The Usefulness of Textual Sentiment Analysis for Macroeconomics:

Predicting Unemployment With Sentiment Measures

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1. Abstract

I develop a process for and evaluate the economic usefulness of a sentiment measure approach to predicting the macroeconomic variable of the unemployment rate from Federal Open Market Committee (FOMC) meeting minutes. Utilizing the Valence Aware Dictionary for Sentiment Reasoning (VADER) and several other computational methods, I generate sentiment scores for various minutes reports from the FOMC. I then analyze this measure's usefulness in conjunction with existing macroeconomic measures within regressions of the unemployment rate. I find that this sentiment measure has statistically significant predictive power within three different prediction time horizons.

2. Introduction

It is true that successful predictive macroeconomics necessitates making smart predictions about the economic world using the maximum amount of useful available information. It is simultaneously true that the Federal Reserve utilizes monetary policy to greatly and directly influence the macroeconomy of not just the United States but also the world.[1] Thus, it would make sense that information released by the Federal Reserve could hold significant predictive power within economics. One of the most easily available and most content-rich sources of information from the Federal Reserve consists of the meeting minutes released following the convenings of the FOMC that provide insight into the thought process of the Federal Reserve in evaluating and communicating changes within the monetary policy of the Federal Reserve as a whole.[2] These meeting minutes have long been vitally important for fundamental and qualitative analysis of the macroeconomy.

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[1] "Monetary Policy Principles and Practice ," Board of governors of the Federal Reserve System (The Federal Reserve, July 29, 2021), https://www.federalreserve.gov/monetarypolicy/monetary-policy-what-are-its-goals-how-does-it-work.htm.

[2] "Federal Open Market Committee," The Fed - Federal Open Market Committee (The Federal Reserve), accessed January 30, 2023, https://www.federalreserve.gov/monetarypolicy/fomc.htm.

In light of this importance, I attempt to transform this textual information into an economic measure suitable for use within an econometric regression of the unemployment rate, while evaluating such a measure's effectiveness. One of the most important types of quantitative data contained within textual information is its sentiment, in other words whether the text is generally of positive or negative attitude towards its subject matter. I utilize methods within the Python Programming Language and the Natural Language Toolkit's (NLTK's) VADER sentiment analyser to generate a continuous quantitative measure of negative sentiment for each FOMC meetings' minutes within a given time period.

From there, I run various regressions using the measure to evaluate its effectiveness. My results indicate that over multiple separate time horizons, the sentiment score of FOMC meeting minutes are a statistically significant predictor of the unemployment rate. Since I control for Federal Reserve policy changes in my regression, this statistical significance is above and beyond that which can be gleaned from measurements of macroeconomic policy instruments.

This reaffirms the macroeconomic predictive power of FOMC meeting minutes content and the general influence of the Federal Reserve over macroeconomic conditions. This also suggests that further natural language processing of FOMC meeting minutes could yield even more predictive power through different generated statistics.

The paper is structured in the following way. Section 3. presents an overview of relevant literature. Section 4. gives an overview of the coding and sentiment analysis methods used to generate the relevant sentiment measure. Section 5. provides an overview of utilized data and descriptive insights about it. Section 6. enumerates the empirical analysis methods of the paper and discusses the results of this analysis. Finally, section 7. discusses the implications of these results and provides some concluding thoughts.

3. Literature Review

Sentiment analysis within the problem space of macroeconomic prediction has become a more popular method in recent years. Sentiment analysis itself has been around in some form since at least the 1950s, but recent years have seen a tremendous increase in the computational complexity and overall usefulness of such sentiment-focused analyses.[3]

Several studies have applied sentiment analysis of various forms of textual data to macroeconomic forecasting. One of the earliest significant papers of this sort that utilized modern sentiment analysis methods was Bollen et al. (2010) which used social media sentiment, specifically tweet sentiment, to predict the stock market and found positive sentimental correlation between their sentiment measure and returns within the stock market.[4] Chen et al. (2017) extended the sentiment-based approach to prediction of the stock market to include sentiment measures drawn from various news articles and select social media posts.[5] The paper found that these sources of sentiment data were useful for predicting changes in the stock market. The overall consensus within the literature is that sentiment analysis can be a viable tool for the prediction of economic indicators.

Furthermore, the literature suggests that FOMC statements and minutes themselves contain valuable information about the macroeconomy. Romer and Romer (2000) showed that the Federal Reserve itself has asymmetric information to the private sector, specifically in terms

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[3]Scott Sims, "Sentiment Analysis 101," KDnuggets (KD Nuggets), accessed January 30, 2023, https://www.kdnuggets.com/2015/12/sentiment-analysis-101.html.
[4]John Bollen, Huina Mao, and Xiao-Jun Zeng, "Twitter Mood Predicts the Stock Market. ," Arxiv (Arxiv, 2010), https://arxiv.org/pdf/1010.3003.pdf.
[5]Mu-Yen Chen and Ting-Hsuan CHen, "Modeling Public Mood and Emotion: Blog and News Sentiment and Socio-Economic Phenomena," ScienceDirect (Future Generation Computer Systems, November 3, 2017), https://www.sciencedirect.com/science/article/abs/pii/S0167739X17323750?via%3Dihub.

of commercial inflation forecasts.[6] It would follow that releasing FOMC meeting minutes closes some of these information asymmetries in a way beneficial to economic forecasters.

In terms of sentiment-based utilization of FOMC meeting minute data within macroeconomic forecasting there is also some literature of note. Gürkaynak et al. (2005) found that FOMC sentiment data was useful for forecasting the federal funds rate.[7] Tadle (2022) utilized sentiment analysis methods on both FOMC statement and minutes data and determined that the sentiments of policy documents contain information that can influence the predictability of a financial market.[8] It specifically focused on implications for the predictability/volatility of fed funds futures contracts, broad equity, real estate investment trust indices, and various exchange rate indices involving the U.S. dollar. It focused less on the prediction of specific macroeconomic indices but rather economic processes as a whole.

The literature has gaps within specific sentiment measurement techniques and specific macroeconomic indicator prediction. The point of departure for my paper is the specific prediction of the unemployment rate using the VADER sentiment analyzer for assessing sentiment's efficacy as an economic prediction tool. It should broadly add to the literature on just how effective sentiment analysis can be for macroeconomic forecasting.

4. Sentiment Analysis and Coding Methodology

The programming portion of this assignment was written entirely in Python 3 within the Jupyter Notebook environment. The coding work itself can roughly be broken up into 4 phases: scraping, data cleaning/processing, regression analysis, and visualization.

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[6] Christina D. Romer and David H. Romer, "Federal Reserve Information and the Behavior of Interest Rates" (The University of California Berkeley, 2000), https://eml.berkeley.edu/wp/c+dromer_aer2000.pdf.
[7] Refet S Gürkaynak, Brian Sack, and Eric Swanson, "Do Actions Speak Louder than Words? the Response of Asset Prices to Monetary Policy Actions and Statements - IJCB - May 2005," Premier issue (May 2005) of the International Journal of Central Banking (International Journal of Central Banking, 2005), https://www.ijcb.org/journal/ijcb05q2a2.htm.
[8] Raul Cruz Tadle, "FOMC Minutes Sentiments and Their Impact on Financial Market," Journal of Economics and Business (Elsevier, 2022), https://ideas.repec.org/a/eee/jebusi/v118y2022ics0148619521000394.html.

The first challenge was to download and integrate FOMC minutes releases on the Federal Reserve's website into an easily accessible .txt file format. Normally, this process is highly labor intensive and requires untold hours of searching, copying, .txt file creation, and filename and directory management. However, I decided to construct a web scraping pipeline through which to obtain all relevant FOMC minutes in separate, organized .txt files. The Beautiful Soup Python library was especially indispensable for this task. It allows one to input the base url of the Federal Reserve and to specify what types of .html files to access and download through parsing of the base url's HTML code. I was able to specify both the years of interest and the types of minutes of interest. They were then all downloaded to separate .txt files based on their date and were labeled as such.

Then, I acquired a .csv file from FRED-MD that contained all macroeconomic indicators necessary for the project. A .csv file was essential, as it easily interfaces with Python's Pandas library through whose framework most of the quantitative work was completed. Pandas essentially constructs a manipulable spreadsheet within the code that Python functions and processing procedures can easily be applied to while maintaining the useful structure and order of the data.

The next major task was matching each text file to the corresponding date within the macroeconomic data and creating a dataframe of just the relevant macroeconomic data and the FOMC minutes that correspond to said date. This involved some creative date format manipulation and regular expression parsing of filenames. This dataframe was then used and modified throughout the rest of the processing and model creation steps.

The next step was to utilize the Natural Language Toolkit's (NLTK's) natural language processing tools and the VADER sentiment analyzer to produce sentiment scores for each row of the dataframe based on the minutes text in each row. VADER stands for Valence Aware Dictionary for sEntiment Reasoning.[9] The key component of VADER is a dictionary that maps various textual elements to corresponding sentiment values. By reading in text, VADER uses its dictionary to get scores for the text. What makes VADER different from other sentiment dictionaries is that it also takes into account heuristics outside of the words themselves. Capitalization, punctuation, degree modifiers, polarity shifting conjunctions, and negations are all used to modify the final sentiment score. This prevents misinterpreting very sentiment-laden lexical features that may have a much different sentiment value when viewed in context of these modifications. For example, the word “hate” is very sentimentally negative and would lower the average sentiment of a sentence it is put into. However, if I say that I “do not hate you” this negative sentiment should clearly be adjusted upward to reflect its true usage. By calculating average sentiment scores for each block of text and using these five modification methods, VADER was able to produce a single sentiment score corresponding to all relevant FOMC minutes.

In my exploration, I found that VADER’s sentiment intensity analyzer’s negative polarity score worked best for the regression as it had more variation in it than the neutral or positive scores. Minutes text, seeing as it is drawn from a formal meeting, is largely neutral in its content. When negative words are used it is usually a significant occurrence. Thus, the specific measure utilized within the regression was the negative polarity score. A higher score indicated a more negative sentiment.

From there, I next needed to prepare the lag variables for the regression using various shift commands. I decided to include a -1,-3, -6, and -10 reading for the unemployment rate

[9] “Python: Sentiment Analysis Using Vader,” GeeksforGeeks (GeeksforGeeks, October 7, 2021), https://www.geeksforgeeks.org/python-sentiment-analysis-using-vader/.

and the federal funds rate when measured in terms of FOMC minutes released as a shift interval. For example, -1 refers to the reading of macroeconomic indicators one FOMC minutes release before the current date. Then, I needed to remove rows that had NA readings for any lag variable.

After completing this step, I went ahead and generated summary statistics and visualizations for my data using NumPy operations and the Matplotlib visualization library. These can both be found in Section 5.

Next, I created three duplicate data frames to specify different prediction horizons for the target future unemployment rate variable. The horizons used were 5, 10, and 15 minutes releases in the future.

All that was left to prepare before the regression was separating out the target variable of future unemployment in each frame and removing duplicate columns and the text column. Then, I fed the fully cleaned data frames into a simple linear regression model with the entire cleaned data frames being the x features and the separated future rates being the y target. From there, I was able to generate R^2 scores, coefficients, and p-values from established regression model object methods.

At this point, no more programming or quantitative information gathering needed to occur for the purposes of the paper.

All code can be found at https://github.com/ferneliusn/sentiment_unemployment.

5. Data and Descriptive Statistics

All data necessary for this paper came from one of two sources. The first source, for all textual data, was a web scraping of the federal reserve website (www.federalreserve.com).[10]

[10]"Home," Federal Reserve Board - Home (The Federal Reserve), accessed January 31, 2023, https://www.federalreserve.gov/.

From that base url all FOMC minutes were located and downloaded. Using the VADER sentiment analyzer, data from this source was processed into the sentiment score that is central to this paper.

One important piece of data exploration was viewing the minutes text for both the highest and lowest negative sentiment scores. These two minutes reports should be instructive for getting an idea of what type of language garners what sentiment scores and to provide a first glance test upon the sentiment analyzer to make sure it seems right. The most negative minutes data was that from October of 2001. The major world historical event of 9/11 the month before was the main reason for the sentimental negativity. Words like “attacks” and “terrorist” are far more sentimentally dense than FOMC minutes language typically is. Also, the attacks shocked investors in the stock market and created a general short term economic downturn further compounding the negative sentiment of the report. It would make sense that this particular minutes report should be a negative sentiment outlier. The fact that it indeed was tentatively increases my confidence in the sentiment analyzer.

January of 2006 and February of 2005 were tied for the most positive set of minutes statements. In both of these statements there was both consumption and job growth increases. Words like “brisk” and “strong” added positive intensifiers to the documents. Also, these dates roughly coincide to near the apex of the U.S.’s housing bubble before the mortgage crisis. The booming real estate market fueled general good performance across nearly all sectors of the economy and both of these dates just represent particularly good times during this period. Also of note, January of 2006 was Alan Greenspan’s last as a member of the FOMC committee so there was a section describing his wonderful service to the Federal Reserve and congratulations on his retirement, artificially increasing the sentimental positivity. I am satisfied with both of these dates appearing to have highly positive sentiment measures.

All other macroeconomic variables used within this paper and its empirical models can be found within the FRED-MD database.[11] This data is produced quarterly by the St. Louis Federal Reserve Banks and includes a wealth of macroeconomic indicators by date. I downloaded the CSV version of this data and converted it into a Pandas dataframe for integration with the textual data as explained in the previous section of this paper. For lag variables, I used the shift method of Python to create new shifted variables from the base ones. All of this data was in the form of continuous, numerical measures. Of special importance were the variables pertaining to the date, federal funds rate, CPI, Industrial Production, S&P 500, and the unemployment rate. Thus, the target variable for prediction, the unemployment rate, was drawn directly from this data source.

Before advancing further, it was important to get an overview of this data's main characteristics and internal interactions. Of primary importance was viewing the relationship between the negative sentiment score and various macroeconomic indicators. If there appeared to be little to no relationship, then it would not bode well for the measure being useful for any meaningful predictions.

At first glance, when the negative sentiment score is compared to both the unemployment rate and federal funds rate at that time period there seems to be no discernable relationship. Figure 5.1 and 5.2 below illustrate this fact.

[11]"Federal Reserve Economic Data: Fred: St. Louis Fed," FRED (Federal Reserve Bank of St. Louis), accessed January 31, 2023, https://fred.stlouisfed.org/.

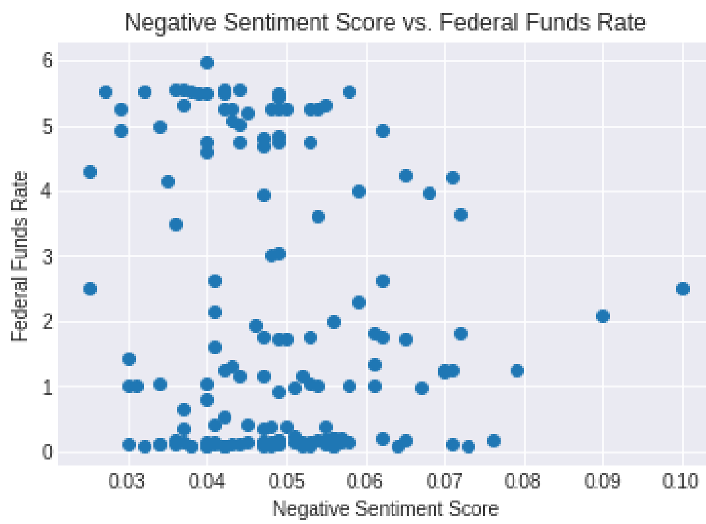

Figure 5.1 Negative Sentiment Score vs. Federal Funds Rate

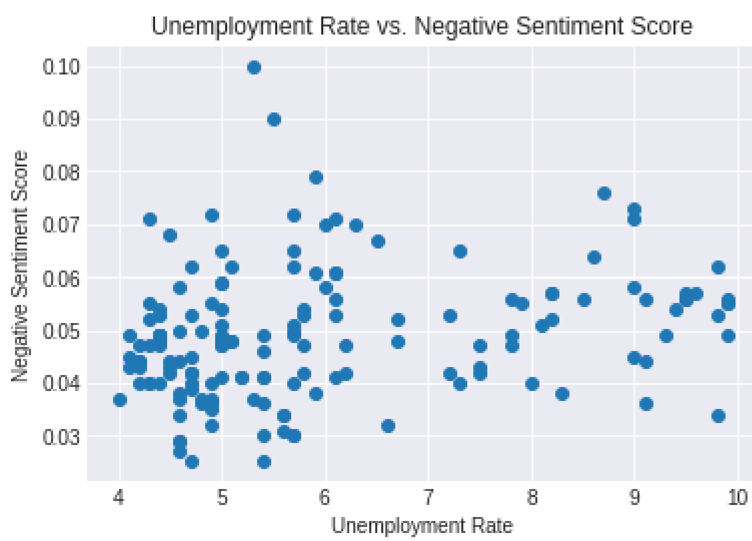

Figure 5.2 Unemployment Rate vs. Negative Sentiment Score

Figure 5.1 shows a particularly egregious non-correlation, while Figure 5.2 may show a slight positive relationship. However, this is not especially damning of the measure. For economic happenings reported by the minutes as indicated by the sentiment to have tangible impacts on the macroeconomy, some amount of time must pass.

For figures 5.3 and 5.4 below I generated measures to take this passage of time into account when determining general relationships. For Figure 5.3 I took the difference between the current unemployment rate and the rate 10 minutes report releases ago as the y variable and utilized the negative sentiment score in the current year as the x variable. For Figure 5.4 I instead took the difference between the unemployment rate ten minutes releases from current and the current rate and plotted it against the negative sentiment score. Figure 5.3 and 5.4 present the results of this setup.

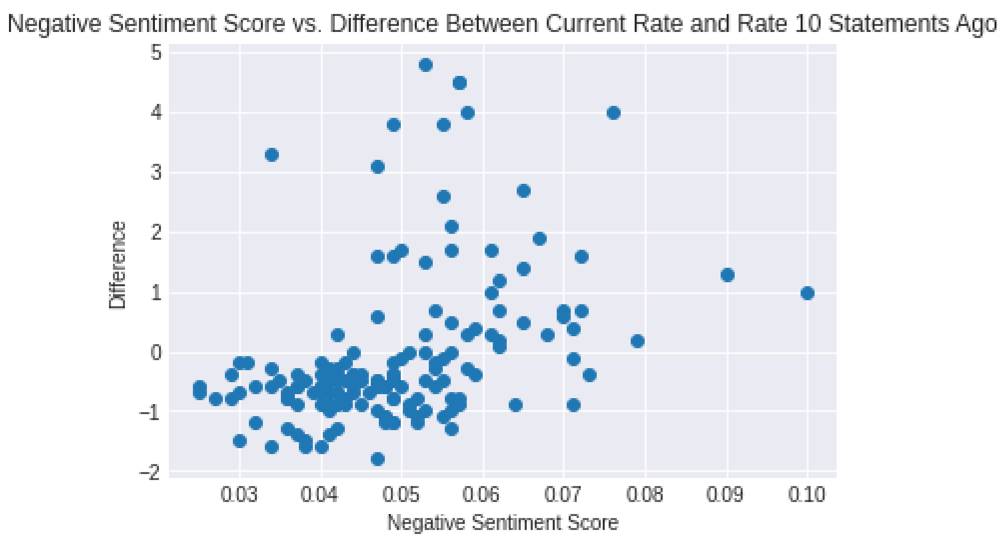

Figure 5.3 Sentiment vs. Difference Between Current and Past Unemployment Rates

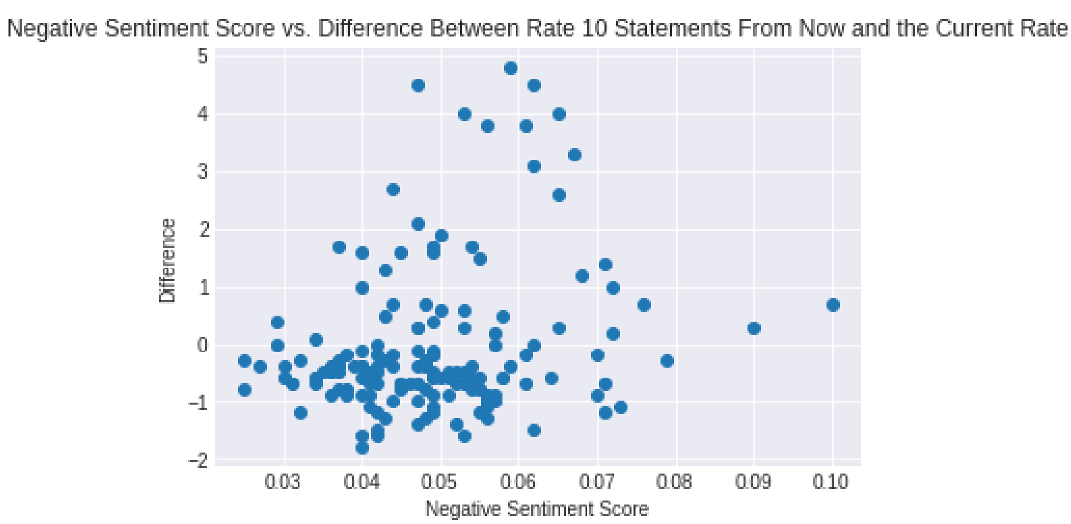

Figure 5.4 Sentiment vs. Difference Between Past and Current Unemployment Rates

From these figures it is clear that there is some relationship between the unemployment rate and the sentiment score of the minutes report when sufficient time is allowed to realize any changes to macroeconomic indices brought on by the events described by each minutes report.

It was also instructive to compare time series graphs of each major variable (the federal funds rate, unemployment rate, and the negative sentiment score) to see if they responded in similar fashions during particularly notable economic events. Figures 5.5, 5.6, and 5.7 below contain time series representations of the aforementioned measures.

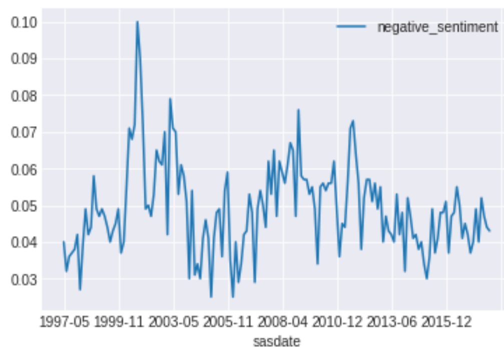

Figure 5.5 Time Series of Sentiment

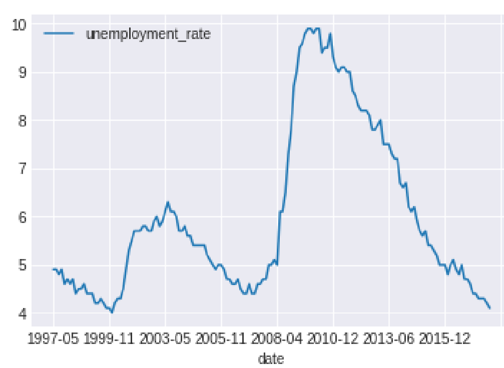

Figure 5.6 Time Series of the Unemployment Rate

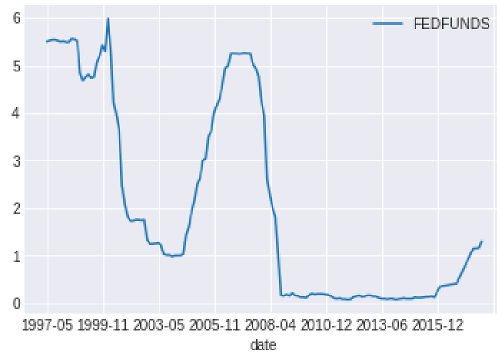

Figure 5.7 Time Series of the Federal Funds Rate

At first glance, the Federal Funds Rate and Unemployment Rate move in opposite directions over time. This makes sense given what we know about the relationship of each. From these graphs it is also clear that the negative sentiment score generally moves in the same direction as the unemployment rate. When the unemployment rate begins to rise or fall, so too does sentiment. This makes some intuitive sense as high unemployment is very generally regarded as a bad thing. Since unemployment moves opposite the federal funds rate, it would make sense that negative sentiment moves opposite the federal funds rate as well. This very relationship can also be observed above.

Thus, when viewed in its totality, my exploration of the data suggested to me that the negative sentiment score may have some explanatory power for predicting the unemployment rate.

6. Empirical Models and Results

In order to evaluate the significance of our generated sentiment measure for macroeconomic prediction of unemployment, several multilinear regressions of various specifications were generated. The models were constructed from nationwide macroeconomic indicator data along with our code-generated negative sentiment score.

$unemp_{+horizon} = \beta_0 + \beta_1 sentiment + \beta_2 sasdate + \beta_3 CPI + \beta_4 INDPRO + \beta_5 S\&P + \beta_6 FEDFUNDS + \beta_7 unemp + lags + u$

A variable without any sub notation denotes the current year of analysis. Positive or negative numbers in a variable's sub field denote how many federal reserve committee reports before or after the current date the variable refers to. Positive numbers indicate future report dates, while negative numbers indicate past report dates.

Unemp refers to the nationwide unemployment rate of the United States as a percentage. *Sasdate* refers to the base date of each row of observations. *CPI* refers to the Consumer Price Index for All Urban Consumers in the base year. *INDPRO* is an index of industrial production with an index base year of 2017. *S&P* refers to the S&P 500 stock index of 500 large companies' performance on the New York stock exchange. *FEDFUNDS* refers to the Effective Federal Funds Rate.

The lag term for all models included a -1,-3, -6, and -10 reading for the unemployment rate, and the federal funds rate.

$lags = \beta_8 unemp_{-1} + \beta_9 unemp_{-3} + \beta_{10} unemp_{-6} + \beta_{11} unemp_{-10} + \beta_{12} FEDFUNDS_{-1} + \beta_{13} FEDFUNDS_{-3} + \beta_{14} FEDFUNDS_{-6} + \beta_{15} FEDFUND_{-10}$

The variable *horizon* represents the prediction horizon for each model. I utilized prediction horizons of 5, 10, and 15 federal reserve minutes releases.

$horizon = \{5, 10, 15\}$

The error term is represented by *u*.

Thus, for this paper, essentially three separate, yet only differing in predictive horizon, regressions were performed.

The results of the 5 minutes release horizon regression are presented in Table 6.1 below.

Table 6.1 Regression Summary

	Coefficient	P-value
sasdate	-9.636e-09	6.410e-02
CPIAUCSL	9.166e-02	1.012e-02
INDPRO	-5.742e-03	8.441e-03
S and P 500	-1.001e-03	1.669e-08
FEDFUNDS	-4.940e-01	8.541e-13
unemployment rate	8.744e-01	1.266e-64
negative sentiment	-2.446e+00	6.089e-07
UNRATE-1	1.002e-01	3.746e-54
UNRATE-3	-3.578e-01	2.261e-38
UNRATE-6	2.400e-01	2.783e-23
FEDFUNDS-1	1.474e-01	3.746e-11
FEDFUNDS-3	3.324e-01	4.284e-08
FEDFUNDS-6	-1.201e-01	1.915e-04
FEDFUNDS-10	2.285e-01	1.395e-01
past rate	-2.073e-01	4.258e-11
r2	0.9621	
MSE	0.1176	
RMSE	0.3429	

In this regression, negative sentiment appears to be significant with a 6.089e-07 p-value ($p<0.0001$). It also notably has a negative coefficient of -2.446.

The 10 minutes release horizon regression had the following results as shown by Table 6.2 below.

	Table 6.2 Regression Summary	
	Coefficient	P-value
sasdate	-6.83e-09	1.723e-01
CPIAUCSL	6.802e-02	2.654e-02
INDPRO	1.126e-01	2.194e-01
S and P 500	-8.561e-04	4.309e-07
FEDFUNDS	-4.507e-01	7.775e-05
unemployment rate	7.694e-01	1.555e-26
negative sentiment	1.646e+00	9.138e-08
UNRATE-1	1.833e-01	1.960e-22
UNRATE-3	-2.575e-02	9.584e-16
UNRATE-6	1.704e-01	9.207e-09
FEDFUNDS-1	1.488e-01	7.722e-04
FEDFUNDS-3	3.172e-01	2.750e-02
FEDFUNDS-6	-9.434e-03	5.947e-01
FEDFUNDS-10	4.980e-01	1.825e-01
past rate	-3.263e-01	1.668e-03
r2	0.9091	
MSE	0.2859	
RMSE	0.5347	

Again, negative sentiment had a highly significant p-value of 9.138e-08 ($p<.0001$). Notably, the sign of its coefficient flipped from negative to positive with a value of 1.646. This would be the expected coefficient sign given that higher unemployment is generally written about in unfavorable terms.

Finally, the results of the 15 minutes release horizon regression are shown as follows in Table 6.3 below.

	Table 6.3 Regression Summary	
	Coefficient	P-value
sasdate	1.298e-08	4.336e-01
CPIAUCSL	-6.150e-02	1.013e-01
INDPRO	2.196e-01	8.941e-01
S and P 500	-1.344e-03	4.511e-05
FEDFUNDS	-1.126e-01	5.534e-01
unemployment rate	7.867e-01	3.630e-10
negative sentiment	2.591e+00	1.003e-06
UNRATE-1	3.477e-01	2.619e-08
UNRATE-3	1.419e-01	2.265e-05
UNRATE-6	1.380e-01	1.396e-02
FEDFUNDS-1	1.222e-02	9.636e-01
FEDFUNDS-3	3.849e-01	3.211e-01
FEDFUNDS-6	3.414e-01	2.332e-02
FEDFUNDS-10	4.264e-01	7.232e-04
past rate	-4.292e-01	6.730e-01
r2	0.9061	
MSE	0.2980	
RMSE	0.5459	

These results largely echoed the results of the previous prediction horizon's regression. Sentiment again had a positive coefficient, this time of even greater magnitude at 2.591. Most importantly, it also again had a significant p-value of 1.003e-06 ($p<.0001$).

Another interesting result came from a regression of the inflation rate (as calculated from CPIAUCSL a year from the base date minus the base date's reading divided by the base date's reading all multiplied by 100). The results of this regression determined sentiment to be a very insignificant macroeconomic predictor in this case (p-value ~ 0.775). This perhaps indicates that inflation is not viewed as clearly semantically as high unemployment. Although, perhaps it merely indicates that inflation is unsuited toward this particular sentiment analysis prediction method due to its inherent instability over time.

Thus, because negative sentiment had statistical significance within the regressions of all 3 time horizons, I am confident in describing the sentiment score as a significant macroeconomic variable for prediction of the unemployment rate.

7. Conclusions and Implications

Given that the sentiment score has a highly significant p-value over all time horizons with non-zero coefficients it would be safe to reject the null hypothesis that the sentiment score of the reports has no predictive power on the macroeconomic measure of the unemployment rate. Thus, the sentiment measure of FOMC meeting minutes is a useful macroeconomic measure in and of itself for predictive macroeconomic researchers of unemployment. The implications of this fact are quite far ranging. It suggests that further research of sentiment analysis as it relates to various other macroeconomic indicators is a fruitful area of study. Some other measures could potentially benefit from these sentiment analysis techniques like the unemployment rate while other measures may not be well suited to it like the inflation rate. It also suggests that other sources of macroeconomic text could potentially be converted into effective quantitative sentiment measures as well.

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