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Exploring the Relationship Between U.S. Unemployment Rate Announcements and the S&P 500 in the Early 21st Century

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Abstract: This study investigates the relationship between monthly unemployment rate announcements by the Bureau of Labor Statistics (BLS) and the performance of the S&P 500 during the early 21st century (2000–2020). We employ Ordinary Least Squares (OLS) regression to examine the correlation between the change in the unemployment rate (total, anticipated, and unanticipated components) and both the S&P 500 daily return on the announcement day and the returns between consecutive reports. The primary empirical analysis reveals no statistically significant linear correlation between these variables, which challenges some findings in existing literature that rely on earlier time periods. To validate this non-correlation result, we use a Monte Carlo simulation framework as an integrated robustness test. The simulation confirms that the OLS estimators for our primary regression model are unbiased, thereby validating the statistical reliability of our finding. Our combined results suggest that, in the contemporary market, the immediate impact of unemployment announcements on S&P 500 returns is negligible, possibly due to increased market efficiency.

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I. INTRODUCTION

The relationship between unemployment and the stock market has been a key topic of research in financial and economic studies. Economists, investors, and policymakers must comprehend this relationship, especially in times of economic turbulence. Because it reflects investor sentiment and expectations regarding future corporate earnings, the stock market is commonly regarded as an indicator of economic health. According to YCharts (2024), unemployment rates provide important insights into the health of the labour market and the state of the economy as a whole.

Interest in the connection between unemployment and stock prices has been reignited by recent economic events, especially the Great Recession of 2007–2009. Significant changes in stock prices during this time were accompanied by rising unemployment, which begs the question of what the underlying causal mechanisms were (Smith, 2010). Studies indicates that as unemployment rises, consumer spending and company profitability may suffer, which could lead to a drop in prices (Investopedia, 2024). According to other research, rising unemployment may occasionally be viewed as positive for stocks, such as during economic expansions (Dua, 2023). Expected monetary policy responses, like the Federal Reserve cutting interest rates, are often the cause of this.

The purpose of this essay is to investigate the connection between US stock market performance and unemployment announcements. There are five chapters in this paper. A review of the literature on the effects of macroeconomic announcements is given in Chapter 2. Our data collection and processing methods are described in Chapter 3. Our empirical approach, which combines OLS regression with a Monte Carlo simulation for robustness, is presented in Chapter 4. Our discussion and conclusion are presented in Chapter 5.

II. LITERATURE REVIEW

Numerous economic theories have been used to explain the relationship between unemployment and stock prices, and numerous studies have looked into the relationship between stock market performance and unemployment rates empirically. Higher unemployment, according to Keynesian economics, results in less consumer spending, which hurts business profits and, in turn, stock prices.

Boyd et al. offer a fundamental analysis, showing that the economic cycle affects how the stock market responds to news about unemployment. According to their research, negative unemployment news can cause stock prices to rise during expansions because of expected interest rate reductions, but it tends to lower stock prices during contractions (Boyd, Hu, & Jagannathan, 2005).

The connection between stock prices and macroeconomic news, such as unemployment rates, is examined in studies by McQueen and Roley (1993) and

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Veronesi (1999). The idea that the relationship is dynamic is further supported by their discovery that the stock market's response to unemployment news depends on the state of the economy.

It turns out that while stock prices frequently influence changes in unemployment rates in developed economies, the opposite is true in developing nations. This implies that institutional factors and the degree of economic development have an impact on the relationship's dynamics (Pan, 2018).

Monetary policy plays a crucial role in determining how the stock market and unemployment rate interact. According to Gertler and Grinols (1982), the Federal Reserve usually lowers interest rates in response to rising unemployment, which can help sustain higher stock prices. The significance of comprehending how policy responses mediate the effects of unemployment on stock market performance is highlighted by this interaction.

Another significant consideration is the equity risk premium, which represents the extra return that investors need when they choose to hold stocks over risk-free assets. According to research, the equity risk premium may be impacted by shifts in unemployment rates, especially during recessions (Farmer, 2012; Fritsche & Pierdzioch, 2016). According to this relationship, stock prices are significantly influenced by investor sentiment and expectations regarding the state of the economy in the future.

Wu and Chong (2021) use a GARCH-MIDAS model to examine the effects of a number of macroeconomic factors, such as shifts in the unemployment rate, on the stock market in various industries. According to their research, important macroeconomic variables that have a notable impact on market volatility include the terms spread and housing starts. They also draw attention to sector-specific effects, pointing out that when macroeconomic factors are taken into account, the consumer staples sector performs better in forecasting.

By analysing the combined effects of unemployment and inflation on stock returns, Gertler and Grinols (1982) add to this discussion. Their research highlights how rising inflation can reduce corporate profits and purchasing power, which in turn can result in lower stock prices. This relationship emphasises how crucial it is to take unemployment and inflation into account when examining the dynamics of the stock market. Fromentin (2023) uses a time-varying Granger causality framework to further investigate the connection between unemployment and stock market returns. According to his research, there is bidirectional causality, especially during recessions, which implies that changes in the stock market can forecast future patterns in unemployment. This study emphasises how the relationship between the real economy and the financial market is dynamic.

The majority of the literature on this topic, we found, used data from 1950 onwards. The market is more developed now, and there are fewer chances to take advantage of its inefficiencies. We chose to use data from 2000 to 2020 in order to have up-to-date information that would represent the market today. The COVID period, which saw an exceptionally high unemployment rate, was chosen to be excluded. Additionally, we observed that certain papers did not use accurate data. For example, they used monthly market returns, even though the unemployment announcement is not made on the first of every month. Our objective is to fix all of those errors so that the true and current relationship between unemployment and the S&P 500 can be seen.

III. DATA AND METHODOLOGY

The collected data and its processing are covered in this chapter. To get the most accurate results, we concentrated on collecting the most accurate data possible. At the conclusion of our work, we attached all of the raw data and calculations.

➢ *Monthly Unemployment Rate*

In the United States of America, the Bureau of Labor Statistics (BLS) announces the monthly seasonally adjusted unemployment rate of the country usually at 8:30 am on the first Friday of the next month. The BLS interviews approximately 60’000 households each month, during a reference week, to calculate this rate in a robust way. They then divide the unemployed by the total labor force. Their definition of unemployment is a person actively looking for work in the last four weeks, that is not working for pay or profit during the reference week and that is willing to work if offered. A person in a temporary layoff that is waiting to be recalled is also by definition unemployed. According to the BLS, the labor force is an addition of all unemployed and employed which are all the people that worked for a pay or for profit during the reference week. Using this method, they accurately approximate the unemployment rate which is then used to judge the state of the economy. In this study, we decided to use the official data released by the BLS because it is the official way to determine the unemployment rate and is probably the most used by other investors. This will lead to more accurate data.

The first step was to extract the data from the official BLS website. We decided to collect the data starting from January 2000, to better reflect the economic reality of the 21st century. The data set will end in February 2020 to avoid outliers during the COVID-19 pandemic. The sample contains monthly seasonally adjusted unemployment rates for a total of 242 observations. All the data related to unemployment rates will be expressed in % form. The unemployment rate is noted u_t where “t” are the unemployment announcement days. To analyze the effect of a change in unemployment rate at time t, we will need to compute it as the following:

$$g_{u,t} = u_t - u_{t-1}$$

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Conducting regressions with differences rather than raw unemployment rate has several benefits: greatly decreasing the autocorrelation of the time series; presenting a more normal distribution; enhancing the stationarity of the time series.

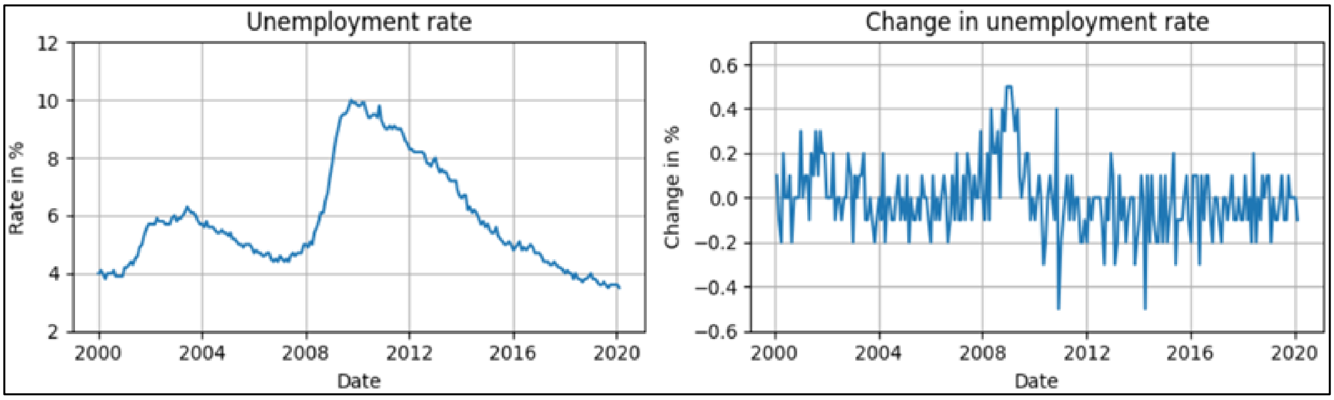

Fig 1 Unemployment Rate (u_t) and Change in Unemployment Rate ($g_{u,t}$)

➢ *Anticipated and Unanticipated Unemployment Rate*

Since the stock market is, at least in theory, efficient, the expectations in unemployment rates of investors should already be priced in the market. The idea here is to break down the unemployment announcement into two components: what the investors expected and the "news" component, that is, the difference between their expectations and the actual announcement. In doing so we will be able to separate and investigate the effects of both parts. We follow the steps of Boyd et. al., (2005) and Gonzalo and Taamouti (2017) and use this method: we create a model predicting the change in unemployment rate in period t+1 using only data available at time t. The predictions will be our estimation of the market anticipated change in unemployment rate. The residuals, the observed minus the anticipated change, will be our unanticipated change in unemployment rates.

As suggested by Gonzalo and Taamouti (2017), we use an Autoregressive model to estimate the anticipated change. The equation to decompose the change in unemployment rate into its anticipated and unanticipated components is as follows:

$$g_{u,t} = \beta_0 + \sum_{j=1}^{p} \beta_j g_{u,t-j} + \varepsilon_t \quad (1)$$

Where $g_{u,t}$ is the change in the unemployment rate between period t and t-1 , β_0 is the intercept of our AR(p) model, (β_1 , ... , β_p) are its coefficients and ε_t is the error term. Performing an Augmented Dickey–Fuller test (ADF) on $g_{u,t}$, we can reject the null hypothesis at a 5% threshold and conclude that the time series is stationary. To determine the number of lags p, we use the Akaike information criteria (AIC) which encourages a balance between model fit and complexity. Applying the AIC on AR models between 1 and 50 lags we find that an AR(5) model is the most suitable. Table 1 presents the estimations from the AR(5) model performed on the change in unemployment rate $g_{u,t}$.

Table 1 Estimates from AR(5) Model Forecasting the Change in Unemployment Rate

	AR(5) model					
	β_0	β_1	β_2	β_3	β_4	β_5
Coefficient	-0.001	0.051	0.192***	0.102*	0.111*	0.230***
Standard error	(0.009)	(0.080)	(0.066)	(0.057)	(0.060)	(0.067)
$R^2 = 0.207$	*MSE = 0.020*					
Note:	*p<0.1; **p<0.05; ***p<0.01					

Ljung-Box, Jarque-Bera and Breusch-Pagan Tests show that the residuals present no autocorrelation, are normally distributed but show heteroscedasticity. HC0 standard errors were used to address heteroscedasticity.

Next, we can decompose the change in unemployment rate into its anticipated and unanticipated components using our estimations : $g_{u,t} = \hat{g}_{u,t} + \varepsilon_t$ with $g_{u,t}$ the observed data that is the change in unemployment rate ; $\hat{g}_{u,t}$ the fitted values and therefore our estimations of the anticipated change in unemployment rate $g^e_{u,t}$; ε_t the residuals as well

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as the unanticipated part of the change in unemployment rate $g^{u}_{u,t}$.

Using this model can be criticized as a rapid estimation of an extremely complex topic, and it will probably not accurately reflect the anticipated unemployment rate of the market, since many investors will have their own calculations. We still found it pertinent to use as some investors could use a similar process and because we think that we could still find interesting results with this approximation.

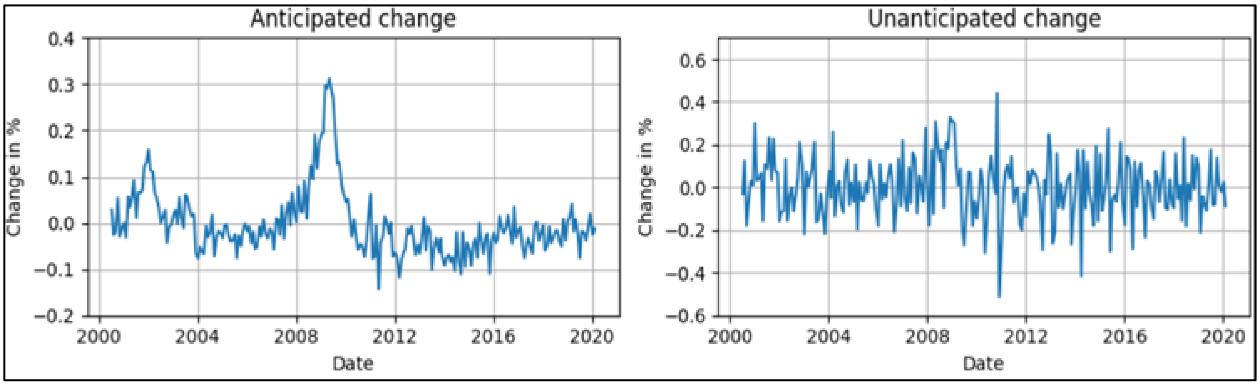

Fig 2 Anticipated ($g^{e}_{u,t}$) and Unanticipated ($g^{u}_{u,t}$) Change in Unemployment Rate

➤ *S&P 500 Returns*

The S&P 500 is a stock market index tracking the valuation of the five hundred largest publicly traded companies in the USA. We took the daily price and price variation of the index in google finance.

In order to see the reaction of the S&P 500 on the announcement day of the unemployment rate by the BLS, we calculated the daily return of the S&P 500 on each announcement day using the following formula: Log Daily Return $_T$ = Ln(Closing Price $_T$ / Closing Price $_{T-1}$) where T is the date. When the market was closed on the announcement day, we took the next open market day. This occurred for six dates. We decided to include them because we think that the reaction of the next open day is still relevant data. We can use the daily return, because the official unemployment rate is released at 8:30 Eastern Time and the market opens at 9:30 Eastern Time. It is in our opinion a good time horizon to reflect the reaction of the market to the unemployment announcement. By taking a full trading day, it lets the market stabilize after the short term, algorithmic trades and other initial reactions are made which could include a mix of emotions, speculative trades, and overreactions. Using an entire trading day, we capture a more balanced and reflective market response as participants have had time to process the information.

To analyze a more long term relationship between the market return and the unemployment rate announcement we computed the return of the S&P 500 between two announcements: Log Monthly Return $_t$ = Ln(Pb_{t+1} / Pb_t) where Pb is the closing price the day before the announcement and t are the announcement days.

We write r^{d}_{t} the daily log return of the S&P 500 after the announcement and r^{m}_{t} the monthly log return of the S&P 500 after the announcement. Please note that it is not exactly the monthly return because the announcement does not take place at the same date every month.

As seen earlier, for our analysis we will use Log Returns. By doing so, we have several benefits such as decreasing the autocorrelation of the time series, presenting a more normal distribution and enhancing the stationarity of the time series.

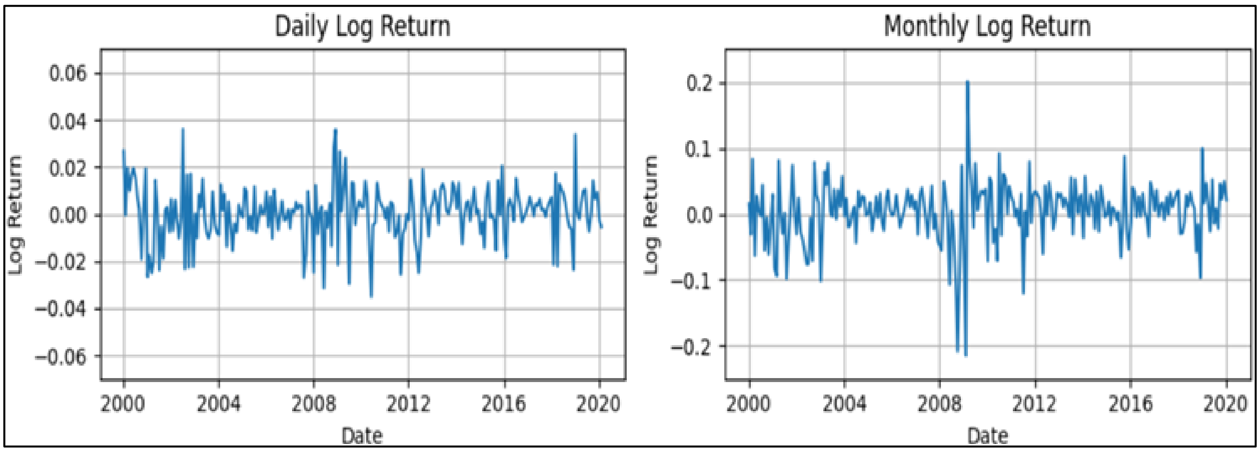

Fig 3 Daily (r^{d}_{t}) and Monthly (r^{m}_{t}) log Returns of of the S&P 500 After the Announcement

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➢ *Carlo Simulation Design*

In this phase, we validate the reliability of our linear regression model (Model A) using a Monte Carlo simulation framework. This robust statistical technique enables us to generate many simulated datasets under controlled assumptions to assess the unbiasedness of the OLS estimators (β_0 the intercept and β_1 the slope).

The first step is to define the variables in the model. In this case, it is the same as the regression we are trying to prove unbiasedness. The dependent variable is the logarithmic S&P 500 daily return on the announcement day, while the independent variable is the change in the unemployment rate from one month to the next.

Let:

- r^d_t represents the S&P 500 daily log return on the announcement day at time t.
- $g_{u,t}$ represents the change in the unemployment rate from the previous month announcement at time t.

The relationship between these two variables can be modeled using the following linear regression equation:

$$r_t^d = \beta_0 + \beta_1 g_{u,t} + \varepsilon_t \quad (2)$$

Where:

- β_0 is the intercept, capturing the baseline return of the S&P 500 when there is no change in the unemployment rate.
- β_1 is the slope, representing how sensitive the S&P 500 daily return is to the change in the unemployment rate.
- ϵt is the error term, accounting for the variability in the daily returns that is not explained by the true model.

This linear relationship allows us to analyze the extent to which changes in the unemployment rate influence stock market movements, particularly on the day when the unemployment rate is announced.

➢ *Specifying the Data Generating Process*

In order to perform a Monte Carlo simulation, we first need to choose the true parameters of the model and to define the distribution of the random variables to generate the simulated datasets. We first define the true values of the parameters β_0 and β_1 and the distribution of the error term ϵt. To do so we use the estimations of the OLS regression on our sample of observed data (Table2) as the true values. The true values of β_0 and β_1 will be: 0.000053 and 0.001777 and we approximate the distribution of the error terms assuming that the error terms will follow a normal distribution N (0 ; 0.01166).

Next, we approximate the distribution of independent variable $g_{u,t}$, the change in unemployment rate. We used the Johnson SU distribution to simulate the unemployment rate change. It effectively handles skewed and heavy-tailed data, which is common in real-world economic data and is the case for our unemployed rate change. It allows for both positive and negative skewness, capturing asymmetry in the data, such as large unemployment spikes. The Johnson SU distribution is a transformation of the normal distribution, making it flexible while maintaining a relationship with normal-like data. By using this distribution, we ensure that the simulated unemployment rate changes closely match the empirical properties of the observed data.

We estimated the four parameters of our distribution using the fit() formula from scipy, which uses the Maximum Likelihood Estimation to find the best fitting parameters to match the distribution of our observed data set. We found:

- "**γ**", the first shape parameter of -0.58. It indicates that the distribution has a longer tail on the right side, meaning that there are more extreme values on the right side of the mean.
- "***δ***", the second shape parameter that controls the heaviness of the tails, of 1.8. A lower value indicates more extreme values.
- "**θ**", the location parameter is -0.090. It shifts the distribution along the x-axis. In this case, the peak of the distribution is shifted slightly to the left of 0.
- "***σ***" the scale parameter that scales the distribution along the x-axis, of 0.233. It determines how far the data points are from the central location. A bigger scale means bigger values.

Then we round up the values to the closest 0.1 increment to match the shape of the actual unemployment change. This ensures that the simulated data generated using these parameters will closely resemble the observed data.

➢ *Generating the Data*

Finally we generate the dependent variable r^d_t using equation (5) where β_0 and β_1 are the real parameters and $g_{u,t}$ and ϵt are the generated independent variable and error term.

After defining the data generating process, we generated close to a million sets of data as 4000 simulations of samples of size 235, to match the 235 data of unemployment rate change we used in our first regression. We first tried to use 1000 simulated sets but the results were not as stable as we would like to. We then decided to increase to 4000 simulations and found that it was a good balance between precision and computing power. In each simulation we regress the generated dependent variable on the generated independent variable. In doing so we get the OLS estimators of β_0 and β_1 of this simulation. We store the results for each simulation and thus get 4000 estimators of β_0 and β_1.

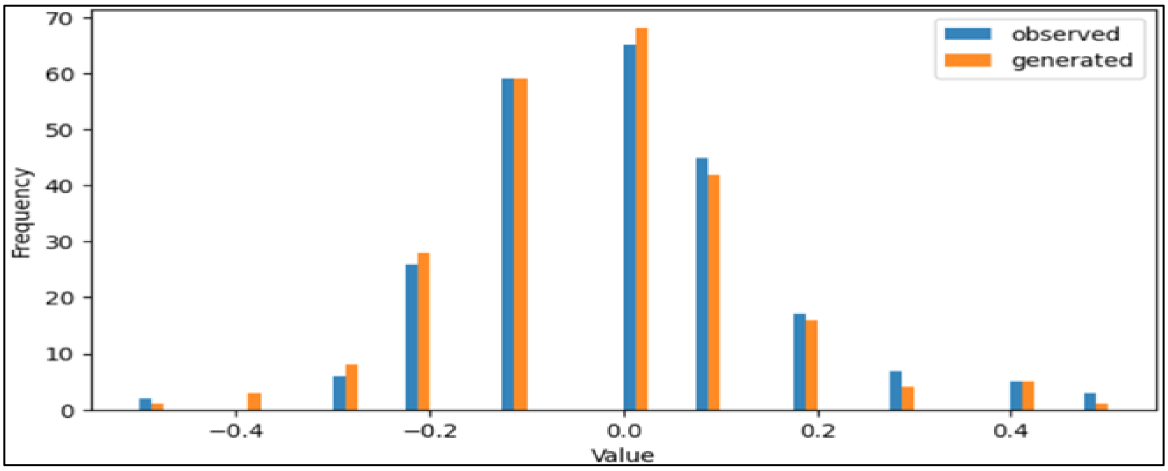

Fig 4 Distributions of One Generated and the Observed Sample of Unemployment Rate Change

In Figure 4 we can see in blue the real unemployment rate change and in orange one of the generated sample data. By comparing them, we can observe that our simulation is very similar to our true data. It helps us visualize that our model for simulating the random change of unemployment rate is correct.

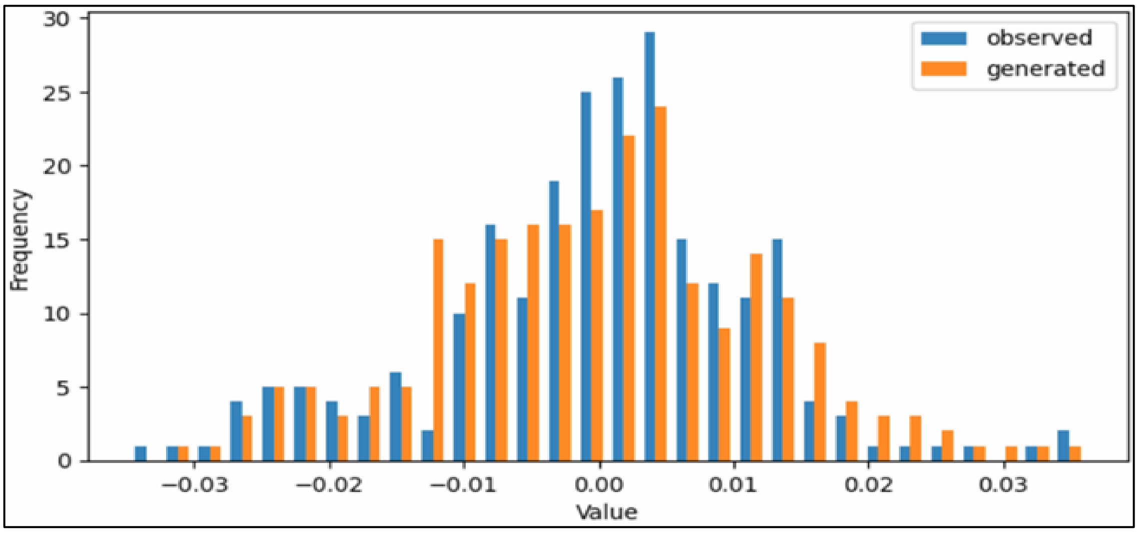

Fig 5 Distributions of One Generated and the Observed Sample of the Error Terms

IV. EMPIRICAL STRATEGY AND RESULTS

In this section we will introduce the models used to study the relationship between the announcements of the unemployment rate by the BLS and the S&P 500 index and present their results. In our calculations and regressions, we used 235 of the 242 unemployment rate data points. We excluded the first six which were used to estimate the changes in the anticipated unemployment rate and the last one was excluded because there was no subsequent data available to compute the last monthly log return. To maintain consistency across our analysis, we used the same set of dates of 235 data points for all the regressions. This ensured that all models and calculations were based on a uniform dataset.

➢ *Ordinary Least Squares (OLS) Regression Models*

- *Change in Unemployment Rate and Daily Return*

In order to investigate the linear relationship between the announcements of the unemployment rate by the BLS and the S&P 500 index we will perform an OLS regression. To eliminate time-related effects in the variables because of the limitations of using OLS on time series data we regress the daily log return of the S&P 500 on the change of unemployment rate by the announcement.

The following equation depicts the OLS regression:

$$r_t^d = \beta_0 + \beta_1 g_{u,t} + \varepsilon_t \quad (3)$$

The model estimates the effect of the change in unemployment rate at the announcement on the daily log return of the S&P 500. We have: r^d_t the daily log return of the S&P 500 after the announcement, β_0 the constant term, $g_{u,t}$ the change in unemployment rate and ε_t the error term.

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Table 2 Estimates from OLS Regression of the Daily Log Return of S&P 500 on the Change in Unemployment Rate at the Announcement

	OLS	
	β_0	$g_{u,t}$
Coefficient	0.000053	0.0018
Standard error	(0.0007)	(0.0059)
$R^2 = 0.0006$	*MSE = 0.0001*	
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

Ljung-Box, Jarque-Bera and Breusch-Pagan Tests show that the residuals present no autocorrelation, are not normally distributed and show heteroscedasticity. HC0 standard errors were used to address heteroscedasticity.

Looking at the results of the regression in Table 2, we can notice that the change in unemployment rate has no significant effect on the daily log return of the S&P 500 since its coefficient is not significant at a 10% level (p-value = 0.7649). The very low R^2 indicates that the model struggles to explain the variance in the dependent variable with the independent variable and thus that there might not be a clear linear relationship between the daily log return of the S&P 500 and the change in unemployment rate at the announcement.

One of the suggestions that could lead to the absence of a significant relationship between the two variables is that in reality a part of the change in unemployment rate is anticipated by the investors and should therefore already be priced in the market. To try to integrate this specificity in our model we will decompose the change in unemployment rate in anticipated and unanticipated components to isolate the "surprise" effect of the announcement.

- *Decomposed Unemployment Rate and Daily Return*

In this part, the change has been decomposed in anticipated and unanticipated components, which are the two independent variables, to isolate the surprise part of the change. To analyze the immediate as well as the more long-term effect of the announcement we conduct two OLS regressions with different dependent variables: the daily and monthly log returns of the S&P 500 after the announcement. After testing the variables, only the estimate of the anticipated change shows autocorrelation and the independent variables manifest no significant correlation between them.

The following equations depict the two OLS regressions:

$$r_t^d = \beta_0 + \beta_1 g_{u,t}^e + \beta_2 g_{u,t}^u + \varepsilon_t \quad (4)$$

$$r_t^m = \beta_0 + \beta_1 g_{u,t}^e + \beta_2 g_{u,t}^u + \varepsilon_t \quad (5)$$

The first equation estimates the daily effect of the anticipated and unanticipated change in unemployment rate at the announcement on the return of the S&P 500 whereas the second estimates the monthly effect. We have: r^d_t the daily log return of the S&P 500 after the announcement, r^m_t the monthly log return of the S&P 500 until the next announcement, $g^e_{u,t}$ the anticipated change in unemployment rate and $g^u_{u,t}$ the unanticipated change in unemployment rate.

Table 3 Estimates from OLS Regressions of the Log Return of S&P 500 on the Anticipated and Unanticipated Change in Unemployment Rate.

	Daily Log Return			*Monthly Log Return*		
	β_0	$g^e_{u,t}$	$g^u_{u,t}$	β_0	$g^e_{u,t}$	$g^u_{u,t}$
Coefficient	0.000062	0.0061	0.0006	0.0035	-0.0192	-0.0260
Standard error	(0.0008)	(0.0133)	(0.0059)	(0.0030)	(0.0787)	(0.0240)
	$R^2 = 0.0015$ MSE = 0.0001			$R^2 = 0.0074$ MSE = 0.0020		
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$					

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Ljung-Box, Jarque-Bera and Breusch-Pagan Tests show that the residuals present no autocorrelation, are not normally distributed and show heteroscedasticity. HC0 standard errors were used to address heteroscedasticity.

As shown in the results of the first regression in Table 3, we can see that neither the anticipated nor the unanticipated change in unemployment rate has a significant effect at the 10% level on the daily log return of the S&P 500. Looking at the second regression we can draw the same conclusions regarding the monthly log return of the S&P 500. Even though both R^2 are bigger than the first model they are still very small. Despite decomposing the change in unemployment rate and looking at a more long term effect we fail to acknowledge a significant relationship between the unemployment rate announcement and the S&P 500 return.

- *Monte Carlo Simulation Results (Unbiasedness Check)*

In this section we will analyze the distribution of the results of the Monte Carlo simulation and perform statistical tests to conclude if the OLS estimators are unbiased. An estimator is unbiased if its expected value is equal to the true parameter. Hence, we want to verify if:

$E(\hat{\beta}_0) = \beta_0$ and $E(\hat{\beta}_1) = \beta_1$ where $\hat{\beta}$ are the OLS estimators of the parameters and β are the true values.

First, we examine some statistics and the distribution of the estimators. As shown in Table 4, the mean of the estimators of β_0 and β_1 are really close to the true value of the parameters. Comparing the mean to the true value we have for β_0 0.0000491 and 0.000053 and for β_1 0.001757 and 0.001777. Looking at Figure 6, we can notice that the distribution of the estimators looks very normal. Both of these characteristics give us hints that the estimators are unbiased.

Table 4 Descriptive Statistics of β Estimates

	count	mean	std	min	max
Parameter					
β_0	4000	0.0000491	0.0007631	-0.0029786	0.0024865
β_1	4000	0.0017571	0.0046737	-0.0132118	0.0181602

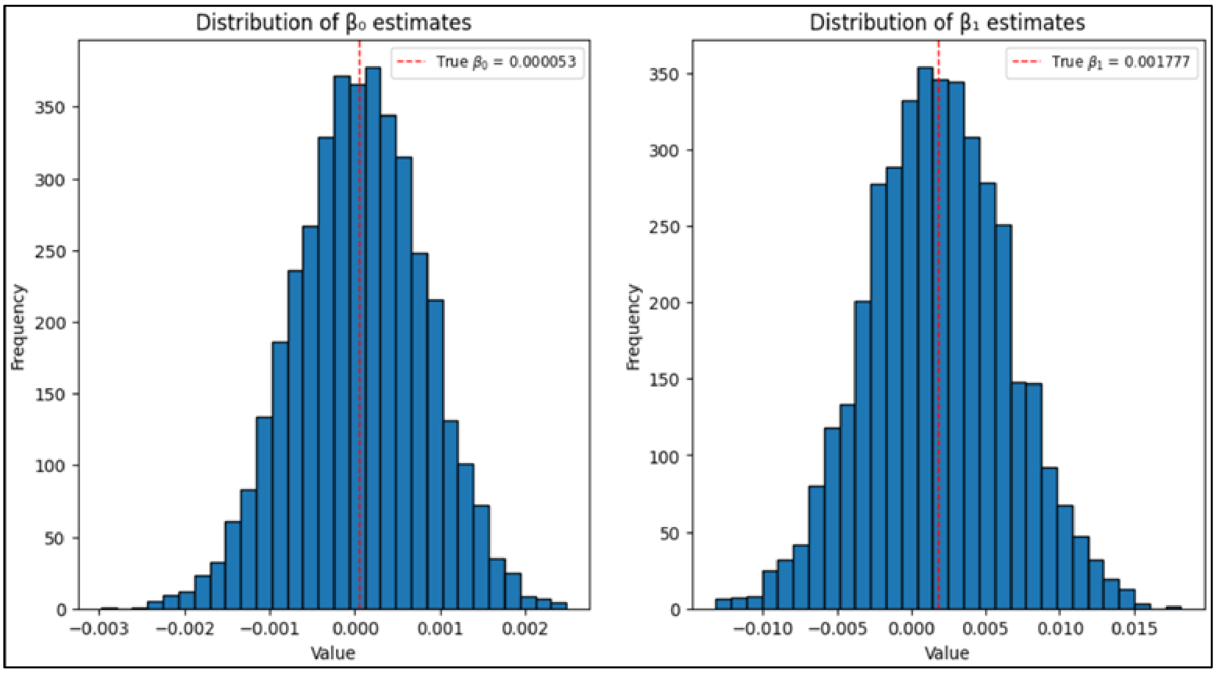

Fig 6 Distribution of the Estimators of β_0 and β_1

Finally, we will perform statistical tests on the mean of the estimators and conclude whether they are unbiased or not. To test if there is a statistically significant difference between the mean of the estimators and the true value of the parameter we perform the following t-test :

- The null hypothesis H0 is "the mean of the estimator is equal to the true value"
- The alternative hypothesis H1 is "the mean of the estimator is not equal to the true value"

If the p-value is smaller than the significance level, we would reject H0 and conclude that the mean of the estimator is different to the true value and consequently that the estimator is biased.

The t-statistics is computed as follow: $t_i = \frac{E(\hat{\beta}_i)-\beta_i}{\sigma(\hat{\beta}_i)}$

Where $E(\hat{\beta}_i)$ is the mean of the estimator $\hat{\beta}_i$, $\sigma(\hat{\beta}_i)$ is the standard deviation of the estimator and β_i is the true value of the parameter.

We find the following results:

- $t_0 = -0.2894$ and $\text{p-value}_0 = 0.7722$
- $t_1 = -0.2647$ and $\text{p-value}_1 = 0.7912$

Since the p-values are greater than any usual significance level we can't reject the null hypothesis H0 "the mean of the estimator is equal to the true value" for both tests. Hence, we can conclude that the means of the estimators are not statistically different to the true values of the parameters and as a consequence conclude that the OLS estimators of β_0 and β_1 are unbiased.

V. DISCUSSION AND CONCLUSION

This study examined the relationship between the S&P 500 and the unemployment announcements of the Bureau of Labor Statistics during the early 21st century. Using linear regressions, we analyzed the change in unemployment rates in relation to the S&P 500 daily log return on the announcement day, the log return over the period between announcements, and the relationship with unanticipated and anticipated unemployment rate change.

Our primary analysis did not reveal a statistically significant relationship between these variables during the early 21st century. Furthermore, this finding was confirmed as robust through a Monte Carlo simulation framework, which demonstrated that the OLS estimators used in the analysis are unbiased.

This finding contrasts with earlier literature that reported a market sensitivity to unemployment announcements. Possible explanations for this discrepancy include:

➢ *Market Efficiency:*
The market may have become more efficient at processing unemployment-related information over the past 25 years, leading to less immediate market reaction compared to earlier periods.

➢ *Structural Shifts:*
Improvements in information availability and the dominance of algorithmic trading may have diminished the visible linear impact of these announcements on the market's daily close-to-close return.

Future papers could investigate the relationship between the unemployment rate and the market in different time frames, for instance, the first hour of market opening or a week after the announcement. This could lead to different results and may be exploited by investors. They could also investigate their relationship during crises like the 2008 recession or the COVID-19 pandemic where the unemployment rate hugely increased and the market drastically lost value.

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