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Job Insecurity and Its Influence on Stock and Unemployment Expectations: An Industry-Specific Sensitivity Analysis

Author:	Kaiyang Sun
Student number:	613725
Thesis supervisor:	Assistant Professor Daniel Karpati
Second reader:	**[**title and name of second reader]
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ABSTRACT

This paper examines the impact of job insecurity on individuals' expectations for stock prices and unemployment rates in the United States, with a particular focus on industry-specific effects. To find the relationships, I apply OLS regression and time-series analysis on panel data from late 2013 to 2023. Results show that higher job insecurity correlates with expectations of rising stock prices, except in less sensitive industries. Additionally, there is a connection between work insecurity and rises in anticipated nationwide unemployment rates by individuals. Household income and gender also influence these expectations, with wealthier households and males being more optimistic about stock prices. My findings highlight the importance of considering industry-specific factors in economic forecasting and policymaking, while acknowledging limitations related to industry categorization and potential biases.

Keywords: job insecurity, unemployment expectations, stock price expectations, industry sensitivity

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CHAPTER 1 Introduction

The COVID-19 pandemic has incurred a loss in labor markets and disrupted the economy in the U.S. (Laura et al.2022). Many people have seen their workplaces change in big ways, and now, as the world is recovering, we can see how these changes might shape the future of work. Previous study has examined unemployed individuals' subjective experiences and their future aggregate expectations (Kuchler & Zafar, 2019). Instead of looking at unemployment and individuals who lose their jobs during this pandemic, this research will draw attention to individuals who managed to keep their jobs or who faced problems of unemployment (illness, complementary leave, et al.). Employment and stock markets are two crucial statuses in economic development, and they both show important characteristics of economy. Therefore, study how the shock changes individuals' expectations on employment nationwide and stock prices will indicate precise information of that period of economy, which provides useful experience for future economy as well. Investment, as an alternative way for individuals or households to maintain their wealth or increase their profits. Will changes in job insecurity have effects on their investment expectations? Do they expect higher stock prices to compensate for the loss they faced previously or currently? Do they foresee the whole society will face the same employment failure as themselves? By focusing on their sense of safety for employment, this study aims to shed light on the relationship between their insecurity and expectations for future stock prices and nationwide unemployment expectations. Moreover, it is crucial to note that different industries reacted to this momentum (COVID-19) distinctly, as shown by research which examines 15 industries with abnormal returns in the markets (Goodell and Huynh, 2020). Thus, since people working in different industries might get influenced by this situation, the paper will also look at the sensitivity of different industries, which will provide a more comprehensive result.

Although COVID-19 stimulates my interest and thoughts on this current state of affairs, I still want to gain more comprehensive and general results. Thus, this paper will not be constrained to the time period of COVID-19, instead, a complete analysis from 2013 will be performed. Through a more comprehensive analysis on a long-period perspective, the relationship found in this paper could be more general and worthy. This research goes beyond just understanding these shifts; it aims to contribute to improving financial policies and support systems for everyone as we move forward into a post-pandemic world. The insights gained from this study might be helpful for policymakers, employers, and financial institutions, helping them to develop related polices and strategies for economic recovery, especially in effects on stock markets and labor markets. Through addressing problems from employees' perspective, we can build a more equitable and supportive environment for society.

CHAPTER 2 Theoretical Framework

2.1 Employment

2.1.1 Job loss and job insecurity

Coibion et al. (2020) estimate that approximately 20 million jobs were lost by early April 2020 due to the pandemic, a number that surpasses the total job losses during the entire Great Recession. This significant reduction in employment is evidenced by a sharp decline in the employment-to-population ratio, marking a nearly 8 percentage point drop. The severity of these job losses underscores the nature of the economic downturn induced by the pandemic. Moreover, pprevious study highlights the significant psychological impacts of the pandemic on the workforce, suggesting that COVID-19-related fear exacerbates concerns regarding job security and satisfaction, thereby potentially influencing individuals' future employment expectations (Rajabimajd et.al, 2021). The review calls for more research using valid and reliable measures to assess the associations between COVID-19-related fear/anxiety and job attributes across diverse jobs. Is unemployment a shock or a trend? Employment losses, while widespread, have been significantly larger and more persistent in lower-paying occupations and industries (Cortes & Forsythe, 2022). Meanwhile, they find that this pandemic has strengthened inequalities, which can be shown from the greater amount of job losses for Hispanic and non-White workers. In sum, COVID-19 challenged employment situations in lots of aspects around the whole world.

2.1.2 Employment experiences

Furthermore, Abraham, Spletzer and Harper (2010) shed light on the intricate relationships that exist between job tenure, job loss, and employment sector. This allows for a more nuanced understanding of how past employment experiences might shape individuals' expectations for future employment. The results on shifting patterns of job tenure and security are highly relevant, even though the direct impact on future employment expectations is not explicitly modelled. This suggests that experiences with decreased job insecurity may modify expectations about the stability of future employment opportunities. Moreover, Nicholson (1984) provides a comprehensive framework for understanding how prior employment experiences influence future employment expectations. The idea provides insights into how people project past experiences onto future career chance by focusing on the adjustment to new responsibilities. This framework can be instrumental in exploring the nuanced ways individuals' history of job transitions impacts their outlook on future employment opportunities, including how they perceive job security, career advancement, and role suitability based on previous roles' characteristics and adjustment outcomes. Besides, while the study of Kuchler and Zafar (2019) specifically examines the effects of personal experiences with unemployment on expectations about unemployment rates, the underlying mechanisms and findings could inform the investigation into how individual employment histories could influence broader job market perceptions and expectations. Meanwhile, their study finds that people who have unpleasant unemployment experience have a negative attitude towards future unemployment expectations nationwide.

2.1.3 Unemployment and gender gap

Previous study (Şahin, Song, & Hobijn, 2010) has examined the gender disparity in unemployment rates during the 2007 recession. By August 2009, the unemployment rate for men was 11.0% while for women that was 8.3%, marking a 2.7% gap. Moreover, the authors consider about industry representation, and they find that females were more represented in more stable sectors such as healthcare or education, which might help to explain this disparity. However, in goods-producing industries, there were substantial job losses, with men losing 2.9 million jobs compared to 765,000 jobs lost by women. Moreover, they mentioned the labor force as a possible result of the higher unemployment rates of men. That is, during the recession, there was a significant increase in the number of men re-entering the labor force, due to declining household illiquidity. To summarize their findings, while both genders faced similar outflow rates from unemployment, the inflow rates were significantly higher for men, leading to a marked gender gap in unemployment.

2.1.4 Unemployment experiences and family wealth

Padoa Schioppa and Lupi (2002) found that personal and family characteristics significantly influence youth activity and unemployment rates in Italy, both shot-term and long-term. They use cross-sectional individual data to examine this relationship. Notably, their research only considered individuals whose ages are between 15 and 29 years old. Moreover, they found that the income effect is significant in participation decisions, and family wealth helps reduce youth unemployment.

2.2 Stock markets

2.2.1 Abnormal returns

Another important thing to note is the behavior of the stock markets during this pandemic. Ashraf (2020) finds that stock markets react negatively to the growth in confirmed COVID-19 cases. As the number of confirmed cases increases, stock market returns tend to decline. This negative reaction is particularly strong during the early days of the outbreak and resurfaces between 40 and 60 days after the initial cases. The initial sharp decline in stock prices can be associated with the immediate uncertainty and fear surrounding the pandemic's potential economic impact.

Recall the shock in the labor markets, its influence might spread to the stock markets. According to Goodell and Huynh (2020), during this pandemic, there are abnormal returns for some industries, especially in medical and pharmaceutical industries. Their study uses daily stock returns from 49 US industries, including NYSE, AMEX, and NASDAQ data. They use event study and analyze abnormal returns on key dates, showed significant market reaction only on February 26. The industries showing negative abnormal returns are services, utilities and transportation.

2.2.2 Stock prices and labor markets

Previous study has shown that an increase in local stock wealth driven by aggregate stock prices promotes local employment (Chodorow-Reich et.al, 2021). Moreover, their paper also examined that this increase in stock wealth promotes payroll in non-tradable industries while having no effects on tradable industries. Their study suggests that a 20 percent increase in stock valuations can increase aggregate labor bill by at least 1.7 percent and aggregate hours by 0.7 percent two years after the shock. Meanwhile, their strategy considers regional heterogeneity in stock market wealth and aggregate movements in stock prices. Their findings support the concept “the Fed put,” where the central bank tends to cut interest rates when stock prices decline. This study shows that such a decline, if not influenced by monetary policies, will reduce local employment and labor bills. Thus, it shows that the effects on employment seem to be different for diverse industries and there is an interaction between stock markets and local employment.

Previous study examines the association between unemployment and stock prices (Boyd et. al, 2005). The authors find that during economic expansions, announcements of rising unemployment are generally good news for stock markets, thus, there will be an increase in stock prices. This seems to be counter-intuitive, but it is mainly because of the expectation of lower future interest rates. Moreover, in this state, the effects of interest rates denominate other factors such as corporate earnings. However, during economic recessions, rising unemployment is bad news for stock markets, which means there will be a decline in the stock prices. In this phase, information on future corporate dividends is more significant. The factors driven by this circumstance are mainly individuals' expectations about future interest rates, corporate earnings and their changes in risk preference. They then conclude that since the whole economy is always in the expanding phase, the stock markets typically react positively to bad news in employment. The signs given by how stock markets react to employment can thus be a signal of which state is the economy in.

2.2.3 Stocks and gender gap

Johan and Anna (2012) examined the gender gap in stock market participation and its relation to financial literacy. They use a survey of 1300 individuals' representative of the Swedish population to analyze this issue. Their findings show that there is a significant gender gap in stock market participation, saying that women participate less than men. Moreover, they think this difference could be partially explained by differences in financial literacy between genders. They categorized financial literacy into two types which are basic financial literacy and advanced financial literacy. They find that basic financial literacy can explain a significant portion of differences in gender differences, while advanced literacy is considered more endogenous as it can be improved through taking part in stock markets. Meanwhile, they have observed that women report being less risk-seeking than men, and the gender differences still occur even if controlling for financial literacy. However, when we reduce the basic financial literacy, there would also be a reduction in the gender gap.

2.3 Motivation

Although the paper shows the concerns of job security and satisfaction for future employment expectations during COVID-19, it does not explicitly find the effects of past employment experience on future expectations (Rajabimajd et.al, 2021). Moreover, their paper emphasizes the effects found during COVID-19, it remains interesting to try finding possible relationships in other time period to see a more general result. Another paper finds noteworthy results of the relationship between past unemployment experience and future unemployment expectations (Kuchler and Zafar, 2019). However, their paper draws more attention to personal experiences including unpleasant employment experiences, and the effects from job insecurity remain unclear. Meanwhile, although they have studied that people with unpleasant employment experience will have negative attitudes towards future employment expectations, they do not consider industries' specialty and they focus on a wider range of employment status. Furthermore, the effects from personal experience on stock prices are not examined in this paper. The research conducted by Padoa Schioppa and Lupi (2002) show relationships between unemployment and family wealth in Italy, also controlling for individuals' ages. Given that specific emphasis on certain religion, there is still space for us to dive deeper into other religions such as United States with a wider time horizon. In conclusion, above literatures share similarities in finding the interplay between individual level factors and their expectations on macro economy. Some of them specifically emphasizes the results induced by pandemic such as Great Recession and COVID-19 which causes shock in unemployment. The differences can be seen from sample selection, different age groups and different religions. Thus, my research aims to contribute to a further step, finding a generality through a longer time horizon as well as adding industry-specific sensitivity analysis. Finally, my paper could help in understanding how society will react to individuals' perspectives on job insecurity and that would help us to conduct future research in this realism and improve labor policies.

The abnormal returns in stock markets shown in this pandemic also drew lots of attention from researchers. Arshraf (2020) provides a comprehensive analysis on how stock markets reacted to this pandemic and finds different reactions of distinct industries. However, in his research, he does not look at the effect on labor markets. Moreover, one study states that rising unemployment should be bad news for stock markets during recession (Boyd et. al, 2005). Nevertheless, there could be more details on the individual level. That is, what are individuals' expectations on stock prices and expectations on losing jobs. And the gender gap in stock markets is also an important factor which should be taken into consideration as a previous study draws a conclusion on that (Johan & Anna, 2012). Their research indicates that men participate more often than women in the stock markets even if controlling for financial literacy. Would individuals' personal behavior be one of leading factors to the abnormal returns in stock markets? If people become positive about future stock prices, they would choose to invest more, which might lead to abnormal returns. Except that, I also consider family characteristics of individuals such as household pre-tax income and thus my research might contribute to the research gap about effects of family wealth on investment. Furthermore, by integrating insights from existing literature on employment experiences, job satisfaction, and future job expectations, this research seeks to contribute to theoretical advancements in understanding the complex interplay between job insecurity and future expectations on stock prices and unemployment. Besides the interaction between unemployment and stock prices, labor markets and stock markets are two crucial economy statues, and understanding individuals' expectations on those two important economy components will shed light in a deeper understanding of economy itself. In other words, it would help us in understanding the economy. Ultimately, the findings of this study aspire to provide actionable insights for policymakers, employers, and stakeholders involved in shaping the future of work. In conclusion, my research question is:

How does individual's job insecurity shift individuals' expectations on stock prices and nationwide unemployment in the U.S. since late 2013?

CHAPTER 3 Data & Methods

3.1 Data

The dataset that will be used in this research is SCE, a monthly survey conducted by the Federal Reserve Bank of New York since 2012. With further consideration in industries' sensitivity, we combine the labor market survey for more information on industries. The period I will use is the time from the end of 2013 to 2023. The reason is that individuals only started to answer questions about their job industries after the end of 2013, and since this categorical variable is specifically crucial in my analysis, I must give up the previous period. It takes 15 to 20 minutes for each respondent to answer the specific questions regarding their expectations on housing prices, inflation rates, employment expectations and other economic indicators. Beyond these specific questions, respondents will also provide their general information such as ages and genders. Meanwhile, both surveys have the same respondents.

To conduct analysis on industry sensitivity level, national unemployment rates from U.S. Bureau of Labor Statistics (2024) are used for time-series regressions. The national unemployment rates are on a monthly basis; thus, it is convenient for me to calculate the change of national unemployment rates per month.

To estimate the effects of job insecurity on an individuals' expectations on future stock prices, we need the dependent variable to measure the percentage chance that stock prices in U.S. stock market will be higher a year later. In the questionnaire, respondents are required to give their thought on what percentage chance that stock prices in U.S. stock market will be higher in 12 months from the time they answered the question. The largest percentage change is 100% for each respondent. The variable is calculated through taking an average of the same respondent' answers over all questionnaires he or she answered.

Meanwhile, to estimate the effects of job insecurity on an individuals' expectations on national employment, we need the dependent variable to measure the percentage chance that unemployment in U.S. stock market will be higher a year later. In the questionnaire, respondents are required to give their thought on what percentage chance that unemployment in U.S. will be higher in 12 months from the time they answered the question. The largest percentage change is 100% for each respondent. The variable is again calculated through taking an average of the same respondent' answers over all questionnaires he or she answered.

Furthermore, to find the effects of job insecurity, the independent variable which measures the respondent's expected percent chance of losing a job in twelve months can be used. The variable is calculated as them same method as calculating dependent variables. Also, pre-tax household income in past 12 months could be a control variable. The income variable in the questionnaire is a categorical variable with 11 categories. Moreover, the control variable I choose is the gender as previous study has observed there is significant gap between two genders about participation in stock markets. I convert gender variables into dummy variables, which means they are either 0 or 1 in my data. There are two questions asking information about occupations in the labor market survey. Participants are required to firstly categorize their current careers into five groups, including government, private sectors, non-profit organizations, family business and others. After the first choice is made, they will further define their careers more specifically if they do not choose government services, such as agriculture, banking and finance, and so on. However, in the later question, which is indicated by the 18^{th} option. There is an option of government. Thus, I categorize people who did choose government in the first question and who choose the 18^{th} option later together.

Indeed, there are individuals who switch their working positions in different industries as the survey records their working life from 2012 to 2023. To reduce inaccuracy while doing analysis, I only use their first position to do a regression, which means I will delete duplicates of repeated individuals in my data and every individual will only be recorded once.

3.2 Method

By focusing on people who had jobs and people who had the problems of losing jobs (currently employed, temporarily laid-off, and on sick), I can specify the groups of respondents I want to study. After a clear definition of all the variables is completed, OLS with robust standard errors will be used to analyse this problem, which aims to solve the heterogeneity. Finally, I will perform a sensitivity analysis on industries to dive deeper into the research question. To conduct the sensitivity analysis, my research will look at the share of employed people in each industry. Then, I calculate what share of these people became unemployed in the next year. These industries will be divided into three distinct categories based on the changes of the shares: high, medium, and low, reflecting the sensitivity of different industries. Another method to supplement the sensitivity analysis is doing time-series regression on distinct industries in each year. After that, rank the betas gained from the time-series regression and categorize those industries into high, medium and low according to their sensitivity. The next step is to regress again according to industry sensitivity obtained from the time-series analysis. Through doing this, I could reduce possible bias and gain a more accurate and comprehensive analysis based on national unemployment rates.

Kuchler and Zafar (2019) finds that people with unemployment experiences are more pessimistic about future unemployment nationwide. Although the effects on stock prices are not clarified in that paper, the previously mentioned study has shown that increasing unemployment during economic recession is bad news for stock markets but generally good news for stock markets. Meanwhile, according to the paper (Abraham et.al, 2010) which emphasizes the increasing importance of security for individuals with insecure employment experiences. Based on the above literature, it is anticipated that I can find significant results in terms of security. Thus, I hypothesize:

H1: People who expected to lose job in future will have a positive attitude towards future stock prices.

$$Expectation_{ij} = \alpha + \beta_1 * Income_{ij} + \beta_2 * Loss_{ij} + \beta_3 * Gender_{ij} + \epsilon_{ij} \qquad (1)$$

where i = individuals, j = industries, ϵ_{ij} is the error term

The above regression will be used to test my hypothesis. The dependent variable $Expectation_i$ is the percentage chance that stock prices in U.S. stock market will be higher a year later. The independent variables are $Income_{ij}$ and $Loss_{ij}$. Furthermore, the $Income_{ij}$ variable looks at how long does the respondent work in his current job position. The income variable in the questionnaire is a categorical variable with 11 categories. The first six options show an increase of 9,999 dollars, while later options start to indicate a larger difference. The highest one represents 200,000 dollars or more. However, participants only provided this answer to past income only once when consistently taking the survey, so the assumption is that this variable is constant overtime, this assumption might cause inaccuracy for our analysis. Moreover, I estimate the effects from job insecurity through looking at the variable $Loss_{ij}$ which gives a clear measurement of the expected probability of losing the current job during the next 12 months. Finally, I take the variable $Gender_{ij}$ as a control variable to determine whether the expectation will be influenced by different genders. Since the dataset contains information about an individual over time, variables relating to his or her future employment expectations, earnings, and probability of unemployment will be measured as averages.

H2: People who expected to lose job in future will have a pessimistic attitude towards employment nationwide.

$$Expectation_{ij} = \alpha + \beta_1 * Income_{ij} + \beta_2 * Loss_{ij} + \beta_3 * Gender_{ij} + \epsilon_{ij} \qquad (2)$$

where i = individuals, j = industries, ϵ_{ij} is the error term

The above regression will be used to test my hypothesis. In my hypothesis, being pessimistic towards future employment means there is a positive correlation between job insecurity and the unemployment expectations. The dependent variable $Expectation_{ij}$ is the percentage chance that unemployment in U.S. will be higher a year later. The independent variables are $Income_{ij}$ and $Loss_{ij}$. All other variables remain the same as in regression (1), except for the fixed effect term. Indeed, it will not be surprised that I found the coefficient of the $Loss_{ij}$ variable is positive as the reverse causality exists: if economy does well, then I expect not to lose my jobs. However, there is still something remaining to be studied since we know that different industries have distinct levels of sensitivity when reacting to the overall performance of the economy (unemployment of the economy). Thus, it is possible that in industries those are not sensitive to the performance of the economy, the coefficient of the $Loss_{ij}$ variable will be negative, which means although the individual expects to lose his or her jobs, he or she still believes the economy will perform better in the future.

$$Share_{jt} = \alpha_j + \beta_j\,(Rate_{jt+1} - Rate_{jt}) + \epsilon_{jt} \qquad (3)$$

where j = industries, t = months, ϵ_{jt} is the error term

To perform sensitivity analysis, I select data from 2014 to 2023 during which time there is enough information for people's positions in different industries. To conduct a time series within each panel (industry), my model regresses on a monthly base to ensure there is a stronger statistical power and reliability for analysis. In the above regression, $Share_{jt}$ is the calculated change in share of unemployment within each industry per month. $Rate_{jt}$ is the monthly national unemployment rate in the U.S.. Through regressing the change of national unemployment rates per month on change in shares of unemployment per month in each industry, I get coefficients which measure the sensitivity of each industry. That is, if national unemployment increases, do many people become unemployed in this given industry?

$$Share_{jt} = Change_{jt} / Total_{jt} \qquad (4)$$

where j = industries, t = months

The other method of categorizing industries is simply calculating the change in share of unemployment like the above one, still monthly. I then create a threshold of 1/3 to divide all individuals into three groups. Here, $Change_{jt}$ represents individuals who become unemployed in certain industry during time t+1, and $Total_{jt}$ means the total amount of individuals in that industry during that period. After that I take the average of all the shares for each industry over that time and rank them from low to high. Remember that I have divided all individuals into three groups, then the amount of people in each sensitive level industry will be close to each other. And since the amount of people in each industry is different, it can cause different number of industries in different sensitivity levels as well. This way I measure the sensitivity level of industries in our data sample but might lose some generality. Thus, I have two methods, the first is the one using national unemployment rates by time-series analysis and the second is the other one without national unemployment rates.

3.3 OLS assumption validity

In this section, I check the robustness of my regression models. I start by checking the normality of residuals. First, I will examine the validity of our first regression, which is the regression on stock price expectations. Given the results in Table 7, we know the p-value for White test is smaller than 0.05, meaning it is significant at 5% level. Therefore, I can reject the null hypothesis that there is constant variance (homoscedasticity) in residuals. This means I need to use robust standard errors to remove effects from heteroscedasticity. Moreover, Figure 6 in the appendix shows that the residuals seem to be normally distributed; to clarify this, the Shapiro-Wilk test is performed. As the results shown in Table 5, with a p-value smaller than 0.05, the null hypothesis that residuals follow a normal distribution is rejected. Again, the robust standard error is needed for our regression. Finally, I look at the endogeneity problems in regression (1). Through examining the correlation among variables and residuals, we can see that in Table 13 in the Appendix, all correlations are close to zero, which means there exists no endogeneity or little endogeneity. In conclusion, by using robust standard errors, my model is consistent with CLRM assumptions. In other words, the estimator in my model is relatively accurate to capture the true parameter value.

Then, I look at my second regression, which is the regression on unemployment expectations. Given Table 5 in the Appendix, we know that the p-value for white test is significant, thus, I can reject the null hypothesis there is a constant variance (homoscedasticity) in residuals. Thus, robust standard error is needed in our regression to get rid of heteroscedasticity. Meanwhile, Figure 7 in the Appendix shows that the residuals are almost normally distributed. To be clearer, I perform the Shapiro-Wilk test to see whether our residuals are normally distributed. As the results shown in Table 7, with a p-value smaller than 0.05, I can reject the null hypothesis that our residuals are normally distributed. Thus, robust standard error is needed for our regression. Again, I can make similar conclusions about endogeneity like in the last paragraph. In conclusion, by using robust standard errors, my model is consistent with CLRM assumptions. In other words, the estimator in my second model is also relatively accurate to capture the true parameter value.

Lastly, since I use time-series data when testing the industry sensitivity level in model (3), it is reasonable to use Durbin-Watson test to test whether there exists auto-correlation. Results in Table 7 show that there is no or little autocorrelation in residuals as the d-statistic in my time-series model (3) is close to 2. However, I also tested for stationarity of my data, according to the test results in notes of Table 4, my data are non-stationary. It is probably because the data sample is not large enough as I only obtained 6443 individuals in my time-series. Also, the time horizon might be influenced by other macro factors such as COVID-19 or monetary policies, accompanying lots of outliers. As shown in the Appendix, the ADF test results in Table 12 indicate that unemployment share is stationary while the national unemployment rate is non-stationary. To correct this, I tried to add logarithms and detrend my variables after dropping outliers. Figure 9 in the Appendix shows that there is a sharp increase in national unemployment rate around 2020. The huge fluctuations can be seen clearly even after taking logarithms. Meanwhile, the third column in Table 12 still shows that corrected nationwide unemployment rates are non-stationary. Thus, I cannot conclude robust results from our industry categorization by time-series analysis since the betas could be inefficient and biased.

3.4 Sample analysis

The sample is created by selecting relevant variables on SCE data, dropping missing values, and calculating values while combining them into an individual level. Meanwhile, data about national unemployment rates from U.S. Bureau of Labor Statistics (2024) is also used for time series analysis. According to Table 1, there are 6443 individuals who provide valid information for our regression analysis. The reason why there is a loss of data in my sample is firstly because there are a lot of individuals who do not choose their past household income as this is relatively a new question. Meanwhile, I only consider people who had a job during selected period, which means I control their employment status. Moreover, lots of missing values in the industry variables make it difficult to categorize industries, thus I must drop those missing values. Finally, after dropping missing values from people who do not specify their genders, there are only 5585 individuals who fulfil our requirement. In the table, except the gender variable, all other variables are measured in percentage since they ask for percent chance of expectations. The mean value of percent chance that average expectations on unemployment will be higher in U.S. is 37.68%. The maximum 100%, meaning that this person is sure that more people will be unemployed for sure in the coming 12 months. However, there are people choosing 0 to show their refuse against higher unemployment. Meanwhile, the mean value of percent chance that average expectations on stock prices in U.S. market will be higher is 43.47%. The maximum is also 100% while the minimum is 0.13%. Furthermore, the average perceived likelihood of losing a job within the next 12 months is 15.19%, with values ranging from a minimum of 0% to a maximum of 100%. Finally, the control variable gender only contains 0 and 1, it seems that in our data, there are 52% male and 48% female.

Table 1: Descriptive statistics

	Mean	Std. Dev.	Max	Min
Average expectations on unemployment (%)	37.46	16.99	98.46	0.00
Average expectations on stock prices (%)	43.09	17.77	100.00	0.00
Average expectations on losing jobs (%)	13.64	14.79	100.00	0.00
Gender	0.52	0.50	1	0
Number of observations	6443	6443	6443	6443

Look at Table 2 which shows the frequency of categorical variable pre-tax household income. There are only 69 individuals whose family have income less than $10,000. For the first six options, the difference between each option is $9,999. However, the range increases after the sixth option, the difference becomes to $14,999 and even to $49,000. The increasing range probably shows that there is a need to increase range for including all observations, and this is also proven by the distribution of these observations. It is clear to see that most individuals' household pre-tax income is in the range from $100,000 to $149,999. And the second largest group ranges from $75,000 to $99,999, reaching 17.31% of the total sample. However, it is difficult to say whether this sample is normally distributed, since the measurement changes within different choices. If we use $100,000 as a division, then we will have 2471 individuals whose family pre-tax income is larger than that boundary, and 3972 individuals whose family pre-tax income is lower than that boundary. Thus, this sample seems to be good to use as there is not an extreme gap in the number of people between low- and high-income groups.

Since there is a great difference among the numbers of individuals in each group, I decided to rearrange these categorical variables to make them more suitable for statistical analysis. Before the combination of several groups, for the income group less than $10,000, there are only a few individuals, which will make results inaccurate. The adjusted data is shown in Table 3, which provides a more balanced distribution across five categories. As the larger sample will have a stronger statistical power, the adjusted pre-tax household income groups are more likely to present a true effect.

Table 3: Frequency statistics for pre-tax household income with corrected groups

	Freq.	Percent	Cum.
Household pre-tax income			
Less than $50,000	1027	15.94	15.94
From $50,000 to $74,999	1061	16.47	32.41
From $75,000 to $99,999	1884	29.24	61.65
From $100,000 to $149,999	1279	19.85	81.50
$150,000 or more	1192	18.50	100.00
Number of observations	6443	100.00	100.00

In Figure 1, regardless of industry categories, we can see that most of respondents think that the percent chance of rising national unemployment in 12 months on average ranges around 40% and 50%. Thus, most people hold a view that the possibility of having a higher unemployment rate in U.S. is lower than 60%, which means that they also have a tender attitude towards nationwide unemployment during this period. The interesting thing is that, even though some individuals are confident about their employment, they still have a pessimistic attitude towards nationwide unemployment. This can be shown by the fact that we can see a lot of people who think their possibilities of losing their job are lower than 20%, however, they think the possibility of facing an increasing nationwide unemployment is larger than 50%. Thus, I can conclude most people tend to have a tender attitude towards future personal employment, that is, most people do not think they will easily lose their jobs. When taking sensitivity of industries into consideration, we can see that in the medium level industries, there are not clear differences as shown in Figure 4.

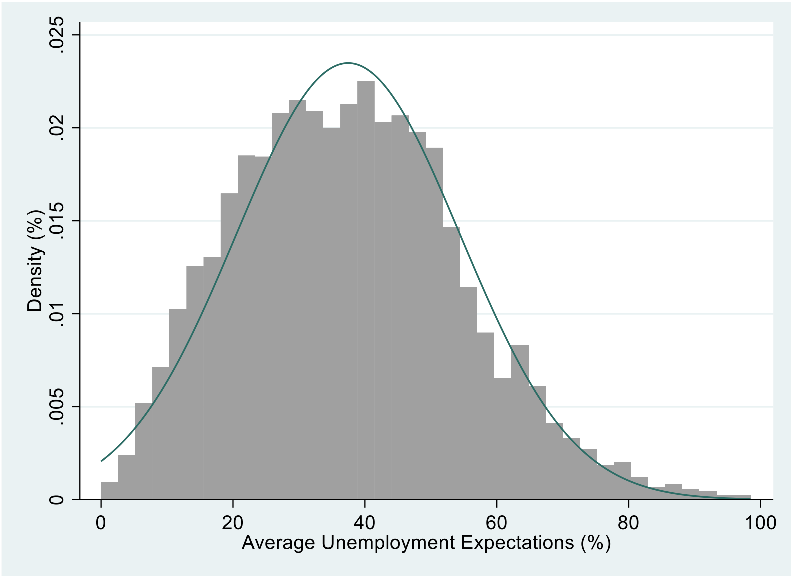

Figure 1: Histograms for average unemployment expectations.

According to Figure 2, like individuals' expectations on rising unemployment, most people hold a tender attitude towards stock prices. That is, without considerations of industrial sensitivity levels, more people thinks that the percent chance of having a higher stock price in U.S. stock market within 12 months is lower than 60%. In other words, more people think the stock price will either stay steady or face a decrease. For industries with higher sensitivity, it seems that more people think the probability of having an increase in stock prices lies between 20% and 60%. In the group with low sensitivity, we can see more people stand that the possibility of having a rise in stock prices is larger than 60%. Therefore, I can say for industries with other two levels of sensitivity, people's expectations on stock price changes vary more widely. Moreover, I can conclude Figure 2 shares similarity with Figure 1, with a skewness to the left side and a concentration around the middle part. Finally, my other conclusion is that more individuals hold a tender attitude towards both changes in unemployment and stock prices in U.S. for next 12 months. And most individuals are confident that the possibility of losing their jobs in the next 12 months is low.

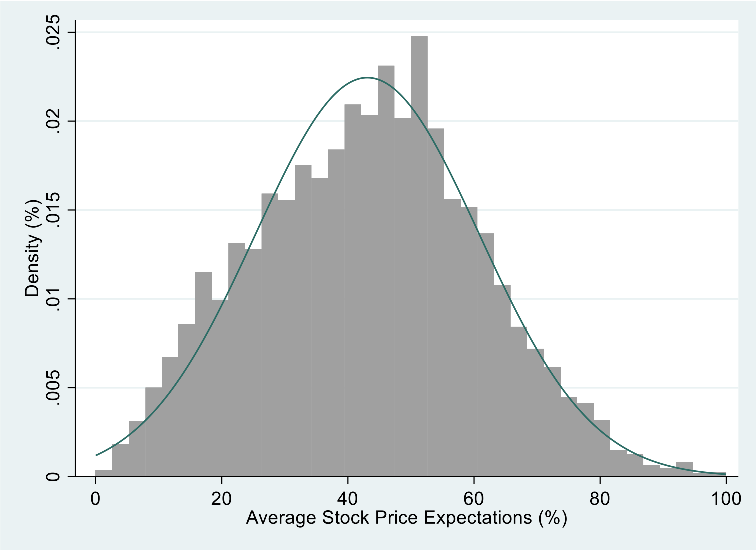

Figure 2: Histograms for average stock price expectations.

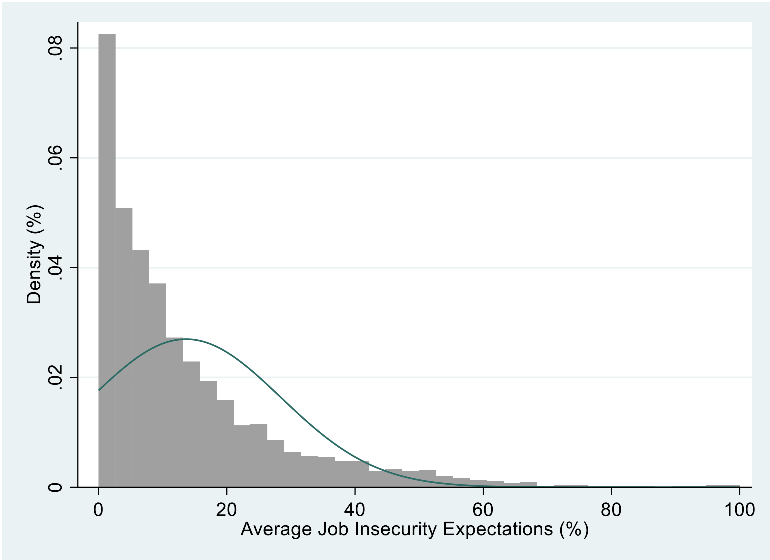

Figure 3: Histograms for average job loss expectations.

3.5 Industry sensitivity level

See Table 4 below, two distinct ways of measuring industry sensitivity level indeed result in different categorizations. In the second column and the fourth column, I perform sensitivity analysis for industries by time-series data. However, since the data of national unemployment rate is non-stationary, which can be proven by the results in the second column of Table 12. Thus, I tried several methods to make it more stationary. After dropping outliers, taking logarithms and detrending, the results of industries obtained are shown in the fourth column of Table 4. Yet, there are few changes compared to the second column and significant industries remain the same. Moreover, the results shown in Table 12 in the Appendix indicate that even though several attempts were implemented, unemployment rates are still non-stationary. Possible reasons are policing and specific time period such as COVID-19 which might have an influence on this variable. Thus, I still categorize industries into three groups like them in the second column as considering the originality of my data. The results in the fifth column show my categorizations with the other method. There are lots of differences between these two methods. For example, under the methods by using time-series data, Banking and Finance should be put in the high-sensitive industries. However, in the later methods only considering change of unemployment shares, Banking and Finance is categorized as the low-sensitive industries. Moreover, since the first method ranks industries based on the coefficients, the number of industries in each group is similar. However, as I first divide individuals into three thresholds and drop individuals who are unemployed, the ranking is based on which threshold the individual is in. Thus, the amount of people in each sensitivity group is similar, but the number of industries in each sensitivity group is largely different. This can be seen from Table 7 below that there are only two high-sensitive industries in the high group.

Table 4: Categories of industries through two methods

	Beta (1)	Sensitivity level (1)	Beta (2)	Sensitivity level (2)	Sensitivity level (3)
Household pre-tax income					
Agriculture (1)	-0.001	Medium	-0.110	Low	Low
Oil & Gas Extraction (2)	-0.011	Low	-0.001	Medium	Medium
Utilities (3)	-0.014	Low	-0.453	Low	Low
Construction (4)	0.024**	High	1.111***	High	Low
Manufacturing (5)	-0.000	Medium	-0.023	Medium	Low
Wholesale Trade (6)	-0.001	Medium	-0.110	High	Low
Retail Trade (7)	0.020	High	0.180	High	High
Transportation & Warehousing (8)	0.020*	High	0.986**	High	Medium
Information Services (9)	-0.019	Low	-0.683	Low	Low

Banking & Finance (10)	0.009	High	0.461	High	Low
Real Estate (11)	-0.002	Low	-0.129	Low	Low
Professional & Business Services (12)	-0.002	Medium	0.004	Medium	Low
Education (13)	-0.011	Low	-0.565	Low	Medium
Health Care (14)	-0.003	Low	-0.060	Low	Medium
Arts & Entertainment (15)	-0.007	Low	-0.223	Low	Medium
Hotel & Restaurant (16)	0.011	High	0.283	High	High
Other Services (except Govern.) (17)	0.004	Medium	0.171	Medium	Low
Government (18)	0.002	Medium	-0.015	Medium	High
Other (19)	0.006	High	0.052	Medium	Medium

Note: The d-statistic of Durbin-Waston test for autocorrelation is 1.875 which is close to 2, indicating that there is little or no autocorrelation in my regression model (3). The second column indicates results from time-series analysis. The fourth column shows results from time-series analysis after dropping outliers, taking logarithm and detrending. The final column shows results from ranking industries only by changes of shares in unemployment.

***Significant at the 1 percent level

**Significant at the 5 percent level

*Significant at the 10 percent level

CHAPTER4 Results & Discussion

4.1 Results of stock expectations

According to Table 8, the coefficients of average expectations on losing jobs are significant in our main regression, meaning that I can reject my null hypothesis that there is no relationship between individuals' job insecurity and their attitudes towards future stock prices in the United States. Take industry categorizations into consideration, the coefficient of independent variable is insignificant at 1% level in the low-sensitivity industry but still significant in other industries. Although coefficients in medium-sensitive and high-sensitive industries are statistically significant, their numerical values are small, saying 1% increase in job loss expectations will lead to around 0.1% increase in stock price expectations.

Firstly, the first column shows us the results from our main regression, the one without considerations of industry sensitivity. All variables are statistically significant. The coefficient of categorical variable that means whose income is from $75,000 to $99,999 is 2.012 and it is significant at a 1% level. This means that, if one individual has a pre-tax household income between $75,000 and $99,999, his average expectations on percent chance of having an increasing stock price is about 2% higher than individuals whose family income is lower than $50,000. Similarly, for people whose pre-tax household income lies in the range between $100,000 and $149,999, their average expectations on percent chance of having an increasing stock price is about 3.76% higher than individuals whose family income is lower than $50,000. And the coefficient 3.766 is significant at 1% level as well. Moreover, for individuals with an even higher household income which is $150,000 or more, their average expectations on percent chance of having an increasing stock price is about 8% higher than individuals whose family income is lower than $50,000. Meanwhile, the coefficient 8.087 is significant at 1% level. It is also important to note that gender plays a role in our main model, the coefficient of gender dummy is 7.538 and significant at 1% level, which means that males seem to expect a higher percent chance of having an increasing stock price than females. And the gap between their expectations is about 7.5%. To conclude, as the revenue amounts increase across these income groups, I observed a corresponding rise in the coefficients associated with these categorical variables.

Secondly, the second column shows the results from our analysis with respect to industries with low sensitivity. In industries with low sensitivity, all income categorical variables are still significant. Moreover, for individuals whose family pre-tax revenue is above $75,000 and under $99,999, their expectations of percent chance are 6.973% significantly higher. And for the other two income groups, one is around 8% significantly higher and the other is about 10% significantly higher. Thus, we can conclude that in these industries, household pre-tax income is positively associated with individuals' expectations of a percent chance of having a higher stock price in future 12 months. We again observe the similar trend as what we have observed in our main regression, that is, as the revenue amounts increase across these income groups, there is a corresponding rise in the coefficients associated with these categorical variables. The conclusion following this observation is that in wealthier families, individuals are more likely to have a cheerful attitude towards future stock prices in the U.S. market. Moreover, we see that the coefficient of the gender dummy is also significant in these industries, which means that males seem to expect a higher percent chance of having an increasing stock price than females. And the gap between their expectations is about 6%.

Thirdly, the third column and fourth column show results from industries with medium and high levels of sensitivity. In the medium group, the second income categorical variable is insignificant, and the rising trend of coefficients is not clear as in previous groups. Moreover, for the high group, the first income categorical variable is insignificant. However, there is still an increasing trend among coefficients associated with higher household income. Both gender variables are significant at 1% level in these two kinds of industries, from 6.749 to 8.741, respectively.

To make a more comprehensive discussion, it is crucial to make comparisons among these four groups. Except individuals working in the medium-sensitive industries, people in other industries seem to have a clear positive association between family pre-tax income and stock price expectations. From my table, individuals with wealthier households seem to be more sanguine about the future stock market. One possible explanation is that wealthier households might have more alternative choices for investment, and then do not be too pessimistic about changes in stock markets.

Compared to people in low-sensitivity industries, individuals in other two kinds of industries seem to perceive a weaker association between expectations on stock prices and their households' income. This can be seen from less significant income categorical variables as well as lower coefficients of those variables. That means they might be influenced more deeply by other factors which are not considered in our model. One possible explanation could be since they are in relatively more sensitive industries, they will be influenced more easily by the fear of job loss. With the possibility of lacking a sustainable source of personal income, they do not pay attention to invest their wealth for larger profits but to save their revenues. Thus, even if they have a wealthier family, they do not invest in stock according to their household income. Meanwhile, this could again be an explanation why the job insecurity variable is only insignificant in the low-sensitive industry. In low-sensitive industries, people might be more aware of storing wealth and do not fear job loss since they have a more stable working environment.

Finally, males in all industries have significantly positive attitudes about future stock prices. The research mentioned in the previous chapter has shown related patterns. For instance, Anna and John (2012) finds that women report being less risk taking than men. They find that the gender gap in risk attitudes remains significant also when controlling financial literacy. Their findings might help to explain what I observed. Since males feel more confident and are more risk-taking, it is reasonable that they have a more optimistic attitude towards future stock prices. Thus, their expectations are significantly higher than females. Moreover, effects from genders also vary within industry groups and the smallest gap is found in low-sensitivity industries. It is possible that in the low-sensitive industries, females begin more confident and risk-seeking to invest as they know the stability of their working positions.

Table 8: Regression results for stock expectations

	(1) Main	(2) Low	(3) Medium	(4) High
Average expectations on losing jobs (%)	0.089***	0.013	0.134***	0.115***
	(0.015)	(0.023)	(0.028)	(0.025)
Income categories				
From $50,000 to $74,999	2.012***	3.441**	3.058**	0.247
	(0.729)	(1.406)	(1.285)	(1.142)
From $75,000 to $99,999	3.766***	6.973***	1.616	2.863***
	(0.673)	(1.299)	(1.173)	(1.070)
From $100,000 to $149,999	5.635***	8.418***	3.004**	5.108***
	(0.724)	(1.331)	(1.316)	(1.183)
$150,000 or more	8.087***	10.149***	6.599***	7.392***
	(0.736)	(1.302)	(1.366)	(1.298)
Gender	7.538***	6.417***	6.779***	8.741***
	(0.437)	(0.733)	(0.827)	(0.730)
Cons	33.942	34.527	34.867	24.023

Number of observations	6443	2369	1811	2263

Notes: The table presents estimated coefficients and constants obtained from regressing average expectations on percent chance of having higher stock prices in the U.S. on sets of characteristics of individuals using OLS with robust standard errors. The unit of observation of the dependent variable is percentage. Column 1 illustrates the results from my main regression regardless of industry sensitivity levels. Column 2 examines effects in low-sensitive industries. Column 3 examines effects in medium-sensitive industries. Column 4 examines effects in high-sensitive industries. Standard errors are reported in parentheses.

***Significant at the 1 percent level

**Significant at the 5 percent level

*Significant at the 10 percent level

Table 9 shows results for stock price expectations when I consider national unemployment rates by time-series regression (3). The results of the sensitivity level test can be seen from Table 4. Similarly, like what I found in Table 8, there is still a growing trend in the coefficients of income categorical variables associated with a higher household income. Showing that average expectations on stock price are positively associated with family household wealth. However, the coefficient of low-sensitive industry becomes significant under this measurement, and all coefficients of job insecure variables are remarkably close to each other. In other words, there is no distinct difference in the relationship between job insecure and average stock price expectations among individuals in different industries. An additional percent increase in job loss expectations will lead to an increase of expectations on percent chance of having higher stock prices around 0.09% in all three kinds of industries. Granted, the increase is statistically significant, it is numerically insignificant since 0.09% is a small difference.

Table 9: Regression results for stock expectations with time-series analysis

	(1) Main	(2) Low	(3) Medium	(4) High
Average expectations on losing jobs (%)	0.089*** (0.015)	0.087*** (0.030)	0.088*** (0.022)	0.088*** (0.254)
Income categories				
From $50,000 to $74,999	2.012*** (0.729)	4.079*** (1.435)	2.517** (1.145)	0.177 (1.275)
From $75,000 to $99,999	3.766*** (0.673)	2.253* (1.341)	5.655*** (1.061)	2.638** (1.185)

From $100,000 to $149,999	5.635***	3.029**	8.136***	4.148***
	(0.724)	(1.475)	(1.106)	(1.338)
$150,000 or more	8.087***	7.051***	8.646***	9.052***
	(0.736)	(1.484)	(1.140)	(1.305)
Gender	7.538***	8.196***	7.867***	6.895***
	(0.437)	(0.902)	(0.625)	(0.844)
Cons	33.942	26.953	24.369	27.956
Number of observations	6433	1541	3066	1836

Notes: The table presents estimated coefficients and constants obtained from regressing average expectations on percent chance of having higher stock prices in the U.S. on sets of characteristics of individuals using OLS with robust standard errors. The categorization in this table is through using time-series data and rank the industries according to the values of their betas. Thus, the number of observations in each group of industries is different to what is in Table 4. The unit of observation of the dependent variable is percentage. Column 1 illustrates the results from my main regression regardless of industry sensitivity levels. Column 2 examines effects in low-sensitive industries. Column 3 examines effects in medium-sensitive industries. Column 4 examines effects in high-sensitive industries. Standard errors are reported in parentheses.

***Significant at the 1 percent level

**Significant at the 5 percent level

*Significant at the 10 percent level

4.2 Results of unemployment expectations

Table 10 shows results related to unemployment expectations, and all independent variables which measure the jobs' insecurity are significant at 1% level. Thus, I can conclude that people's job insecurity is positively associated with nationwide unemployment. In other words, I can reject my null hypothesis that there is no relationship between nationwide unemployment and personal expectations on job failure. And this result is reasonable as what I mentioned in previous chapters, what remains more interesting is whether this characteristic is different among different industries. In the first column, the coefficient of average expectations on losing jobs is 0.324, which means that, with 1% more percent chance on such expectations, there will be 0.324% on their expectations of percent chance of having more nationwide unemployment. Note that two out of four categorical variables are significant in our main regression regardless of industries' sensitivity level, however, there is not a clear increasing or decreasing trend along with growth in family income. Even for individuals with wealthier households, their expectations on unemployment do not change greatly, and this can be seen from the little difference between 1.476 and 1.173. Meanwhile, the gender variable is significant at 5% level.

Furthermore, the second to the fourth columns show results within diverse groups of industries. It is not surprising that the coefficients of job insecurity variables are similar in the low and medium groups. However, the coefficient of that variable in the high group is slightly lower than that in other two groups. This means there is less increase in unemployment expectations compared to other groups when there is a same level of increase about the job insecurity variable. Recall that the high group means a more sensitive group of industries, that is, more individuals in this group of industries become unemployed when real unemployment rate increases. Thus, the previous belief that in the high group, people will be more pessimistic about nationwide employment as they might face more unemployment challenges is not accurate. Moreover, half of income categorical variables in the low and medium groups are insignificant and the significant variables do not show trends associated with increasing wealth. Interestingly, the income categorical variables in the medium group are negative, meaning that there is a negative association between unemployment expectations and household pre-tax income. The interpretation is that, if you are in a medium-sensitive industry with family income from $75,000 to $99,999, on average, you will expect a 2.485% lower percent chance of rising national unemployment.

Critically, gender variables are significant at 5% level in the low group, which provides more possibility of explorations on expectations on nationwide unemployment. In the low group, being male means that on average you will expect a 1.756% chance higher for having an increasing unemployment than females. The gap between these two groups is less than 2%, which is not a decent difference to be discussed. However, the gender variables are not statistically significant in the medium group and high group.

I initially hypothesized that individuals in the high-sensitivity industry group would be more pessimistic about nationwide unemployment due to facing more frequent and severe unemployment challenges. Surprisingly, the coefficient for job insecurity in the high-sensitivity group is lower than in the low and medium groups. This indicates that an increase in job insecurity has a smaller impact on their expectations of nationwide unemployment than I expected. The possible explanation would be that individuals in those kinds of industries might already expect to have higher unemployment rates due to the nature of their industry, and thus, additional job insecurity does not alter their already elevated expectations. On the other hand, the informativeness of these individuals also draws our concerns. To be more specific, people in these industries might not recognize they are facing more severe unemployment problems than people in other industries, which makes them not behave distinctly.

Moreover, contrary to previous expectations, there is no clear increasing or decreasing trend in unemployment expectations across different income categories. The coefficients for income categories do not show a consistent pattern, even among wealthier households. One possible explanation for this situation is the behavioural factor. For instance, individuals in higher-income households might feel more optimistic about their ability to find new employment quickly, leading to less pronounced changes in their unemployment expectations despite changes in job insecurity. In other words, they would be less sensitive to unemployment, and that could be why there are insignificant results.

Finally, gender differences are significant in the low-sensitive industry but not in the medium group or high group. Males in the low-sensitivity group expect a 1.756% higher chance of increasing unemployment. That is, unlike their expectations on stock prices, males are more pessimistic about future unemployment than females in this industry. These differences could come from gender-specific roles and experiences within different industries.

Table 10: Regression results for unemployment expectations

	(1) Main	(2) Low	(3) Medium	(4) High
Average expectations on losing	0.324***	0.327***	0.330***	0.321***
jobs (%)	(0.015)	(0.026)	(0.027)	(0.026)
Income categories				
From $50,000 to $74,999	0.075	2.987**	-2.485**	0.027
	(0.705)	(1.349)	(1.249)	(1.101)
From $75,000 to $99,999	0.367	1.598	-2.222**	1.588
	(0.629)	(1.170)	(1.134)	(1.003)
From $100,000 to $149,999	1.476**	2.392**	0.189	2.061*
	(0.687)	(1.225)	(1.293)	(1.111)
$150,000 or more	1.173*	1.836	-0.780	2.827**
	(0.713)	(1.216)	(1.364)	(1.254)
Gender	0.866**	1.756**	0.785	0.186
	(0.416)	(0.705)	(0.794)	(0.694)

Cons	31.096	28.428	32.985	31.474
Number of observations	6433	2369	1811	2263

Notes: The table presents estimated coefficients and constants obtained from regressing average expectations on percent chance of having higher unemployment rates in the U.S. within next 12 months on sets of characteristics of individuals using OLS with robust standard errors. The unit of observation of the dependent variable is percentage. Column 1 illustrates the results from my main regression regardless of industry sensitivity levels. Column 2 examines effects in low-sensitive industries. Column 3 examines effects in medium-sensitive industries. Column 4 examines effects in high-sensitive industries. Standard errors are reported in parentheses.

***Significant at the 1 percent level

**Significant at the 5 percent level

*Significant at the 10 percent level

Results from Table 11 indicate the regression results under different categorizations of industries. According to Table 4, it is clear that under time-series analysis for industry sensitivity, there is a huge difference between low-sensitive and medium-sensitive industries compared to previous measurement. A lot of industries in the low group switch to the medium group, this might be useful to help for explaining results in Table 9. The crucial change is the difference in the coefficients of job insecurity variables. Under this categorization, there is a 10% increase in the coefficients from low-sensitive industries to high-sensitive industries, which means that in a more sensitive industry, people's fear of job loss will lead to higher expectations of facing increasing national unemployment. This is consistent with what I hypothesized earlier, individuals in highly sensitive industries are more pessimistic about future national unemployment when they are facing unemployment problems. Another important finding is that, within this assessment, income categorical variables become insignificant in the low and high group, while representing a significant result in the medium group.

Table 11: Regression results for unemployment expectations with time-series analysis

	(1) Main	(2) Low	(3) Medium	(4) High
Average expectations on losing jobs (%)	0.324*** (0.015)	0.282*** (0.030)	0.308*** (0.023)	0.389*** (0.028)
Income categories				
From $50,000 to $74,999	0.075 (0.705)	-2.078 (1.367)	2.489** (1.085)	-1.217 (1.273)

From $75,000 to $99,999	0.367	-1.758	2.600***	-0.942
	(0.629)	(1.255)	(0.962)	(1.124)
From $100,000 to $149,999	1.476**	0.213	3.191***	0.198
	(0.687)	(1.399)	(1.027)	(1.262)
$150,000 or more	1.173*	-0.125	3.065***	-0.389
	(0.713)	(1.440)	(1.065)	(1.311)
Gender	0.866**	0.631	0.807	1.282*
	(0.416)	(0.868)	(0.600)	(0.795)
Cons	31.096	33.483	29.968	29.900
Number of observations	6433	1541	3066	1836

Notes: The table presents estimated coefficients and constants obtained from regressing average expectations on percent chance of having higher stock prices in the U.S. on sets of characteristics of individuals using OLS with robust standard errors. The categorization in this table is through using time-series data and rank the industries according to the values of their betas. Thus, the number of observations in each group of industries is different to what is in Table 7. The unit of observation of the dependent variable is percentage. Column 1 illustrates the results from my main regression regardless of industry sensitivity levels. Column 2 examines effects in low-sensitive industries. Column 3 examines effects in medium-sensitive industries. Column 4 examines effects in high-sensitive industries. Standard errors are reported in parentheses.

***Significant at the 1 percent level

**Significant at the 5 percent level

*Significant at the 10 percent level

Overall, I can reject the null hypothesis that there is no relationship between individuals' job insecurity and their attitudes towards future stock prices in the U.S.. This can be seen from the results in my main regression. And if industry sensitivity level is taken into consideration, the only insignificant coefficient occurs in the low-sensitivity industries when I do not consider time-series analysis. In conclusion, most cases, people have a cheerful outlook towards future stock prices within increasing percent of job insecurity. Meanwhile, I can reject my null hypothesis that there is no relationship between nationwide unemployment and personal expectations of job failure. All coefficients associated with job insecurity are positive and significant when regressing on national unemployment expectations, which means people have a pessimistic attitude towards future employment within increasing percent of job insecurity, which is not so surprising. Moreover, household income plays a more significant and clearer role in stock expectations but not in individual-level unemployment expectations. The gender gap is significant in stock expectations regardless of industry sensitivity. For unemployment expectations, the gender gap is only significant in low-sensitivity industries.

CHAPTER 5 Conclusion

This research is conducted in aims to study the relationship between unemployment/stock expectations and individuals' job insecurity. Apart from that, I add some individuals' characteristics variables as control. A panel data setting consists of data from the late 2013 to 2023 is constructed. Using OLS with robust standard errors and time-series analysis respectively, I am able to answer my research question and hypotheses.

First, the effect of job insecurity on average expectations of percent chance of stock prices (stock expectations) is examined. Within my first method of industry categorization, the results indicated that job insecurity has a positive effect of future stock price expectations. This finding is consistent with previous literature which says that rising unemployment is generally good news for stock markets. However, my results also indicated that for low-sensitive industries, this effect seems to be insignificant. This finding suggests that future research could be done more deeply to find out distinctive characteristics within different industries. However, within my second method of industry categorization which ranks betas from time-series analysis, the results indicated that job insecurity in all industries has similarly significant effects. Note that in the time-series analysis, I only got 2 significant estimators out of 19 estimators, thus, the accuracy and efficiency of this method remains unclear.

Second, the effect of household pre-tax income and gender on average expectations of percent chance of stock prices (stock expectations) is examined as well. Under both methods of categorizing industries, household pre-tax income has a positive effect on individuals' future stock price expectations. That is, with increasing household pre-tax income, individuals seem to expect higher chance of having rising stock prices. This indicates that wealthier family seems to be more sanguine towards future stock markets. Moreover, the gender gap is statistically significant in my results. This is supported by previous literature saying that males are more risk-seeking than females even controlling for the financial literacy. Generally, males in all industries expect higher chance of having rising stock prices.

Third, the effect of job insecurity on average expectations of percent chance of unemployment rates (unemployment expectations) is examined. With my first method of industry categorization, the results indicated that job insecurity has a positive effect of future nationwide unemployment expectations. This finding is supported by previous literature showing that people with unpleasant employment experience become more pessimistic towards future nationwide unemployment. The surprising finding is that among all levels of industries, the effects of job insecurity do not vary a lot. However, my second way of industry categorization shows that there is 0.1% difference between low-sensitive industries and high-sensitive industries. This finding is more consistent with my primitive belief that people in high-sensitive industries also react more sensitively to unemployment. Again, 0.1% is not an enormous difference and it is still reasonable to speculate there is no or trivial difference in effects from job insecurity across different industries.

Finally, I examined the effect of household pre-tax income and gender gap on average expectations of percent chance of unemployment rates. Similarly, under both methods of industry categorizations, there is no clear effect from household pre-tax income. Even though under the second method, the coefficients are significant in medium-sensitive industries, those coefficients are numerically close to each other, and then I cannot conclude trends or important findings from those values. Meanwhile, even though main regressions reflect a significant gender gap in unemployment expectations in both methods, this gap diminishes when I control for industry groups.

To conclude, my research highlights job insecurity has possible nuanced impact on stock markets and unemployment across different industries. Meanwhile, the differentiation in industry sensitivity to job insecurity adds a new layer of understanding to how various sectors respond to economic changes. Possible implications for policymakers are that understanding job insecurity would be helpful to stabilize stock markets. While for companies in different industries, these findings would be useful to understand that employee’s job insecurity may affect overall market expectations and corporate performance.

One limitation for my research is that those methods of categorization might not be efficient. There is a violation of assumptions that time-series data should be stationary to gain accurate and unbiased results. Thus, my second method to categorize industries within time-series data might cause biases, which means there are no robust conclusions can be drawn from my second methods and associated coefficients in expectations on unemployment and stock prices. Therefore, further research could build up more complicated and efficient models to understand distinct industries. For example, consider seasonality and downtown in economics to remove the bias from non-stationary. Another limitation is that reverse causality exists in nationwide unemployment and personal job insecurity, and thus my model does not provide a causal effect. However, it may still provide insights and evidence for the existence of relationships among studied variables. Moreover, this research provides a long-term perspective, future research could dive deeper into short-term horizon or specific cases to analyse those effects, which might provide a more detailed and accurate results.

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APPENDIX

Table 2: Frequency statistics for pre-tax household income

	Freq.	Percent	Cum.
Household pre-tax income			
Less than $10,000	69	1.07	1.07
From $10,000 to $19,999	166	2.58	3.65
From $20,000 to $29,999	331	5.14	8.78
From $30,000 to $39,999	461	7.16	15.94
From $40,000 to $49,999	524	8.13	24.07
From $50,000 to $59,999	537	8.33	32.41
From $60,000 to $74,999	769	11.94	44.34
From $75,000 to $99,999	1115	17.31	61.65
From $100,000 to $149,999	1279	19.85	81.50
From $150,000 to $199,999	659	10.23	91.73
$200,000 or more	533	8.27	100.00
Number of observations	6443	100.00	100.00

Table 5: White test for the regression on unemployment

	Chi	df	P-value
Heteroskedasticity	55.34	16	0.000***
Skewness	171.33	6	0.000***
Kurtosis	0.47	1	0.493
Total	227.14	23	0.000***

Note: ***Significant at the 1 percent level
**Significant at the 5 percent level
*Significant at the 10 percent level

Table 6: White test for the regression on stock price

	Chi	df	P-value
Heteroskedasticity	81.41	16	0.000***
Skewness	39.27	6	0.000***
Kurtosis	44.77	1	0.000***
Total	165.45	23	0.000***

Note: ***Significant at the 1 percent level
**Significant at the 5 percent level
*Significant at the 10 percent level

Table 7: Shapiro – Wilk for the regression on stock price

	Obs	W	V	z	P-value
Residuals (1)	6443	0.997	11.285	6.408	0.000***
Residuals (2)	6443	0.989	34.326	9.346	0.000***

Note: ***Significant at the 1 percent level
**Significant at the 5 percent level
*Significant at the 10 percent level

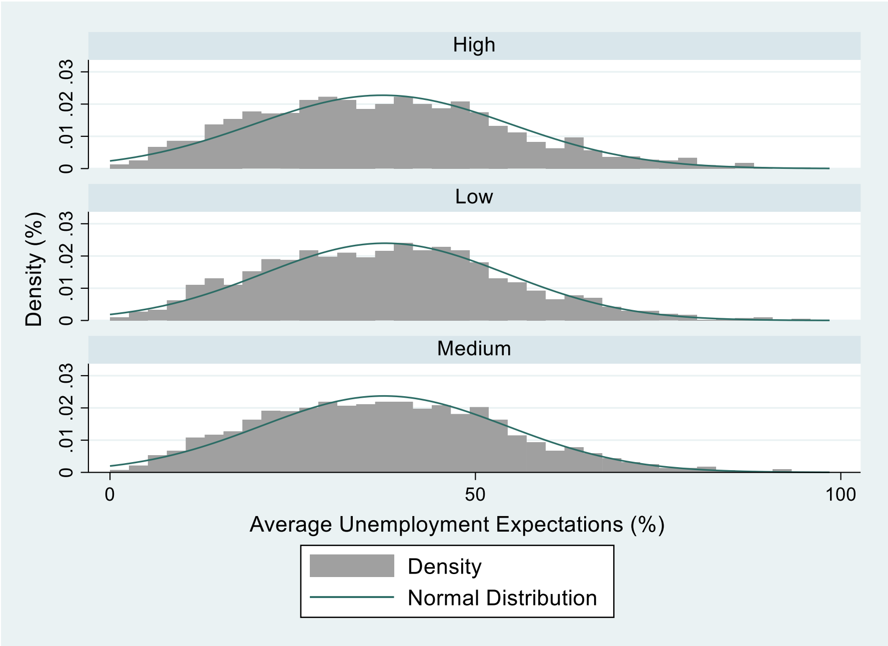

Figure 4: Histograms by industry category for average unemployment expectations.

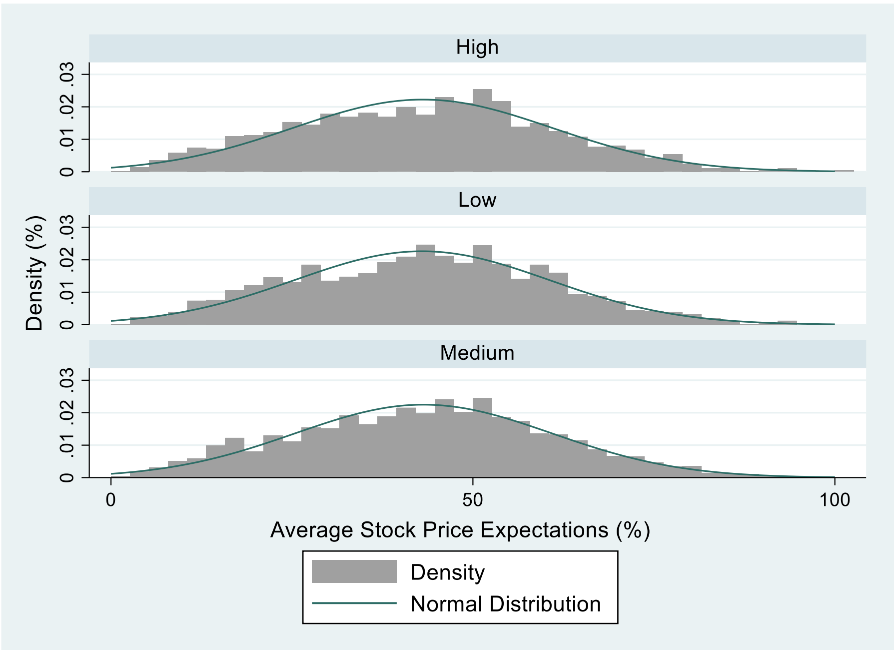

Figure 5: Histograms by industry category for average stock price expectations.

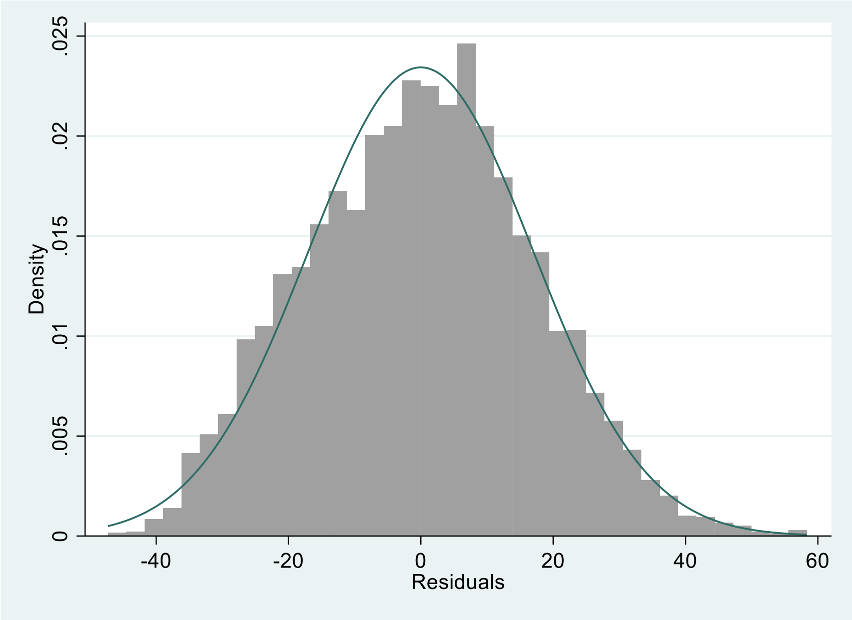

Figure 6: Histogram for residuals in regression (1)

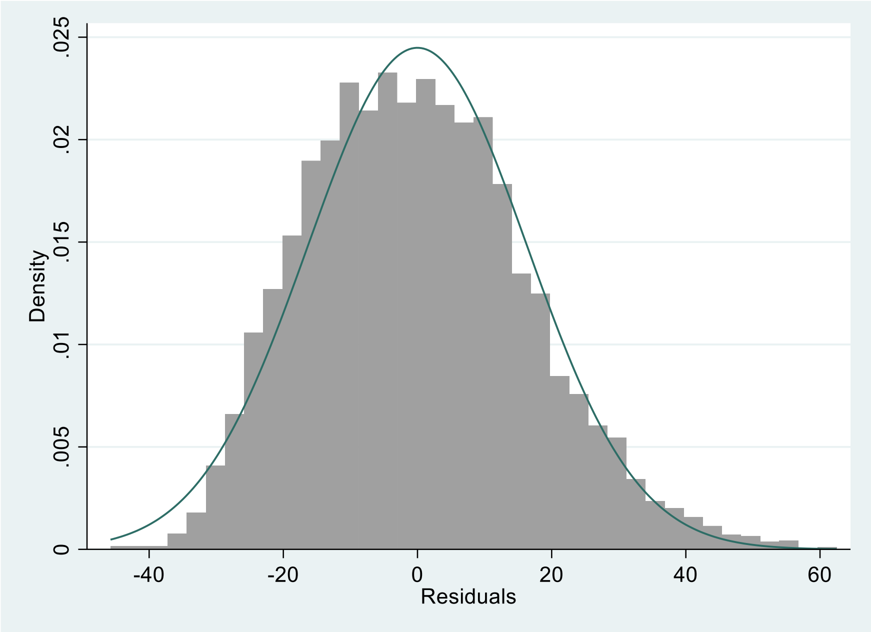

Figure 7: Histogram for residuals in regression (2)

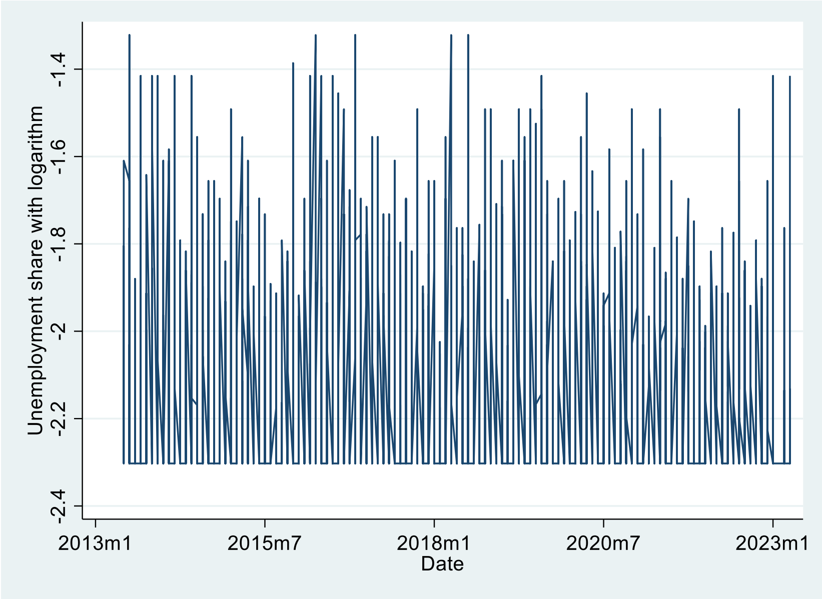

Figure 8: Line graph of time-series data on unemployment share with logarithm

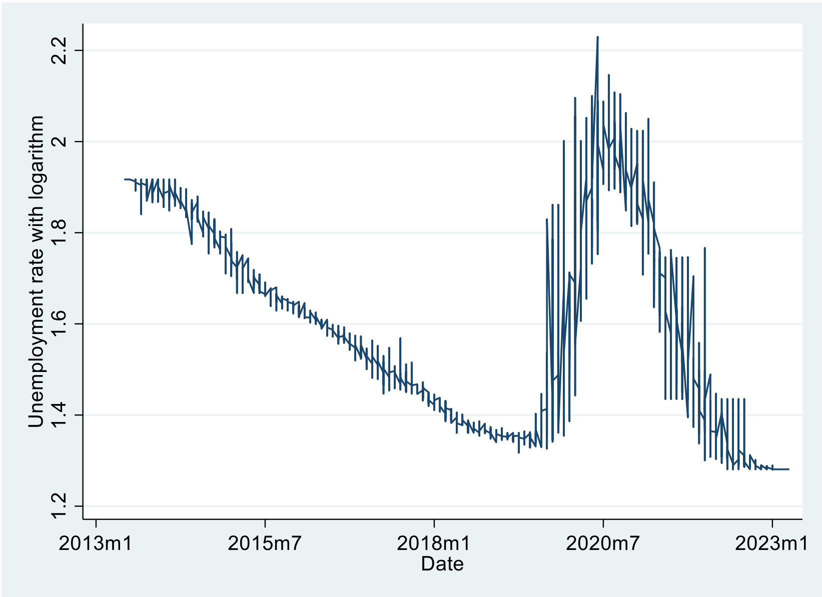

Figure 9: Line graph of time-series data on unemployment rate with logarithm

Table 12: ADF test results for unemployment share and national unemployment rates

	p-value (1)	p-value (2)	p-value (3)	p-value (4)
Household pre-tax income				
Agriculture (1)	0.000***	0.421	0.000***	0.578
Oil & Gas Extraction (2)	0.000***	0.461	0.000***	0.636

Utilities (3)	0.000***	0.422	0.000***	0.509
Construction (4)	0.000***	0.581	0.000***	0.648
Manufacturing (5)	0.000***	0.482	0.000***	0.592
Wholesale Trade (6)	0.000***	0.313	0.001***	0.328
Retail Trade (7)	0.000***	0.492	0.000***	0.609
Transportation & Warehousing (8)	0.000***	0.656	0.000***	0.703
Information Services (9)	0.000***	0.572	0.000***	0.693
Banking & Finance (10)	0.000***	0.589	0.000***	0.691
Real Estate (11)	0.000***	0.599	0.000***	0.735
Professional & Business Services (12)	0.000***	0.535	0.000***	0.641
Education (13)	0.000***	0.543	0.000***	0.639
Health Care (14)	0.000***	0.533	0.000***	0.643
Arts & Entertainment (15)	0.000***	0.561	0.000***	0.627
Hotel & Restaurant (16)	0.000***	0.619	0.000***	0.659
Other Services (except Govern.) (17)	0.000***	0.468	0.000***	0.396
Government (18)	0.000***	0.539	0.000***	0.540
Other (19)	0.000***	0.583	0.000***	0.694

Note: ***Significant at the 1 percent level

**Significant at the 5 percent level

*Significant at the 10 percent level

Table 13: Correlation matrix for variables in regression models

	residuals	1	2	3	4	5
1. Average expectations on losing jobs (%)	0.000	-				
2. Lower than $50,000	-0.000	0.129	-			
3. From $50,000 to $74,999	-0.000	0.032	-0.193	-		
4. From $75,000 to $99,999	0.000	-0.064	-0.280	-0.285	-	
5. From $100,000 to $149,999	0.000	-0.039	-0.217	-0.221	-0.320	-
6. Gender	-0.000	-0.017	-0.158	-0.081	-0.002	0.083