francisco Bay Area

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Abstract: This study conducts a rigorous investigation into the financial and economic implications of tech sector layoffs on consumer spending patterns in the San Francisco Bay Area. Utilizing a unique dataset comprising daily and weekly data from March 13, 2020, to February 19, 2023, the analysis employs local projection methods to explore the dynamic relationship between layoffs and consumer spending. The daily data analysis reveals a statistically significant negative correlation between tech layoffs and consumer spending, with an estimated decrease of 0.002 percentage points in spending per additional layoff at day 8 (p-value of 1.71e-12). These findings align with the theoretical underpinnings of Mueller (1966) and Reich (2001), which emphasize the impact of unemployment on consumer spending. Conversely, the weekly data analysis yields mixed results, with significant fluctuations challenging the derivation of concrete insights. To alleviate the detrimental effects of job losses, the study recommends implementing comprehensive severance packages, outplacement support services, and fostering a culture of continuous learning within the workforce. By providing a robust analysis of the intricate relationship between tech sector layoffs and consumer spending patterns, this research offers valuable insights for future studies and policy development in the context of workforce displacement.

Keywords: tech sector layoffs, consumer spending, local projection method, San Francisco Bay Area, economic implications, workforce displacement, financial assistance, policy development, unemployment

I Introduction

The pandemic brought about a hiring boom for technology companies in Silicon Valley. However, this trend took a turn with significant layoffs in the tech sector beginning in 2022. This research investigates the implications of these layoffs on the financial well-being of affected employees and the wider economy, with a focus on the San Francisco Bay Area, home to numerous leading technology firms.

Job losses can have financial consequences for employees, which may lead to cautious spending behavior. When unemployment rates increase and people become more apprehensive about their financial future, they tend to cut back on their spending. This, in turn, can affect businesses and contribute to economic stagnation.

This study aims to assess the financial implications of layoffs on employees and to explore the potential effects of these layoffs on spending behavior through regression analysis. Furthermore, the research will touch upon possible strategies for mitigating the negative impacts of layoffs on both employees and companies and the role of governmental and non-governmental organizations in addressing the issue of job losses.

By examining the relationship between tech sector layoffs and consumer spending patterns in the Bay Area's local economy, this research intends to offer a holistic understanding of the technology sector's present situation and its influence on the economy. The insights gathered will inform future policies and practices that can minimize the detrimental effects of downsizing while fostering sustainable growth and development in the technology industry and beyond.

II Previous Work

By building on prior findings, this study seeks to contribute to the current understanding of the relationship between layoffs and consumer spending, exploring the delineated case study in the introduction. Previous research has examined the impact of unemployment on consumer confidence, with Eva Mueller's (1966) work building on how awareness of unemployment was a significant contributor to the decline in consumer optimism between 1958 and 1963. Additionally, she explored a developed Index of Consumer Confidence, which has proven to be an effective predictor of consumer spending. This proven relationship affirmed in Eva's work is one of the factors I will investigate in my body of work, though I will not be focusing that much on consumer's confidence.

Robert Reich's (2001) paper examined how long consumers can keep spending, as layoffs and debt may dampen buyers' enthusiasm. Reich noted that a slowdown usually starts the other way around, with consumers reducing their spending because they have depleted too much of their savings and can no longer afford or choose not to borrow more. This, in turn, causes companies to cut back on their spending due to declining sales. However, during his research, he stated that companies started the downturn, which is an angle I plan to approach.

Oscar Jorda's (2005) paper, "Estimation and Inference of Impulse Responses by Local Projections," introduces a state-of-the-art method for computing impulse responses. The core concept of an underlying dynamic system involves estimating local projections at each period of interest, rather than extrapolating into distant horizons using a model, as is done with Vector Autoregression (VAR). This is the ideal methodology that I will employ in my research to reveal the truth behind my thesis statement.

Arindam Mandal and Joseph McCollum (2013) examined the short-term and long-run relationships between unemployment rates and the Consumer Confidence Index across five Metropolitan Statistical Areas (MSAs) in New York State. They found that there is a negative causality between consumer sentiment and unemployment in the, with each factor reinforcing the other. In the long term, a significant negative causality from consumer confidence to unemployment was identified. In a related study, Olivier Coibion, Yuriy Gorodnichenko, and Michael Weber (2020) evaluated the economic impact of the COVID-19 crisis by assessing the effects of lockdowns on macroeconomic expectations and consumer spending. Their findings suggest that the implementation of lockdown measures contributed significantly to the decline in employment and reductions in consumer spending in recent months. Although my research approach is not a direct replication of the methodologies used in these two studies, it shares similarities with their work. By employing a comparable analytical framework, I aim to determine whether my findings will resonate with their conclusions.

III Data

The impact of recent tech sector layoffs on consumer spending within the San Francisco Bay Area was evaluated by using a distinctive dataset derived from two primary sources. The first source contained layoff information specific to the San Francisco Bay Area, gathered from Layoff.fyi. This dataset was updated daily, featuring the number of tech sector layoffs alongside corresponding dates from March 13, 2020, through to June 5, 2022. Subsequently, the dataset was restructured to a weekly format due to the transition of consumer spending data into a weekly frequency around the same period. This transition necessitated a calculation of the average number of weekly layoffs. Consequently, I opted to work with both daily and weekly datasets, with the weekly data offering a comprehensive view of the data available from March 13, 2020, through February 19, 2023.

The process of manually collating the data and keeping track of the counts in real-time was both time-consuming and labour-intensive. Nevertheless, this comprehensive dataset will enable a thorough analysis of the relationship between tech sector layoffs and consumer spending patterns in the San Francisco Bay Area. The dual daily and weekly data formats will allow for a nuance examination of short-term fluctuations and long-term trends, providing valuable insights into the local economy's resilience and adaptability during periods of workforce upheaval.

The second data source for my research was obtained from OpportunityInsight.org/Affinity Solutions, which provided information on the total consumer spending percentage change in the San Francisco Bay Area, relative to consumer spending in January 2020. This dataset was aligned with the daily layoff data, spanning from March 13, 2020, to June 5, 2022, before transitioning to a weekly average rate. As a result, the data will be analyzed on both daily and weekly timeframes, with the weekly dataset extending from March 13, 2020, to February 19, 2023. Unlike the layoff data, the consumer spending dataset exhibited fewer gaps and offered more comprehensive coverage of the relevant period.

Table 1. Summary Statistics for Daily Data

Variables	Min	1st Quarter	Median	Mean	3rd Quarter	Max
Layoff Count	0.0	0.0	0.0	45.7	0.0	3750.0
Consumer Spending Rate	-0.4440	-0.1770	-0.1310	-0.1406	-0.0805	0.0417

Table 2. Summary Statistics for Weekly Data

Variables	Min	1st Quarter	Median	Mean	3rd Quarter	Max
Layoff Weekly Average	0.0	0.0	2.0	114.7	87.5	1898
Consumer Spending Rate Weekly Average	-0.42900	-0.16243	-0.09868	-0.11292	-0.04095	0.04410

Tables 1 and 2 present the summary statistics for the daily and weekly layoff and consumer spending percentage change, respectively. From these data, we can observe some noteworthy trends. The layoff daily count demonstrates a wide range, with a minimum of 0 and a maximum of 3,750, indicating significant fluctuations in the tech sector's employment landscape. The average layoff count of 45.7 further highlights the presence of extreme values affecting the mean. In contrast, the consumer spending daily rate exhibits a relatively tighter distribution, with the minimum and maximum values being -0.4440 and 0.0417, respectively. The median spending rate of -0.1310 and mean of -0.1406 suggest a general decline in consumer spending during the analyzed period.

We notice some differences when comparing the summary statistics of the weekly averaged data to the daily data. For the layoff count, the weekly data demonstrates a narrower range (Min=0.0, Max=1898) compared to the daily data. The median value increases from 0.0 to 2.0, while the mean rises from 45.7 to 114.7, indicating a higher average number of layoffs per week. The consumer spending rate exhibits a smaller range in the weekly data (Min=-0.429, Max=0.04410) compared to the daily data, and both the median (-0.09868) and mean (-0.11292) values are less negative, suggesting a slightly better consumer spending trend on a weekly basis.

IV Empirical Strategy

In this analysis, we will employ the local projection method for impulse response calculation, which obviates the need for specifying or estimating an underlying dynamic system. Instead, local projections are estimated for each period of interest, circumventing the necessity for future extrapolation commonly associated with vector autoregression (VAR) analysis.

The primary advantage of the local projection method is its reliance on simple regression techniques, executable using standard regression packages. Consequently, our methodology is both accessible and user-friendly, as it does not necessitate comprehensive knowledge of intricate econometric models. Additionally, by using these regression techniques, we reduce the likelihood of errors and complications arising from estimating complex dynamic systems. Furthermore, the local projection method enables straightforward joint or point-wise analytic inference due to its independence from complex dynamic systems and interrelated parameter estimation, typically found in VAR analysis.

Another noteworthy usefulness of the local projection method is its capacity for exploring highly non-linear and flexible specifications that may be difficult to implement within a multivariate context such as VAR analysis. Local projections allow researchers to incorporate various non-linear forms and interactions in their models, effectively capturing the complex relationships between economic variables that might be overlooked in conventional multivariate frameworks.

Chart 1 (Daily Data)

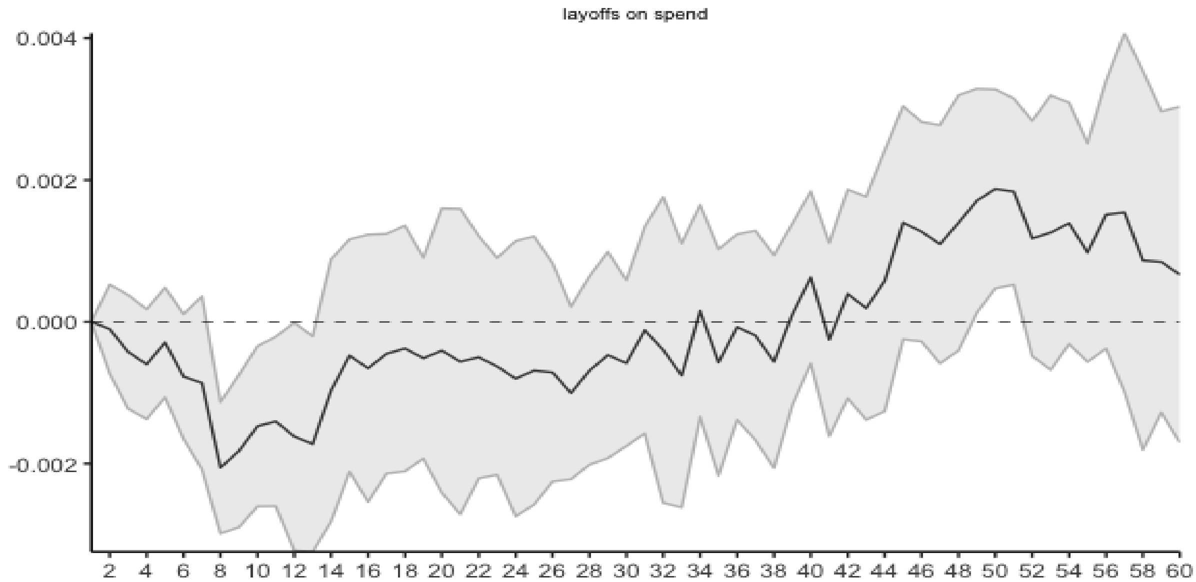
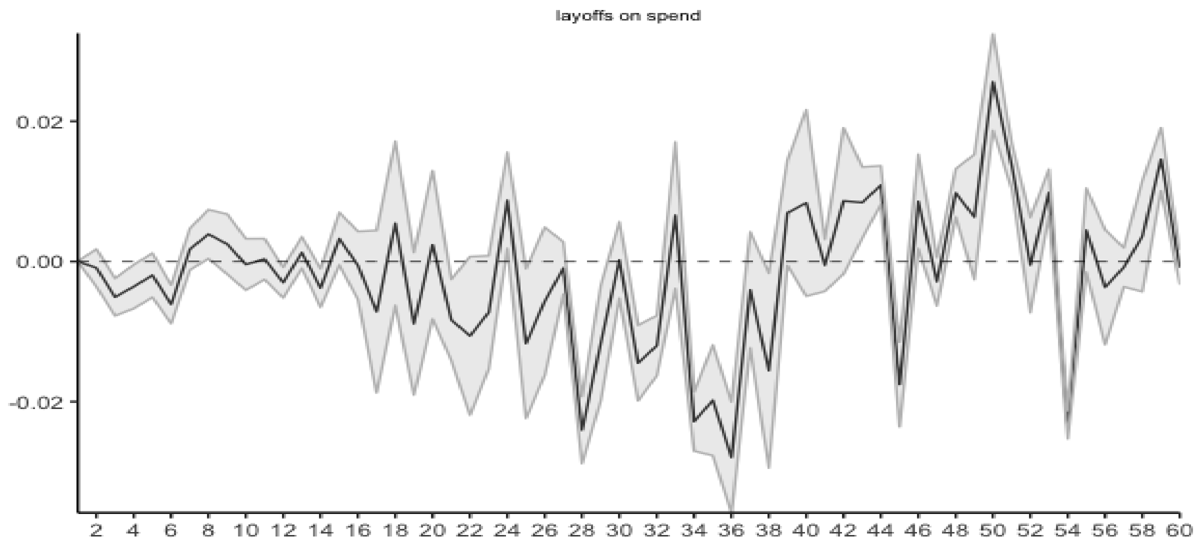


Chart 2 (Weekly Data)



The y-axis represents our regression coefficients, while the x-axis represents the 60 horizons into the future, which are days in the daily chart and weeks in the weekly chart. The shaded area in the trend represents the degree of freedom, visually representing the confidence intervals associated with the estimated coefficients.

The Impact of the recent Tech layoff on consumer spending was estimated using the regression equation below.
$C_{t+h} - C_{t-1}/\underline{C} = \alpha_h + \beta_h LO_t + U_{t,h}$

In this equation, C_{t+h} represents consumer spending at time t+h, where various horizons h ranges from 1 day to 60 days for daily data and 1 week to 60 weeks for weekly average data. C_{t-1} denotes consumer spending at time t-1, and $\underline{C}$ symbolizes consumer spending in January 2020. As such, $C_{t+h} - C_{t-1} / \underline{C}$ represents the percentage change in consumer spending relative to that of January 2020. LOt refers to the layoffs at time t, and $U_{t,h}$ represents the error term. The local projection method is based on sequential regressions of the endogenous variable shifted several steps ahead. The findings based on this regression specification are discussed in the next section.

V Results

Charts 1 and 2 present the result of estimating the above equation using local projections for daily and weekly data. In the daily data analysis, a negative correlation between tech layoffs and consumer spending emerges around day 8, indicating that as layoffs increase, consumer spending declines. For example, at day 8, each additional layoff decreases consumer spending by 0.002 percentage points (p-value of 1.71e-12), signifying a statistically significant relationship at the 95% confidence interval. This trend continues until around day 48, where the relationship becomes statistically insignificant. Interestingly, at approximately 50 days, the relationship turns positive, with consumer spending increasing by 0.001 percentage points per layoff. While this positive relationship may appear counterintuitive, it is important to note that the 50-day mark is quite far into the future, and drawing conclusions based on this relationship may not be reliable. In summary, the analysis reveals a complex relationship between tech sector layoffs and consumer spending patterns, with varying degrees of correlation and significance depending on the time frame examined. The statistically significant negative relationship is observed in the initial days, while the positive relationship observed at 50 days should be interpreted with caution due to its distance into the future.

With respect to the weekly average data, the observed trends remained statistically insignificant until approximately 20 weeks into the analysis. At this point, a negative relationship emerged, suggesting that as tech layoffs increased, consumer spending declined—a relationship that appears plausible. Between 20 and 38 weeks, numerous fluctuations occurred, but each time a significant trend was identified, it reaffirmed the negative correlation between tech layoffs and consumer spending. Interestingly, the relationship became more erratic after 38 weeks, with periods of significant positive correlations appearing at around 42 weeks, 51 weeks, and 53 weeks, and negative correlations at 45 weeks and 54 weeks. These fluctuations make it challenging to draw definitive insights from the data. The analysis concluded with a positive relationship at approximately 59 weeks.

The weekly average data revealed a dynamic and nuanced relationship between tech sector layoffs and consumer spending patterns. However, the alternating periods of negative and positive correlations with varying degrees of statistical significance make it difficult to draw any concrete insights from the data. As such, the findings were inconclusive.

VI Robustness Check

In an effort to ensure that the outcomes of my analysis are not influenced by unobserved factors associated with specific days of the week or months, I incorporated certain control measures in the form of dummy variables. For the daily data, I included a separate dummy variable for each day of the week as well as for each month to account for all the potential underlying factors. In the case of the weekly data, I solely incorporated dummy variables for each month, given that days of the week are less relevant in this context. Upon integrating these control measures, I re-executed the analysis. This meticulous approach to the analysis not only addresses potential confounding factors but also bolsters the validity and robustness of the findings, thereby providing a more comprehensive understanding of the intricate relationship between tech sector layoffs and consumer spending patterns.

Chart 1 (Daily Data)

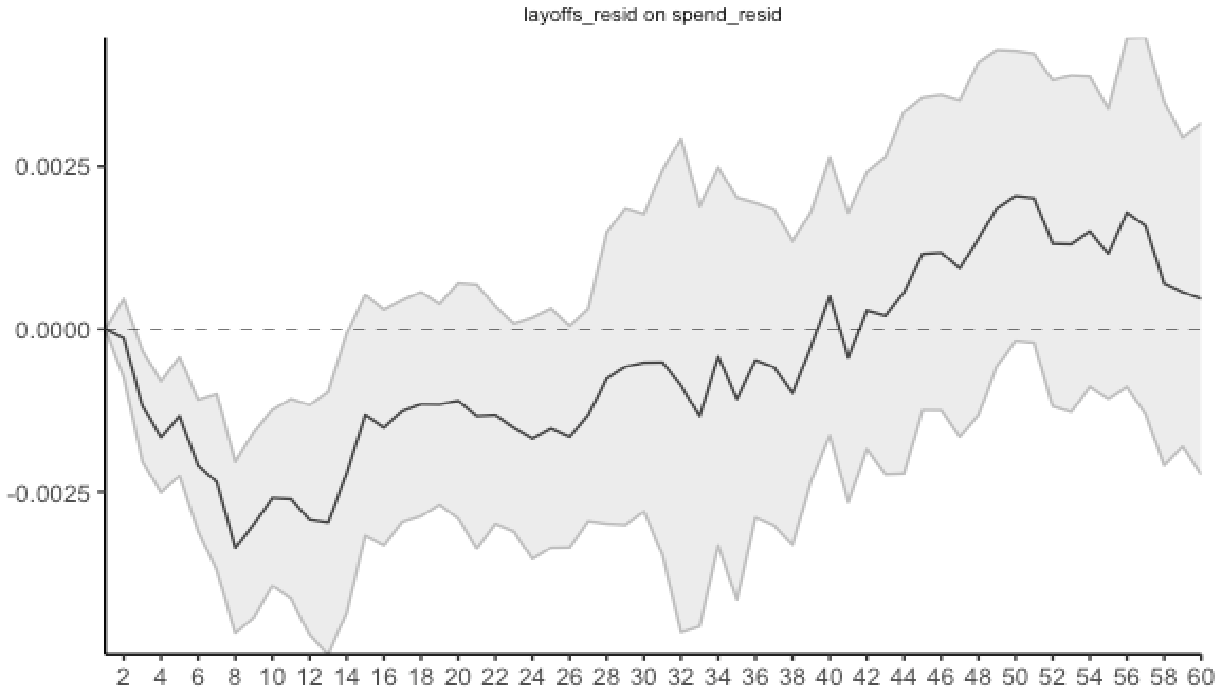
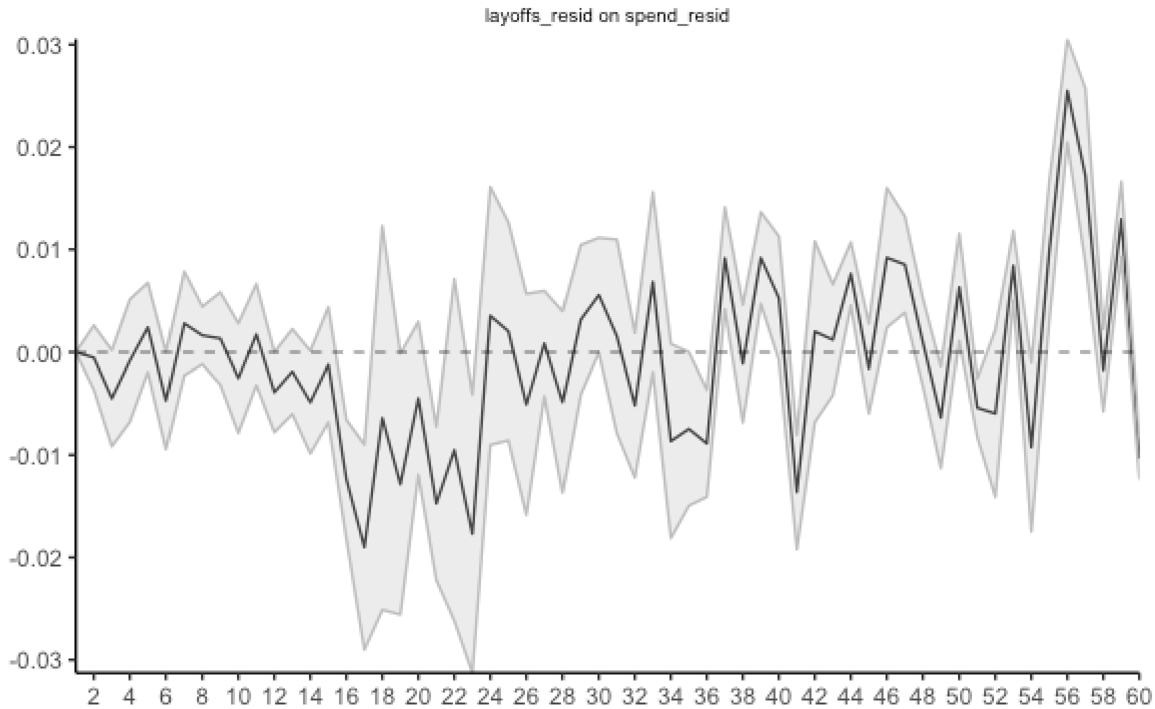


Chart 2 (Weekly Data)



The y-axis represents our regression coefficients, while the x-axis represents the 60 horizons into the future, which are days in the daily chart and weeks in the weekly chart. The shaded area in the trend represents the degree of freedom, visually representing the confidence intervals associated with the estimated coefficients. Upon conducting a thorough robustness check, I observed minor adjustments to the results previously obtained. These slight alterations, however, do not undermine the overall integrity of the findings. Consequently, it is reasonable to conclude that the outcomes of the analysis are sufficiently robust, instilling confidence in the subsequent interpretation and discussion of these results. With this reassurance, I am now prepared to proceed to the next section of my paper, wherein I will delve into a detailed examination and interpretation of the findings from the analysis. This comprehensive discussion will facilitate a deeper understanding of the intricate relationship between tech sector layoffs and consumer spending patterns, ultimately contributing to the broader knowledge base on this topic.

VII Discussion and Conclusion

The outcomes of my analysis for the daily data during the initial eight days reveal a negative correlation, which is deemed plausible. This suggests that as the number of tech layoffs increases, the consumer spending rate of San Francisco Bay Area residents decreases. However, in the longer term, specifically after approximately 50 days, a positive correlation emerges, which appears too far into the future to be easily interpreted. The robustness check that I carried out subsequently rendered the positive relationship at 50 days statistically insignificant.

As a result, the analysis aligns with the findings from Eva Mueller's (1966) paper, which posits that as unemployment rises, consumer confidence decreases, and this decline serves as a significant predictor of consumer spending decline. Furthermore, the daily data findings are consistent with Robert Reich's (2001) paper, which suggests that company layoffs initiated the slowdown in consumer spending. In contrast, the weekly data analysis mostly yielded insignificant results, and when significant trends were observed, they fluctuated considerably, making it challenging to derive any concrete insights. For future research, obtaining more detailed data would be advantageous, as my current dataset contains numerous missing values for the layoff data. So layoff data is highly skewed. By addressing these limitations and incorporating a more comprehensive dataset, future studies may yield more refined and definitive insights into the relationship between tech sector layoffs and the consumer spending patterns of San Francisco Bay Area residents.

With the result of my research, I will recommend that companies develop comprehensive severance packages and outplacement support services for employees affected by layoffs. This may include providing financial assistance, career counseling, and job placement services to help workers transition smoothly into new roles or industries. Companies can also invest in upskilling or reskilling programs to prepare employees for in-demand jobs within or outside the tech sector. Also, governmental and non-governmental organizations can collaborate to create policies that promote job stability, economic growth, and workforce development. This may involve investing in infrastructure projects, research and development, and incentives for entrepreneurship and innovation. Furthermore, these organizations can develop social safety nets, such as unemployment benefits and retraining programs, to support individuals who have lost their jobs. Fostering a culture of continuous learning and adaptability within the workforce is crucial for navigating the ever-changing landscape of the technology industry. Encouraging employees to engage in lifelong learning and acquire new skills can help them remain valuable and employable, regardless of fluctuations in the job market.

In conclusion, this research has shed light on the complex relationship between tech sector layoffs and consumer spending patterns, particularly in the San Francisco Bay Area. By considering potential strategies for mitigating the negative impacts of job losses and the roles of various stakeholders, this study contributes to a more comprehensive understanding of the issue. It provides a foundation for future research and policy development.

VIII References

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