Allegheny College
Department of Computer Science

Senior Thesis

Do macroeconomic decisions and indexes have a direct effect on major layoffs in the technology sector from 2000 to 2023?

by

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Abstract

This paper delves into identifying key macroeconomic variables that have significantly influenced the layoffs within the technology sector from 2000 to 2023. It explores how overarching decisions and external macroeconomic factors have driven the layoff trends. Additionally, this research has led to the development of a dashboard web application using Streamlit, which showcases the findings through vector auto regression (VAR) graphs, providing a visual representation of how these macroeconomic variables correlate with layoffs in the tech industry. The paper posits that four major macroeconomic variables will be significant predictors of layoffs. Furthermore, it concludes that the Economic Uncertainty Index and Industrial Production emerge as significant predictors, whereas the Federal Funds Rate and inflation do not demonstrate significant predictive value. It is crucial to note, however, that these findings do not imply a causal relationship between these variables and layoffs. This distinction emphasizes the complex interplay of factors at play and invites further exploration into the dynamics shaping the labor market in the technology sector.

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Introduction

Although the unemployment rate was at its lowest in 2023 as of September, there needed to be an explanation as to why the hundreds of thousands of tech company layoffs from 2021 to 2023 seemed to have minimal impact and, most importantly, why they happened. This paper identified the most important key macroeconomic variables that contributed to the layoffs of technology workers, without delving into the smaller details related to the companies. While there had been some research done similar to mine, those studies mainly focused on microeconomic variables. For example, these variables included company product or service demand, restructuring of a company, and financial issues within the company. Thus, these previously mentioned variables provided information that was closely related to the specific company itself. What I demonstrated and did in this paper included examining macroeconomic variables such as interest rates, monetary policy, and, on a larger scale, how these major decisions and factors affected the firms' layoffs. Not only that, through this research, I developed a dashboard web application using Streamlit that displayed my findings, such as regression graphs and correlation plots.

Motivation

For my motivation, as a junior developer who has been navigating the challenges of finding internships in the software engineering job market since the beginning of 2023, and continuing to face challenges in securing full-time employment into 2024, I was compelled to explore the economic factors influencing such market dynamics with the analytical depth of an economist. To make this exploration feasible, I leveraged both my economics and computer science skills. This interdisciplinary approach enabled me to construct a dashboard website on Streamlit to display my results and share them with

others interested in this topic. Recognizing the lack of extensive research on the factors affecting layoffs, I aimed to illuminate the significant, often uncontrollable forces that influence these occurrences. While there were number of research that highlighted company metrics that affected layoffs, there were no much research on what macroeconomic indicators had an impact. This is why in the real world, individuals are frequently not directly responsible for layoffs; these are outcomes shaped by forces beyond our individual control. With this perspective, I sought to delve into an in-depth analysis of these external factors. Moreover, the reason why I used Layoffs.fyi was to conduct a data analysis and make some predictions on top of that.

Current State of the Art

No existing research project has precisely addressed the questions I'm exploring. However, several studies have touched on related aspects, particularly from a business perspective, and how these factors influence layoffs. For instance, the paper by Hossen, Md Nayem; Mollah, Md Alamgir; Lipy, Nusrat Sharmin titled "FACTORS AFFECTING LAYOFF IN HIGH-TECH INDUSTRY: EVIDENCE FROM USA" highlights that business demand, organizational changes, and the financial performance of companies play significant roles in determining layoffs[10]. This paper, which can be found in the related works section, posits that the internal dynamics of firms heavily influence their layoff decisions. While it's logical to consider that business considerations compel companies to reduce their workforce, this research aims to uncover the external factors that prompt these decisions.

A study called "What explains high unemployment? The aggregate demand channel." by Amir Sufi examines how consumer demand impacts unemployment, yet it stops short of delving into the macroeconomic variables that directly contribute to the fluctuation in layoff rates[11]. The methodologies and experiments conducted for the current project are detailed in the experimental design subsection, offering a new perspective on the macroeconomic drivers behind layoffs.

Goals of the Project

The primary objective of this project is to rigorously test and validate a set of hypotheses concerning the job market's dynamics, utilizing the analytical framework provided by Vector Autoregression (VAR) models. The main reason why I incorporated VAR was because VARs are inherently multivariate, allowing one to capture the dynamic interaction between multiple time series variables. Moreover, VAR models facilitate impulse response analysis, which helps in assessing the effect of a shock to one variable on the system of variables over time. I wanted to see how a shock in one variable would affect layoffs in the Information Technology industry. This investigation is motivated by a thorough review of existing literature and a deep contemplation of the factors influencing the job market. The hypotheses formulated for this study are as follows:

- H1: Increase in Federal Funds Rate increases Layoffs
- H2: Increase in Inflation increases Layoffs
- H3: Increase in Industrial Production decreases Layoffs
- H4: Increase in Economic Uncertainty index increases layoffs

These hypotheses stem from intuitive reasoning about the economic forces at play. By employing VAR analysis on historical data, this project aims to empirically substantiate these relationships, providing a clearer understanding of how specific economic indicators influence labor market outcomes.

Ethical Implications

For the ethical considerations concerning our data, it's important to note that it does not contain any private information or anything of a similar nature. All the data utilized in this experiment is publicly available, with the exception of the Python script, which I developed myself. Additionally, I would like to clarify that the Streamlit website hosting our findings does not collect any user data.

Regarding the potential applications of this research, it's crucial to emphasize that this paper should not be interpreted as financial advice or be associated with financial consulting in any manner. This study is purely an economic analysis conducted with a specific academic objective in mind. I

personally disclaim any responsibility for financial losses incurred as a result of interpretations or actions taken based on this paper.

Data

In addition, reflect on ways that the above harms can be or are mitigated by your work In this study, a significant data source I utilized was from layoffs.fyi , a website that provides live tracking of all tech startup layoffs and maintains lists of employees who have been laid off[4]. This resource contained cross-sectional data of over 1074 companies, including the number of workers laid off in various countries and companies. Besides the number of laid-off workers, the data also provided the date of layoffs, company funding status (e.g., Series A or D), total funds raised, and the industry to which each company belongs. The numbers in this data were sourced from reputable places like journals, news articles, and publications spanning from 2021 to 2023.

With the layoff data I had, I expanded my research to include more information about variables relevant to predicting layoffs. Driven by this goal and my intuition, I incorporated macroeconomic indicators into the analysis to potentially enhance the results of my linear regression. Specifically, I added data on the Federal Funds Rate from 2021 to 2023, aligning it with the layoff dates. Additionally, I included the Economic Uncertainty Index from [5]Federal Reserve Economics Data (FRED). These macroeconomic variables were anticipated to significantly influence the outcomes. Although adding GDP was a consideration, to avoid collinearity, I chose not to include it in my regression analysis but decided to Industrial Production.

One challenge I faced was integrating these new variables, the Federal Funds Rate and Economic Uncertainty Index (which are time-series data), with the cross-sectional data from Layoffs.fyi. The integration required careful consideration of the effects and limitations of combining time-series and cross-sectional data. Nevertheless, I was optimistic, given that the cross-sectional data was organized by date and the number of layoffs. In the process of visualizing key variables from the cross-sectional company data, I identified four significant trends. These trends were instrumental in formulating robust hypotheses and developing meaningful research questions.

In my study, I analyzed a dataset containing information about numerous tech employees who were laid off and the industries to which their compa-

nies belong. Refer to Figure 1: the bar chart titled "Industry vs. #Layoffs" presents a visual comparison of the number of layoffs across different industries. The axis displays the range of individuals laid off, with increments reaching up to 52,000, while the vertical axis shows the industries.

The "Consumer" industry stands out with a significant number of layoffs, indicating a substantial impact within this sector. Following this are the "Retail" and "Transportation" industries, with "Retail" experiencing more layoffs than "Consumer," and "Transportation" showing even fewer. This suggests that industries directly influenced by consumer behavior and mobility are facing notable job cuts. As we move down on the graph, sectors like "Finance," "Healthcare," and "Real Estate" show a considerable number of layoffs. This could reflect a combination of resilience and the consequences of market changes. Additionally, industries such as "Sales" and "Food" demonstrate a level of job reductions, which might be attributed to fluctuations in demand and operational adjustments.

On the other hand, sectors like "AI," "Aerospace," and "Legal" are at the lower end of the layoff spectrum. This implies either a lesser impact from market conditions or a more stable employment landscape in these particular fields. The "Unknown" category, representing job cuts that cannot be directly linked to an industry, includes a range of possibilities, including emerging sectors.

The overall trend suggests that consumer-facing industries have been more susceptible to layoffs, potentially due to shifts in consumer spending and habits, especially in scenarios that affect large numbers of frontline workers. In contrast, more specialized or less consumer-dependent industries seem to have been somewhat insulated from extensive layoffs. This distribution of layoffs across industries provides a snapshot of economic vulnerability and resilience in the face of market or external pressures such as technological change or economic downturns.

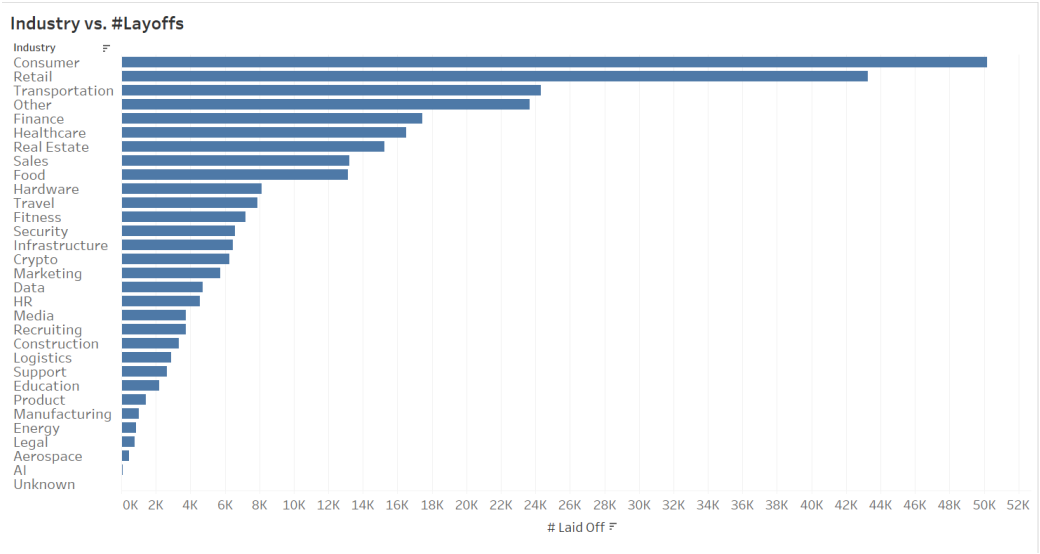


Figure 1: Industry vs. Number of Tech Layoffs

In my thesis, I presented a detailed analysis using the "Cities vs. #Layoffs" vertical bar chart, which provided an insightful look at layoff patterns within tech companies across various global cities and regions. This analysis employed a dual approach: it displayed, horizontally, the staggering total of over 150,000 layoffs at these workplaces, and vertically, it focused on specific urban areas.

At the top of the chart was the San Francisco Bay Area, with a number exceeding 140,000 layoffs. This figure significantly overshadowed those from other regions, a likely consequence of the Bay Area"s status as a crucial hub for global tech jobs. Seattle, another significant player in the tech industry, followed, with its layoffs attributed to the high concentration of tech jobs in the area.

New York City ranked third, with approximately 27,000 layoffs. Interestingly, this statistic also reflected the city"s economic diversity, which appeared to buffer it against the more severe impacts evident in more tech-centric locales. Boston and Los Angeles followed, each with their industrial sectors reporting under 15,000 layoffs.

As the analysis of the chart progressed, a distinct pattern became apparent: the number of layoffs in U.S. cities was on the rise, while those in international cities exhibited a declining trend. This trend underscored

the broader, albeit less obvious, impact of technological evolution on the global economy. Cities like Oxford, Tel Aviv, and Berlin were indicative of the far-reaching effects of an economy increasingly centered on technological innovation.

This visualization underscored not only the disproportionate impact of tech layoffs in areas densely populated by tech companies, such as the San Francisco Bay Area and Seattle, but also illuminated the ripple effects across the global tech workforce. The data provided insights into how economies heavily reliant on technology are susceptible to industry downturns, while also highlighting the resilience of more diversified economies.

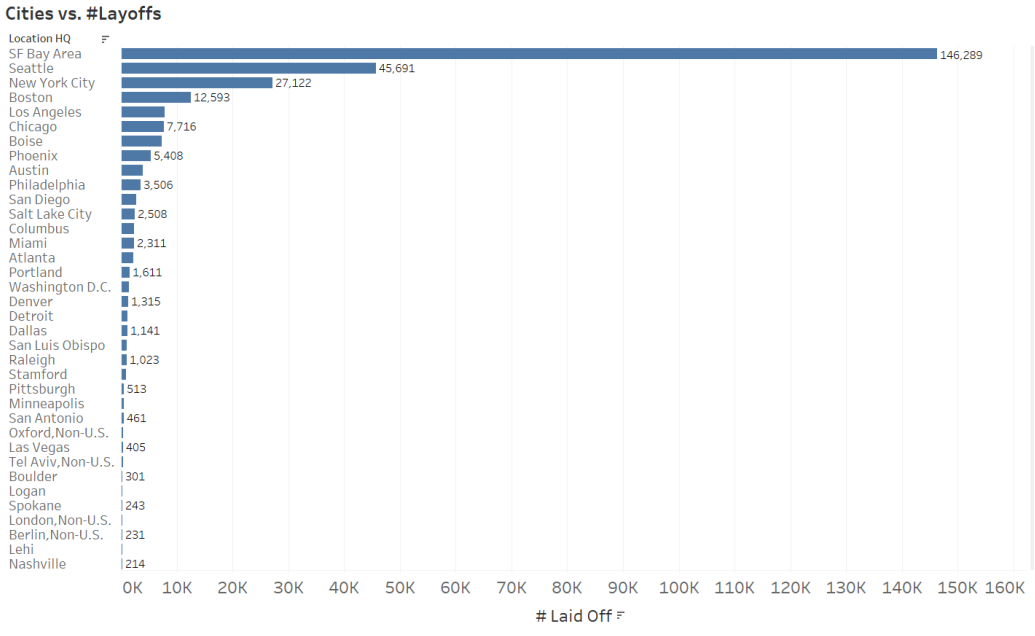


Figure 2: Cities vs. Number of Tech Layoffs

Figure 3, titled "Stage vs. Layoffs", showcased a horizontal bar chart that drew a connection between the stages of a tech company's growth and its layoff patterns. The chart's horizontal axis quantifies layoffs, peaked at nearly 190,000, while the vertical axis classified companies based on their lifecycle stage, ranging from "Seed" and progressing through "Series A" to "Series I", and included "Private Equity", "Acquired", "Subsidiary", "Unknown", and

culminated in "Post-IPO".

This data showed a trend: as tech companies evolve and mature, especially those reaching the "Post-IPO" phase, the number and frequency of layoffs tend to climb sharply. The highest incidence of layoffs was seen in the "Post-IPO" category, possibly reflected the restructuring and efficiency measures typical after a company goes public. In contrast, startups in their early stages, like those in "Seed" and "Series A", reported far fewer layoffs. This aligned with these companies' focus on growth and expansion, rather than reducing staff.

This pattern highlighted an aspect of the tech industry: larger and more mature companies, particularly those that are publicly traded, are more likely to implement significant layoffs compared to their smaller, startup counterparts. This might be attributed to a range of factors such as the larger workforce in big companies, meaning more people are affected by layoffs, or the intense pressure from shareholders and market performance expectations faced by public companies. It also suggested that job stability in tech may be inversely proportional to the company's size and age, with startups experiencing fewer layoffs, perhaps due to their focus on growth and lean operations.

Overall, Figure 3 presented a clear correlation between a company's size and stage in its lifecycle and the likelihood of layoffs, offering key insights into the employment risks at various points in a tech company's development.

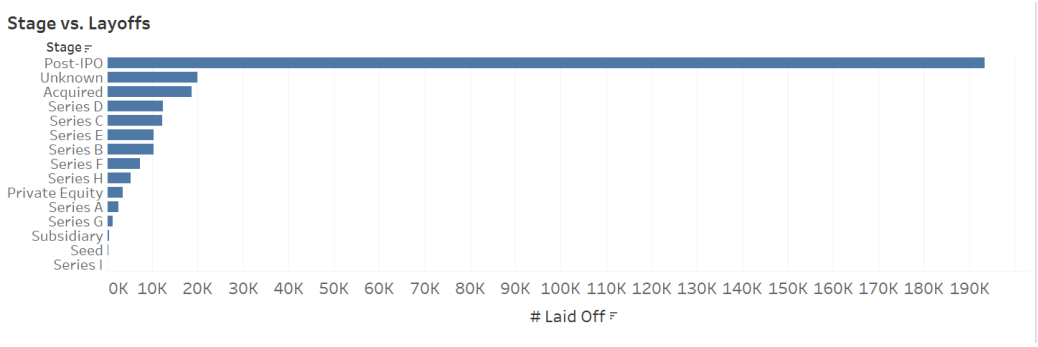


Figure 3: Stage vs. Number of Tech Layoffs

Figure 4 offered a detailed visualization of layoff patterns in the tech industry, tracing the impact from the first quarter of 2020 through to the

fourth quarter of 2023. This bar chart is bifurcated into two key metrics: the count of laid-off employees, represented by red bars, and the tally of companies executing layoffs, shown in blue. The left vertical axis mapped the number of individual layoffs, with a peak value of 200,000, while the right vertical axis enumerated the number of affected companies, scaling up to 800. The horizontal axis was divided into quarterly segments, providing a temporal frame for the data. The chart revealed a significant surge in layoffs during the second quarter of 2020, coinciding with the immediate ramifications of the COVID-19 pandemic. This initial spike was followed by a fluctuating pattern of layoffs over subsequent quarters, indicating an ongoing but irregular impact on employment within the tech sector. The trend in the number of companies reporting layoffs mirrors this pattern to some extent, with noticeable surges, especially in the first and second quarters of 2023. While the graph suggested a relationship between the two metrics of layoffs, the differing scales necessitate caution in interpreting these as directly proportional. Nonetheless, this representation starkly illustrated the profound disruptions caused by the pandemic in the tech landscape, underscoring the sector's vulnerability to economic fluctuations and their consequential effects on employment.

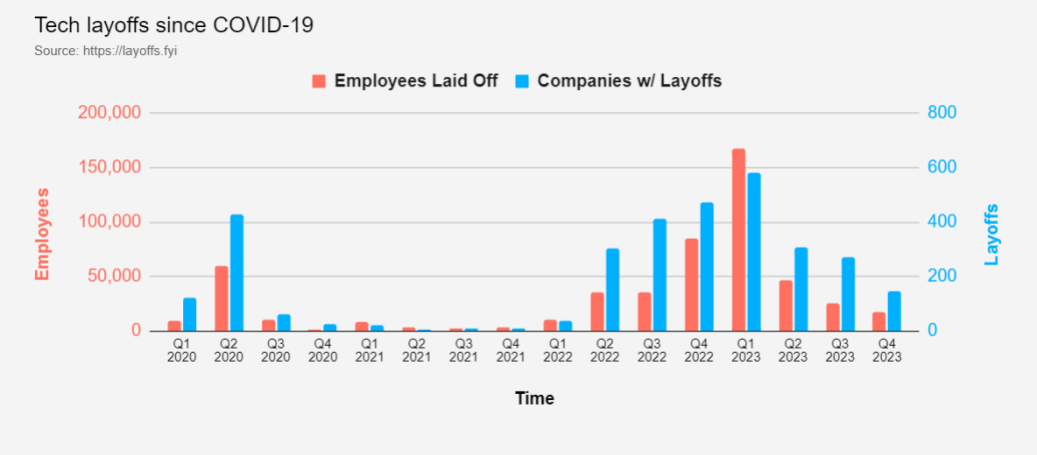


Figure 4: Tech Layoffs since COVID-19

The data we've examined paints a vivid picture of employment volatility within the tech sector, particularly highlighted in regions heavily concen-

trated with technology companies, such as the San Francisco Bay Area and Seattle. These tech hubs experienced the most acute effects in terms of layoffs, which is likely a direct consequence of their dense populations of tech sector employees. Intriguingly, the "Stage vs. Layoffs" graph adds another dimension to this understanding. It suggests that tech companies in more mature stages of development, especially those that are post-IPO, are more prone to announcing significant layoffs compared to their early-stage counterparts. This trend could be indicative of the unique pressures and restructuring challenges that mature companies face, particularly under the scrutiny and demands of the public market. Based on this correlation and the data, I decided to come up with a hypothesis. My first hypothesis was that when the FED increases interest rates for contractionary economic policy, companies respond by taking less investment due to high interest rates. Figure 4 seemed to support this because companies started their layoffs when the economy was recovering in Q1 of 2022. My second hypothesis is that when there is negative growth in the Industrial production, it causes tech companies to reduce their cost by laying off employees.

I needed more reliable data to test my hypotheses and see the general trend of how macroeconomic variables affect the overall layoffs. Thus, I have another dataset that I used to prove my hypothesis. The data came from the Federal Reserve Economic Data (FRED), and the macroeconomy variables I chose were Layoffs and Discharges for the information sector, the Economic Uncertainty index for the United States, the Federal Funds Effective rate, and industrial production. Here is the data, I chose to include for my regression analysis.

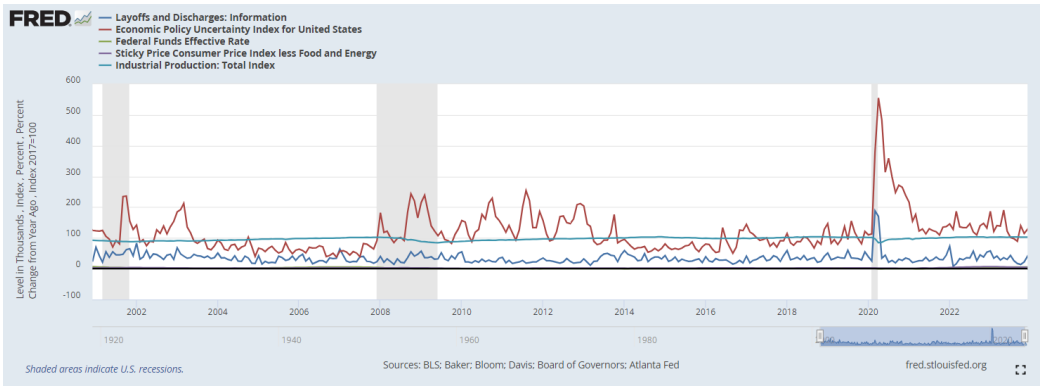


Figure 5: Macroeconomic variables for hypotheses testing

Related work

In my research on the variables impacting major layoffs in technology companies from 2022 to 2023, integrating and replicating the methodologies from the literature, "WHAT HAPPENS TO THE EMPLOYERS INVOLVED IN MASS LAYOFFS?", will be instrumental[13]. To enhance my dataset, I plan to incorporate similar microdata sources as used in the literature, such as the Mass Layoff Statistics (MLS) and the Quarterly Census of Employed Workers (QCEW). These sources offer a detailed view of employment cutbacks, total layoffs, and the underlying reasons, providing a comprehensive backdrop for my analysis. I will emulate the literature's analytical approach to discern the patterns and relationships between mass layoffs and employment, offering a nuanced understanding of layoff dynamics in the technology sector. Further, I will explore the impact of demand and supply shocks on various industries and countries in my dataset, paralleling the literature's examination of these factors. Lastly, I will harness the extensive references from the literature to broaden my understanding and perspectives on layoffs, ensuring a robust and well-rounded foundation for my research and analysis.

Upon investigating kind of literature, I found another research paper that tries to answer what I wanted to answer through my research question. The paper named "FACTORS AFFECTING LAYOFF IN HIGH-TECH INDUSTRY: EVIDENCE FROM USA" delves deep into the intricacies of this issue, aiming to identify the primary factors influencing layoffs and their interrelationships within the tech sectors of the USA[10]. While my research question may be similar to this article's question, the methodologies that I will implement beg to differ from what this paper offers. In their literature review section, they hypothesized these five reasons for workforce reduction in the tech industry based on some previous research done by Handwerker and Mason in 2011. Handwerker and Mason's paper also hypothesized that these five factors below contribute to significant roles

- H1: Business Demand significantly impacts Layoffs.
- H2: Organizational Changes significantly impact Layoffs.
- H3: Financial Issues significantly impact Layoffs.
- H4: Product Specifications significantly impact Layoffs.
- H5: Layoff Announcements significantly impact Layoffs.

In their empirical approach, the authors conducted a comprehensive survey, engaging with 1000 individuals working in high-tech firms. The survey participants were asked to rate the importance of the aforementioned factors on a scale from 1 to 5, with 1 being "not important" and 5 "very important". This survey was designed to gather the ratings of these factors above that are contributing to layoffs. In addition to the survey, they used secondary data, which were sourced from various web portals, journals, online newspapers, and magazines to provide context and support the primary findings. Additionally, to reinforce the questionnaire's reliability and consistency, Cronbach's alpha method was used.

One striking aspect of their study is the near-perfect R-squared value of 0.995 they achieved. This suggests a very high level of explanation by the variables they identified for the layoffs in the high-tech industry. Although they have a close to perfect R-squared value of 0.995, the variables I chose do not belong in these categories. For my next step, I will incorporate macroeconomic variables that affect these five factors. At first glance, it is noticeable that these five variables above are microeconomic factors/variables. While they are microeconomic variables, my research will find that macroeconomic variables can predict the firm's likeliness to lay off people in the future.

Multiple scientific studies have highlighted that certain variables are good indicators for understanding layoffs, and I plan to utilize these in my analysis. For my macroeconomic variables, I will focus on specific economic factors that influence business demand, organizational changes, financial issues, product specifications, and layoff announcements in the high-tech industry. For instance, I hypothesize that higher interest rates typically used to control inflation during economic expansions, can lead to reduced business activity and investment, signaling an upcoming economic slowdown or recession. This, in turn, may impact business demand adversely, which is a significant factor affecting layoffs in the high-tech sector. This is just one example, and I will present more detailed and impactful variables later in this paper.

Another literature paper titled "What Explains High Unemployment? The Aggregate Demand Channel." by Atif R. Mian and Amir Sufi delves into

the factors contributing to high unemployment rates [11]. Mian and Sufi's paper takes a close look at why unemployment rates are high, questioning the common belief that it's mostly due to policy, regulatory, or business uncertainties. Instead, they examine how things like wages, the movement of workers, and different industry impacts play a role, especially in places with a lot of debt. Their approach gives a more detailed view of how complex unemployment issues can be.

In their methodology, Mian and Sufi classify industries into tradable and non-tradable sectors. Tradable sectors are those with significant import and export activities, measured against set monetary thresholds. Non-tradable sectors, mainly identified as retail and restaurants, have more localized economic activities. A stricter definition includes only grocery retail stores and restaurants. Construction is considered separately due to its unique economic characteristics.

They pay special attention to construction because it's unique. The authors use a thorough statistical method to figure out how employment growth between 2007 and 2009 and the debt-to-income ratio of counties in 2006 are connected. Also, they use a technique called Instrumental Variables (IV) to make sure their findings are solid and not skewed by unnoticed factors. The paper highlights that the impact of the recession varied across different regions. Specifically, it notes that regions with higher levels of debt before the recession experienced more severe job losses. This finding indicates a significant link between the pre-recession debt levels of a region and the extent of its employment challenges when the economy declined.

The authors noticed that the recession hit non-tradable sectors like retail and restaurants harder than tradable ones. This is important because it shows domestic economic conditions are key to understanding unemployment, not international trade. Another important part of their findings is how the recession's effects varied across different areas. Counties with more debt beforehand saw bigger drops in jobs, showing how complicated and uneven the effects of economic downturns can be.

Lastly, the paper looks at how changes in industry types and the ability of workers to move around or switch sectors affected jobs. Places where workers could more easily change jobs or move suffered less. They also talk about how wages not falling enough in areas with a lot of debt might have made unemployment worse. Since unemployment varies from county to county in the U.S., Sufi's paper made me think of whether tech companies in certain counties or states laid off more workers compared to other counties. In their

paper, the authors ran an OLS regression with the Y variable being the unemployment rate. For my future work, I can incorporate the Instrumental Variables (IV) approach.

Another paper "ON THE THEORY OF LAYOFFS AND UNEMPLOYMENT" by Blau and Kahn from 1981 studies the factors influencing layoffs. They employ probit analysis to model the probability of layoffs as a function of various factors[6]. The variables considered in their model were comprehensive, including education, experience, tenure, military draft status, marital status, dependents, wages, occupational category, collective bargaining coverage, industry, regional unemployment rates, company size, and year. Each variable was chosen based on its predicted influence on layoffs, creating a robust framework for analysis.

The study specifically used data from the National Longitudinal Surveys (NLS), focusing on young men and women. This demographic was selected due to their early career stages and the prevalence of job shifting. The sample included nonagricultural wage and salary workers who had completed their schooling. For examining layoff probabilities, all individuals employed in the initial year of the survey were included, while the analysis of layoff consequences was limited to those employed on both survey dates.

Incorporating theories of human capital and search theory, the study suggested that the quantity of employer-owned specific human capital and the total amount of specific capital are significant factors negatively affecting layoffs. This includes the value of specifically trained workers and the incentives for firms regarding severance pay or pensions in the event of layoffs .

The empirical results of the study revealed key differences in layoff determinants based on race and sex. It was found that tenure had an inverse relationship with layoff probability, and married individuals were generally less prone to layoffs. Interestingly, having additional dependents increased the probability of layoffs among women and black males. The impact of collective bargaining on layoff probabilities also varied among different demographic groups, suggesting a complex interplay of workplace dynamics and policies. Furthermore, the study observed that wage levels differently influenced layoff probabilities across different groups, pointing to significant heterogeneity in the acquisition of specific capital among white males, black males, and females.

Regional factors, particularly residents in southern states, were also found to be significantly associated with layoff probabilities among blacks. This

indicates that regional economic conditions and institutional factors played a role in influencing layoffs.

Lastly, the study acknowledged a potential bias in its estimates, as the analysis was based on a sample of people who were employed at the initial survey dates. This means that those not employed, who might have different characteristics affecting their layoff probabilities, were not included in the analysis, potentially limiting the generalizability of the findings.

The constructed probit regression model had the probability of getting laid off as its dependent variable and education and experience, tenure at current employer, military draft status for males, marital status, number of dependents, the natural logarithm of wages, the logarithm of the three-digit occupational category indicating long-term earnings, coverage by collective bargaining agreements, industry of occupation, regional unemployment rates, size of the company, and year of data collection as the independent variables.

This paper by Blau and Kahn was the most relevant and the closest to my research topic, it had over three hundred citations on Google Scholar and it had to be in my research paper's literature review. In my research project, I have company size/funding as one of the independent variables. However, all the dependent variables mentioned above are microeconomic too. Therefore, since I have a new pool of variables I will implement what I planned to do with the [10]"FACTORS AFFECTING LAYOFF IN HIGH-TECH INDUSTRY: EVIDENCE FROM USA" literature. I identified and chose macroeconomic variables that directly affect those microeconomic variables.

To conclude this literature review section, there was no scientific literature that was closely similar to mine and related to macroeconomic factors. Information and resources about any macro factors that affect layoff were scarce and the studies were minimal. However, I did construct a simple regression model, in which I chose the variables. I do have some sense that business demand and the company's financial situation are the two biggest factors when it comes to determining future layoffs. I leveraged this information and chose my regression-independent variables wisely.

Method of approach

At the core of this study lies the implementation of two sophisticated econometric models: Multiple Regression and Vector Autoregression (VAR). I used our main five variables *(Figure 5: Macroeconomic variables for hypotheses testing.)* to populate both models. These economic models were chosen due to their distinctive capabilities in showing the multifaceted nature of the data at hand. Unlike the Multiple Regression model, which provides a static snapshot of relationships at a given point in time, the VAR model captures the evolution of these relationships, offering insights into how changes in one variable might lead to adjustments in others across different time lags. This approach is particularly adept at uncovering the intricate causal networks that underpin the observed layoff patterns, revealing not only the immediate impacts of economic fluctuations but also their delayed effects. By incorporating time series data from FRED, this model illustrates the temporal causality and feedback loops that characterize the complex interdependencies between macroeconomic health and employment trends in the tech industry. Thus, the multiple regression and the Vector Autoregression model both play a huge role in proving my hypothesis that the macroeconomic variables I chose specifically have or do not have a direct effect on the layoffs in the information industry. The hypotheses for the experiment that the Vector Auto Regression will prove are:

- H1: An increase in Federal funds rate increases layoffs.
- H2: An increase in Inflation increases layoffs.
- H3: An increase in Industrial production decreases layoffs.
- H4: An increase in Economic uncertainty index increases layoffs.

The dataset that informed the Vector Autoregression (VAR) model in my study comprises monthly data spanning from December 2000 to December 2023. This rich time series dataset incorporated several key variables,

including Layoffs and Discharges in the Information Sector, the Economic Uncertainty Index, the Federal Funds Effective Rate, the Sticky Price Consumer Price Index (CPI) excluding Food and Energy, and the Industrial Production Index.

In this VAR model, I designated the Layoffs and Discharges variable as the dependent variable (Y variable), aiming to uncover how it is influenced by the other macroeconomic factors, which served as the independent variables. This choice was driven by a desire to understand the direct impact of economic conditions and policies on employment trends within the tech sector, particularly in terms of layoffs and discharges.

The software implementation for the econometric analysis in this study was meticulously designed to ensure robustness, reproducibility, and validation of the results. The initial models were constructed using Python, a versatile and widely used programming language known for its extensive libraries that cater to data analysis and econometric modeling. Python was selected as the primary tool for model development due to its flexibility, the availability of open-source libraries, and its widespread acceptance within the scientific and research communities[1].

The Python environment facilitated the use of libraries such as Pandas for data manipulation and preprocessing, which was crucial for handling the dataset comprising tech layoffs and macroeconomic variables. Pandas provided the necessary functionality to clean, transform, and prepare the data for analysis, ensuring that the dataset was in an optimal format for modeling[12]. For the econometric analysis, the Statsmodels library was employed to construct the Multiple Regression and Vector Autoregression (VAR) models. Statsmodels is renowned for its comprehensive range of algorithms and functions for statistical modeling, making it an ideal choice for conducting advanced econometric analysis. The initial simple linear regression model was developed to identify the linear relationships between the dependent variable, tech layoffs, and a set of independent macroeconomic variables. This model provided insights into the direct impacts of these variables on layoffs within the tech sector.

Subsequently, the VAR model was implemented to explore the dynamic interactions and temporal dependencies among the macroeconomic variables over time. This model was particularly useful in capturing the complex, interrelated effects of economic indicators on tech layoffs, offering a deeper understanding of the causality and temporal dynamics inherent in the data.

Upon the completion of the model development in Python, the results

were then validated using Stata, a powerful statistical software renowned for its advanced econometric capabilities. Stata was chosen for this secondary phase of analysis due to its robustness in statistical computations and its widespread use in academic and professional research, providing an authoritative basis for result verification. The use of Stata complemented the Python analysis by offering a platform for rigorous econometric testing and validation. The Multiple Regression and VAR models were replicated in Stata, ensuring that the results were consistent and reliable across different software platforms. This dual-platform approach not only reinforced the credibility of the findings but also demonstrated the versatility and adaptability of the methodology to different computational environments[2].

In addition to Python, I employed a suite of Python libraries for econometric analysis and data visualization for my research. Each library was chosen for its distinct capabilities and how it contributed to my research. These libraries: Streamlit, Pandas, NumPy, Seaborn, Matplotlib, and Statsmodels, constituted a comprehensive toolkit that underpinned my study's analytical and interactive aspects. I found Streamlit to be an invaluable open-source app framework tailored for data science projects. With just a few lines of Python code, Streamlit allowed me to develop an interactive website for my research question. I used it to create a dashboard that dynamically presented the results of my econometric analysis, enhancing the accessibility of my research by posting it on a website.

Panda was a cornerstone for data manipulation and analysis. Its DataFrame structures greatly simplified the data cleaning, transformation, and analysis processes. I relied on Pandas throughout my study, especially for preprocessing the dataset(filtered_data.csv), handling missing values, and performing the necessary data transformations for my econometric modeling. NumPy was essential for supporting large, multi-dimensional arrays and matrices, along with a vast collection of mathematical functions. It served as the backbone for Pandas and was crucial for the numerical operations required in my data preprocessing and VAR modeling.

The tool Matplotlib complemented Seaborn by offering extensive control over visualization elements, allowing me to customize plots for publication. I used Matplotlib in tandem with Seaborn to fine-tune visualizations, ensuring that each plot effectively communicated the insights derived from my analysis. In addition, the statsmodels library was the core of the statistical modeling aspect of my research. It provided the tools for estimating various statistical models and was particularly valuable for implementing the

Multiple Regression and Vector Autoregression (VAR) models. I was able to replicate my Stata results using the statsmodel library in Python, although it took an immense amount of work to replicate the exact vector autoregression. Collectively, these libraries supported every facet of my research, from data preprocessing and analysis to visualization and the development of an interactive application. Their integrated use not only facilitated a thorough investigation of my research questions but also ensured that the findings were accessible and engaging for a broad audience.

As for the management of the application and its dependencies, I turned to Poetry, an advanced dependency manager for Python. Poetry's ability to resolve dependencies in a deterministic manner was invaluable, especially when dealing with complex dependency trees[**?**].

In the deployment of my interactive application, I decided to use Docker's multi-architectural capabilities to ensure that the application could run seamlessly across different operating systems. By doing so, I ensured that my application would run smoothly regardless of the underlying system, eliminating the "it works on my machine" problem that often plagues software development. Furthermore, I encapsulated the entire environment within a Docker container, making the most of Docker's ability to package applications with all their dependencies into a single unit that can run on any Linux, Windows, or macOS system that has Docker installed. This approach leverages the lightweight and portable nature of containers to guarantee consistency across varied computing environments, a crucial factor for the reproducibility and reliability of scientific research[3].

The Docker setup for my project was based on the python:3.10-slim image due to its minimal overhead and pre-configured Python environment. This slimmed-down version of the Python Docker image was ideal for my application, providing just the necessary components to run the Python code while ensuring the application's efficiency and responsiveness. Moreover, by utilizing Docker's multi-architectural build options, I was able to create a container image compatible with different hardware architectures, thus enhancing the compatibility of my application on different devices. This feature was particularly beneficial for ensuring that users on various platforms, from traditional x86_64 to newer ARM-based systems, could run the application without any modifications or additional configuration.

So here is a diagram that contains every single one of the steps and processes on how the application runs.

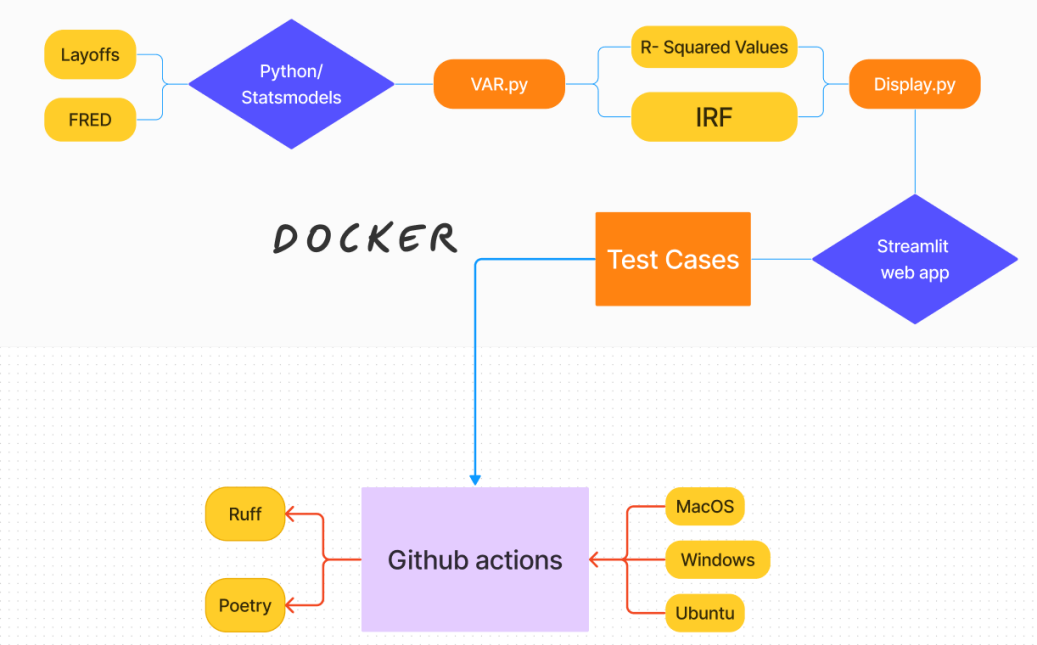


Figure 6: High-Level Workflow Diagram

To explain this diagram here are the important steps that are happening:

1. **Import Data:** Import raw-data from Layoffs.fyi and FRED
2. **Sort Data:** Use the statsmodels library and `VAR.py` module to sort, clean data, and run the VAR.
3. **Results:** Grab the `VAR.py` results and use `display.py`to display the R-Squared values and the Impulse Response Functions
4. **Streamlit:** The `display.py` is a module solely for displaying it on streamlit.
5. **Testing:** Then I test every functions I wrote in the codebase to ensure the app runs correctly
6. **Dockerize:** Then I use docker containers to make an image so anyone can use docker to access this app
7. **Software Engineering:** For my last step, I ensured the source code followed the latest software engineering standart practices. Thus, I used ruff - a linting tool used to make your code more readable for other developers.

8. **Github Actions CI/CD:** Finally in Github Actions, I ensured the linting is checked, the app runs correctly on multiple OS such as: Linux, MacOS, and Windows.

Moreover to access the project and view the dashboard so you can see the experiment results.

1. **Navigate to the Github Repository(Optional)**

   ```
   https://github.com/ReadyResearchers-2023-24/Tugi-Artifact
   ```

In your terminal:

2. **Clone Repository**

   ```
   git clone git@github.com:ReadyResearchers-2023-24/Tugi-Artifact.git
   ```

   ```
   cd Tugi-Artifact
   ```

3. **Set up Virtual Environment**

   ```
   python -m venv venv
   ```

   ```
   source venv/bin/activate
   ```

4. **Install Dependencies**

   ```
   poetry install
   ```

5. **Run App**

   ```
   streamlit run app.py
   ```

6. **Visit** http://localhost:8501

Or there is also another way of running the repository. You can follow step one to navigate to the repository. Keep scrolling down and it will tell you how to access the project via Docker, which only requires you to download docker and paste in a command!

To conclude this section, I was able to incorporate multiple technologies to illustrate the results of my multi-linear regression and my vector auto-regression model. In the next section, we will go over in-depth the experiments done and the results it yielded.

Experiments

This chapter describes my experimental set up and evaluation. The section will have three sub-chapters such as Experimental Design, Evaluation, and Threats to Validity and these titles below offer a typical structure used for this chapter.

Experimental Design

This section outlines the experimental design and hypotheses for the research paper, aiming to explore the relationship between various economic indicators and layoffs. Our hypotheses are as follows:

- H1: An increase in Federal funds rate increases layoffs.
- H2: An increase in Inflation increases layoffs.
- H3: An increase in Industrial production decreases layoffs.
- H4: An increase in Economic uncertainty index increases layoffs.

Leveraging FRED data for our analysis, the experimental procedure will unfold in the following stages:

1. **Initial Setup**: All experimental processes will be conducted using both STATA and a custom Python script thst I wrote to ensure a rigorous and fair analysis.
2. **Stationarity Testing**: The Augmented Dickey-Fuller (ADF) test will be applied to the Federal Funds Rate, layoffs, inflation, industrial production, and the Economic Uncertainty Index to assess stationarity.
3. **Data Transformation**: Non-stationary variables (with the exception of the Federal Funds Rate, as per standard practice) will be differenced to improve VAR model accuracy.

4. **Reassessment of Stationarity**: A second round of ADF tests will be conducted on all variables post-transformation.
5. **Lag Determination**: Optimal time lag for the VAR model will be identified using Information Criteria (IC) indicators.
6. **VAR Analysis**: The VAR model, incorporating the optimal time lag determined in step 5, will be run to obtain results and R-squared values for the independent variables.
7. **Impulse Response Function (IRF) Plotting**: IRFs will be plotted to visualize the dynamic impact of one standard deviation shock to one of the variables on the system.
8. **Interpretation of Results**: The outcomes depicted by the IRF plots will be analyzed and interpreted to understand the implications of economic indicators on layoffs.

Evaluation

First, I assessed whether each variable (Federal Funds Rate, Inflation, Industrial Production, The Economic Uncertainty Index) was stationary or non-stationary. Testing for stationarity was necessary due to the inherent challenges of forecasting future values from non-stationary time series. These challenges arise because the statistical properties of non-stationary series, such as mean, variance, and autocorrelation, vary over time. Such variability introduces complications in modeling and forecasting efforts, as many statistical methods presuppose or necessitate stationary data. Therefore, identifying and addressing non-stationarity was crucial to ensure the reliability of our analyses. Thus, I used the Augmented Dickey-Fuller (ADF) test, which is a statistical test for determining if a time series variable is non-stationary. A critical value in the context of the ADF test is a threshold against which the p-value of the test statistic is compared to determine the stationarity of the series. In simpler terms, if the model has a variable with a p-value less than the critical value, then that variable is considered stationary, which could help in predicting a better model.

Now, to provide a specific reference for why testing for stationarity, particularly using tests like the Augmented Dickey-Fuller (ADF) test, is considered standard practice in econometrics, I would like to share a few resoruces that will help you digest this whole section.

A texbook named Time Series Analysis published by by Princeton Uni-

versity Press is a comprehensive resource on time series analysis, which emphasizes the importance of testing for stationarity as a fundamental step in the analysis of time series dat [9]. Hamilton discusses the implications of non-stationarity on econometric modeling and the necessity of using unit root tests to ensure the robustness of econometric models.

Moreover, another resource titled Applied Econometric Time Series written by Wiley and Enders, W is widely used in graduate-level econometrics courses and explicitly details why tests for stationarity are essential before performing time series analysis[8]. Enders explains how non-stationary data can lead to spurious regression results, thereby making the identification of true relationships between variables problematic unless the data are first confirmed to be stationary.

Using the methods and practives of these two resources, I conducted my experiment, which we will go over now.

Here are the initial results after running ADF tests on the chosen macroeconomic variables.

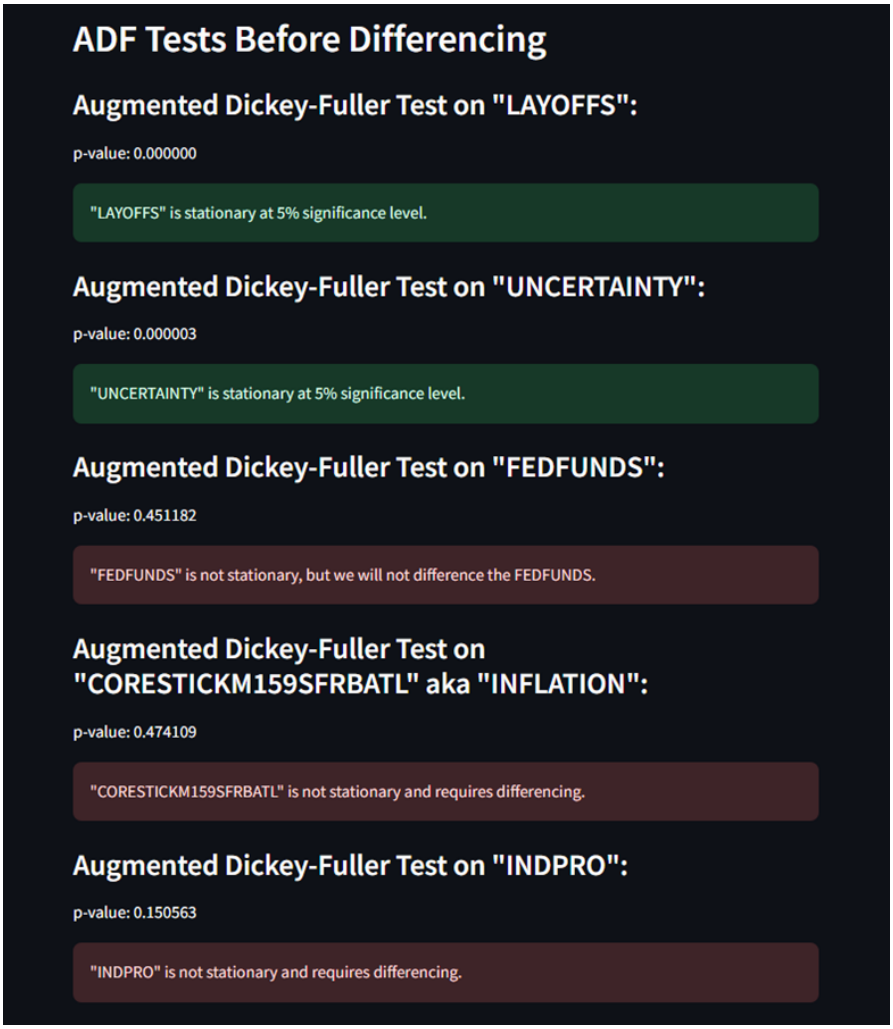


Figure 7: Dickey fuller Results from Python Statsmodels

As you can see from Figure 7., the "LAYOFFS" and " UNCERTAINTY" indexes both were stationary at a 5% significance level with p-values of 0.000000 and 0.000003 respectively. However, the "FEDFUNDS", "INFLATION RATE", and "INDUSTRIAL PRODUCTION" variables had p-values greater than 0.05, which indicates that they were all non-stationary. To mitigate this situation, I opted for the differencing method, which is a fundamental technique used in time series analysis to make a non-stationary time series stationary. I ran the differencing commands on both Stata and

Python. Then I ran the ADF test again to ensure they were all stationary. Now, both the INFLATION RATE and INDUSTRIAL PRODUCTION were both stationary.

```
. dfuller D_inflation, lag(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =       274

                                 ———— Interpolated Dickey-Fuller ————
                 Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value            Value
——————————————————————————————————————————————————————————————————————————
 Z(t)            -6.879            -3.458            -2.879           -2.570
——————————————————————————————————————————————————————————————————————————

MacKinnon approximate p-value for Z(t) = 0.0000
```

Figure 8: STATA | Augmented Dickey fuller (ADF) test result on Differenced Inflation

```
. dfuller D_industrial_production, lag(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =       274

                                 ———— Interpolated Dickey-Fuller ————
                 Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value            Value
——————————————————————————————————————————————————————————————————————————
 Z(t)           -12.514            -3.458            -2.879           -2.570
——————————————————————————————————————————————————————————————————————————

MacKinnon approximate p-value for Z(t) = 0.0000
```

Figure 9: STATA | Augmented Dickey fuller (ADF) test result on Differenced Industrial Production

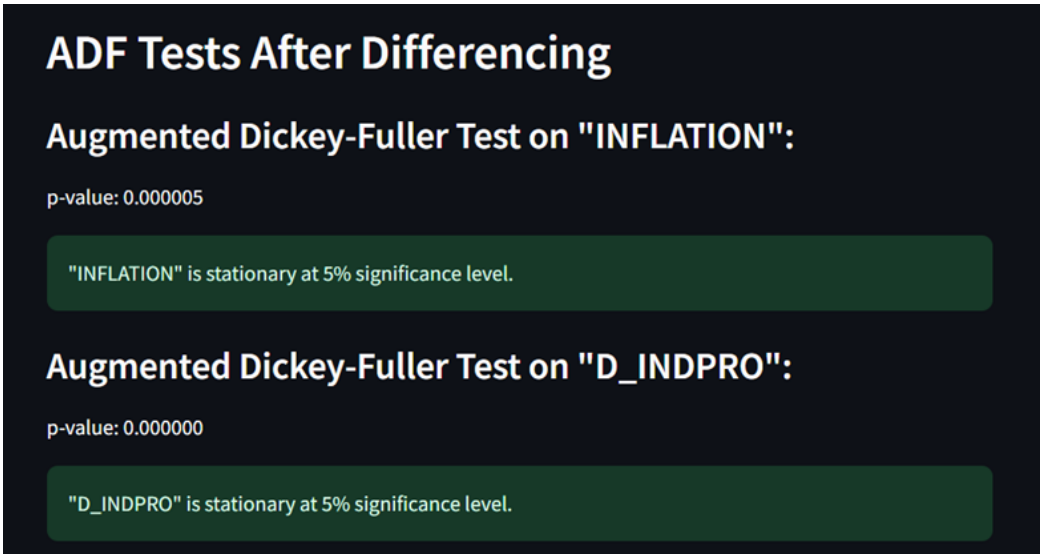


Figure 10: Python | ADF test results on Differenced Inflation and Industrial Production using Python Statsmodels

However, for the sake of this research, I did not bother to difference the Federal Funds Rate because most economists do not difference the variables when they are conducting research. Thus, the Federal Funds Rate was the only variable that was not differenced.

After ensuring all the necessary variables were stationary, we needed to determine which lagged time frame would best describe the relationships between these variables. For more background on lags, the Lagged Time Effect in VAR models captures the dynamic relationship between multiple time series by using the past values (lags) of all variables in the system to predict their current values. Ultimately, past values affect present values, known as the lagged time effect. It assumes that the present state of a variable is affected not just by its own past values but also by the past values of other variables in the model. This makes VAR models particularly useful for understanding and forecasting systems where variables interact with each other over time. In this test, we are testing to determine which time lag is the best for this research study.

I ran the VARSOC command in Stata and the equivalent code in Python to identify which time lag is the best, and here are the outputs from Stata and the Python code:

```
. varsoc layoffs fedfunds D_inflation uncertainty D_industrial_production, maxlag(12)

   Selection-order criteria
   Sample:  2002m1 - 2023m12                       Number of obs      =       264
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-3343.18				71366.4	25.365	25.3922	25.4327
1	-2426.05	1834.3	25	0.000	82.853	18.6064	18.7697	19.0128
2	-2315.78	220.54	25	0.000	43.4359	17.9604	18.2598*	18.7054*
3	-2289.66	52.231	25	0.001	43.0921	17.952	18.3874	19.0356
4	-2267.2	44.929	25	0.009	43.9692	17.9712	18.5427	19.3934
5	-2247.2	40.002	25	0.029	45.7358	18.0091	18.7166	19.7699
6	-2232.32	29.745	25	0.234	49.4936	18.0858	18.9294	20.1853
7	-2213.29	38.059	25	0.046	51.9448	18.131	19.1107	20.5692
8	-2182.74	61.118	25	0.000	50.0084	18.0889	19.2047	20.8657
9	-2161.77	41.941	25	0.018	51.8321	18.1194	19.3713	21.2348
10	-2131.47	60.581	25	0.000	50.1266	18.0794	19.4673	21.5334
11	-2093.75	75.452	25	0.000	45.8906	17.9829	19.507	21.7756
12	-2035.64	116.21*	25	0.000	36.0621*	17.7321*	19.3922	21.8634

```
   Endogenous:  layoffs fedfunds D_inflation uncertainty
                D_industrial_production
    Exogenous:  _cons
```

Figure 11: STATA | Optimal time lag result



Lag	AIC	HQIC	BIC
1	4.565	4.7234	4.9596
2	3.8629	4.154	4.5882
3	3.8406	4.2652	4.8984
4	3.8366	4.3954	5.2285
5	3.8673	4.5611	5.5952
6	3.9515	4.781	6.0172
7	4.0263	4.9923	6.4317
8	3.991	5.0943	6.7379
9	3.9688	5.21	7.0589
10	3.9179	5.298	7.3532
11	3.7859	5.3056	7.5682
12	3.5428	5.2028	7.6741

Figure 12: Python | IC result from Python Statsmodels

The evaluation metrics such as FPE and AIC suggest that the 12-lag frame would be ideal for the VAR model. To give more details on The Akaike Information Criterion (AIC), it is a sophisticated tool that enhances the Vector Autoregression (VAR) analysis by methodically evaluating the model across a spectrum of 12 different lag lengths. Its primary goal is to identify the specific lag that ensures the model is as accurate as possible by minimizing information loss. Thus, the smallest value in the AIC column is considered the one with the smallest loss. Thus, from our result 12th lag is the most suitable one. You also might see that HQIC and SBIC both point to a lag of 2. However, most economists use AIC to determine the lag.

I ran the vector autoregression with 12 lags, and here are the results in Stata and the Python script I came up with. Although certain values are different such as AIC, HQIC, and SBIC from both results, the RMSE and R-squared values are similar from both results. Also, from the Stata results you can see all the p-values are significant. Moreover, I would like to mention that I used [7] "Chapter 2 Monetary Policy Shocks: What have we learned and to what end?" paper for ordering my variables for the vector auto-regression model.

```
. var D_industrial_production D_inflation fedfunds uncertainty layoffs,lags(1/12)

Vector autoregression

Sample:  2002m1 - 2023m12                       No. of obs      =       264
Log likelihood = -2035.642                      AIC             =  17.73214
FPE            =  36.06213                      HQIC            =  19.39222
Det(Sigma_ml)  =  3.428584                      SBIC            =  21.86344

Equation           Parms      RMSE     R-sq      chi2     P>chi2
------------------------------------------------------------------
D_industrial_p~n      61     .865909   0.5720   352.8027   0.0000
D_inflation           61      .08247   0.7008   618.3512   0.0000
fedfunds              61     .162514   0.9959   64252.26   0.0000
uncertainty           61     29.9639   0.8301   1289.825   0.0000
layoffs               61     13.6818   0.4088   182.5695   0.0000
------------------------------------------------------------------
```

Figure 13: STATA | VAR result

VAR Model Summary:

```
Summary of Regression Results
==================================
Model:                         VAR
Method:                        OLS
Date:           Mon, 18, Mar, 2024
Time:                      20:51:24
--------------------------------------------------------------------
No. of Equations:         5.00000    BIC:                    7.67406
Nobs:                     264.000    HQIC:                   5.20284
Log likelihood:          -2035.64    FPE:                    36.0621
AIC:                      3.54275    Det(Omega_mle):         12.7542
--------------------------------------------------------------------
```

Figure 14: Python | VAR results from Python Statsmodels

Equation	RMSE	R-squared
D_INDPRO	0.865909	0.572
INFLATION	0.08247	0.7008
FEDFUNDS	0.162514	0.9959
UNCERTAINTY	29.9639	0.8301
LAYOFFS	13.6818	0.4088

Figure 15: Python | R-Squared values from Python Statsmodels

Before evaluating these numbers, one must know what are R-squared values and RMSE are. Thus, R-squared is a statistical measure that tells you how closely the data in your model fits the predicted model. It is expressed as a percentage. A higher R-squared value (close to 100%) indicates a better

fit between your model and the actual data. A lower R-squared value shows that the model explains less variability of the response data around its mean.

RMSE is a standard way to measure the error of a model in predicting quantitative data. It represents the average difference between the observed known values of the outcome and the values predicted by the model. An RMSE of 0 means that your model perfectly predicts the target variable, with no error. The smaller the RMSE, the closer you are to finding the line of best fit. Higher RMSE values indicate greater prediction errors, which suggests that the model may not fit the data well and could benefit from improvement or the consideration of additional variables.

The Industrial Production (D_INDPRO) variable has an R-squared of 0.572, which means that the model explains 57.2% of the variability in industrial production changes. The RMSE of 0.865909 tells the typical deviation of the observed values from the predicted values. This is a moderate result suggesting there is room for improvement in the model.

The Inflation variable has a substantial 70.08% inflation variability and has an R-squared of 0.7008. An RMSE of 0.08247 reflects that the predictions are quite close to the actual values, meaning high predictive accuracy for inflation within the model.

Furthermore, the Federal Funds Rate (FEDFUNDS) variable is highly explained by the model, with an R-squared of 0.9959, indicating that 99.59% of its variability is captured. This is further substantiated by a low RMSE of 0.162514, suggesting that the model's predictions are very close to the actual observed values, and thus the model is highly accurate in predicting the Federal Funds Rate. This 0.0059% is an exceptional result but it is not the indicator we are trying to predict in this research paper.

Moreover, the Economic Uncertainty variable is well-accounted for by the model, with an R-squared of 0.8301, translating to the model explaining 83.01% of its variation. An RMSE of 29.9639, while relatively large, needs to be considered in the context of the data's scale, indicating that the model still provides reasonably accurate predictions of economic uncertainty.

On the other hand, the Layoffs variable presents a lower R-squared of 0.4088, meaning that the model explains 40.88% of its variability. Coupled with an RMSE of 13.6818, this suggests a larger average error in the model's predictions compared to the actual values, pointing to the possibility of significant factors influencing layoffs that are not included in the current model.

We observe that our model yields an R-squared value of 0.40 for the layoffs variable. While this figure may not be particularly impressive, it does reflect

the best model that could be devised with the available variables. However, these numbers are not the best way to describe the economic phenomenon. Thus, I generated impulse response functions to make it easier to interpret the results. Here are the impulse response functions I plotted in my Python script and the Stata plots:

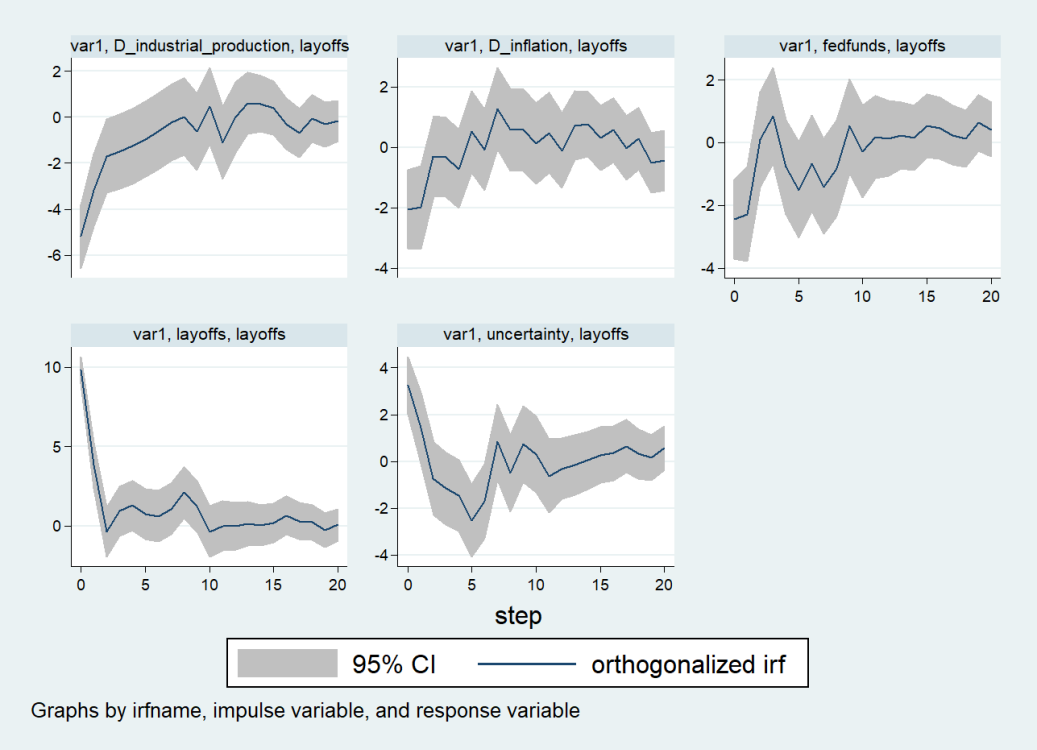


Figure 16: STATA | Impulse Response Functions from Stata

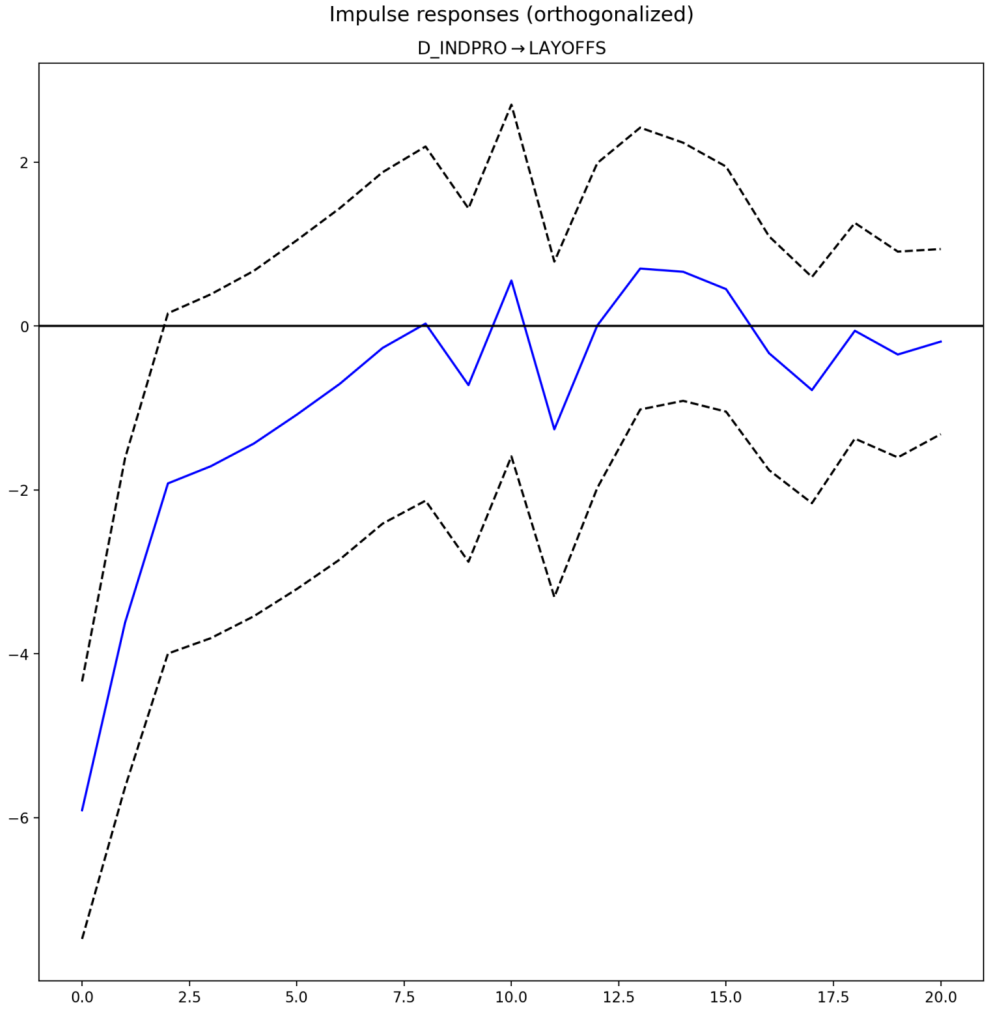


Figure 17: Python | Industrial Production on Layoffs from Python Statsmodels

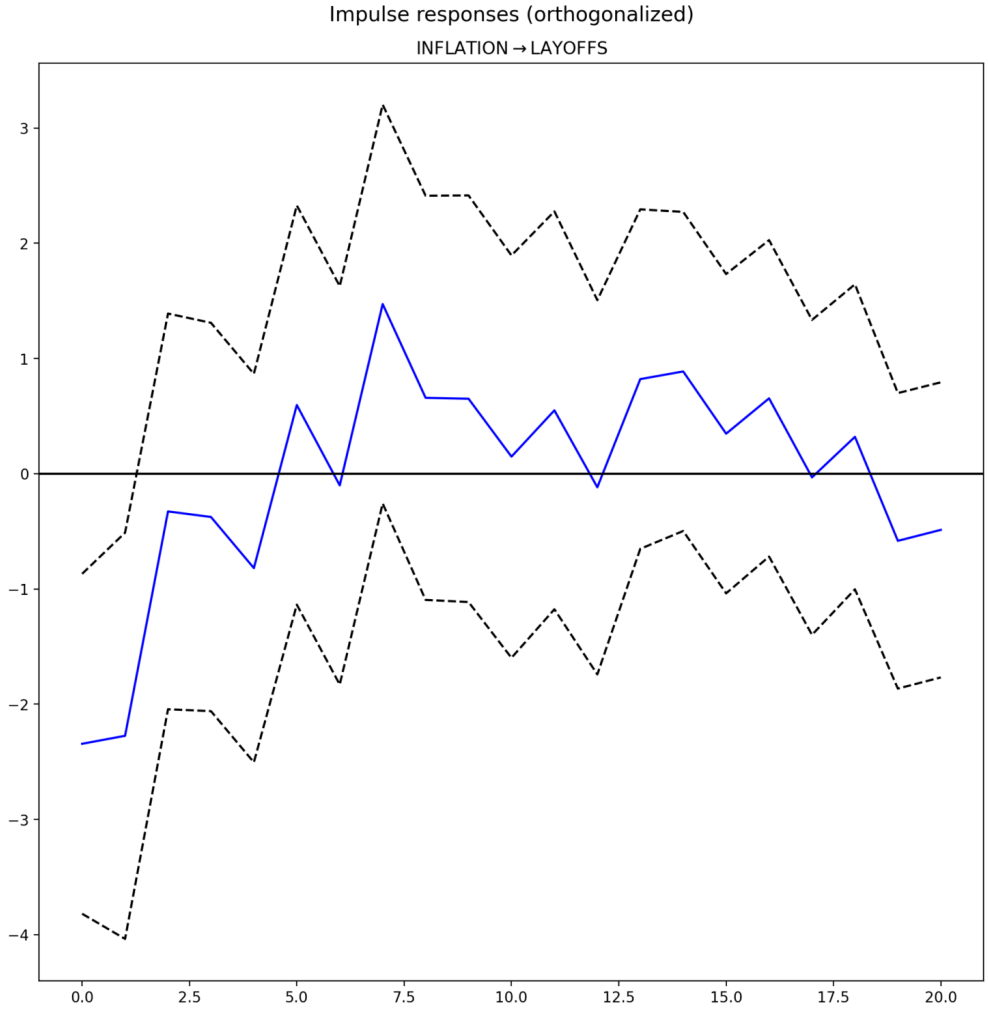


Figure 18: Python | Inflation on Layoffs from Python Statsmodels

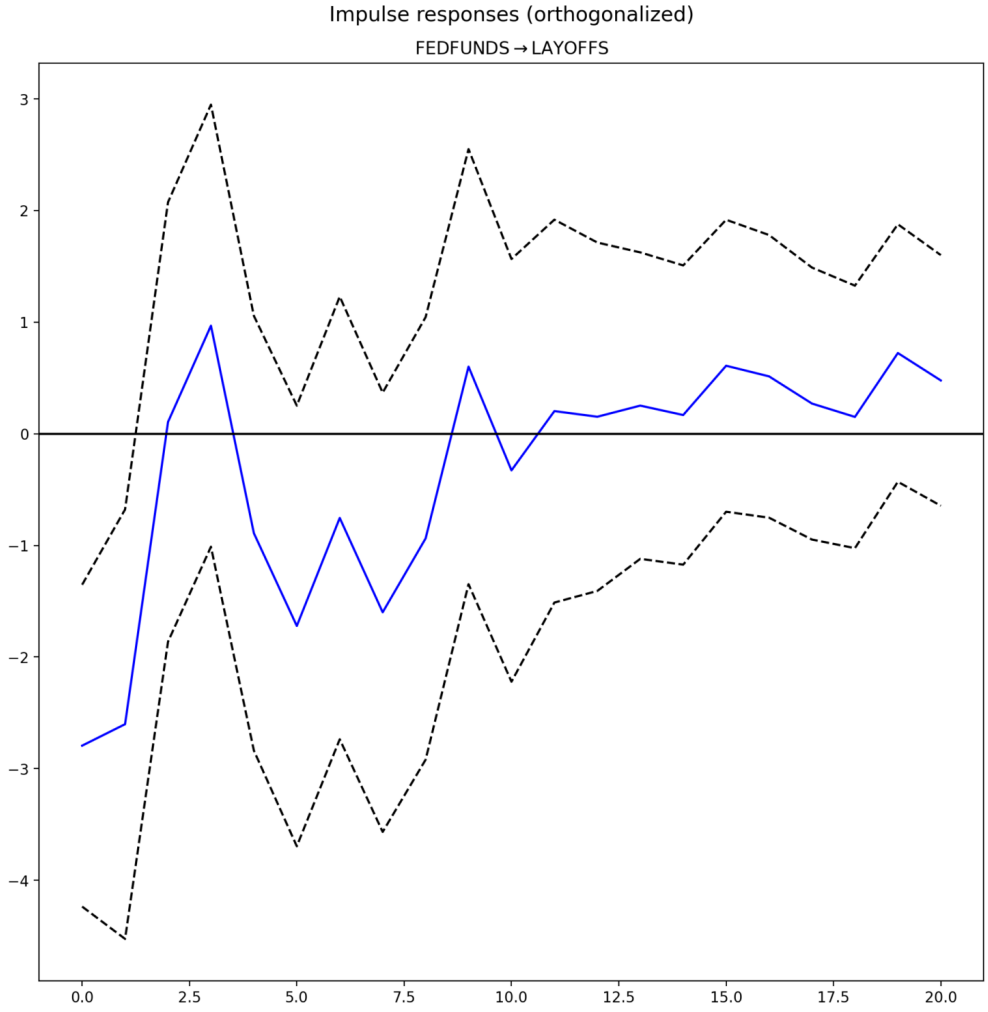


Figure 19: Python | Federal Funds Rate on Layoffs from Python Statsmodels

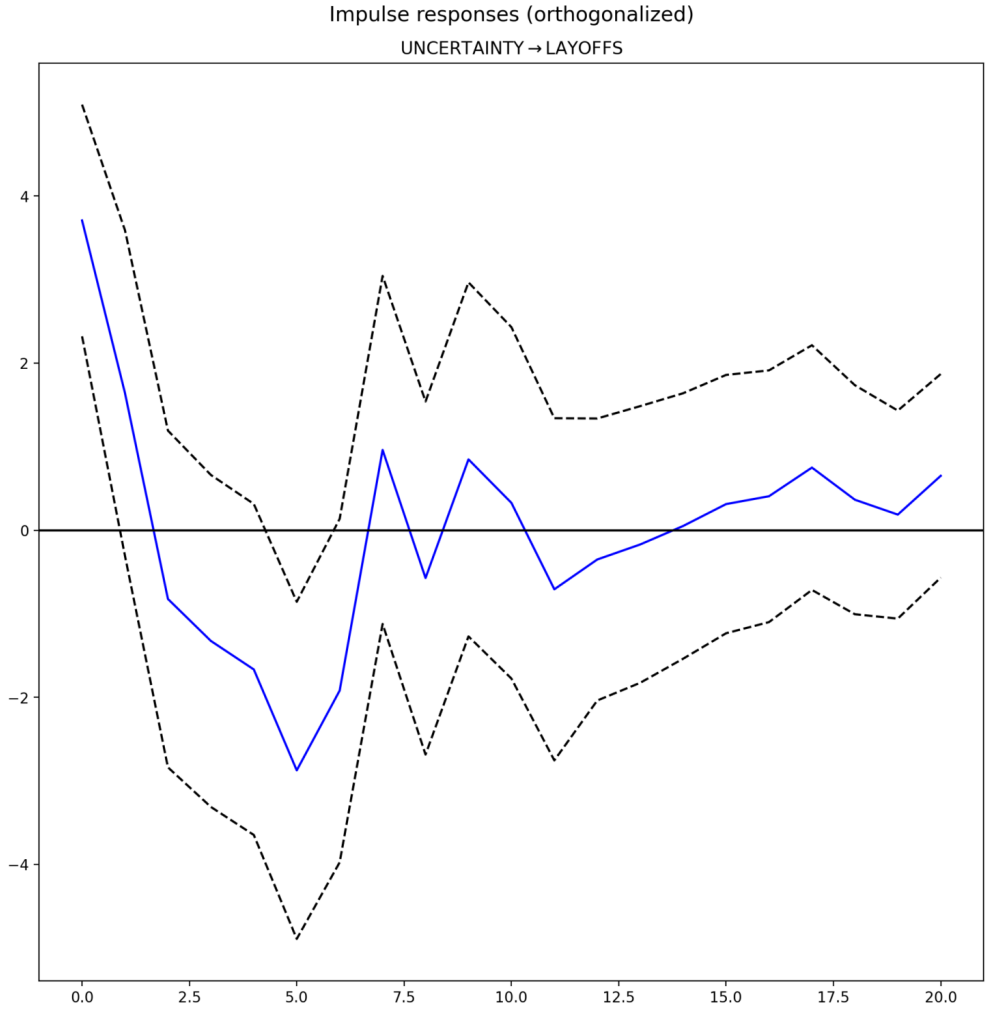


Figure 20: Python | Economic Uncertainty Index on Layoffs from Python Statsmodels

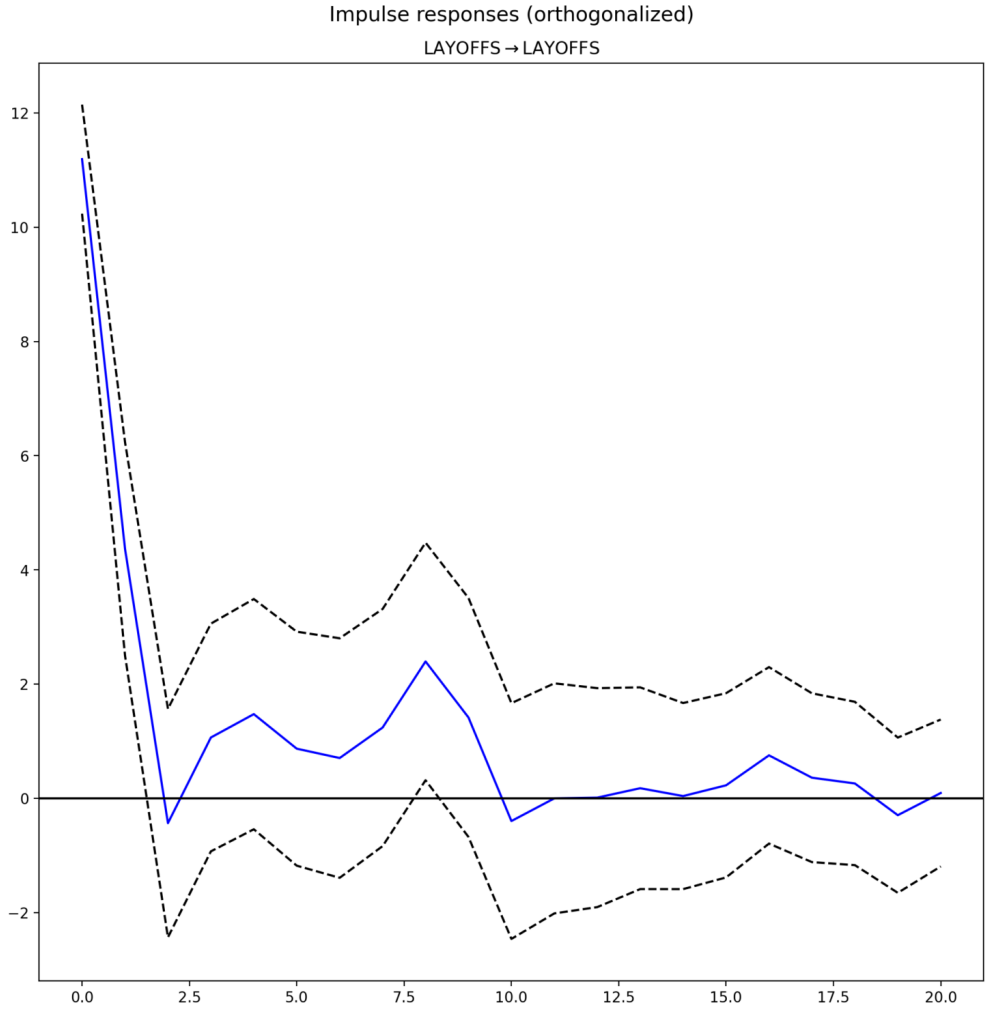


Figure 21: Layoffs on Layoffs from Python Statsmodels

As you can see there are five numbers of impulse response functions, which illustrate how each one of these affects the number of people laid off. Given our result, let's interpret what the impulse response functions gave us.

Figure 17: Industrial production on Layoffs graph shows a positive shock in the industrial production decreases layoffs until it reached 0 in the 8th month. This result lines up with Hypothesis 2: An increase in Industrial Production decreases Layoffs. This makes economic sense because if there is more production, there is more workforce behind the produced goods.

Figure 18: Inflation on Layoffs graph illustrates how a positive shock in inflation affects the number of layoffs. We can see that a positive shock in inflation decreases the number of layoffs until it hits 0 in the 6th month. This does not seem to match the hypothesis that I initially came up with.

Figure 19: Federal Funds Rate (aka Interest Rates) on Layoffs graph tells how the federal funds rate affects the number of layoffs. According to the graph, we can see a positive shock in federal funds, layoffs decrease until the 3rd month. My hypothesis disagrees with this result because in economic theory, at times when interest rates are high, people save more and consume as little as possible. Moreover, jobs will not be created due to the businesses not borrowing any money with high-interest rates to do more projects. Thus, it is intuitive to think that higher interest rates will lead to more layoffs due to the slowing down of the economy and the increase in borrowing of money for businesses makes it expensive to hire employees. Thus, the VAR IRF does not support the economic theory.

Figure 20: Economic Uncertainty Index on Layoffs graph illustrates how the U.S economic uncertainty index affects layoffs. The graph starts with a positive spike and is on the positive side until it hits 0 at around the 2nd period. This is in line with the economic theory that supports that businesses are cutting back on the workforce during economic challenging times. Moreover, after the 2nd period in the IRF graph, the response(layoffs) fluctuates above and below the zero line, which suggests the impact of layoffs changes over time. Thus, the VAR IRF result was consistent with the H4: Increase in Economic Uncertainty index increases Layoffs.

Threats to Validity

Addressing the potential threats to the validity of my study, particularly in the selection of the Information Technology sector for analyzing layoffs, introduces a risk of selection bias. This focus might limit the generalizability of the findings across different industries. Additionally, while I am aware of the possibility of model specification errors, my choice to employ Cholesky's Vector Auto Regression lends a strong degree of confidence to the robustness and appropriateness of the model for this research project.

Regarding the reliability of the data, I have strong confidence in its source, given that it originates from the Federal Reserve, which is renowned for its accuracy and comprehensiveness. However, a significant concern arises from

the Information Criteria (I.C) indicators producing varying results between STATA and my Python script. While the STATA outcomes are believed to be reliable, discrepancies in computing the optimal lag for the VAR model pose a challenge. Despite this, both STATA and the Python script eventually converge on a single result, suggesting a level of consistency that supports the overall integrity of the analysis, albeit with an acknowledgment of the need for careful interpretation of these differences.

Conclusion

This chapter addresses the areas proposed below as sections, although not necessarily in this order or organized as offered.

Summary of Results

Through thorough analysis using both STATA and my custom Python script, the results from the Vector Auto Regression (VAR) illustrated that the R-squared value was 0.40 when it comes to predicting number of Layoffs in the Information Technology. Admittedly, this is not outstanding, but the Impulse Response Functions (IRF) yielded partially encouraging results.

Using the Impulse Response functions (IRF), we found out that it proves:

- H3: An increase in Industrial production decreases layoffs.
- H4: An increase in Economic uncertainty index increases layoffs.

It also disagreed and proved the total opposite of:

- H1: An increase in Federal funds rate increases layoffs.
- H2: An increase in Inflation increases layoffs.

Future Work

For the future work of this senior project, I plan to revise the macroeconomic variables that I chose that affect layoffs. It is quite difficult to predict layoffs because it depends more on the company, its structure, Business Demand, Organizational change, product specification, etc. Thus, it may be difficult to quantify all those specific numbers and statistics for more accurate results.

Furthermore, since the SBIC and HQIC results both illustrated that a 2-month lag was suitable for the VAR, I will need to run the VAR with a 2-month lag in the future and compare if the Impulse Response Function results are any different from the 12-month one. In addition, I would like to incorporate different predictive models such as neural networks and other machine learning algorithms. Then, I would compare if they would yield different impulse response functions that might have a different narrative.

One could also extend the time intervals and go back from the year 2000. In this paper, I analyzed monthly from the year 2000 to 2023. However, one could go back to expand the time length.

Moreover, the library statsmodels use different kinds of computations to compute the AIC, HQIC, and FBIC. Thus, I would like to investigate how to make the variables the same values in Python by following the same procedure and computations.

Future Ethical Implications and Recommendations

Analyzing macroeconomic factors influencing tech layoffs presents significant ethical challenges, especially in the risk of stigmatizing specific sectors or companies. Identifying the tech industry as particularly prone to layoffs due to macroeconomic factors may lead to unjust assumptions and discrimination against the industry. To mitigate this, it's crucial to contextualize the results with comprehensive explanations, ensuring that readers understand the broader economic environment influencing layoffs rather than attributing the blame solely to industry-specific factors. By providing a nuanced interpretation of the findings, this research aims to offer a balanced understanding that helps avoid unwarranted stigma.

Another ethical challenge lies in the potential misuse of macro-level interpretations. Misinterpretation of economic data can lead to generalized, incorrect assumptions about job security, influencing individual and corporate decision-making. To prevent this, it's essential to clearly distinguish correlation from causation in research findings, emphasizing the role of multiple uncontrollable external factors. This approach helps ensure that the research informs decisions more accurately, acknowledging the complexity of macroeconomic influences.

Policy implications present further concerns. Policymakers might misuse the research to justify controversial economic measures, like sudden changes in monetary policy, which could negatively impact individuals and businesses. Therefore, conclusions must be framed carefully and responsibly, offering a balanced view that includes potential unintended consequences of policy changes. Providing context around the broader economic environment can lead to more informed and effective policy decisions.

Finally, the impact of layoffs on vulnerable groups must be considered. If layoffs disproportionately affect marginalized groups, these trends should be highlighted to inform better policy and organizational strategies. This requires advocating for inclusive data collection to ensure that the analysis considers the effects on vulnerable demographics and promotes equitable policy solutions. By understanding and addressing these ethical implications, the research aims to provide a more comprehensive and empathetic analysis of layoffs in the tech industry.

Conclusions

In summary, this study utilized Vector Autoregression (VAR) to investigate the impact of various macroeconomic variables on layoffs within the Information Technology sector. Although the model's explanatory power was modest with an R-squared of 0.40, the Impulse Response Functions provided valuable insights, affirming some hypotheses while refuting others. Notably, increases in industrial production appear to mitigate layoffs, while heightened economic uncertainty exacerbates them. Contrary to initial expectations, the Federal Funds Rate and inflation rates did not behave as predicted in relation to layoffs. You can see more in details on the official research website.

These results from both STATA and custom Python script underscore the multifaceted nature of the job market and the complex interplay of economic forces at work. Future research could expand on these findings by exploring additional variables, employing alternative models, or examining other industry sectors to gain a more holistic understanding of the factors driving layoffs. This paper serves as a stepping stone in the ongoing quest to decipher the economic undercurrents that shape our labor markets.

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