Unanticipated unemployment rate news on the Stock market

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Abstract

This paper studies the causal effect of unemployment rate on the financial market. With monthly unemployment rate data from the U.S. BUREAU OF LABOR STATISTICS and stock market data from Yahoo Finance, this paper applies the OLS regression model as the fundamental empirical model to investigate how the announcement of unemployment rate can carry shock to the U.S financial market. As the stock market is highly event-driven, this paper uses various approaches to limit the potential bias caused by different market news. Its attempts include controlling market volumes and narrowing experiment focus to a shorter time window to analyze the immediate effect of the announcements of unemployment rate news. With the result obtained from the regression model and validated by robustness checks, this paper finds a high degree of surprise in the unemployment rate will have a larger effect on the volatility of the U.S stock market while a less pronounced effect on the returns of the U.S stock market.

Keywords: unemployment rate; stock market returns; stock market volatility;

1. Introduction

Recently, the US labor market has witnessed an unprecedented rise in the unemployment rate resulting from the Coronavirus pandemic. The sudden drop in employment rate shocked the stock market and contributed to a degree of “fear” to the economy. As a result, it has been noticed that in March, April and May, when the LBS released its unemployment rate report on the first Friday of the month, the stock market all experienced some degree of shock to prices and volatility.

Previous research disagrees about the impacts of unexpected changes in unemployment on the stock market." Bernanke and Kuttner (2005) have provided evidence that rising unemployment would lead to lower consumptions which will negatively influence companies’ balance sheets and thus decrease stock market returns. However, Gonzalo and Taamouti (2017) suggest a positive relationship between the growth in unemployment rate and stock prices. On the other hand, with regard to the market volatility, Flannery and Protopapadakis (2003) actually pointed out that instead of stock market returns, the unemployment rate news has a more obvious casual relationship with the stock market volatility. These findings motivated me to look for statistical and theoretical evidence to examine whether unemployment rate news could affect stock market returns measured by the S & P 500 index or is it more likely to contribute to stock market volatility measured by VIX, Chicago Board Options Exchange's CBOE Volatility Index.

As there has not been a consensus of how unemployment rate announcements will affect the stock market, my paper will examine the relationship not only between unemployment rate and the stock market returns, but also between unemployment rate and stock volatility. The goal of this paper is to find out which factor is more strongly correlated with the surprise in the unemployment rate.

My hypothesis is that the degree of surprise in the unemployment rate will be more positively related to market volatility as rising unemployment rate signals a rising level of uncertainty. On the other hand, the surprise in the unemployment rate will have a less pronounced effect on stock market returns. Even though higher unemployment rate could signal a lower consumption in the future, according to the Fisher and Phillips curve equations, the rising unemployment rate will also lead to monetary policies, such as reduction of interest rates, which will almost even out the effect of lower consumption. Thus,when it comes to market expectations, investors will not be likely to lower their estimate for stock market returns based on surprise in the unemployment rate. Therefore, the future market returns of the stock market will likely not be affected by surprise in the unemployment rate.

2. Literature Review and My Contributions

Many papers in the late 1900s investigated how macroeconomic factors, such as inflation, interest rates and GDP, affect the stock market. Following Chen, Roll, and Ross (1986) 's research on how security prices will be affected by macroeconomic forces from the perspective of efficient-market theory, Grant and V. Vance (1993) pointed out there exists a strong relationship between stock market and macroeconomic news, such as inflation news and unemployment rate news in *stock prices, news, and Business Conditions.* Unemployment rate, as an important macroeconomic factor, and how it affects the stock market also have been popular research topics. Hu and Li (1998) investigated how Dow Jones and Russel 2000 respond to unemployment rate differently. Miao and her colleagues' (2020) also research on the relationship between the unemployment bubble and the stock market indicate the interesting relationship between unemployment rate and the stock market. More specifically, in *Macroeconomic Factors Do Influence Aggregate Stock Returns* by Flannery and Protopapadakis (2003), it examines 17 macroeconomic factors and their casual relationship with the stock market. It actually pointed out that unemployment rate news does not affect stock market returns, "Three real factor candidates (Balance of Trade, Employment/Unemployment, and Housing Starts) affect only the returns' conditional volatility."

A more recent paper by Boyd, Hu, and Jagannathan (2005), contradictory to Protopapadakis's argument, argues that the unemployment rate news does have an impact on the stock market returns. Boyd, Hu, and Jagannathan(2005) also pointed out that during economic recessions and expansions, surprise in the unemployment rate are having different effects on the stock market. When the economy is expanding, such news will actually drive up stock returns; whereas when the economy is in recession, it will have negative impacts on the stock returns. Another recent paper by Gonzalo and Taamouti (2017) also provided an opinion about this topic. Using more innovative analytical approaches such as nonparametric Granger causality and quantile regression-based tests, it found out an increase in the anticipated growth rate of the unemployment rate leads to an increase in stock market prices.

Compared with other papers, my paper will be different in many ways and provide novel results on the effect of surprise in the unemployment rate on the stock market. First of all, given the market is highly event-driven and can have large intraday fluctuations due to different news, examining the stock market reactions on a daily basis can lead to lots of biases and generate many noise factors. Therefore, I want to limit my focus to the 30 minutes window after the announcement of the unemployment news. Due to the difficulty of retrieving data from 20 years ago, I was only able to find the 30 minute timeframe data for the last 5 years. Thus, I will use the data from the last 5 years to do robust checks. Secondly, in order to further minimize the influence of noise factors and endogeneity, I will be comparing daily trading volume of the announcement date with the trading volumes of the previous dates. A significantly higher trading volume on the announcement date will signal an unusual market condition. By setting a proper threshold on the trading volume, I can then eliminate the data entries that have a high degree of noise. In addition, another reason that not only motivates me to conduct the research but also differentiate this paper from all previous research is that most of the relevant papers I found were in the late 1900s or early 2000s, like Barro (1977, 1978), Sheffrin (1979), and Makin (1982). Back then, the internet was not as well-accepted and broadly used as it is today. Thus, the spread of news would be much slower back then, thus leading to a less pronounced effect of macroeconomic news on the stock market. As Garz (2014) pointed out, modern news media has to a large extent shortened the delivery time of unemployment rate news. This is also the reason why I would love to investigate time periods in recent 20 years where people had easy access to macroeconomic news and data. With these approaches, I believe I can find not only more accurate but also more reliable reflection of how unemployment rate news impacts the stock market.

3. Description of data

3.1 Data sources and preprocessing

U.S. Bureau of Labor statistics releases unemployment rate announcements on the first Friday of each month. In order to investigate the stock market reactions, the data of interest will only be using market data on these Fridays. This paper is only interested how the surprise of unemployment rates affect the degree of changes in market returns and volatility.

This paper will be using daily SPY (S&P 500 index) and daily VIX(Chicago Board Options Exchange's CBOE Volatility Index) from October 2000 to October 2020 , to reflect stock market returns and volatility respectively. Yahoo Finance provides important market data for this paper. On the other hand, the dependent variable of interest is surprise in unemployment rate announcement, which is the difference between actual unemployment rate announced and forecasted unemployment rate. In order to find the data, I used data from the monthly unemployment rate report by the U.S. Bureau of Labor Statistics and forecasted unemployment rate by the Federal Reserve bank of philadelphia.

The main method used in this experiment is OLS regression. However, as the data sources are categorized as time-series, which can undermine the validity of OLS regression due to autocorrelation, I will use several approaches to avoid that. Firstly, in order to limit the presence of potential autocorrelation or time-related effects in the dataset, I will use monthly adjusted unemployment rate forecasts provided by the Federal Reserve bank of philadelphia. Therefore, the surprise of unemployment rates each month will be dependent on previous or future months. In addition, for the financial market data on each Friday, I will calculate the percent change in stock market returns and volatility upon announcement of the unemployment report. Therefore, the stock market reactions adjusted in percentages will limit its dependence on the market reactions on previous or future Fridays in the dataset. In addition, I will randomly order the data entries in different orders to fully get rid of the time-related effects on the dataset. Thus, the dataset will exhibit no time-related effects and only describe each Friday’s market reaction to surprise in the unemployment rate announcement.

Furthermore, for robustness checks for endogeneity and omitted-variable bias, I used several approaches including event study analysis and dummy variables. Data used to support robustness checks comes from the Federal Reserve Bank of St. Louis, a credible source of information for economic research purposes. Data cleaning and preprocessing are performed using Python and Microsoft Excel and that leaves a total 1816 data entries in the sample that will be used to perform OLS regressions and robustness checks.

3.1.1 Dependent variables

Two dependent variables are used to capture how the market reacts to the surprise in unemployment rate announcements. For this paper, I will be using SPY and VIX to capture stock market reactions in terms of returns and volatility. SPY is a popular indicator of the returns of the stock market as it reflects the stock performance of 500 largest public companies traded in the US stock market. VIX, also known as the "fear index", captures the US stock market volatility based on options data of the S&P 500 companies. In addition, due to the unemployment rate announcement only taking place once a month on the first Friday, the SPY and VIX data of interest will only be the closing price of the first Friday of each month.

3.1.2 Independent variables

In order to figure out how surprise in unemployment rate announcements affect the stock market, the dependent variable will be calculated based on the difference between two sets of data. The first one is the unemployment rate announced each month by the U.S. Bureau of Labor Statistics from October 2000 to October 2020 and will therefore be a total of 240 announcements. The second dataset is the forecasted unemployment rate surveyed and modeled by the Federal Reserve bank of philadelphia for the same time range of interest. As both datasets are from credible government sources, they provide accurate information on the degree of surprise for each month's unemployment rate announcement.

3.1.3 Control Variables

As this paper is investigating how an macroeconomic factor would affect the stock market, there could be a lot more factors that can add noises to the research result. Therefore, it is important to add control variables to empirical strategy to ensure the result is valid. Based on previous research regarding how macroeconomic variables affect the stock market, I found interest rate and productivity are the two most recognized variables that have been proven to have a significant effect on stock market returns (Flannery and Protopapadakis, 2003). Therefore, for control variables, I used data of federal interest rates and productivity of labor from the Federal Reserve Bank of St. Louis from October 2000 to October 2020. By controlling these two macroeconomic factors, I will be able to limit the extent of bias that will exist in my empirical strategy.

In addition, due to the unpredictable nature of the stock market, the measures on SPY and VIX could be affected by numerous factors such as breaking market news. In order to control such noise, I added a dummy variable that indicates whether the trading volume of the announcement date is normal or abnormal. This is because when the market experiences unexpected news, such as success in Covid Vaccine or the agreement on a stimulus package for Covid, market sentiment will be strongly affected and thus cause the trading volumes to be higher than normal trading days. The high trading volumes can therefore add noise to the dataset and obscure the effect of surprise in the unemployment rate announcement. The mechanism for determining the normality of trading volume is to use the average of the previous 4 days of trading volumes as the threshold and if the trading volume on Friday exceeds the threshold, it will be considered to have an abnormal trading volume. More details on controlling for trading volumes will be discussed in 4.2.1 section.

4. Empirical strategy and Robustness checks

4.1 Empirical Strategy

4.1.1 OLS Regression

Understanding the limitations of using OLS regression on time series data, the preparation of the data used different techniques to eliminate time-related effects to ensure the OLS regression will provide valid results. In order to find the casual relationship between stock market reactions and surprise in unemployment rate, we use the following OLS regression:

$$CIV = \alpha + \beta * SUER + \beta_2 * MP + \beta_3 * MIR + \epsilon$$

$$CIS = \alpha + \beta * SUER + \beta_2 * MP + \beta_3 * MIR + \epsilon$$

The first equation estimates the correlation between unemployment rate surprise (SUER) and CIV (Change in VIX) . The dependent variable is VIX index and the control variables are MP (Monthly Labor productivity data) and MIR (Monthly Federal interest rate data). $\alpha$is constant and $\epsilon$is the error item.

The second equation estimates the correlation between unemployment rate surprise and Change in Inflation- ADJUSTED S&P 500 index (CIS). The dependent variable is CIS and the control variables are MP(Labor productivity data) and MIR(Federal interest rate data). $\alpha$is constant and $\epsilon$is the error item.

4.2 Robustness checks

As discussed earlier, daily change in these indexes could be affected by lots of market news other than unemployment report announcements and therefore add noises to our final result. In order to minimize these noise effects, this paper takes two approaches to addressing this.

4.2.1 Robustness checks through trading volumes

It is common that breaking news could lead to negative or positive market reactions. Normally, breaking news is positively related to trading columns. For example, on 11/09/2020 when there was news about success in vaccine development, the trading volume of SPY was twice as much as the previous day. In this case, the market will reflect little about the unemployment rate news announcement and thus create noises for the date. The degree that the market reacts to the unexpected market news can cause unwanted bias for the experiment result. Therefore, I don't want these cases to affect my final result and cause omitted-variable bias in the regression model. Thus, in order to account for this factor, I took two steps to do robustness checks for the original OLS regression. I first took the average of the trading volumes of the previous 4 days as the threshold for abnormal trading volumes. I made the decision to have the average of the previous 4 days' trading volumes with the following ratinoals: 1) By taking the average of the previous 4 days, I can effectively get an overview of the average trading volumes of the market for the week. If I only took a time range of 2 or 3 days, it might have some outliers that can affect the calculation of the threshold. Due to the limited size of the dataset, I don't want to reduce the data size even more by mistake. 2) As the unemployment rate was released on the first Friday of the month, normally no major announcements will be made during that week except for the unemployment report. For example, if I extend the time range to the previous 9 days, it would include days of monthly Import/Export index announcement or Monthly CPI announcement, which could potentially affect the accuracy of the threshold.

Thus, I decided to use the average of the previous 4 days' trading volumes as the proper threshold to determine normality in trading volumes on announcement date. With the threshold, I then categorize each announcement date by 1 as "normal trading day" or 0 as "abnormal trading day" and obtain the new OLS regression function as :

$$CIV = \alpha + \beta * SUER + \beta_2 * MP + \beta_3 * MIR + \beta_4 * TVT + \epsilon$$

$$CIS = \alpha + \beta * SUER + \beta_2 * MP + \beta_3 * MIR + \beta_4 * TVT + \epsilon$$

Where TVT stands for Trading Volume Type, which could either be 1 or 0. By plotting the graph out based on the regression, I can then visualize how much the market news will affect my experiment result.

In order to further reduce the effect of abnormal trading volumes caused by unexpected market news, I also drop the data entries whose TVT value is 0, which represents an abnormal trading volume on that day. Then I run the regression again and compare the results without abnormal trading days with previous results with abnormal trading days to see if there exist any significant differences. With the two steps discussed above, I will be able to conduct my first robustness checks.

4.2.2 Robustness checks through shorter time windows (30mins)

The US stock market is highly event-driven and unpredictable, and the fluctuations of stock prices in a single day could be a result of a number of different factors. The unemployment rate report is announced at 8:30 AM Eeastern Time and the most popular financial media such as

Yahoo Finance, Marketwatch and Wall street Journals all report the news in less than an hour. Therefore, by the time the stock market opens at 9:30 AM, it can be assumed that the institutional and retail investors are well informed about the unemployment rate. Therefore, using daily market data will lead to potential threat to the regression method and cause omitted-variable bias about daily news' effect on stock market reactions. In order to find the effect of unemployment rate news announcements on the stock market and minimize the influence of other factors, I initially want to restrict my focus to the first 30 minutes of SPY price changes and VIX index changes. However, due to the lack of sufficient 30 minute time frame data on these two indexes from 2000 to 2020, I was only able to find the 30 minute data from 2015 to 2020. Therefore, I decided to use the 30 minute data from the last 5 years to do robust checks on the initial regression. I will use the following equation to check how unemployment rate announcement will impact the stock market in 30 mins of its opening on Friday of each month:

$$CIV30 = \alpha + \beta_{30min} * Surprise + \beta_2 * MP + \beta_3 * MIR + \epsilon$$

$$CIS30 = \alpha + \beta_{30min} * Surprise + \beta_2 * MP + \beta_3 * MIR + \epsilon$$

Where CIV30 and CIS30 measure the change in VIX in 30 minutes of the announcement and Change in S&P 500 index in 30 minutes of the announcement. In order to have a proper comparison, I will only be using the daily data after 2015 and comparing it to the regression result outputted by the equation above. By comparing β_{30min} with β , I can figure out whether the result obtained by using daily stock price and volatility changes upon unemployment rate announcement is noise-free and statistically significant.

5. Results

5.1 OLS regression result

Table 1 shows the relationship between surprise in unemployment rate announcement and market reaction. In terms of market volatility, surprise in the unemployment rate announcement has a positive relationship with daily change in stock market volatility. A 0.0379 unit of surprise in the unemployment rate announcement will lead to a 1% increase in VIX that reflects the market volatility. Also, it is statistically significantly at 1 percent level as its t statistics is 4.42, which is larger than the critical value 1.96. On the other hand, Surprise in the unemployment rate announcement has a negative relationship with daily change in stock market returns. That means a positive surprise in the unemployment rate announcement will actually lead to lower market returns. As discussed in the introduction, a rising unemployment rate that's larger than expected will signal lower consumption, thus causing the public to be pessimistic about the market and leading to decreasing stock market returns. A -0.0049145 unit of surprise in the unemployment rate announcement will lead to a 1% increase in SPY index that reflects the market returns. Also, it is statistically significantly at 1 percent level as its t statistics is 3.38, which is larger than the critical value 1.96.

Table 1: OLS results for effect of SUER(Surprise in unemployment rate) on stock market

	(1) CIV (Change in VIX)	(2) CIS (Change in SPY)
SUER	0.0379***	-0.00491***
	(0.00859)	(0.00145)
MIR	0.00639***	-0.00113***
	(0.00220)	(0.000371)
MP	-0.000711	-5.12e-05
	(0.000666)	(0.000113)
Constant	0.0484	0.00724
	(0.0664)	(0.0112)
Observations	240	240
R-squared	0.107	0.079

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

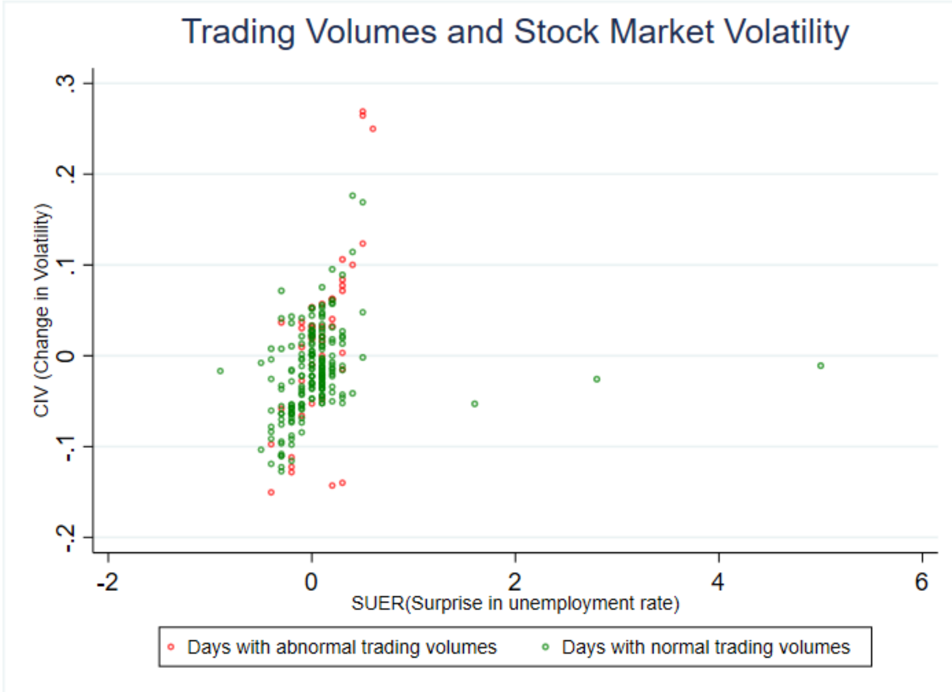
This preliminary result regarding volatility is consistent with my hypothesis that a positive surprise in the unemployment rate will lead to a rising level of uncertainty in the stock market and affect the investing sentiment of the market. Therefore, the uncertainty will cause differences in expectations for the future market returns and thus lead to a higher market volatility. On the other hand, although my hypothesis is that surprise in unemployment rate's effect on market returns will not be as pronounced as the effect on market volatility, the result indicates the effect on market returns is also highly statistically significant with a P-value less than 0.01.

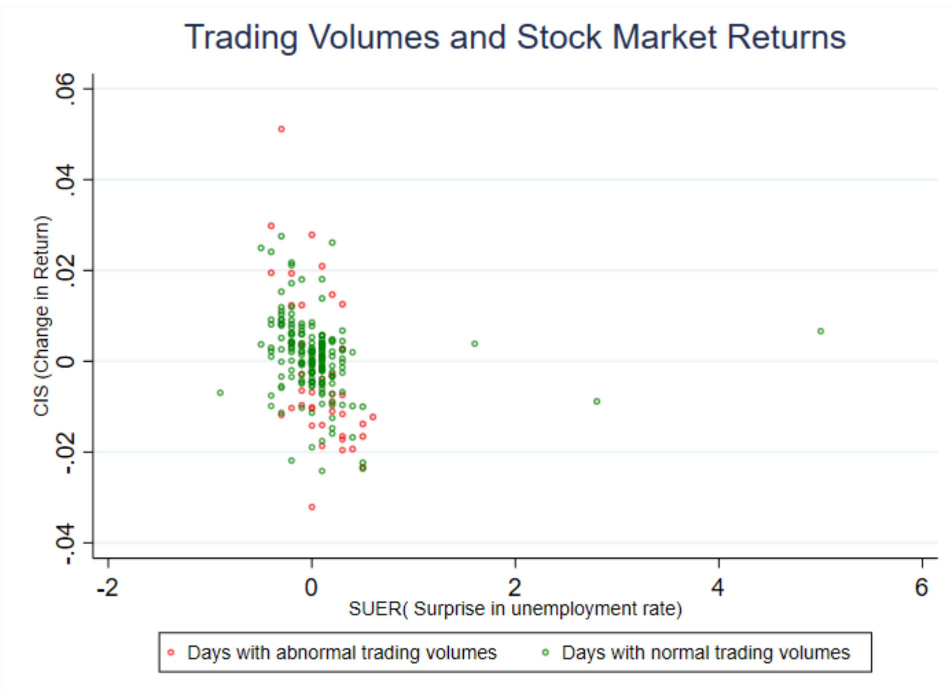
5.3 Robustness checks

5.3.1 Trading volumes robustness check result

The first robustness checks is to mitigate the problem of omitted-variable bias and specifically how breaking news would affect the stock market. As trading volumes are highly effective at reflecting the market sentiment and thus can be used to indicate whether there could potentially be some breaking news on the unemployment rate announcement day. As discussed in section 4.2.1, the mechanism to determine whether a day has abnormal trading volumes is to compare it to the average of the previous 4 days' trading volumes. By taking out the dates with abnormally high trading volumes, which could potentially add noise to the final result, I can then mitigate the effect of breaking news on market returns and volatility.

The two graphs below describe how trading volumes are correlated with stock market returns and volatility based on my dataset. It shows that when there are abnormal trading volumes on announcement days, the change in VIX and change in SPY will likely be larger than announcement days with normal trading volumes. Therefore, it is important to control for trading volumes in order to mitigate the bias regarding market news.





After taking out the days with abnormal trading volumes, the results were consistent with the previous results. As Shown in table 3 column (2), a 0.0225 unit of surprise in the unemployment rate announcement will lead to a 1% increase in VIX index that reflects the market volatility.

Also, it is significant at 1 percent level. The new coefficient is lower than the previous coefficient, which is 0.0379. Thus, by accounting for omitted variable bias, the surprise in the unemployment rate will not affect the stock market volatility as much as predicted in the preliminary result. This could be due to the fact that high trading volumes often come with higher volatility and by taking out data entries with abnormal trading volumes, the effect on market volatility will thus be less pronounced than before. On the other hand, as Shown in table 3 column (2), a -0.00288 unit of surprise in the unemployment rate announcement will lead to a 1% increase in SPY index. The new coefficient is much higher than the previous value, which was -0.0049145. This means that when taking out the days with abnormal trading volumes, the surprise in the unemployment rate announcement will have a less negative relationship to the stock market returns. In another word, a rising unemployment rate that was not expected will be less destructive for the market returns.

Table 3 OLS regression result of SUER on stock market (without abnormal trading days)

	(1) CIV	(2) CIS
SUER	0.0225***	-0.00288**
	(0.00698)	(0.00122)
MIR	0.00576***	-0.000717**
	(0.00193)	(0.000337)
MP	-0.000494	-5.66e-05
	(0.000591)	(0.000103)
Constant	0.0226	0.00755
	(0.0588)	(0.0102)
Observations	198	198
R-squared	0.089	0.050

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Therefore, after applying the trading volumes robustness checks, coefficients for both OLS regression decreased. Although it makes the correlation between market returns/ volatility and surprise in the unemployment rate weaker, the result is more reliable as it takes out the data entries that might either cause noise to the result or act as outliers for the experiment. Another interesting find is that when taking out abnormal trading days, the P-value for change in SPY decreased and is now only smaller than 0.05 but larger than 0.01, signaling a weaker statistically significant correlation between the market returns and surprise in the unemployment rate.

5.3.2 Short time window robustness check result

The second robustness check also aims to factor out omitted-variable bias. As discussed in section 4.2.2, the growing popularity in online stock news and easier access to information allow the investors to be informed about the macroeconomic news faster than ever before. Therefore, they can make adjustments in their portfolios as soon as they see important news online. The assumption for this robustness check is that all investors should be well informed about the updated unemployment rate after the market opens for 30 minutes on the first Friday of each month. Due to the limitation of data, I was only able to find the 30 minute time-frame data from 2015 to 2020. Thus, this robustness check will be only using data after 2015. The following table displays the result:

Table 4 OLS regression result for SUER on stock market after 2015(30-minute time frame)

	(1)	(2)	(3)	(4)
	CIV	CIV30	CIS	CIS30
SUER	0.0334***	0.0290***	-0.00184**	-0.00141
	(0.0154)	(0.00377)	(0.00191)	(0.00106)
MIR	-0.00361	-0.00754	0.000330	0.00395***
	(0.0187)	(0.00457)	(0.00231)	(0.00128)
MP	0.00501	0.00159	-0.000220	-0.000920***
	(0.00463)	(0.00113)	(0.000571)	(0.000317)
Constant	-0.558	-0.163	0.0244	0.0920***
	(0.472)	(0.115)	(0.0582)	(0.0323)
Observations	68	68	68	68
R-squared	0.076	0.579	0.015	0.136

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

In the table above, columns (2) and (4) represent result for 30-minute time frame stock data (from 9:30 am to 10:00 am) after 2015, while columns (1) and (3) represent result for daily stock data after 2015. In terms of effect of surprise in unemployment rate on market volatility, both daily data and 30-minute data show surprise in unemployment is statistically significant in explaining change in market volatility. Although the coefficient for SUER is smaller while using 30-minute data, it is reasonable as the market is not likely to fluctuate as much for the first 30 minutes of market opening. When using daily data, the fluctuation is likely to be larger and thus cause higher market volatility. On the other hand, although daily data on change in SPY shows surprise in unemployment is statistically significant in explaining change in market returns, the result outputted by using 30-minute data rejects the hypothesis that surprise in unemployment rate is statistically significant in explaining market returns.

6. Conclusions

This study aims to investigate the causal relationship between surprise in unemployment rate and stock market reactions in two dimensions, stock market returns and stock market volatility. The recent Covid-19 pandemic and spike in the unemployment rate inspired me to delve into this topic. However, the main motivation comes from unsettled discussion in the field on whether unemployment rate will have a more significant causal effect on stock market volatility or returns. With the data I obtained from different credible sources, I used OLS regression to explore the statistical significance of the proposed relationships. Also, I applied various robustness checks to ensure the validity of the result and reduce the effect of various kinds of biases that might exist in this study.

In terms of the result, although the preliminary result indicates surprise in unemployment rate can have a causal effect on both market volatility and market returns, further research after controlling for various omitted-variable biases shows that the actual result is slightly different from the preliminary result. By using 30-minute data on the stock market from 9:30am - 10:00 am, it shows that after the 30 minutes of the market opening, changes in SPY exhibit no statistically significant causal relationship with surprise in the unemployment rate. In addition, by taking out days with abnormal trading volumes, the casual relationship between change in market returns and surprise in unemployment rate is weaker than what's presented in the preliminary result. Therefore, it can be concluded that there was omitted-variable bias that existed in the raw data and it caused the false interpretation with the preliminary OLS regression. On the other hand, the positive causal relationship between surprise in unemployment rate and market volatility is consistent throughout the experiment. Thus, it can be concluded that the surprise in unemployment rate announcement will raise the level of uncertainty in the stock market and thus increase VIX, which represents the volatility of the market.

Therefore, the experiment result is consistent with the study's hypothesis that surprise in the unemployment rate will affect the market more on its volatility and less on its return expectations. As discussed earlier in the paper, a positive unemployment rate will not only reduce future levels of consumption but also cause governments to implement policies that are beneficial for the stock market, such as decreasing interest rates or introducing more unemployment benefits. Therefore, it will cancel out the negative sentiment regarding future stock market returns and leave the stock market index as unaffected. However, a surprise in the unemployment rate could cause fear in the market for retail investors and thus lead to a temporary rise in market volatility.

Although the paper carefully designed the empirical strategy and added many robustness checks to ensure the validity of the result, several limitations remain. Due to limitation of data sources, no other valid instrumental variables are found to fully address endogeneity as well as reverse causality. However, for future research, a possible instrumental variable could be the number of words in unemployment rate news that shows a sentiment of surprise. For example, the number of words, like "surprise", "unexpected", "spike" in unemployment rate related news from popular news journals could reflect the level of surprise in the unemployment rate announcement, and will be unlikely to be correlated with omitted variables in the error terms. Another limitation of this paper is the size of data. Because unemployment rate announcements are released monthly, only 240 months are there from 2000 to 2020. When investigating the macro level causal relationship, 240 data entries seem insufficient. For future research, it would be beneficial to include the previous 40 years of data to the experiment to ensure the accuracy of the result. In addition, further research could also include more control variables, apply more regression models such as quantile regression analysis and better unemployment forecasting techniques to further restrict biases and produce more accurate and valid results.

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7. References

Barro, R.J. (1978), "Unanticipated money, output and the price level in the United States," Journal of Political Economy, vol 86, pp. 549-80.

Barro, R.J. (1977), "Unanticipated money growth and unemployment in the United States," American Economic Review, vol. 67, pp. 101-15.

Bernanke, B.S., and Kuttner, K. (2005), "What explains the stock market's reaction to Federal Reserve policy?" The Journal of Finance, vol. LX (3), pp. 1221-1257

Boyd, J., Hu, J., & Jagannathan, R. (2005). The Stock Market's Reaction to Unemployment News: Why Bad News Is Usually Good for Stocks. *The Journal of Finance, 60*(2), 649-672. Retrieved December 18, 2020, from http://www.jstor.org/stable/3694763

Chen, N.F., Roll, R. and Ross, S. (1986), "Economic forces and the stock market," Journal of Business, vol. 59, pp. 383-403.

Flannery, M. J., & Protopapadakis, A. (2002). Macroeconomic Factors DO Influence Aggregate Stock Returns. *SSRN Electronic Journal*, 2–23. https://doi.org/10.2139/ssrn.314261

Garz, M. (2014). Good news and bad news: Evidence of media bias in unemployment reports. Public Choice, 161(3/4), 499-515. Retrieved December 18, 2020, from http://www.jstor.org/stable/24507505

Gonzalo, J., & Taamouti, A. (2017). The reaction of stock market returns to unemployment. *Studies in Nonlinear Dynamics & Econometrics*, *21*(4), 1–28. https://doi.org/10.1515/snde-2015-0078

Hu, Z., & Li, L. (1998). Responses of the Stock Market to Macroeconomic Announcements Across Economic States. *IMF Working Papers*, *98*(79), 1. https://doi.org/10.5089/9781451850178.001

Miao, J., Wang, P., & Xu, L. (2016). Stock market bubbles and unemployment. *Economic Theory, 61*(2), 273-307. Retrieved December 18, 2020, from http://www.jstor.org/stable/24735335

Sheffrin, S.M. (1979), "Unanticipated money growth and output fluctuations," Economic Inquiry, vol. 17, pp. 1-13.

Makin, J.H. (1982), "Anticipated money, inflation uncertainty and real economic activity," The Review of Economics and Statistics, vol. 64, pp. 126-134.

8. Appendix

Table 5: Summary Statistics

VARIABLES	(1) N	(2) mean	(3) sd	(4) median	(5) min	(6) max
MIR	240	1.571	1.727	1.01	0.0500	6.510
MP	240	99.86	5.708	100.9489	87.07	110.6
CIS	240	0.000126	0.0102	0.00018	-0.0321	0.0512
CIV	240	-0.0109	0.0612	-0.0151	-0.150	0.269
SUER	240	0.0437	0.441	0	-0.900	5
TDT	240	0.825	0.381	1	0	1
GS	240	74.04	156.8	35.75	19.20	1,405
CIS30	68	-0.000820	0.00515	0.000051	-0.0307	0.00966
CIV30	68	-9.31e-05	0.0263	-0.0058	-0.0400	0.103