Unveiling the Market's Pulse: Short-Term Stock Market Reactions to Employment Report Announcements

by

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Abstract

This paper examines the short-term relationship between the percentage surprise in unemployment rates and the percentage change in U.S. stock market returns. In addition to analyzing the relationship between the level and change in monthly unemployment rates and the level and change in stock market returns for both the whole market and different sectors, I address time-series issues such as stationary and seasonality in the stock data. By utilizing short-window financial data, this research aims to minimize the influence of other events and capture investors' immediate reactions. The results of the regression analysis reveal that positive (negative) surprises have a significant negative (positive) impact on the overall stock market but not on individual sectors. Furthermore, the surprises introduce more uncertainty for investors, as demonstrated by the increased trading volume and volatility.

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Chapter 1

Introduction

Investors rely on macroeconomic indicators, such as GDP and employment reports, to predict future trends so that they are able to make appropriate investment strategies. A large body of existing literature focuses on the stock markets in the past years analyzing the surprise effect given by the announcement of the news. One common method is to calculate the difference between the predicted value and the announced read value to define the positivity or negativity of the announcement to investigate the relationship with stock price (Kocenda and Hanousek, 2011; Hanousek et al., 2009). A relationship between stock prices and macroeconomic factors in the US, such as unemployment rate and inflation rates, based on their definitions of business cycles, is also suggested (McQueen and Roley, 1993, and Pearce and Roley, 1983,1985). Some literature uses behavioral finance to explain the relationship between the financial market and news (Tetlock, 2007 and Pericoli and Veronese, 2016). As the current theory cannot explain the empirical results clearly (Greenwood et al, 2022), this paper pays more attention to the short-run changes in the stock price regardless of whether it is an overreaction or rational behavior to the news.

The conventional economic and financial theory posits that stock prices are primarily influenced by factors related to market and firm characteristics. Firms operating within the same industry typically face similar macroeconomic conditions, and regulatory and policy environments. Therefore, changes in the economic environment tend to affect companies within the same sector in a highly correlated manner (Moskowitz and Grinblatt, 1999). However, there was no literature investigating how the stock prices of different industries are affected by the news to varying degrees. To comprehensively evaluate the impact of news on the stock prices of various industries, we examine the stock prices of industries that react to the news, particularly, the employment report.

The connection between stock prices and employment has long been a subject of interest for economists and financial analysts. The stock market is frequently regarded as an indicator of economic health, and employment plays a vital role in economic growth. Stock market values reflect a company's financial performance and future prospects, while employment is a key determinant of consumer spending and confidence. According to the U.S. Bureau of Economic Analysis, personal consumption has accounted for nearly 70% of the U.S. GDP in the 21st century, meaning that employment and labor market changes also affect other macroeconomic indicators. Moreover, a 2020 Pew Research Center survey found that 52% of U.S. households participated in the stock market, and their aggregate demand significantly influences stock market asset prices.

The relationship between employment and stock market performance has often been studied in terms of how stock prices impact employment. However, the reverse relationship—how changes in employment affect short-term stock market dynamics—has not received as much attention. This research paper seeks to explore the influence of employment fluctuations on short-term stock market performance, with a focus on daily or intraday timeframes. Although identifying specific channels is challenging, understanding this relationship is essential for investors, policymakers, and companies to make informed decisions regarding investment strategies, economic policies, and business planning. Most literature in the past century has relied on daily data for modeling; however, the stock market is heavily influenced by events. In today's world, where people can easily access up-to-date information via the internet, daily data encompasses many events that create noise in the analysis. This paper's primary objective is to investigate how surprises in employment reports immediately impact the stock market across various sectors using high-frequency, minute-level data.

The rest of the paper is organized as follows. Section 2 discusses some related literature and the contribution of this paper. Section 3 describes the data used in the following models. Section 4 constructs the models to test the hypothesis. Section 5 outlines the results and Section 6 concludes the results and discusses future work.

Chapter 2

Literature Review

2.1 Interest Rate

There is an abundance of literature that offers various theoretical frameworks explaining the relationship between rising interest rates and declining stock market returns. The Discounted Cash Flow Model posits that a stock's value is determined by the present value of its future cash flows, discounted at a suitable interest rate. When interest rates rise, the discount rate increases, leading to a decrease in the present value of future cash flows and negatively impacting stock prices. The Cost of Capital Model demonstrates that higher interest rates raise borrowing costs, deterring companies from investing in projects with greater returns. This may result in reduced corporate profits and, subsequently, lower stock prices. The Risk-Return Trade-Off Model suggests that increased interest rates can prompt investors to move their investments from riskier assets, such as stocks, to fixed-income securities, causing a decline in demand and prices for equities. Many studies, including those by Fama (1981), Thorbecke (1997), Rigobon and Sack (2004), and Alam and Uddin (2009), have explored the inverse relationship between interest rates and stock market performance. Therefore, I will use interest rate as a control variable in the following regression design.

2.2 Employment

The relationship between employment and short-term stock market performance can be linked to various economic theories. According to the aggregate demand theory, changes in employment levels affect overall consumer spending, which in turn influences corporate profits and stock prices (Keynes, 1936). Additionally, the labor market efficiency theory posits that fluctuations in employment may provide signals about the health of the economy, thereby affecting investor sentiment and stock prices (Lucas, 1978).

2.2.1 Positive

Several studies have found a positive relationship between employment changes and short-term stock market performance. For instance, Schwert (1990) demonstrated that positive surprises in monthly employment data are associated with higher stock returns on the announcement day. Similarly, Boyd et al. (2005) state that the news of the rising unemployment rate would raise the stock market values during the economic expansion and would decrease stock market returns during the economic contraction.

2.2.2 Negative

In contrast, some studies have reported a negative relationship between employment fluctuations and short-term stock market performance. For example, Veronesi (1999) found that a sharp rise in unemployment could lead to a decline in stock prices, as investors may interpret this as a sign of deteriorating economic conditions and lower future corporate earnings. Furthermore, Fleming et al. (1997) observed that significant job losses, particularly during economic downturns, are often associated with stock market declines, reflecting heightened uncertainty and risk aversion among investors.

2.3 Contribution

Some studies have reported mixed or inconclusive results regarding the relationship between employment changes and short-term stock market performance. For example, Faust et al. (2007) found that the impact of employment news on stock prices varies depending on the overall state of the economy and investor sentiment. In some cases, positive employment news can boost stock prices, while in others, it may have little or no effect.

Several moderating factors can influence the relationship between employment changes and short-term stock market performance. These factors include the nature and magnitude of the employment change, the sector or industry affected, and the overall economic context (Campbell and Shiller, 1988; Stock and Watson, 2003). For example, large and unexpected changes in employment may have a more significant impact on stock prices than small or anticipated changes, as they can alter investor expectations about future economic conditions and corporate earnings more dramatically.

Despite the growing body of literature on the relationship between employment and short-term stock market performance, more research is needed to disentangle the complex interplay between these variables. This research paper aims to contribute to the existing literature by providing a more comprehensive analysis of the impact of employment surprise on short-term stock market performance and discussing the potential channels that how these effects may work.

Chapter 3

Data

I use three primary data sources in this paper. In this section, we discuss each data source and its corresponding descriptive statistics.

3.1 Labor Data

This study employs monthly unemployment data from the Bureau of Labor Statistics (BLS) for the period between 2001 and 2021. Originally, the plan was to create a surprise index utilizing a Natural Language Processing (NLP) model that would analyze textual data from social media. NLP is a type of artificial intelligence that allows computers to understand and process text in a manner similar to humans. Unlike traditional models with multiple dependent variables, such as unemployment rates from the previous month, the NLP-based prediction model would more accurately represent the decision-making process of a typical investor. Financial markets are highly influenced by events, and market participants often pay close attention to announcements from respected institutions or individuals. The precise index value is calculated by subtracting the actual monthly unemployment rates provided by the U.S. Bureau of Labor Statistics from the NLP model's forecasted monthly unemployment rates. The model will be further detailed later.

According to Ryu (2018), the social media sources used in the experiment include news articles, blogs, and tweets. News articles from top financial journals serve as a vital source of reliable information. Blogs, typically authored by the general public, can convey opinions and evidence-based signals. Another significant source of textual data is Twitter, where users can share their thoughts with a vast audience. With over 200 million users, the collective opinions on the labor market can also send signals to the

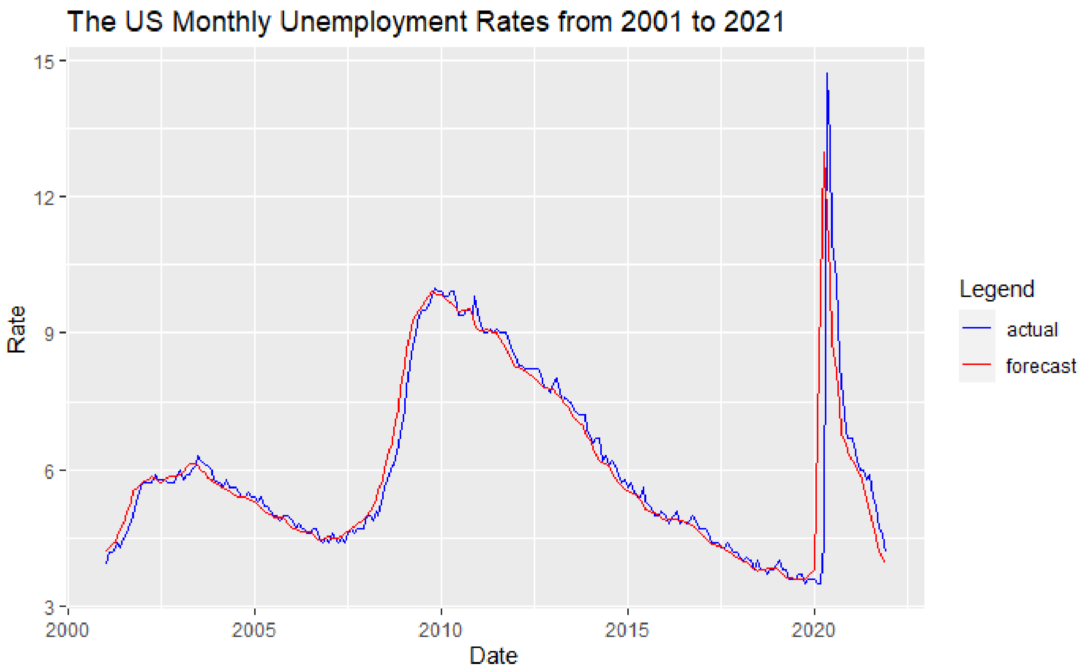

FIGURE 3.1: The US Monthly Actual/Forecasted Unemployment Rate 2001 - 2021

public. Daily updates provide immediate insights into societal views. However, due to limitations in the Twitter API, the data I collected was insufficient for creating a reliable model. I discuss the data, method, and results in the final section. Instead, I used Bloomberg's predicted unemployment data to represent the actual surprise. Since the forecasted unemployment data is quarterly, I employed linear interpolation to convert it to monthly adjusted data. The surprise is calculated as the difference between the forecasted and actual unemployment rates. Scotti (2016) states that a positive (negative) reading of the surprise index suggests that economic releases have on balance been higher (lower) than consensus, meaning that agents were more pessimistic (optimistic) about the economy. Figure 3.1 displays the historical values of both real and predicted unemployment data. In addition to employment data, it is well-known that the federal interest rate significantly impacts the stock market. Therefore, when investigating changes in stock return values, I will introduce the effective federal interest rate, obtained from FRED, as an independent variable.

3.2 Stock Data

I collect the stock index data from Morgan Stanley Capital International (MSCI) and Yahoo Finance. The industry data is collected from MSCI and eleven industries are categorized by Global Industry Classification Sector Level I. The dataset contains the index data of 11 industries, Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financials Information Technology, Communication Services, Utilities, and Real Estate from late 2000 to late 2021. The definition of each sector and an example weighted of each sector can be found in Appendix A. Specifically, I use the index data at 9:30 AM each day in the further analysis as the stock market formally "begins" at 9:30 AM and there is an hour for investors to make reactions to the employment-related report released at 8:30 AM. Figure 3.2 provides an overview of the trend of each industry over years.

To observe the overall impact on all industries, we need to focus on a comprehensive index. Regarding each industry having different weights due to its total market value, I use S&P 500 index as an overall index from 2012 to 2021. In addition, to observe the immediate effect of the investor's reaction to the employment report, I also collect 1 – minute intraday data of the S&P 500 index. The summary statistics of different industry index data and S&P 500 index data are shown in Table 2.

Table 3.1: Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
SPX_open_price	5846	1895	984	679	1185	2414	4805
SPX_volume	5847	948749883	446797195	1133600	566892740	1266959933	2952551300
S5ENRS_open_price	5847	430	144	164	297	544	737
S5ENRS_volume	5847	60051164	27001707	11308400	41323806	71235500	254309400
S5MATR_open_price	5847	261	113	103	170	326	570
S5MATR_volume	5847	31454429	13080216	5187194	21013847	39171600	161984800
S5INDU_open_price	5846	417	194	133	271	558	906
S5INDU_volume	5847	70592016	31874202	6200	46607158	87499000	354902100
S5COND_open_price	5846	520	366	126	251	712	1673
S5COND_volume	5847	123003182	55254884	64600	77953351	162320500	395142800
S5CONS_open_price	5595	407	179	183	242	553	842
S5CONS_volume	5595	53562289	21753690	10060892	37148362	66073825	243607200
S5HLTH_open_price	5845	654	385	253	362	891	1664
S5HLTH_volume	5847	80449667	38060852	37800	49993988	104817750	407169400
S5FINL_open_price	5846	362	119	82	287	438	689
S5FINL_volume	5847	142854658	91098437	28900	83158654	166812250	1260798000
S5INFT_open_price	5846	796	690	173	341	956	3108
S5INFT_volume	5847	297638580	226204356	974200	125168074	420240235	1517021500
S5TELS_open_price	5845	156	44	79	123	170	322
S5TELS_volume	5847	46465871	37119227	21900	20376070	61195458	758086100
S5UTIL_open_price	5847	209	71	77	156	257	395
S5UTIL_volume	5847	31756781	16942075	6512820	20735948	37752800	259717700
S5RLST_open_price	4999	156	55	43	112	193	325
S5RLST_volume	4999	20640902	32824497	0	0	42995000	245720000
vix_open	5855	20	8.7	9	14	24	83
vix_end	5855	20	8.7	9.1	14	24	83

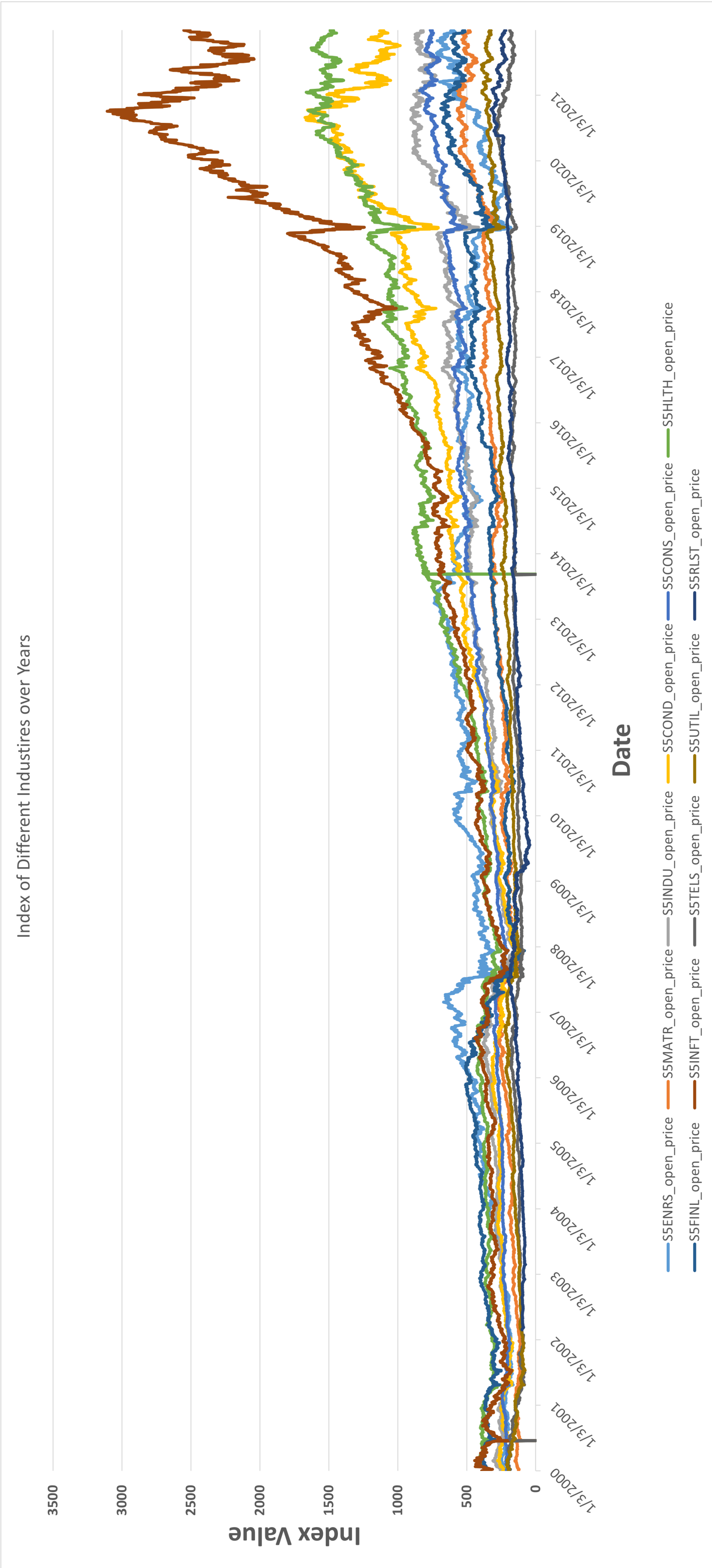

Figure 3.2: Index of Different Sectors over years

Chapter 4

Methods

4.1 Time Series

4.1.1 Stationary Check

When running a regression analysis, it is important for the time series data to be stationary to ensure that the results are valid and interpretable. Stationarity means that the statistical properties of the time series (mean, variance, and autocorrelation) do not change over time. If a time series is non-stationary, it can result in spurious regressions, where the regression appears to be significant, but the relationship between the variables is not actually meaningful. Therefore, we verify this assumption by conducting stationarity tests (Augmented Dickey-Fuller test) before performing regression analysis. The ADF test is an extension of the Dickey-Fuller test, which addresses the issue of autocorrelation in the time series data by adding lagged differences of the dependent variable as additional regressors. The null hypothesis of the ADF test is that the time series contains a unit root (i.e., it is non-stationary), while the alternative hypothesis is that the time series is stationary.

4.1.2 Seasonality

Seasonality is a critical factor to consider in time series analysis, including when examining stock market returns. Seasonality refers to regular, predictable fluctuations in the data that occur periodically (e.g., daily, monthly, or annually). Seasonal effects can mask the actual relationship between stock market returns and other variables, such as unemployment rates. By determining the existence of seasonality, I can adjust the regression design in the following parts and better understand the true relationships between variables and gain more accurate insights into the factors driving stock market returns. I use two methods – Seasonal Autoregressive Integrated Moving Average (SARIMA) and monthly dummy variables to check the existence of seasonality.

The SARIMA(p, d, q)(P, D, Q)m formula is

$$\begin{aligned} Y_t = \mu + \phi_1 Y_{t-1} + \cdots + \phi_p Y_{t-p} - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} + \varepsilon_t - \Phi_1 \varepsilon_{t-m} - \cdots - \\ \Phi_P \varepsilon_{t-pm} + \theta_1 \varepsilon_{t-Dm} - \cdots - \theta_D \varepsilon_{t-Dm} \end{aligned} \tag{4.1}$$

where Y_t is the value of the time series at time t, μ is the overall mean of the time series, p is the order of the autoregressive (AR) component, d is the order of the differencing component, q is the order of the moving average (MA) component, P is the seasonal order of the autoregressive (AR) component, D is the seasonal order of the differencing component, Q is the seasonal order of the moving average (MA) component, m is the number of time periods in each season, $\phi_1, \ldots, \phi_p$ are the autoregressive coefficients, $\theta_1, \ldots, \theta_q$ are the moving average coefficients, $\Phi_1, \ldots, \Phi_P$ are the seasonal autoregressive coefficients, ε_t is the error term at time t, $\varepsilon_{t-1}, \ldots, \varepsilon_{t-q}$ are the lagged error terms from the moving average component, $\varepsilon_{t-m}, \ldots, \varepsilon_{t-Dm}$ are the lagged error terms from the seasonal component.

The monthly dummy variable regression is

$$\begin{aligned} \overline{S\&P500} = \beta_0 + \beta_1 \text{AUR} + \beta_2 \text{positive surprise} + \beta_3 \text{AUR} * \text{positive surprise} + \\ \beta_4 \text{negative surprise} + \beta_5 \text{AUR} * \text{negative surprise} \beta_6 \text{EIR} + \beta_7 \sum_{i=1}^{11} month_i + \epsilon \end{aligned} \tag{4.2}$$

where $\overline{S\&P500}$ is the average monthly S&P 500 index, AUR is the actual unemployment rate, $\sum_{i=1}^{11} month_i$ is the monthly dummy variables, positive surprise (negative surprise) denotes the surprise larger (smaller) than average difference between the actual unemployment rate and forecast unemployment rate, and ϵ is the error term.

4.2 OLS Regression

In this research, the main technique used is OLS regression. However, because the data sources are time-series, the validity of OLS regression might be affected by autocorrelation. To address this issue, various approaches will be implemented. Furthermore, for the financial market data corresponding to each Friday, both the change and percentage change in stock market returns following the employment report announcement will be determined. This way, the percentage-adjusted stock market reactions will reduce reliance on market reactions to other factors, such as a higher overall index in March compared to April. Additionally, the data entries will be randomized in different sequences to effectively eliminate any time-related effects on the dataset. As a result, the dataset will not display time-related effects, concentrating solely on the market reaction to surprises in the unemployment rate announcement every Friday. Theoretically, there should be 252 observations. However, stock data for 4/2/2021, 3/4/2015, 6/4/2012, 2/4/2010, and 6/4/2007 are not available, leaving us with 247 observations.

4.2.1 Value and percent data: Basic format of S&P500

The basic forms of the linear model will be introduced to investigate the response of stock market value to the unemployment rate. The linear equation between the change in the stock market return and the surprise index in unemployment rates are given by:

$$\Delta\text{S\&P500} = \beta_0 + \beta_1\text{Surprise} + \beta_2\text{EIR} + \epsilon \tag{4.3}$$

where ΔS&P500 denotes the change in the value of the inflation-adjusted S&P 500 index, Surprise denotes the level of surprise by the employment report, EIR denotes the effective federal monthly interest rate, and ϵ is the error term.

Percent changes help to normalize the magnitude of changes in the S&P 500 index and unemployment rate, allowing for more meaningful comparisons over time. By focusing on percentage changes, we can better understand the relative significance of a change in each variable, regardless of its absolute value. In addition, percent changes make it easier to compare the performance of the S&P 500 and the unemployment rate across different time periods, even when the absolute values of these variables are significantly different – the overall market value increases continuously. This can be particularly useful when evaluating the historical impact of economic policies, market events, or other factors on the stock market and labor market. Hence, the modified percentage version of the formula is:

$$\%\Delta\text{S\&P500} = \beta_0 + \beta_1\%\text{Surprise} + \beta_2\text{EIR} + \epsilon \tag{4.4}$$

4.2.2 Sector

The differences in stock returns across industries in response to employment reports can be attributed to various factors such as sensitivity to economic conditions, labor intensity, consumer sentiment, interest rates and inflation, and market expectations. To check which industries work as the main mover of the stock market return, we run regression on the index of 11 sectors as mentioned in the Data Chapter, respectively.

$$\begin{aligned} \Delta\text{Sector Index}_i &= \beta_0 + \beta_1\text{Surprise} + \beta_2\text{EIR} + \epsilon \\ \%\Delta\text{Sector Index}_i &= \beta_0 + \beta_1\%\text{Surprise} + \beta_2\text{EIR} + \epsilon \end{aligned} \tag{4.5}$$

4.3 Robustness Check

4.3.1 Minute-Level Data

The stock market is highly event-driven and unpredictable, with stock price fluctuations within a single day potentially influenced by a variety of factors. The employment report is released at 8:30 AM Eastern Time, and other news may introduce bias. As a result, using daily market data poses a potential risk to the regression method and can lead to omitted-variable bias regarding the effect of daily news on stock market reactions. To address this issue, intraday data such as minute-by-minute stock index data is used instead. This approach captures the immediate market response to the announcement and minimizes the impact of other news or events occurring later in the trading day. Daily stock market return values might be affected by factors beyond unemployment report announcements, so these values could be influenced by factors not accounted for in regression models. To mitigate the effects of other factors, this paper employs five short-window data sets to examine investor reactions more closely.

$$\begin{aligned} \%\Delta\text{S\&P500}_{1min} &= \beta_0 + \beta_1\%\text{Surprise} + \beta_2\text{EIR} + \epsilon \\ \%\Delta\text{S\&P500}_{5min} &= \beta_0 + \beta_1\%\text{Surprise} + \beta_2\text{EIR} + \epsilon \\ \%\Delta\text{S\&P500}_{10min} &= \beta_0 + \beta_1\%\text{Surprise} + \beta_2\text{EIR} + \epsilon \\ \%\Delta\text{S\&P500}_{15min} &= \beta_0 + \beta_1\%\text{Surprise} + \beta_2\text{EIR} + \epsilon \\ \%\Delta\text{S\&P500}_{30min} &= \beta_0 + \beta_1\%\text{Surprise} + \beta_2\text{EIR} + \epsilon \end{aligned} \tag{4.6}$$

where $\%\Delta\text{S\&P500}_{tmin}$ denotes the percentage change in S&P 500 index t minutes from 8:30 AM, respectively, % Surprise denotes the percentage level of a surprise given by the employment report, EIR denotes the effective federal monthly interest rate, and ϵ is the error term.

4.3.2 Volume

It is also essential to consider the impact of unemployment news on trading volume, as this can offer a more comprehensive understanding of the market's reaction to such news. Trading volume signifies the total number of shares exchanged during a specific period and can provide valuable insights into investor activity, liquidity, and overall market dynamics. By analyzing trading volume in conjunction with stock market returns, we can gain a deeper understanding of how unemployment news affects not only stock prices but also the degree of market participation and investor confidence. This supplementary analysis will contribute to a more thorough evaluation of the relationship between unemployment news and the financial market. To do this, I created a time range that includes the 2 trading days before and the 2 trading days after the announcement. Generally, the employment report is released on the first Friday of each month, so we retain data for Wednesday and Thursday of the same week and Monday and Tuesday of the following week.

$$\%\Delta \text{Volume}_i = \beta_0 + \beta_1 \text{Announcement} + \epsilon \tag{4.7}$$

where $\%\Delta\text{Volume}_i$ denotes the percentage change in trading volumes of the whole market and 11 sectors, respectively, compared with the previous days, Announcement is a dummy variable with 1 meaning that that day is the announcement releasing day, and ϵ is the error term.

4.3.3 Volatility

The firms selected for the S&P 500 Index are generally those with large market values. The trading volume of the S&P 500 as a whole could be affected by a single firm if it releases significant news. Therefore, it is crucial to further investigate their impact on stock market volatility using the VIX (Chicago Board Options Exchange's CBOE Volatility Index). By comparing the opening VIX value to the closing VIX value, we can assess how investors respond to the surprise brought by the employment report. This additional analysis enables us to gain a more comprehensive understanding of how unemployment news affects various aspects of the financial market. While trading volume offers insights into market participation and liquidity levels, stock market volatility represents the extent of uncertainty and market fluctuations. By examining the relationship between unemployment report releases and market volatility, we can better understand investor sentiment, risk perception, and the potential consequences of unemployment news on portfolio management and investment strategies.

$$\begin{aligned} \Delta\text{VIX} &= \beta_0 + \beta_1\text{Surprise} + \beta_2\text{EIR} + \epsilon \\ \%\Delta\text{VIX} &= \beta_0 + \beta_1\%\text{Surprise} + \beta_2\text{EIR} + \epsilon \end{aligned} \tag{4.8}$$

where ΔVIX denotes the change in intraday (open and end between two days) CBOE volatility index, Surprise denotes the level of a surprise given by the employment report, EIR denotes the effective federal monthly interest rate, and ϵ is the error term. The % simply means that the value is calculated by percentage.

Chapter 5

Results

5.1 Stationary Result

Table 5.1: Augmented Dickey-Fuller Test Results of Original S&P 500 Index

Statistic	**Value**	**P-value**
ADF Test Statistic	-1.2732	0.8862
Lag Order	18	
Alternative Hypothesis	Stationary	

Table 5.2: Augmented Dickey-Fuller Test of First Order Difference S&P 500 index

Statistic	**Value**	**P-value**
ADF Test Statistic	-17.754	0.01
Lag Order	18	
Alternative Hypothesis	Stationary	

Table 5.1 shows the Augmented Dickey-Fuller Test of the original time series S&P 500 index over years. It has a p-value of 0.8862 which is larger than 0.05, so I fail to reject the null hypothesis and conclude that the data is non-stationary. Table 5.2 shows the ADF Test results of the S&P 500 index after detrending by first-order difference, it has a p-value of 0.01 which is less than 0.05, so the data is stationary. Similarly, I also use the difference between the S&P 500 data of each period to detrend and run the ADF test, all of them have a p-value less than 0.05, which makes the results from subsection 5.2 meaningful. The graph of two time-series data could be found in Appendix.

Table 5.3 shows the regression results of detrending S&P 500 index data on (log value of) effective interest rate and (log value of) surprise. We found that a unit percentage increase in surprise value caused a decrease of 4.416 percent in S&P 500 data statistically significantly at the 1 percent level. However, there is no statistically significant relationship between stock market return and effective interest rate. It is reasonable

Table 5.3: First Order Difference Results

	Dependent variable:	
	first order difference S&P500 Index	
	(1)	(2)
log effective rate	-0.565	
	(1.154)	
log surprise	-4.146^{***}	
	(1.516)	
effective rate		1.787^{**}
		(0.786)
surprise		-1.760
		(1.531)
Constant	-11.735^{***}	-3.355^{**}
	(4.062)	(1.695)
Observations	153	247
Adjusted R^2	0.037	0.019
Note:		*p<0.1; **p<0.05; ***p<0.01

as this regression only contains 247 observations on the day when the employment report is released besides the 5 missing values. Therefore, each difference has a huge time gap, which is meaningless. Therefore, I will use the daily difference in values and the daily percentage difference in values between the day and the previous day in the following subsection 5.2. For example, today's open price is 1500 and yesterday's value is 1480, it has a difference value of positive $1500 - 1480 = 20$ and a percentage difference (1500-1480)/1500 = 0.013.

5.2 Seasonality

Table 5.4: Your table caption

ar1	ar2	ar3	ma1	mean
0.4927	-0.0280	-0.0117	-0.4648	-0.4300
0.2627	0.0165	0.0138	0.2626	0.2875

Table 5.4 shows the SARIMA results of detrending S&P 500 data.

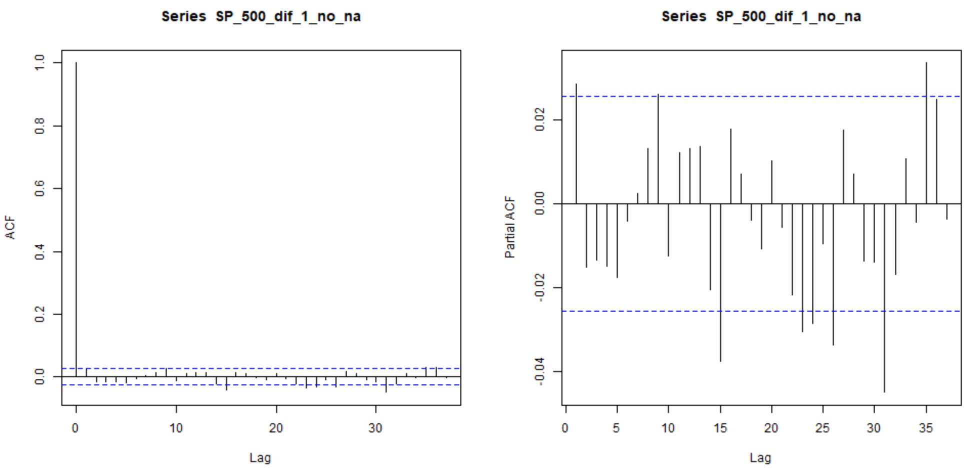

FIGURE 5.1: ACF (left) and PACF (right)

The Autocorrelation Function (ACF) revealed a cutoff at lag(0), while the Partial Autocorrelation Function (PACF) exhibited spikes at various lag terms, suggesting no autocorrelation but the possibility of correlation with past error terms. By observing Figure 5.1, there is no seasonality suggested by the SARIMA.

Besides the SARIMA, the monthly dummy variable regression also shows that there is no seasonality. In addition, by Table 5.5, a unit increase in the actual unemployment rate could result in an increase of 84.435400 in monthly average return at the 5 percent statistically significant level and a unit increase in the effective interest rate could result in a decline of 119.064100 in monthly average return at the 1 percent statistically significant level. And the high degree surprise (larger than the median surprise) does not build a relationship, where the positive median is 0.23395 and the negative median is -0.37526. It can be explained that the actual unemployment is released at the beginning of a month so play a role to lead the stock market in the following days and the result is consistent with the past literature. The increased effective interest rate attracts more capital into government bonds rather than the stock market. The surprise does not affect the market as the surprise's effect commonly will be diminished in a few days.

5.3 Difference in Values Results

Table 5.6 displays the relationship between the surprise in unemployment rate announcements and market reactions. In the context of overall market returns, there is a negative relationship between surprise in unemployment rate announcements and daily changes in stock market returns. This indicates that a positive surprise in the unemployment rate announcement will lead to lower market returns. As mentioned in the

Table 5.5: Seasonality with Monthly Dummy Variables

	Dependent variable:
	monthly average S&P 500 index
actual unemployment rate	84.435400**
	(36.814170)
positive surprise	457.424300
	(489.011200)
negative surprise	886.941500
	(677.598000)
effective interest rate	-119.064100***
	(36.922200)
Feb	17.047200
	(230.795700)
Mar	−36.914480
	(231.523400)
Apr	−60.955070
	(231.341300)
May	−30.730370
	(231.605900)
Jun	−10.057700
	(231.205700)
Jul	−17.105220
	(232.020700)
Aug	32.768910
	(232.397800)
Sep	18.580790
	(231.116000)
Oct	−24.701400
	(231.257300)
Nov	7.928562
	(231.336500)
Dec	74.097670
	(231.111900)
actual*positive surprise	−105.184200
	(64.595200)
actual*negative surprise	−87.223520
	(110.344100)
Constant	858.873100***
	(296.151800)
Observations	252
Adjusted R^2	0.268126
Note:	*p<0.1; **p<0.05; ***p<0.01

TABLE 5.6: Difference in Values

	S&P 500	Energy	Materials	Industrials	Consumer Discretionary	Real Estate
	(1)	(2)	(3)	(4)	(5)	(6)
effective_rate	−0.100197	0.080669	0.118634	−0.192241	−0.341602	−0.184236
	(0.818468)	(0.287496)	(0.151653)	(0.207238)	(0.277917)	(0.246211)
surprise	4.674592***	0.045565	0.485356	0.718333*	1.845836***	−0.345881
	(1.595093)	(0.560294)	(0.295553)	(0.403881)	(0.541626)	(0.643227)
Constant	1.641766	−0.660695	−0.092584	0.502207	1.035862*	0.084534
	(1.765288)	(0.620077)	(0.327089)	(0.446975)	(0.599416)	(0.753942)
Observations	247	247	247	247	247	218
Adjusted R^2	0.026493	−0.007856	0.004637	0.009154	0.045663	−0.004137

	Consumer Staples	Health	Financials	IT	Communication	Utilities
	(7)	(8)	(9)	(10)	(11)	(12)
effective_rate	−0.010822	0.101402	−0.367319*	−0.916371	−0.160660**	−0.097780
	(0.129042)	(0.259662)	(0.191722)	(0.571694)	(0.080587)	(0.097484)
surprise	−0.430318*	−0.757830	0.974712***	0.135080	0.232421	−0.047464
	(0.251486)	(0.506050)	(0.373642)	(1.114161)	(0.157053)	(0.189985)
Constant	0.174134	−0.259289	0.402545	1.508998	0.075500	0.134102
	(0.278319)	(0.560045)	(0.413510)	(1.233041)	(0.173811)	(0.210256)
Observations	247	247	247	247	247	247
Adjusted R^2	0.003762	0.001980	0.036131	0.002528	0.018374	−0.003923

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

introduction, a higher-than-expected increase in the unemployment rate signals lower consumption, causing the public to become pessimistic about the market and resulting in declining stock market returns. A 1-unit increase in surprise in the unemployment rate announcement will lead to a 4.674592 increase in the SPY index, reflecting market returns. This relationship is statistically significant at the 1 percent level. Moreover, different sectors react differently due to the nature of their products or services. The above-mentioned relationship is only present in the Consumer Discretionary and Financials sectors. The effective interest rate does not have an effect, and the positive surprise could actually boost the stock market. This contradicts the hypothesis, and a potential reason is that the S&P 500 index has continuously increased over the years, and the effect of the increase is larger than the effect of a surprise when considering a 20-year time range, even though the S&P 500 has already adjusted for inflation. Therefore, examining the change in percentage could provide more insightful results, as shown in the next subsection.

5.4 Difference in Percentage Results

Table 5.7: Percentage Change Regression Results

	Dependent variable:					
	S&P 500	Energy	Materials	Industrials	Consumer Discretionary	Real Estate
	(1)	(2)	(3)	(4)	(5)	(6)
effective rate	−0.001183***	0.000375	0.000984*	0.001070**	0.000824	−0.000064
	(0.000443)	(0.000567)	(0.000544)	(0.000513)	(0.000520)	(0.000680)
percentage surprise	−0.002579**	−0.019141***	−0.011927**	−0.011211**	−0.006525	0.004587
	(0.001125)	(0.004905)	(0.004704)	(0.004434)	(0.004497)	(0.005427)
Constant	−0.001689*	−0.002152*	−0.002654**	−0.002643**	−0.000949	0.000334
	(0.000956)	(0.001226)	(0.001175)	(0.001108)	(0.001124)	(0.001389)
Observations	247	247	247	247	247	218
Adjusted R^2	0.022636	0.053118	0.031234	0.035323	0.010973	−0.005913
	Dependent variable:					
	Consumer Staples	Energy	Health	Financials	IT	Communication
	(1)	(2)	(3)	(4)	(5)	(6)
effective rate	0.000307	0.001268*	0.000797	0.000235	0.000438	0.000445
	(0.000402)	(0.000659)	(0.000598)	(0.000444)	(0.000456)	(0.000322)
percentage surprise	−0.001992	−0.011512**	−0.007640	−0.005004	−0.008188**	0.000021
	(0.003475)	(0.005698)	(0.005169)	(0.003837)	(0.003945)	(0.002786)
Constant	−0.000981	−0.002769*	−0.001098	−0.000186	−0.000329	−0.001362*
	(0.000868)	(0.001424)	(0.001292)	(0.000959)	(0.000986)	(0.000696)
Observations	247	247	247	247	247	247
Adjusted R^2	−0.004357	0.023714	0.008303	0.000067	0.013362	−0.000362
Note:						*p<0.1; **p<0.05; ***p<0.01

Regarding percentages in Table 5.7, a unit increase in the percentage surprise in unemployment rate announcements leads to a 0.002579 decrease in the percentage change in the S&P 500 index, reflecting market returns at a 5 percent statistically significant level. Additionally, a unit increase in the effective interest rate results in a 0.001183 decrease in the percentage change in the S&P 500 index. However, there are still no similar patterns observed across different sectors.

5.5 Minite-Level Results

Then, I focus on the minute-level data to observe how investors react to the surprise in a shorter time. Table 5.8 shows that 1 minute after the release of the employment report, a unit increase in the percentage surprise will lead to a 0.000558 decrease in the S&P 500 index at the 5 percent statistically significant level. and 5 minutes after the release, a unit increase in the percentage change surprise will lead to a 0.001081 increase in the S&P 500 index at the 1 percent statistically significant level. Then, the

Table 5.8: Minute-Level S&P500 Index Change Rate

	Dependent variable:				
	1_min	5_min	10_min	15_min	30_min
	(1)	(2)	(3)	(4)	(5)
effective rate	0.000058	−0.000101	−0.000105	0.000012	0.000021
	(0.000069)	(0.000109)	(0.000169)	(0.000215)	(0.000265)
percentagesurprise	−0.000558**	0.001081***	0.000556	−0.000125	0.000017
	(0.000235)	(0.000369)	(0.000574)	(0.000731)	(0.000902)
Constant	−0.000041	0.000048	0.000131	−0.000154	−0.000090
	(0.000070)	(0.000111)	(0.000172)	(0.000219)	(0.000270)
Observations	155	155	155	155	155
Adjusted R^2	0.028742	0.047964	−0.003982	−0.012938	−0.013113
Note:					*p<0.1; **p<0.05; ***p<0.01

stock market seems no pattern in reacting to the surprise brought by the employment report.

5.6 Uncertainty

The chaos observed five minutes after the release of the employment report raises questions about whether the surprise element contributes to uncertainty, prompting various investors to take unusual actions that further cause disruptions in the stock market. To investigate this, abnormal trading volume and intraday changes in the VIX on the release day are examined. Table 5.9 reveals that, with the exception of the real estate and energy sectors, the overall market and the remaining nine sectors experience a decline in trading volume compared to the two trading days before and after the release. In addition, the degree of the surprise and the positive (negative) surprise does not have a statistically significant effect on the trading volume.

Table 5.10 shows the intraday changes in the VIX in Columns (1) and (2). A unit increase in the surprise corresponds to a 0.114 decrease in the intraday changes of the VIX at a 10 percent statistically significant level. Additionally, a unit increase in the percentage change in surprise results in a 0.538 decrease in the intraday changes of the VIX at a 5 percent statistically significant level. This suggests that investors' uncertainty increases throughout the day. Table 5.11 displays the differences between the opening (closing) value on the release day and the previous day's closing values.

Table 5.9: Effect of Employment Report Released on Trading Volume

	Dependent variable:					
	S&P 500	Energy	Materials	Industrials	Consumer Discretionary	Real Estate
	(1)	(2)	(3)	(4)	(5)	(6)
announcement	−0.079***	−0.110***	−0.079***	−0.059***	−0.111***	−0.012
	(0.020)	(0.023)	(0.024)	(0.022)	(0.020)	(0.034)
Constant	0.046***	0.060***	0.059***	0.051***	0.053***	0.033**
	(0.009)	(0.010)	(0.011)	(0.010)	(0.009)	(0.015)
Observations	1,230	1,230	1,230	1,230	1,230	373
Adjusted R^2	0.011	0.018	0.008	0.005	0.024	−0.002

	Dependent variable:					
	Consumer Staples	Energy	Health	Financials	IT	Communication
	(1)	(2)	(3)	(4)	(5)	(6)
announcement	−0.102***	−0.039	−0.056***	−0.134***	−0.080***	−0.114***
	(0.023)	(0.024)	(0.021)	(0.029)	(0.025)	(0.024)
Constant	0.054***	0.051***	0.043***	0.079***	0.062***	0.060***
	(0.010)	(0.011)	(0.009)	(0.013)	(0.011)	(0.011)
Observations	1,230	1,230	1,230	1,230	1,230	1,228
Adjusted R^2	0.015	0.001	0.005	0.016	0.007	0.017

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5.10: Intraday VIX Regression Results

	Dependent variable:	
	VIX intraday change	
	(1)	(2)
effective rate	0.028	0.030
	(0.030)	(0.030)
surprise	−0.114*	
	(0.059)	
percent change in surprise		−0.538**
		(0.259)
Constant	−0.087	−0.097
	(0.065)	(0.065)
Observations	247	247
Adjusted R^2	0.012	0.014

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5.11: Open and End VIX Regression Results

	Dependent variable:			
	open_change		end_change	
	(1)	(2)	(3)	(4)
effective rate	-0.177^{***}	-0.170^{***}	0.001	-0.008
	(0.065)	(0.065)	(0.092)	(0.091)
surprise	-0.332^{***}		0.426^{**}	
	(0.127)		(0.178)	
percent change in surprise		-1.489^{***}		2.222^{***}
		(0.564)		(0.786)
Constant	-0.019	-0.046	-0.589^{***}	-0.552^{***}
	(0.141)	(0.141)	(0.197)	(0.196)
Observations	247	247	247	247
Adjusted R^2	0.044	0.044	0.015	0.024
Note:	*p<0.1; **p<0.05; ***p<0.01			

In the morning, the VIX declines when there is a higher expected unemployment rate. However, by the end of the day, the VIX increases. This pattern indicates that investor sentiment and uncertainty evolve during the day as market participants process and respond to the new information presented in the employment report.

Chapter 6

Conclusion

This study aims to investigate the relationship between surprises in employment report releases and stock market returns. Using the obtained data, I first examined the time-series data to check the stationary properties of stock data and the presence of seasonality, and transformed the data to ensure stationarity for further OLS regression analysis. OLS regression was employed to explore the statistical significance of the proposed relationships, and various robustness checks were conducted to validate the results and minimize the potential impact of biases inherent in the study.

In terms of results, I have resolved the non-stationary issue and discovered that there is no seasonality in the stock data. Through the analysis of the relationship between unemployment rate surprises and the stock market, I found that positive (negative) surprises lead to a decrease (increase) in stock market returns on the day the employment report is released. However, this pattern is only observed in the overall market (S&P 500) and not in individual sectors. There are several possible explanations for this. First, the S&P 500's pool of firms within each sector is small, making firm-specific factors crucial. The performance of individual companies can impact the sector index. Factors such as earnings reports, mergers and acquisitions, product launches, and management changes can cause stock prices of individual companies to rise or fall, thus affecting the overall sector index. Second, sector-specific trends, regulations, and competitive dynamics can significantly influence a sector index's performance. For example, a breakthrough in renewable energy technology may enhance the clean energy sector's performance, while stricter environmental regulations could negatively impact the fossil fuel industry. Third, market sentiment plays a substantial role in driving sector indices' performance. Periods of optimism or pessimism among investors can result in increased buying or selling pressure in specific sectors, causing their respective indices to rise or fall. In a short time window, the stock market return initially declines within the first minute and then increases over the next five minutes, after which the market becomes uncertain. This could be due to the uncertainty introduced by the surprise as well as the prevalence of passive management in the stock market. While the unemployment rate surprise may not have a universal effect on stock market returns, it does introduce additional uncertainty for investors. Analyzing the trading volume on the announcement day in comparison to the two days before and after reveals a significant decrease in trading volume for both the overall market and individual sectors. The pattern observed in VIX changes could potentially be attributed to the varying ways investors respond to the market at different times throughout the day. When there is a high level of uncertainty in the market, investors and traders might adopt a wait-and-see approach when they don't have enough time to analyze completely, which can lead to reduced trading volume. This cautious behavior can stem from concerns about the future direction of the market, making it difficult for participants to make informed decisions about buying or selling securities. As a result, the trading volume may decrease as market participants observe and analyze the situation before committing to any trades.

Google Index (GI) has been proven useful to forecast unemployment rates in the United States by D.Amuri and Marcucci (2017). Therefore, there is a correlation between search engine query data and the unemployment rate. The traditional methods predicting the future unemployment rates include the initial claims, employers' expectations, consumers' expectations, the economic policy uncertainty index given by Baker et al. (2016), etc, but D.Amuri and Marcucci (2017) use a time-series causality approach showing more accuracy compared with other similar models. Social media content has been used as a source for analyzing social emotions. Through analyzing the textual information typed by individuals, it is possible to infer what the individuals want to express, such as positive feelings like happiness and negative feelings like sadness, based on some words used. Most of the prediction work using social media content is to find leading indicators by measuring the correlation between the outbreak of keywords in social media and the outbreak of actual events. Ryu (2018) proposed a new method to generate a numerical prediction of the unemployment rate by analyzing social media content. Ryu found that the frequency trend of keywords is closely related to the change in the unemployment rate and then used the frequency trend of keywords and the data of past unemployment rates to establish a prediction model.

All available data sources for forecasting unemployment rates are in a quarterly format, so we must devise a suitable method to convert this quarterly data into monthly data. This may involve linear interpolation, moving averages, or more advanced statistical techniques, but it is crucial to understand the real-world dynamics of employment.

I employ simple linear interpolation, but this approach inevitably results in approximation errors. An alternative solution is to develop a model that directly predicts the monthly unemployment rate. A potential model could involve natural language processing techniques. However, due to limitations in the Twitter API I used, my model's performance is not optimal. This research is still in its early stages, and there are numerous potential ideas to explore in future work. Furthermore, due to data limitations, no other independent variables or valid instrumental variables have been identified to fully address endogeneity and verify causality. Once a better surprise estimator is obtained, additional work can be conducted to consider more independent variables and examine the structural framework to identify the channels that influence the stock market.

Bibliography

[1] Scott R. Baker, Nicholas Bloom, and Steven J. Davis. Measuring Economic Policy Uncertainty*. *The Quarterly Journal of Economics*, 131(4):1593–1636, 07 2016. ISSN 0033-5533. doi: 10.1093/qje/qjw024. URL https://doi.org/10.1093/qje/qjw024.

[2] James H. Stock and Mark W.Watson. Forecasting output and inflation: The role of asset prices. *Journal of Economic Literature*, 41(3):788–829, September 2003. doi: 10.1257/002205103322436197. URL https://www.aeaweb.org/articles?id=10.1257/002205103322436197.

[3] Pietro Veronesi. Stock market overreaction to bad news in good times: A rational expectations equilibrium model. *The Review of Financial Studies*, 12(5):975–1007, 1999. ISSN 08939454, 14657368. URL http://www.jstor.org/stable/2645973.

[4] John Y. Campbell and Robert J. Shiller. The dividend-price ratio and expectations of future dividends and discount factors. *The Review of Financial Studies*, 1(3): 195–228, 1988. ISSN 08939454, 14657368. URL http://www.jstor.org/stable/2961997.

[5] John H. Boyd, Jian Hu, and Ravi Jagannathan. The stock market's reaction to unemployment news: Why bad news is usually good for stocks. *The Journal of Finance*, 60(2):649–672, 2005. ISSN 00221082, 15406261. URL http://www.jstor.org/stable/3694763.

[6] Tobias J. Moskowitz and Mark Grinblatt. Do industries explain momentum? *The Journal of Finance*, 54(4):1249–1290, 1999. ISSN 00221082, 15406261. URL http://www.jstor.org/stable/798005.

[7] Grant McQueen and V. Roley. Stock prices, news, and business conditions. *Review of Financial Studies*, 6:683–707, 07 1993. doi: 10.1093/rfs/6.3.683.

[8] U.S. Bureau of Economic Analysis. National data. 2022. URL https://apps.bea.gov/iTable/?reqid=19&step=3&isuri=1&1921=survey&1903=84.

[9] Francesco D'Amuri and Juri Marcucci. The predictive power of google searches in forecasting us unemployment. *International Journal of Forecasting*, 33(4): 801–816, 2017. ISSN 0169-2070. doi: https://doi.org/10.1016/j.ijforecast.2017.03.004. URL https://www.sciencedirect.com/science/article/pii/S0169207017300389.

[10] Jon Faust, John H. Rogers, Shing-Yi B. Wang, and Jonathan H. Wright. The high-frequency response of exchange rates and interest rates to macroeconomic announcements. *Journal of Monetary Economics*, 54(4):1051–1068, 2007. ISSN 0304-3932. doi: https://doi.org/10.1016/j.jmoneco.2006.05.015. URL https://www.sciencedirect.com/science/article/pii/S0304393206001565.

[11] Michael J Fleming and Eli M Remolona. What moves the bond market? *Economic policy review*, 3(4), 1997.

[12] Jan Hanousek, Evzen Kocenda, and Jan Svejnar. Divestitures, privatization and corporate performance in emerging markets. *The Economics of Transition*, 17: 43–73, 01 2009. doi: 10.1111/j.1468-0351.2009.00334.x.

[13] Jan Hanousek, Evžen Kočenda, and Mathilde Maurel. Direct and indirect effects of fdi in emerging european markets: A survey and meta-analysis. *Economic Systems*, 35(3):301–322, 2011. URL https://EconPapers.repec.org/RePEc:eee:ecosys:v:35:y:2011:i:3:p:301-322.

[14] G. WILLIAM SCHWERT. Stock returns and real activity: A century of evidence. *The Journal of Finance*, 45(4):1237–1257, 1990. doi: https://doi.org/10.1111/j.1540-6261.1990.tb02434.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.1990.tb02434.x.

[15] PAUL C. TETLOCK. Giving content to investor sentiment: The role of media in the stock market. *The Journal of Finance*, 62(3):1139–1168, 2007. doi: https://doi.org/10.1111/j.1540-6261.2007.01232.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.2007.01232.x.

[16] ROBIN GREENWOOD, SAMUEL G. HANSON, ANDREI SHLEIFER, and JAKOB AHM SØRENSEN. Predictable financial crises. *The Journal of Finance*, 77(2):863–921, 2022. doi: https://doi.org/10.1111/jofi.13105. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/jofi.13105.

[17] J. M. Keynes. *The General Theory of Employment, Interest and Money*. Macmillan, 1936. 14th edition, 1973.

[18] Marcello Pericoli and Giovanni Veronese. Monetary policy surprises and channels of transmission. Technical report, Working Paper-Banca d'Italia, 2016.

[19] Kim Parker and Richard Fry. More than half of u.s. households have some investment in the stock market. 2020. URL https://www.pewresearch.org/fact-tank/2020/03/25/more-than-half-of-u-s-households-have-some-investment-in-the-stock-market/.

[20] Douglas Pearce and V Vance Roley. The reaction of stock prices to unanticipated changes in money: A note. *Journal of Finance*, 38(4):1323–33, 1983. URL https://EconPapers.repec.org/RePEc:bla:jfinan:v:38:y:1983:i:4:p:1323-33.

[21] Jr Lucas, Robert E. Asset Prices in an Exchange Economy. *Econometrica*, 46(6):1429–1445, November 1978. URL https://ideas.repec.org/a/ecm/emetrp/v46y1978i6p1429-45.html.

[22] Douglas Pearce and V Vance Roley. Stock prices and economic news. *The Journal of Business*, 58(1):49–67, 1985. URL https://EconPapers.repec.org/RePEc:ucp:jnlbus:v:58:y:1985:i:1:p:49-67.

[23] Pum-Mo Ryu. Predicting the unemployment rate using social media analysis. *Journal of Information Processing Systems*, 14:904–915, 01 2018. doi: 10.3745/JIPS.04.0079.

[24] Chiara Scotti. Surprise and uncertainty indexes: Real-time aggregation of real-activity macro-surprises. *Journal of Monetary Economics*, 82:1–19, 2016. ISSN 0304-3932. doi: https://doi.org/10.1016/j.jmoneco.2016.06.002. URL https://www.sciencedirect.com/science/article/pii/S0304393216300320.

[25] MSCI, 2023.

[26] Md. Mahmudul Alam and Md Uddin. Relationship between interest rate and stock price: Empirical evidence from developed and developing countries. 4, 02 2009. doi: 10.5539/ijbm.v4n3p43.

[27] WILLEM THORBECKE. On stock market returns and monetary policy. *The Journal of Finance*, 52(2):635–654, 1997. doi: https://doi.org/10.1111/j.1540-6261.1997.tb04816.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.1997.tb04816.x.

[28] Roberto Rigobon and Brian Sack. The impact of monetary policy on asset prices. *Journal of Monetary Economics*, 51(8):1553–1575, 2004. URL https://EconPapers.repec.org/RePEc:eee:moneco:v:51:y:2004:i:8:p:1553-1575.

[29] Eugene F. Fama. Stock returns, real activity, inflation, and money. *The American Economic Review*, 71(4):545–565, 1981. ISSN 00028282. URL http://www.jstor.org/stable/1806180.

[1] [2] [3] [4] [5] [6] [7] [8] [9] [10] [11] [12] [13] [14] [15] [16] [17] [18] [19] [20] [21] [22] [23] [24] [25] [26] [27] [28] [29]

Appendix A

Global Industry Classification Sector

A.1 Definition of Each Sector

Energy Sector: The Energy Sector comprises companies engaged in exploration & production, refining & marketing, and storage & transportation of oil & gas and coal & consumable fuels. It also includes companies that offer oil & gas equipment and services.

Materials Sector: The Materials Sector includes companies that manufacture chemicals, construction materials, forest products, glass, paper and related packaging products, and metals, minerals and mining companies, including producers of steel.

Industrials Sector: The Industrials Sector includes manufacturers and distributors of capital goods such as aerospace & defense, building products, electrical equipment and machinery and companies that offer construction & engineering services. It also includes providers of commercial & professional services including printing, environmental and facilities services, office services & supplies, security & alarm services, human resource & employment services, research & consulting services. It also includes companies that provide transportation services.

Consumer Discretionary Sector: The Consumer Discretionary Sector encompasses those businesses that tend to be the most sensitive to economic cycles. Its manufacturing segment includes automobiles & components, household durable goods, leisure products and textiles & apparel. The services segment includes hotels, restaurants, and other leisure facilities. It also includes distributors and retailers of consumer discretionary products.

Consumer Staples Sector: The Consumer Staples Sector comprises companies whose businesses are less sensitive to economic cycles. It includes manufacturers and distributors of food, beverages and tobacco and producers of non-durable household goods and personal products. It also includes distributors and retailers of consumer staples products including food & drug retailing companies.

Health Care Sector: The Health Care Sector includes health care providers & services, companies that manufacture and distribute health care equipment & supplies, and health care technology companies. It also includes companies involved in the research, development, production and marketing of pharmaceuticals and biotechnology products.

Financials Sector: The Financials Sector contains companies engaged in banking, financial services, consumer finance, capital markets and insurance activities. It also includes Financial Exchanges & Data and Mortgage REITs.

Information Technology Sector: The Information Technology Sector comprises companies that offer software and information technology services, manufacturers and distributors of technology hardware & equipment such as communications equipment, cellular phones, computers & peripherals, electronic equipment and related instruments, and semiconductors and related equipment & materials.

Communication Services Sector: The Communication Services Sector includes companies that facilitate communication and offer related content and information through various mediums. It includes telecom and media & entertainment companies including producers of interactive gaming products and companies engaged in content and information creation or distribution through proprietary platforms.

Utilities Sector: The Utilities Sector comprises utility companies such as electric, gas and water utilities. It also includes independent power producers & energy traders and companies that engage in generation and distribution of electricity using renewable sources.

Real Estate Sector: The Real Estate Sector contains companies engaged in real estate development and operation. It also includes companies offering real estate related services and Equity Real Estate Investment Trusts (REITs).

Source: MSCI

A.2 Example of Sectors' Weight and Components

S&P 500 GICS Sector Scorecard (3/31/23)

See the last page for disclosure information.	Index Value	% of 500 or Sector	Price Changes (%) 1 Wk.	13 Wks.	YTD	2022	5-Yr CAGR	5-Year Beta	Std. Dev.	52-Wk. % Chg. Rank
S&P 500	**4,109.31**	**100.00**	**3.5**	**7.0**	**7.0**	**(19.4)**	**9.2**	**1.0**	**18.5**	**NM**
Growth	2,579.29	53.17	3.0	9.2	9.2	(30.1)	10.6	1.1	20.3	NM
Value	1,500.86	46.83	4.1	4.6	4.6	(7.4)	6.8	0.9	18.5	NM
Pure Growth	15,255.14	14.93	4.2	(0.2)	(0.2)	(28.1)	6.7	1.1	22.4	NM
Pure Value	7,633.91	9.47	5.9	(2.6)	(2.6)	(3.3)	3.3	1.2	25.8	NM
Communication Services	**191.53**	**8.11**	**1.5**	**20.2**	**20.2**	**(40.4)**	**4.8**	**1.0**	**21.4**	**9**
Advertising	444.92	1.21	7.1	14.0	14.0	0.4	NA	NA	27.5	15
Broadcasting	359.71	0.92	6.1	19.7	19.7	(31.7)	NA	NA	40.3	101
Cable & Satellite	394.07	7.16	5.3	7.1	7.1	(35.5)	NA	NA	26.8	100
Integrated Telecommunication Services	116.85	10.79	3.3	1.3	1.3	(15.8)	(5.9)	0.5	16.4	79
Interactive Home Entertainment	533.23	3.99	1.3	8.1	8.1	(3.6)	NA	NA	24.8	36
Interactive Media & Services	159.37	58.89	(0.5)	29.6	29.6	(46.4)	NA	NA	27.9	95
Movies & Entertainment	394.19	13.65	6.0	18.4	18.4	(50.2)	NA	NA	33.4	98
Publishing & Printing	379.96	0.31	6.5	(5.2)	(5.2)	(18.3)	NA	NA	37.2	97
Wireless Telecommunication Services	182.30	3.08	1.6	3.5	3.5	20.7	NA	NA	24.3	13
Consumer Discretionary	**1,163.98**	**10.13**	**5.6**	**15.8**	**15.8**	**(37.6)**	**7.6**	**1.2**	**24.4**	**10**
Apparel Retail	2,442.26	3.65	4.7	(3.7)	(3.7)	4.1	10.9	1.0	25.4	4
Apparel, Accessories & Luxury Goods	153.97	0.65	8.5	0.5	0.5	(45.4)	(13.6)	1.5	35.5	103
Automobile Manufacturers	65.33	18.93	9.0	55.2	55.2	(61.8)	(2.1)	1.5	46.1	106
Automotive Parts & Equipment	313.21	1.20	4.4	20.9	20.9	(37.2)	3.9	1.9	41.8	29
Automotive Retail	1,787.78	3.35	5.9	(0.7)	(0.7)	(0.3)	21.5	0.9	24.6	17
Broadline Retail	104.43	27.56	5.2	NA	NA	NA	NA	NA	NA	NA
Casinos & Gaming	746.15	1.58	7.8	25.4	25.4	(22.3)	(8.5)	1.8	44.6	20
Computer & Electronics Retail	488.85	0.44	5.3	(2.4)	(2.4)	(21.1)	2.3	1.5	39.1	78
Consumer Electronics	128.60	0.44	5.2	9.4	9.4	(32.2)	11.4	1.0	25.1	73
Distributors	477.96	1.48	6.0	3.1	3.1	(12.9)	7.2	1.1	26.3	9
Footwear	3,724.22	4.39	1.6	4.8	4.8	(29.8)	13.0	1.1	29.0	58
Home Furnishings	86.71	0.15	5.1	(2.0)	(2.0)	(43.9)	(14.8)	1.3	36.7	90
Home Improvement Retail	3,123.35	12.12	4.6	(4.6)	(4.6)	(23.5)	12.6	1.0	24.4	38
Homebuilding	1,851.86	2.51	1.7	16.2	16.2	(20.2)	14.0	1.4	34.7	2
Hotels, Resorts & Cruise Lines	515.31	6.60	6.6	21.5	21.5	(24.4)	(2.3)	1.7	41.8	61
Household Appliances	443.05	0.21	3.8	(6.7)	(6.7)	(39.7)	(2.9)	1.5	38.9	99
Housewares & Specialties	96.00	0.13	7.0	(4.9)	(4.9)	(40.1)	(13.4)	0.9	44.1	108
Leisure Products	100.46	0.20	9.5	(12.0)	(12.0)	(40.1)	(10.7)	0.8	28.0	104
Other Specialty Retail	175.93	1.78	4.5	6.4	6.4	(8.4)	18.2	1.0	24.3	10
Restaurants	2,554.63	12.62	4.1	7.0	7.0	(10.1)	13.1	0.8	20.2	12
Consumer Staples	**780.38**	**7.23**	**2.5**	**0.2**	**0.2**	**(3.2)**	**7.6**	**0.6**	**14.3**	**3**
Agricultural Products & Services	1,342.07	2.33	3.4	(16.4)	(16.4)	37.4	12.4	0.8	25.0	82
Brewers	597.28	0.39	1.9	0.3	0.3	11.2	(7.3)	0.8	31.3	37
Consumer Staples Merchandise Retail	434.06	23.36	2.7	6.2	6.2	(11.7)	15.6	0.6	18.4	60
Distillers & Vintners	1,033.79	1.95	3.3	(2.4)	(2.4)	(8.2)	0.5	0.9	24.1	46
Drug Retail	509.50	1.00	5.7	(7.4)	(7.4)	(28.4)	(11.0)	0.7	30.8	96
Food Distributors	926.25	1.58	3.5	1.0	1.0	(2.7)	5.2	1.1	32.2	52
Food Retail	359.03	1.29	0.7	10.7	10.7	(1.5)	15.6	0.5	26.9	80
Household Products	871.37	20.12	1.6	(1.2)	(1.2)	(8.3)	9.9	0.4	16.0	43
Packaged Foods & Meats	686.89	13.72	2.3	1.3	1.3	6.6	6.1	0.5	15.3	22
Personal Care Products	891.43	2.30	2.0	(0.7)	(0.7)	(33.0)	7.0	1.0	28.9	63
Soft Drinks & Non-alcoholic Beverages	723.22	22.69	1.9	(0.3)	(0.3)	5.2	9.3	0.6	16.4	23
Tobacco	1,012.15	9.27	5.1	(3.4)	(3.4)	2.8	(2.8)	0.7	23.4	49
Energy	**634.90**	**4.61**	**6.2**	**(5.6)**	**(5.6)**	**59.0**	**5.0**	**1.3**	**37.4**	**1**
Integrated Oil & Gas	687.71	49.74	5.5	(3.9)	(3.9)	70.3	7.1	1.1	33.8	6
Oil & Gas Equipment & Services	346.76	8.05	8.6	(9.8)	(9.8)	62.0	(6.4)	1.8	51.6	40
Oil & Gas Exploration & Production	563.37	24.63	6.2	(12.1)	(12.1)	49.7	6.1	1.5	46.4	51
Oil & Gas Refining & Marketing	1,267.58	10.25	8.1	8.0	8.0	65.1	7.9	1.5	44.0	1
Oil & Gas Storage & Transportation	188.23	7.32	5.3	(4.9)	(4.9)	17.7	3.2	1.2	31.3	62
Financials	**535.28**	**12.91**	**3.7**	**(6.0)**	**(6.0)**	**(12.4)**	**3.2**	**1.1**	**23.2**	**8**
Asset Management & Custody Banks	277.31	5.67	4.6	(2.7)	(2.7)	(22.3)	0.5	1.3	27.2	74
Consumer Finance	1,232.64	3.92	4.4	6.1	6.1	(19.9)	6.5	1.3	31.6	85
Diversified Banks	525.82	21.47	4.7	(6.9)	(6.9)	(19.3)	(1.3)	1.2	29.4	87
Financial Exchanges & Data	235.96	8.96	4.0	7.5	7.5	(25.2)	10.5	0.9	20.0	70
Insurance Brokers	1,378.90	5.10	3.0	1.4	1.4	(1.1)	15.8	0.9	20.3	42
Investment Banking & Brokerage	230.09	7.30	3.0	(13.7)	(13.7)	(7.5)	5.8	1.2	28.8	76
Life & Health Insurance	402.66	3.05	5.0	(15.2)	(15.2)	6.9	0.8	1.2	28.7	86
Multi-line Insurance	117.54	1.48	6.1	(15.2)	(15.2)	7.3	1.6	1.0	28.8	88
Multi-Sector Holdings	156.51	12.55	3.3	(0.0)	(0.0)	3.3	9.1	0.9	20.6	71
Property & Casualty Insurance	862.42	6.76	3.5	(3.9)	(3.9)	17.2	9.2	0.6	17.7	39
Regional Banks	77.25	2.73	3.3	(31.6)	(31.6)	(27.8)	(9.0)	1.1	33.1	109
Reinsurance	140.08	0.32	3.8	8.1	8.1	20.9	6.9	0.6	26.0	5
Transaction & Payment Processing Services	104.15	20.69	2.8	NA	NA	NA	NA	NA	NA	NA
Health Care	**1,510.73**	**14.20**	**1.8**	**(4.7)**	**(4.7)**	**(3.6)**	**9.9**	**0.7**	**15.8**	**5**
Biotechnology	5,324.24	16.16	1.4	(1.4)	(1.4)	12.8	7.3	0.6	18.3	21
Health Care Distributors	1,071.68	2.16	3.5	(3.4)	(3.4)	38.1	13.5	0.6	21.4	8
Health Care Equipment	2,085.15	19.10	2.6	2.6	2.6	(19.8)	9.8	0.8	18.5	77
Health Care Facilities	1,092.96	1.31	3.7	6.9	6.9	(4.5)	17.9	1.6	36.1	25

See the last page for disclosure information.	Index Value	% of 500 or Sector	Price Changes (%) 1 Wk.	13 Wks.	YTD	2022	5-Yr CAGR	5-Year Beta	Std. Dev.	% Chg. Rank
Health Care Services	905.92	4.35	0.6	(18.7)	(18.7)	2.7	6.2	0.7	21.5	81
Health Care Supplies	327.83	1.05	7.0	32.9	32.9	(52.2)	5.0	1.3	32.4	93
Life Sciences Tools & Services	993.15	12.97	3.3	1.3	1.3	(23.1)	15.7	0.9	22.3	64
Managed Health Care	3,784.07	13.59	(0.8)	(11.2)	(11.2)	6.3	15.3	0.7	23.2	57
Pharmaceuticals	921.37	29.31	1.7	(8.9)	(8.9)	5.8	8.5	0.5	16.2	47
Industrials	**856.59**	**8.66**	**4.4**	**3.0**	**3.0**	**(7.1)**	**6.5**	**1.1**	**22.3**	**2**
Aerospace & Defense	1,419.88	20.24	2.7	(1.4)	(1.4)	15.5	2.3	1.0	26.0	28
Agricultural & Farm Machinery	480.48	3.75	6.8	(3.7)	(3.7)	25.0	21.6	1.0	30.4	33
Air Freight & Logistics	1,012.71	7.52	4.5	15.3	15.3	(22.4)	7.6	1.1	29.0	41
Building Products	564.60	5.08	3.1	5.0	5.0	(23.6)	10.6	1.2	25.8	30
Cargo Ground Transportation	103.42	1.53	4.1	NA	NA	NA	NA	NA	NA	NA
Construction & Engineering	862.87	0.80	3.6	16.9	16.9	24.3	26.3	1.0	26.7	3
Construction Machinery & Heavy Transport. Equip.	1,436.47	7.04	5.5	(1.0)	(1.0)	13.8	8.9	1.1	26.7	14
Data Processing & Outsourced Services	104.15	0.58	2.8	NA	NA	NA	NA	NA	NA	NA
Diversified Support Services	1,140.67	2.43	5.7	10.9	10.9	(7.9)	22.8	1.3	28.5	7
Electrical Components & Equipment	1,133.97	6.45	4.6	3.4	3.4	(14.8)	9.4	1.3	26.2	45
Environmental & Facilities Services	426.10	3.26	4.7	4.1	4.1	(5.4)	13.4	0.7	18.3	26
Human Resource & Employment Services	207.23	4.63	4.6	4.7	4.7	(33.8)	5.9	1.3	32.8	102
Industrial Conglomerates	342.59	9.74	3.1	3.8	3.8	(10.3)	0.6	1.1	24.4	31
Industrial Machinery & Supplies & Components	1,683.71	9.98	5.5	8.3	8.3	(16.3)	7.9	1.2	24.4	18
Passenger Airlines	192.44	2.39	9.2	5.9	5.9	(19.2)	(11.1)	1.3	38.6	89
Rail Transportation	2,509.24	7.88	6.4	(5.5)	(5.5)	(17.6)	9.5	1.2	25.4	94
Research & Consulting Services	284.27	3.71	2.7	(1.9)	(1.9)	(14.3)	11.3	1.1	23.2	72
Trading Companies & Distributors	1,214.95	3.00	4.5	16.4	16.4	(7.8)	17.1	1.3	29.0	19
Information Technology	**2,638.98**	**26.08**	**3.4**	**21.5**	**21.5**	**(28.9)**	**18.2**	**1.1**	**22.8**	**4**
Application Software	307.85	9.05	3.9	22.5	22.5	(37.2)	15.5	1.2	26.5	48
Communications Equipment	283.26	3.62	3.3	12.6	12.6	(21.8)	7.3	1.0	25.2	34
Electronic Components	344.45	0.84	5.2	8.4	8.4	(13.4)	10.0	1.2	25.6	24
Electronic Equipment & Instruments	510.61	0.88	5.5	5.5	5.5	(31.7)	14.2	1.4	31.1	68
Electronic Manufacturing Services	301.85	0.46	5.2	14.2	14.2	(30.9)	2.6	1.3	29.4	35
Internet Services & Infrastructure	957.96	0.35	4.0	(1.2)	(1.2)	(23.0)	NA	0.9	23.0	92
IT Consulting & Other Services	198.82	4.22	5.0	0.6	0.6	(24.7)	2.7	1.1	23.7	66
Semiconductor Materials & Equipment	2,752.03	3.27	4.7	14.2	14.2	(28.2)	19.8	1.5	36.5	32
Semiconductors	2,145.92	21.48	3.3	39.9	39.9	(38.3)	17.5	1.3	30.3	44
Systems Software	5,187.15	27.20	3.1	19.8	19.8	(28.2)	24.2	0.9	21.2	53
Technology Distributors	160.99	0.29	1.7	9.1	9.1	(12.8)	NA	1.1	28.7	16
Technology Hardware, Storage & Peripherals	721.38	28.32	3.0	26.3	26.3	(27.1)	28.6	1.3	31.4	50
Materials	**507.92**	**2.64**	**4.9**	**3.8**	**3.8**	**(14.1)**	**7.3**	**1.1**	**21.9**	**6**
Commodity Chemicals	160.08	6.89	6.8	10.4	10.4	(9.2)	(2.9)	1.3	32.6	65
Construction Materials	346.55	4.94	4.3	1.3	1.3	(19.5)	9.8	0.8	25.5	54
Copper	411.57	6.45	7.6	7.7	7.7	(8.9)	18.4	2.0	50.7	91
Fertilizers & Agricultural Chemicals	2,591.19	9.73	5.8	(1.1)	(1.1)	19.6	15.7	1.0	26.4	69
Gold	118.28	4.29	1.0	3.9	3.9	(23.9)	5.2	0.3	33.1	107
Industrial Gases	2,400.73	26.33	4.2	4.3	4.3	(3.8)	17.1	0.9	21.3	11
Metal, Glass & Plastic Containers	256.57	1.91	4.0	7.8	7.8	(46.9)	6.8	0.8	28.1	105
Paper & Plastic Packaging Products & Materials	267.59	7.88	5.0	(1.7)	(1.7)	(15.3)	(2.1)	1.0	24.3	83
Specialty Chemicals	1,404.61	25.19	5.3	1.6	1.6	(28.6)	4.2	1.2	24.4	67
Steel	355.75	6.39	4.0	16.7	16.7	14.4	20.1	1.6	45.1	27
Real Estate	**234.78**	**2.56**	**5.2**	**1.0**	**1.0**	**(28.4)**	**4.1**	**0.8**	**19.2**	**11**
Data Center REITs	102.27	10.81	5.3	NA	NA	NA	NA	NA	NA	NA
Health Care REITs	89.68	7.19	4.9	NA	NA	NA	NA	NA	NA	NA
Hotel & Resort REITs	85.55	1.34	9.5	NA	NA	NA	NA	NA	NA	NA
Industrial REITs	111.86	13.10	6.6	NA	NA	NA	NA	NA	NA	NA
Multi-Family Residential REITs	103.70	11.28	5.9	NA	NA	NA	NA	NA	NA	NA
Office REITs	97.99	3.13	6.1	NA	NA	NA	NA	NA	NA	NA
Other Specialized REITs	280.18	5.47	5.0	NA	NA	NA	NA	NA	NA	NA
Real Estate Services	557.08	2.62	5.7	NA	NA	NA	NA	NA	NA	NA
Retail REITs	85.00	11.95	6.1	NA	NA	NA	NA	NA	NA	NA
Self-Storage REITs	102.17	7.92	5.7	NA	NA	NA	NA	NA	NA	NA
Single-Family Residential REITs	102.43	2.06	6.1	NA	NA	NA	NA	NA	NA	NA
Telecom Tower REITs	101.96	20.62	2.6	NA	NA	NA	NA	NA	NA	NA
Timber REITs	103.15	2.51	5.6	NA	NA	NA	NA	NA	NA	NA
Utilities	**344.01**	**2.86**	**3.1**	**(4.0)**	**(4.0)**	**(1.4)**	**6.1**	**0.5**	**16.4**	**7**
Electric Utilities	395.71	65.35	2.7	(4.4)	(4.4)	(0.8)	6.8	0.5	16.9	56
Gas Utilities	117.09	1.64	2.7	0.3	0.3	7.0	NA	0.7	21.3	55
Independent Power Producers & Energy Traders	137.44	1.64	8.4	(16.3)	(16.3)	18.4	12.8	0.9	29.6	59
Multi-Utilities	42.14	28.51	3.5	(2.6)	(2.6)	(2.4)	3.8	0.5	16.7	84
Water Utilities	215.74	2.87	3.3	(3.9)	(3.9)	(19.3)	12.3	0.6	21.2	75

12-Mo. % Chg. Rank: 1=Best, 11=worst (Sector) 124=worst (Sub-industry).

Source: S&P Dow Jones Indices. "S&P", "S&P 500", "S&P MidCap 400" and "S&P SmallCap 600" are trademarks of S&P Global.

Appendix B

Figure

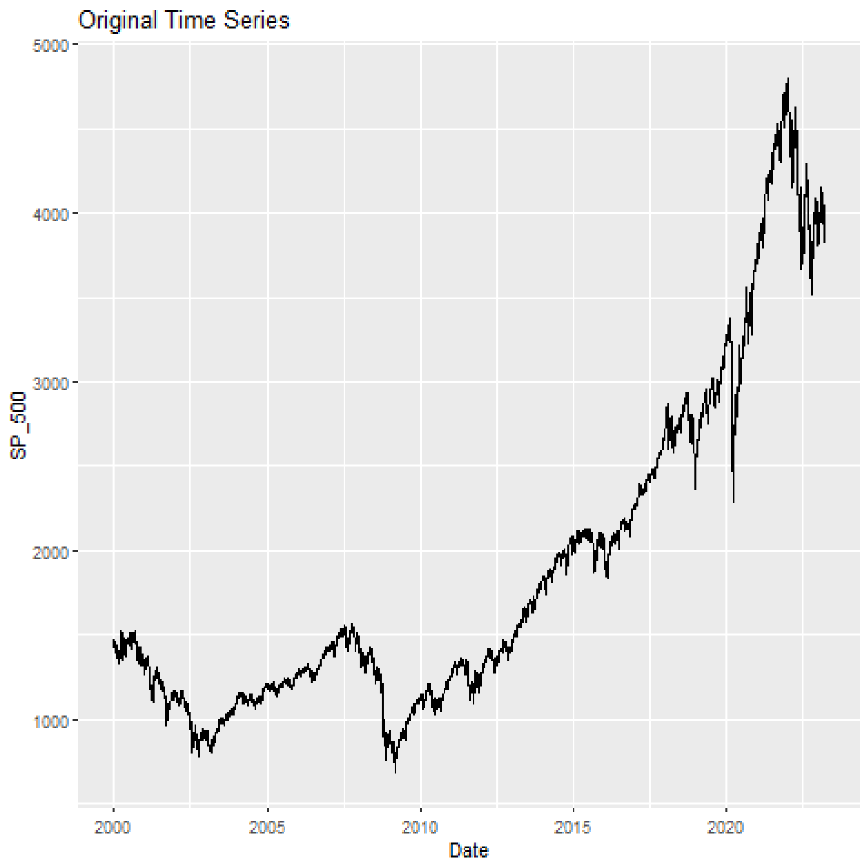

FIGURE B.1: Original S&P 500 Time Series

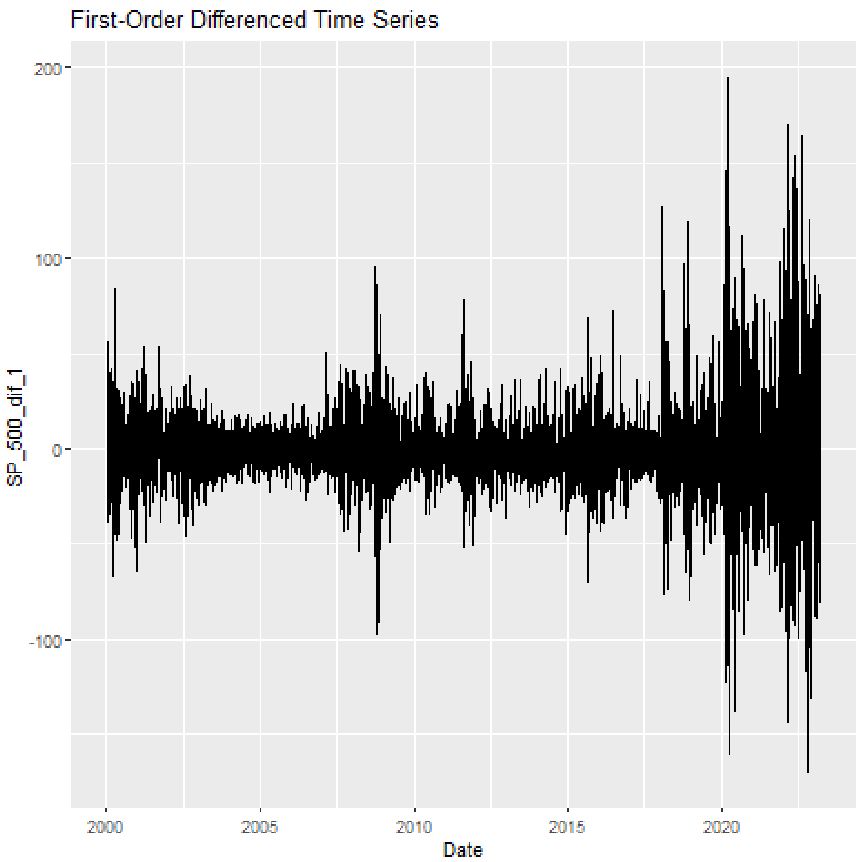

FIGURE B.2: OFirst-Order Difference S&P 500