Federal Open Market Committee Statements, Sentiment, and the United States Stock Market

Using public releases from Federal Open Market Committee meetings between January 2000 and March 2019, I analyze the relationship between the sentiment in the statements and possible short-term effects in the S&P 500 Index. I generate sentiment using several sentiment dictionaries, relating to finance and otherwise, created from previous bodies of work. I find that regular and financial sentiment dictionaries do not have a significant relationship with short-term returns in the S&P 500 Index. A sentiment dictionary constructed specifically for language use in central banks, however, has a correlation with future returns when compared with negative sentiment.

Sentiment analysis is a branch of textual analysis where a piece of text is given a quantitative number, usually representing the text's polarity, where polarity is a measurement of the overall positivity or negativity of the text. Because the applied use of sentiment analysis in economics and finance is still growing, there are opportunities to apply this analytical method to statements from the United States central bank. In the stock market, movements and policy changes from the Federal Reserve, the United States' central bank, are closely watched. However, there is a gap in the research that studies the sentiment of key press releases and statements. This paper seeks to examine whether there exists a relationship between Federal Reserve statement sentiment and the Standard and Poor's 500 Index. I take a 19-year period of the Federal Reserve statements that follow policy meetings and generate a quantitative proxy for sentiment in order to study the sentiments' short-term effects on the United States stock market. To generate a measure representing sentiment, I take three differing sentiment dictionaries from existing literature on this topic and compare the results. A sentiment dictionary is a dictionary where, instead of meanings, words are given a value to quantify the positive or negative feeling that they reflect. One dictionary is generated from non-economic or finance-related context (De Smedt & Daelemans, 2012). Another dictionary is derived from Finance specific terms and meanings (Loughran & McDonald, 2011). The last sentiment dictionary was created by a collection of central bank statements collected from 63 different monetary bodies (Correa, Garud, Londono, & Mislang, 2017). In this paper, I describe the parts of the United States monetary system that are relevant to this study, and I also look at previous literature that analyzes central bank public statements and conducts text-based analysis. After retrieving and parsing the relevant statements, I use Python to convert the text data into variables such as polarity, subjectivity, and positive and negative word counts. I find that sentiment dictionaries that were created for general use are ineffective in economic or finance related works. I also find that in a central banking context, the amount of negative words from a Federal Open Market Committee statement have a negative correlation with the one-day future change in the S&P 500. I begin by outlining the Federal Open Market Committee and relevant institutions in Section I, followed by a brief overview of the Standard's and Poor 500 Index in Section II. I then review the academic literature on Federal Reserve actions and statements, sentiment analysis, and applications of sentiment in Finance in Section III. Next, I summarize and describe the sources of data used in this paper, with Financial data in Section IV-A and Sentiment data in Section IV-B. There, I also describe the methodology I used in order to generate custom variables. In Section IV-C, I note the political and regime leaders that I used as categorical control variables in this study. Section V outlines the specification of the models that I test for relationships between sentiment and the stock index. Section VI reveals and discusses the statistical results from the regressions. Finally, Section VII summarizes the results, while discussing the implications of the findings, as well as potential areas for further research.

I. FOMC, Meetings, and Statements.

The FOMC (Federal Open Market Committee) is a group within the United States' Federal Reserve that meets and sets the monetary policy of the United States Central Bank. In this case, monetary policy refers to the actions made by the Federal Reserve that affect the nation's money supply and interest rates. The main goal of monetary policy is to maintain a steady inflation rate, while balancing variables such as employment, wage growth, economic growth, and gross domestic product. Currently, the Federal Reserve conducts monetary policy using three tools: reserve requirements, the ability to set the discount rate, and the ability to conduct open market operations. The discount rate is an integral part of the financial system as it determines the overnight interest rate that financial institutions charge to lend to each other within the Federal Reserve. Reserve requirements are the requirements for banks and similar institutions to place a portion of their total capital in Federal Reserve banks. This requirement serves to not only ensure that there is sufficient capital on hand for banks, but also to control money liquidity and supply. One of the reasons for the capital requirement is to meet potential withdrawal demand for example, in the case of a run on banks. Open market operations refer to the Reserve's ability to buy and sell government securities in the open market. These tools seek to target a Federal Funds rate that the Committee sets between meetings. These tools and the Federal Funds rate are integral in determining the rate of new investments, and the discounting of future cash flows.

The FOMC meets regularly to discuss and determine the current and future economic state, and how to set monetary policy. Since 1981, there have been eight scheduled meetings each year, in addition to numerous varied unscheduled meetings and conference calls between them (Lucca & Moench, 2015). Since May 1999, a public statement is always released after each scheduled meeting, even if no actions are taken (Lucca & Moench, 2015). Subsequent minutes to each meeting are released approximately 20 days after the release of a post-meeting statement. Lucca and Moench also indicate the statements were released roughly around 2:15 PM Eastern Standard Time from September 1994 to March 2011 (2015). However, they note that release time has fluctuated since April 2011, with release times ranging between 12:30 to 2:00 PM. Generally, FOMC statements will include the Committee's view on the economy, projections into the future, and changes in monetary policy, all of which will affect an investor's expectations of future cash flows. Changes between statements are monitored very closely by investors and capital market participants as they judge both the tone and words used.

II. The US Stock Market and the S&P 500 Index

The S&P (Standard and Poor's) 500 Index is a price return stock market index that is comprised of 500 publicly traded firms of the United States that are listed either on the New York Stock Exchange or the NASDAQ Stock Market (S&P Dow Jones Indices, 2019). This index is market capitalization weighted, meaning each constituent of the index is more heavily weighted the larger its market capitalization is. By nature of the methodology used, the index consists of only "large-cap" firms. This is due to the component requirement of a market capitalization of at least 8.2 billion United States Dollars as of February 20th, 2019 (S&P Dow Jones Indices, 2019). However, as the S&P 500 Index represents 80% of the total market capitalization in the United States, it can be a suitable proxy for the stock market (S&P Dow Jones Indices, 2019). As the constituents are publicly traded equities, the Index is constrained to market hours, where the market open takes place at 9:30 AM and the market is closed at 4:30 PM, Eastern Standard Time.

III. Related Literature

The idea of examining FOMC statements and subsequent reactions from the stock market is heavily discussed in business media and is widely watched by participants in capital markets. Every time an FOMC meeting nears, there is a flurry of articles and commentary that attempt to predict the Federal Reserve's tone and how it will affect the markets. For example, a *Forbes* article published in September 2018, suggested that the Federal Reserve would almost definitely raise Federal Fund rates at the next meeting, and that "the stock-market could get more challenging and volatile" (Sarhan, 2018). More recently, an article on *The Motley Fool* discussed why and how the recent FOMC statement has led the stock market to gain (Frankel, 2019). Research conducted by Neuhierl and Weber indicates that the equity markets may have a predictable effect post-policy decision announcement (Neuhierl & Weber, 2018). Their research identifies a shock in prices that may continue for 15 days, averaging returns of 4.5% (Neuhierl & Weber, 2018). Neuhierl and Weber's *Monetary Momentum* is important as they discover that stock prices move in a predictable pattern prior to monetary policy releases, and they continue to exhibit a predictable return after the release (2018). The returns pre and post release depends on whether the monetary policy was a contractionary or expansionary surprise (Neuhierl & Weber, 2018). While Neuhierl and Weber's research did not work with sentiment, their analysis shows the effect that central banks may have on international markets, simply through monetary policy releases. Carlo Rosa, an economist in the Federal Reserve Bank of New York, has authored an article on the effect of FOMC minutes on general capital markets. In the article he found that trading volume and volatility greatly increase in a short window post-release, but the effect of the FOMC minutes release is less than that of the FOMC statement and some important economic indicators, like the non-farm payroll employment numbers (Rosa, 2018). Rosa also identified a weakening response to the minutes since 2008, suggesting the increased transparency of the Federal Reserve may have caused the weaker response (2018). Rosa's research supports that there is a tangible effect of FOMC statements to the capital markets (2018). In Lucca and Moench's research, they describe an observed effect in U.S. equities where there are abnormal risk-adjusted returns occurring in the 24-hour period leading up to scheduled FOMC meetings (Lucca & Moench, 2015).

In recent years, with the increasing popularity of natural language processing and computational sentiment analysis techniques, research has been conducted on modeling stock market returns according to various sources of sentiment. A commonly cited piece of research linking textual sentiment analysis and finance is Loughran and McDonald's *When is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks* (Loughran & McDonald, 2011). Loughran and McDonald find ineffectiveness in the Harvard Psychosocial Dictionary when used to process finance-related text data (2011). Specifically, they find that nearly 75% of negative words in the Harvard Dictionary are not considered negative in a financial context (2011). Loughran and McDonald create a dictionary of finance-related words, relating positivity, negativity, and other affective attributes (2011). In *Model and Forecast Stock Market Behavior Integrating Investor Sentiment Analysis and Transaction Data*, Zhang et al. study social media and internet news using statistical techniques to model returns in a select set of individual Chinese stocks (Zhang, Xu, & Xue, 2017). Bognár looked at financial news from Google News RSS Feeds; created sentence, document, and daily sentiment scores; and compared them to Apple's daily closing price (Bognár, 2016). In this case, Bognár used two different sentiment dictionaries to compare his results. Ren et al. also studied potential predictive effects of sentiment on the stock market, by using a Support

Vector Machine model to process sentiment and market data (Ren, Wu, & Liu, 2019). To collect sentiment data, Ren et al. used web page crawlers on a set of pages to collect text data and converted the text into sentence-based sentiment scores (2019). More closely related is Smales and Apergis's *Does More Complex Language in FOMC Decisions Impact Financial Markets?* where they describe effect of the Federal Reserve's increasingly complex statements due to the evolution of unconventional monetary policy over time (Smales & Apergis, 2017). Smales and Apergis show that there is a correlation between language complexity of FOMC statements and trading volume and volatility across equity, debt, and currency markets (2017). Ito et al. studied the minutes of FOMC meetings and used a networked machine learning approach to create a polarity dictionary of words in the minutes (Ito, Izumi, Sakaji, & Suda, 2017). An internal working paper from the Federal Reserve specifically studies the text of financial stability reports (Correa, Garud, Londono, & Mislang, 2017). Correa et al. create a dictionary of positive and negative words specifically addressing sentiment of these words from a central bank financial stability context (2017). In this paper I take techniques learned from the literature and apply it to Federal Reserve statements in order to find whether the sentiment of the statements released by the Federal Reserve have a meaningful relationship.

IV. Data and Key Variables

A. Financial Data

The scope of my analysis focuses on the effects of FOMC statements on the stock market from January 2000 to March 2019, partially due to changes in the post-meeting statement releases in 1999. Subsequently, the first relevant statement takes place on February 2nd, 2000, and the range of the acquired data for the S&P 500 Index is January 3rd, 2000 to March 1st, 2019. The Index data is at a daily level, with *Open*, *High*, *Low*, *Close*, and *Volume* variables, and is obtained from Norgate Investor Services. For my research, only the Close is used, but not directly. The key variable that I create from the S&P 500 Index is the future percentage changes over an n-period of days. The formula for calculating the n-day percentage change is

(1) $$\%\Delta y_n = \frac{y_{t+n} - y_t}{y_t}$$

where y_t is the value closing value of the index at time t and n is the number of future days forward. I also use the absolute value of the one-day future return as a measure of the short-term magnitude of price changes.

TABLE 1—SUMMARY STATISTICS OF S&P 500 CHANGES

	No. Obs.	Mean	St. Dev.	Min	Max	50%
1-Day Percentage Change	4814	0.000207	0.012017	-0.090350	0.115800	0.000533
2-Day Percentage Change	4814	0.000413	0.016342	-0.124174	0.132064	0.001036
3-Day Percentage Change	4814	0.000607	0.019335	-0.139059	0.139480	0.001834
5-Day Percentage Change	4814	0.000999	0.024410	-0.183401	0.191112	0.002649
Previous Day Pct. Change	4814	0.000208	0.012046	-0.090350	0.115800	0.000533
1-Day Absolute Pct. Change	4814	0.008000	0.008969	0.000000	0.115800	0.005335

Notes: These values are raw calculations, not adjusted to percentage points. For example: 0.01 = 1%

Source: Author calculations.

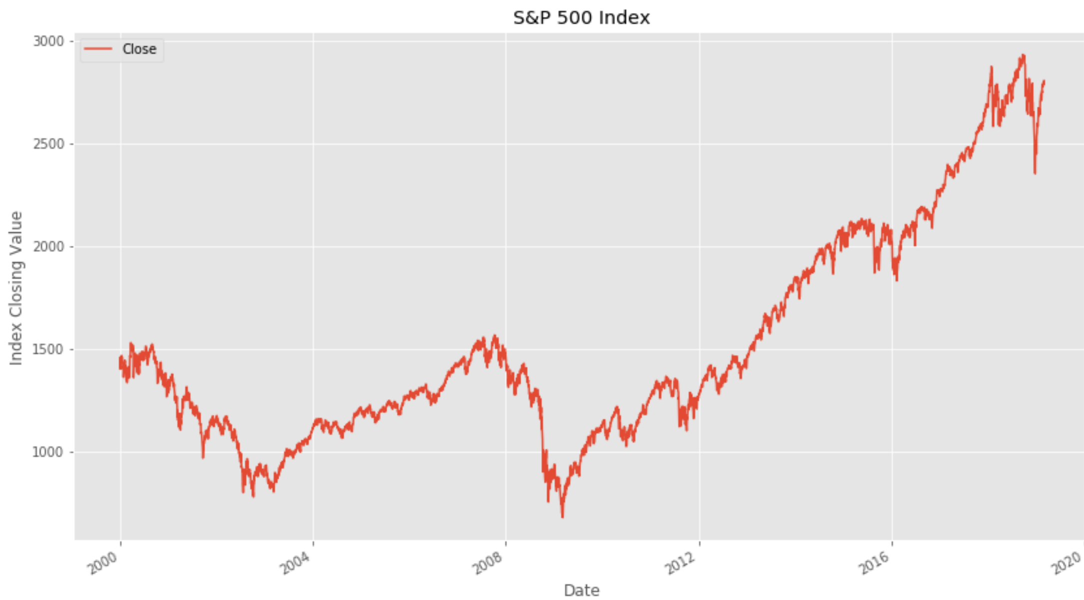

FIGURE 1. S&P 500 INDEX, DAILY CLOSE, JANUARY 2000 TO MARCH 2019

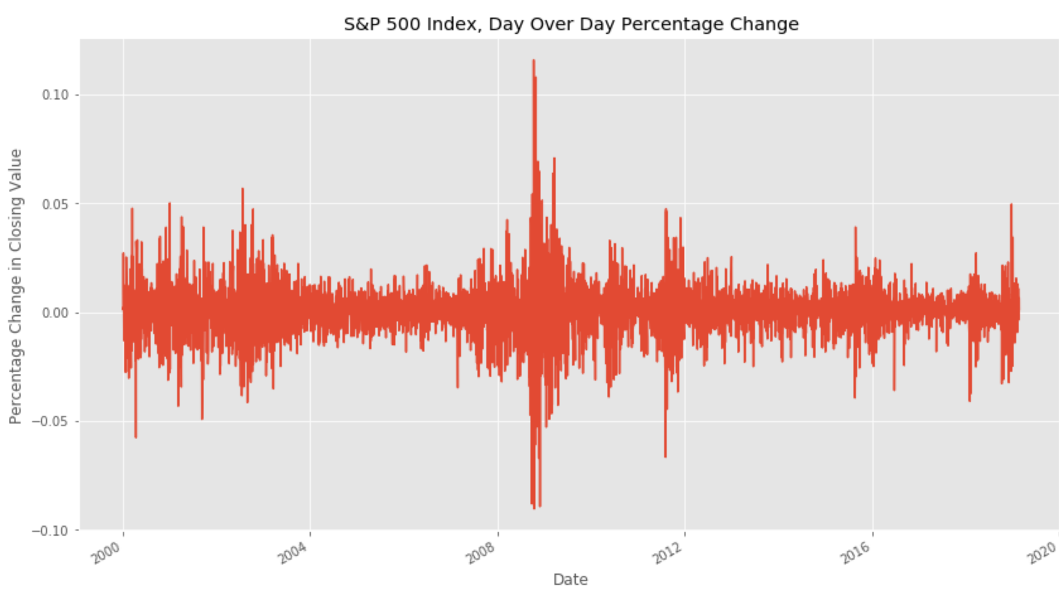

FIGURE 2. S&P 500 INDEX, DAILY PERCENTAGE CHANGE ON CLOSE,
JANUARY 2000 TO MARCH 2019

B. Sentiment Data

FOMC statements were acquired from the Federal Reserve Board website, (https://www.federalreserve.gov/monetarypolicy.htm). I programmed a Python-based web crawler program for this specific purpose. The script retrieves all webpages that contain press releases from the Federal Reserve Board within a specified time range and parses the HTML to retrieve the relevant text data. The program cleans the text by removing escape characters from the text data (\n, \r, \t, \xa0, \u2003, \u2011). These escape characters are deemed unnecessary as their only purpose is to change the visual display of the text. The text is then stored in comma-separated value files, each file storing one statement, with each paragraph separated by a comma. I then created a script to retrieve a list of all the dates where an FOMC meeting statement was released. I wrote another web crawler which parsed the relevant dates from the calendars available on the Federal Reserve Board website. I then used the retrieved dates as a filter for the press releases to determine which retrieved statement was relevant.

From this retrieved text data, I was able to programmatically process the data using several methods to return sentiment and text related variables as listed in the following table:

TABLE 2—SUMMARY STATISTICS OF SENTIMENT DATA

	No. Obs.	Mean	St. Dev.	Min	Max
polarity	163	0.080199	0.039870	-0.008750	0.212000
subjectivity	163	0.351940	0.067781	0.100000	0.574091
LM_POS	163	7.785276	5.112008	0	28
LM_neg	163	7.134969	5.285101	0	31
CB_POS	163	4.036810	3.331276	0	20
CB_neg	163	2.656442	2.623212	0	13
word count	163	528.570552	287.55263	70	2122

Source: Author calculations.

The polarity and subjectivity variables are generated by means of a Python package named *TextBlob* (Loria, 2019). This package itself is a wrapper of several natural language processing libraries in Python, including *Pattern* and *NLTK* (2019). Polarity is a measure of the positive versus negative sentiment of the evaluated text. This value can theoretically be any number in the range of [-1,1], where a negative number represents a stronger negative sentiment connotation from the text, and a positive number is stronger positive connotation. The subjectivity is a measure of the text's objectivity versus subjectivity, where the value can take on any number in the range of [0,1], where 0 is objective and 1 is subjective. Both Polarity and Subjectivity are generated by means of a vast sentiment dictionary used in *Pattern* (De Smedt & Daelemans, 2012).

LM_POS and LM_neg are both counts of words from the passed text data which match with the Loughran and McDonald financial sentiment dictionary (2011). LM_POS is the count of positive words in the text as defined by the dictionary. LM_neg is the count of negative words in text, defined by the dictionary. These word counts were generated using a function that I wrote that takes three variables, the text, a list of positive words, and a list of negative words, and returns the positive count, negative count, and total word count. In calculating the negative word count, I also applied the method used by Loughran and McDonald on negation, where if the words 'NO', 'NOT', 'NONE', 'NEITHER', 'NEVER', 'NOBODY', are within three preceding words of a positive sentiment word, the word is then considered a negative sentiment word, and added to the count (2011). Loughran and McDonald's research explains that double negatives rarely, if ever occur in financial related text and thus negative sentiment words that are negated would not need to be counted (2011).

CB_POS and CB_neg are positive and negative word counts generated using the same method as the LM_POS and LM_neg counts. In this case, the difference is in the positive and negative word lists that are passed in into the function. The dictionary used for these values was pulled from the work of Correa et al. in *Sentiment in Central Banks' Financial Stability Reports*, where the used words and their contexts are derived from central bank reports (Correa, Garud, Londono, & Mislang, 2017). The methodology I used to retrieve positive and negative word counts is the same method used as the previous Loughran and McDonald sentiment word counts. The method of negation words is also applied.

The word count variable is the count of words in each statement. This is created by processing the text data and using the *NLTK* stop words corpus to remove all stop words from the statement. A stop word is a word that usually does not carry much meaning in the English language and is used as part of grammatical structuring. In this case, it would be words such as 'the', 'or', 'a', and 'and'. Only the remaining words are counted and added to the word count variable.
With this sentiment data, I explore some preliminary relationships between them.

Here, it is interesting to note that there is an evident positive linear correlation between the positive word counts from the Loughran McDonald (LM) dictionary and the Central Bank (CB) sentiment dictionary.

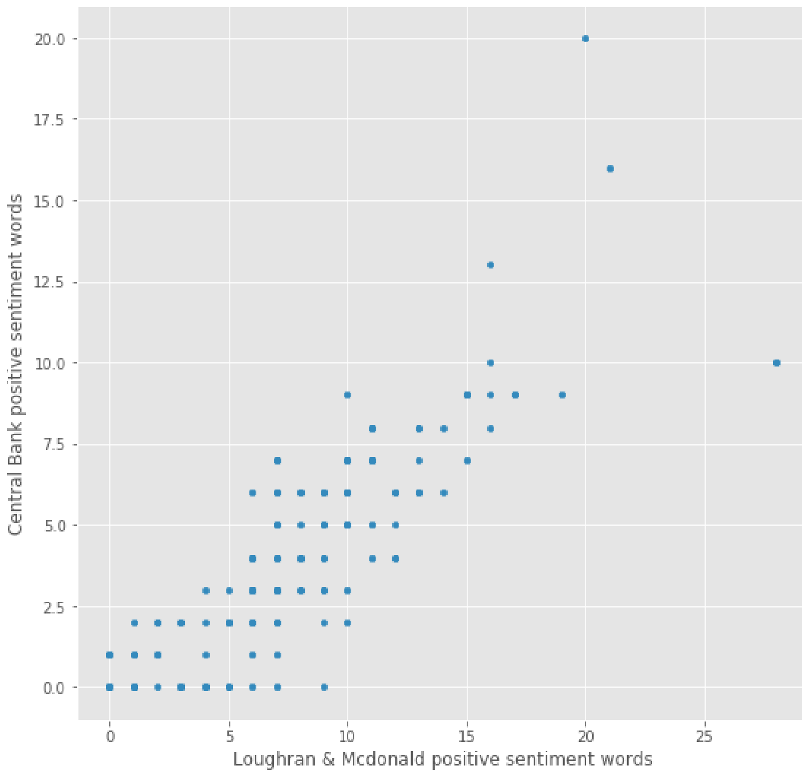

FIGURE 3. POSITIVE WORD COUNTS BETWEEN LOUGHRAN AND MCDONALD DICTIONARY AND THE CENTRAL BANK SENTIMENT DICTIONARY

Conversely, the linear correlation of between the negative word counts of both dictionaries is less evident.

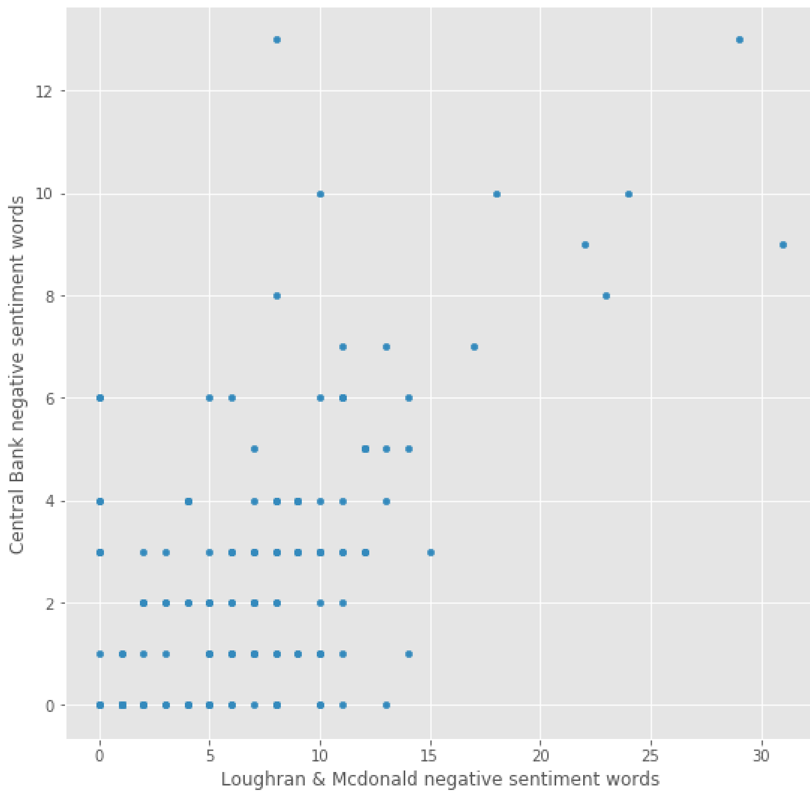

FIGURE 4. NEGATIVE WORD COUNTS BETWEEN LOUGHRAN AND MCDONALD DICTIONARY AND THE CENTRAL BANK SENTIMENT DICTIONARY

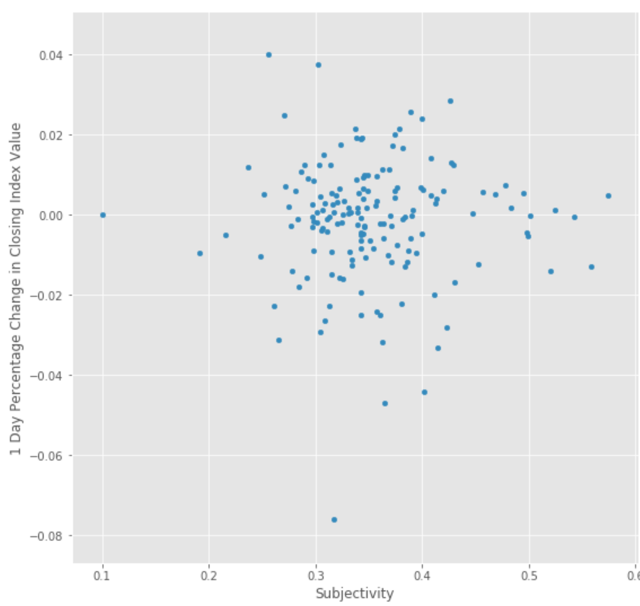

FIGURE 5. RELATIONSHIP BETWEEN SUBJECTIVITY AND THE 1 DAY PERCENTAGE CHANGE

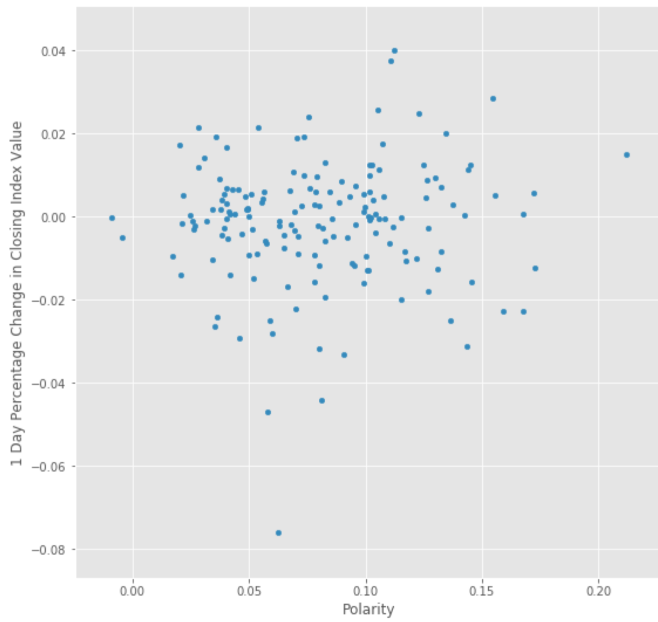

FIGURE 6. RELATIONSHIP BETWEEN POLARITY AND THE 1 DAY PERCENTAGE CHANGE

Finally, a look at the absolute value of the 1 Day percentage changes with polarity and subjectivity shows a slight negative correlation between subjectivity and absolute returns, and a more muddled relationship between polarity and the absolute change.

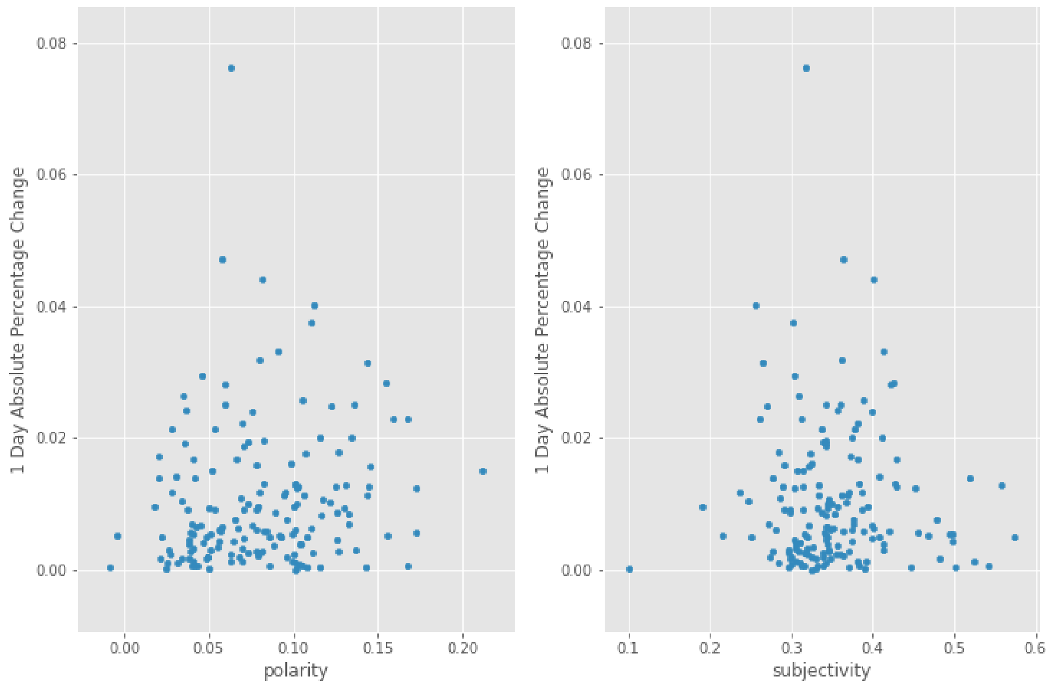

FIGURE 7. POLARITY, SENTIMENT AND THE ABSOLUTE 1-DAY PERCENTAGE CHANGE

C. Political and Policy Leaders

I include the terms of Federal Reserve Chairs and United States Presidents as categorical control variables in my data. These variables are included in part to control for political regimes, as the Federal Reserve is part of the United States Federal government. To create this set, I matched each date in the existing dataset with the relevant Federal Reserve Chair and the President.

TABLE 3—FED CHAIRS AND PRESIDENTS

Fed Chair	Greenspan	Bernanke	Yellen	Powell
Relevant business days as Chairman of the Federal Reserve	1327	2088	1045	280
Start	1/1/2000	2/1/2006	2/3/2014	2/5/2018
End	1/31/2006	1/31/2014	2/3/2018	1/3/2019
President	Clinton	Bush	Obama	Trump
Relevant days as President of the United States	275	2087	2089	551
Start	1/1/2000	1/20/2001	1/20/2009	1/20/2017
End	1/20/2001	1/20/2009	1/20/2017	1/3/2019

Note: Start dates for Greenspan and Clinton only point to the first date of the relevant period, not the start of their term.

Note: End dates for Powell and Trump only point to the last date of the relevant period, not the end of their term.

V. Models

To determine the relationship between FOMC meeting statements, related sentiment, and the stock market, I first look at the immediate effects of a Meeting Statement release itself. This is done using the following two specifications:

$$(2) y_1 = \beta_0 + \beta_1(Statement_i) + \beta_{2,j}(President_{i,j}) + \beta_{3,k}(Fed\_Chair_{i,k}) + e$$

$$(3) y_0 = \beta_0 + \beta_1(Statement_i) + \beta_{2,j}(President_{i,j}) + \beta_{3,k}(Fed\_Chair_{i,k}) + e$$

where:

- y_1 is the one-day future change in price,
- y_0 is the change in price between the close at time = 0 and the previous close.
- $Statement_i$ is whether a statement was released that day, 1 if yes, 0 if no.
- $President_{i,j}$ is a categorical variable, where the value is 1 for each jth President, with Bush as the base group.

- $Fed\_Chair_{i,j}$ is a categorical variable, where the value is 1 for each kth President, with Bernanke as the base group.

These two models are not yet enough to answer whether sentiment influences future stock price changes, but they are needed to examine the baseline effect of a statement itself.

The next three models will use the three sets of sentiment data that I generate from *TextBlob* eq. (4), the Loughran and McDonald Financial Sentiment dictionary eq. (5), and the Correa et al. Central Bank sentiment dictionary eq. (6) (Loria, 2019), (2011), (Correa, Garud, Londono, & Mislang, 2017). The dataset used in the following models contains only the data points corresponding to when a statement was released. This is done to avoid issues where a 0 for any of the sentiment variables can mean that there is no statement, or that the statement is neutral.

Below are the three models:

(4) $$y_1 = \beta_0 + \beta_1(Polarity) + \beta_2(Subjectivity) + \beta_{3,j}\left(President_{i,j}\right) + \beta_{4,k}\left(Fed\_Chair_{i,k}\right) + e$$

where *polarity* is the measure of polarity from each statement, and *subjectivity* is each statement's subjectivity. y_1 is the 1-day future change of the stock index. I use polarity as a proxy for positive and negative sentiment, with subjectivity to determine the effects they may have on short-term future returns. I keep these variables together in this specification mainly due to their origin from the same sentiment dictionary. A significant result from the polarity and subjectivity of the text will reinforce whether sentiment from FOMC meeting statement has an effect on future stock index prices.

(5) $y_1 = \beta_0 + \beta_1(LM\_POS) + \beta_2(LM\_neg) + \beta_{3,j}(President_{i,j}) + \beta_{4,k}(Fed\_Chair_{i,k}) + e$

(6) $y_1 = \beta_0 + \beta_1(CB\_POS) + \beta_2(CB\_neg) + \beta_{3,j}(President_{i,j}) + \beta_{4,k}(Fed\_Chair_{i,k}) + e$

Equations (5) and (6) are similar in that they are essentially the same model, but with different inputs. The two specifications seek to find a relationship between both the existence of positive and negative sentiment words and future returns. Unlike the method used in *Sentiment in central banks' financial stability reports*, where an index was created based on the counts of negative words, positive words, and total word count, I decide to keep the positive and negative counts in their raw form to avoid losing any information in index creation (Correa, Garud, Londono, & Mislang, 2017). Using this method, I can determine whether the presence of purely positive and negative sentiment words can affect returns. For all models mentioned above, categorical variables or Federal Reserve Chair and President are in place to act as control variables for political regimes.

VI. Results

The first model, examining only statement effects on a one-day future percentage change, shows a small but significant estimated effect at the 10% level, which can be explained by the price change of the previous day. Interestingly, when Presidents and Fed Chairs are controlled for, the coefficients during President Barack Obama's term returns a more statistically significant, positive number (Table 4). However, little can be drawn from this as equities were in an uptrend for most of President Obama's term. The returned estimate from the Statement coefficient with the Previous Day percentage change is positive, and significant at the 1% level. This result is in line with Lucca and Moench's research on Pre-FOMC Announcement price drifting (Lucca & Moench, 2015). While I measured the change from previous close to current close, and their study focuses on the period before announcements. Although my results do not confirm Lucca & Moench's study, it reinforces their argument.

TABLE 4—REGRESSION RESULTS, STATEMENT ONLY

	1-Day Percentage Change Model No Dummies	1-Day Percentage Change Model All Dummies	Prev. Day Percentage Change
Intercept	0.0003	-0.000414	-0.000534
	(0.000176)	(0.000441)	(0.000442)
Statement	-0.0017*	-0.001654*	0.003113***
	(0.000960)	(0.000960)	(0.000962)
Clinton		-0.000082	-0.000236
		(0.000813)	(0.000815)
Obama		0.0011**	0.001101**
		(0.000554)	(0.000555)
Trump		0.0014	0.001568
		(0.001020)	(0.001022)
Greenspan		0.0005	0.000460
		(0.000555)	(0.000556)
Powell		-0.0008	-0.001071
		(0.001175)	(0.001177)
Yellen		-0.000296	-0.000327
		0.000553	(0.000554)
No. Obs.	4814	4814	4814
R^2	0.001	0.002	0.003

Standard errors in parentheses.

Source: Author calculations.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Next, I look at the results of applying a polarity and subjectivity variable to all statement dates. Upon doing so, I find that both polarity and subjectivity returns positive coefficients. A positive coefficient for polarity indicates a positive correlation between polarity and the subsequent percentage change for the next day.

That is positive sentiment is tied to positive price changes, while a higher subjectivity measure representing These results are statistically insignificant at any meaningful P-value level. This is not surprising, as Loughran and McDonald's research indicated the possibly of irrelevance and differing sentiment meanings when applying non-financial sentiment analysis to a financial text (2011). With this method, it may be impossible to predict the direction of future returns. When the percentage change value is converted to an absolute number, it becomes significant among the polarity and subjectivity variables. While I am wary of the results' polarity significance, as mentioned previously, the significance of the negative subjectivity coefficient has interesting implications. This implies that a higher subjectivity measure, where subjectivity is close to 1, will yield a lower absolute value of the one-day future return (Table 5). As the subjectivity variable exists between 0 and 1, where 0 is objective and 1 is subjective, this may possibly indicate that a more objective statement would lead to a higher magnitude of the one-day future price change (Table 5). The subjectivity measure is also interesting, as subjectivity is based mainly on the existence of modal words, specifically language intensifiers, which mostly hold similar meanings across different contexts.

TABLE 5—REGRESSION RESULTS, POLARITY, SUBJECTIVITY

	1-Day Percentage Change Model All Dummies	Absolute 1-Day Percentage Change Model All Dummies
Intercept	-0.0155	0.0230***
	(0.008600)	(0.006)
Polarity	0.013056	0.0427 *
	(0.035487)	(0.025)
Subjectivity	0.025274	-0.0289 **
	(0.020089)	(0.014)
Clinton	-0.011336*	0.0001
	(0.005818)	(0.004)
Obama	0.000704	-0.0038
	(0.003804)	(0.003)
Trump	-0.000528	-0.0066
	(0.006352)	(0.004)
Greenspan	0.010148**	-0.0072**
	(0.004294)	(0.003)
Powell	0.003429	-0.0030
	(0.007268)	(0.005)
Yellen	0.005696	-0.0058**
	(0.003771)	(0.003)
No. Obs.	162	162
R^2	0.067	0.11

Standard errors in parentheses.

Source: Author calculations.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Finally, in Table 6, I examine the results of both the LM sentiment dictionary model, as well as the CB sentiment dictionary model. For the Loughran – McDonald dictionary, there seems to be a weak relationship between the number of positive and negative words as described by the dictionary. Again, in this case, I propose that this may be a result of Loughran and McDonald's idea that only contextual sentiment dictionaries should have relatable effects.

TABLE 6—REGRESSION RESULTS: LM, CB SENTIMENT

	LM 1-Day Percentage Change Model All Dummies	CB 1-Day Percentage Change Model All Dummies
Intercept	-0.003148	-0.002177
	(0.002983)	(0.002929)
Pos Words	-0.000010	0.000382
	(0.000304)	(0.000441)
Neg Words	-0.000333	-0.001315**
	(0.000250)	(0.000532)
Clinton	-0.009012	-0.009534
	(0.005629)	(0.005565)
Obama	0.002096	-0.000063
	(0.004599)	(0.004094)
Trump	-0.001386	-0.001687
	(0.006378)	(0.006227)
Greenspan	0.009721**	0.009934**
	(0.004294)	(0.003946)
Powell	0.001279	-0.000660
	(0.007254)	(0.007200)
Yellen	0.005696	0.001717
	(0.003748)	(0.003865)
No. Obs.	162	162
R^2	0.067	0.093

Standard errors in parentheses.

Source: Author calculations.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

However, when applying the Central Bank method, there is a negative correlation between negative words as defined by the Central Bank dictionary, and by the one period future price change. Essentially, it appears that the greater number of negative words present in the statement, the larger the effect, as multiplied by the negative coefficient, on following prices. Conversely, positive words appear to have a positive coefficient as expected, but this approach does not yield a statistically significant result (Table 6).

VII. Discussion and Conclusion

This paper produces three notable results. First, it appears that polarity sentiment created by a non-contextual sentiment dictionary will not be effective in financial applications (Table 5). Second, the subjectivity of a statement has a negative but limited correlation with the magnitude of the future one-day returns (Table 5). While this may be a result of using non-contextual subjectivity values, it could also mean that market participants view the Federal Reserve's subjective statements as having greater clarity regarding the direction that the Committee will take. A more subjective statement from the Federal reserve may give clearer signals, resulting in smaller price movements. In Table 5, the regression result suggests a maximum subjectivity measure of 1 may have an attributable effect on the magnitude equal to 0.0289, or 2.89%. Third, the quantity of negative sentiment words as defined by a central bank focused dictionary has a significant effect on the immediate one-day returns of the S&P (Table 6). For each negative word derived from the Central Bank dictionary in the statement, the correlating percentage change is -0.001315, or -0.13%. Positive words, defined in the same context, do not have the same significance in effect. An explanation for this effect is that market participants may not be looking at FOMC meetings for significant good news. As markets represent the present value of future earnings and future economic factors, FOMC meeting statements may only be used for participants to decide whether the current economic environment is increasing or decreasing in risk. In the event of increasing risk while financial stability is decreasing, market participants may be engaged in liquidating activity in the market. However, if risk is decreasing in the economic environment, market participants may look back towards discounting individual corporate earnings. From a Central Bank perspective, if the goal is to avoid declines and the creation of risky environments in the stock market following a statement release, the Bank could limit its use of negative sentiment words in a financial stability context. While some of these results are statistically significant, the R-squared value for these regression models are extremely small. With 0.067 and 0.093 between the two regressions in Table 6, the models only explain 6 to 9 percent of the total variation seen in the Index price changes. These results may indicate an effect, but they are not predictive. Luckily for economic theory and unluckily for us, the stock market remains difficult to predict.

As the study of natural language processing is still growing, there is high potential for further studies that aim to decipher sentiment. As suggested by my research, the idea of sentiment does not hold across multiple disciplines, even ones that are similar in nature. This study has showcased this using the disciplines of finance and economics. Further non-lexicon-based analyses can be done to expand upon this work, such as a study that uses machine learning techniques to determine significant words and phrases that give sentiment in a central banking context. My data in this study was also limited, as the available data I had was at a daily level; thus, the only dependent variables available to study were the changes on a day-by-day basis. As many stock market participants know, large changes and fortunes can happen in the span of minutes. An intra-day study of FOMC meeting statement sentiment effects might prove fruitful.

REFERENCES

Board of Governors of the Federal Reserve System. (2019, April 20). *The Fed - Federal Open Market Committee*. Retrieved from Federal Reserve Board: https://www.federalreserve.gov/monetarypolicy/fomc.htm

Bognár, E. K. (2016). Applying big data technologies in the financial sector – using sentiment analysis to identify correlations in the stock market. *Computational Methods in Social Sciences, 4*(1), 5-12.

Correa, R., Garud, K., Londono, J., & Mislang, N. (2017). Sentiment in central bank's financial stability reports. *IFDP working paper series.*(Federal Reserve Board).

De Smedt, T., & Daelemans, W. (2012). Pattern for Python. *Journal of Machine Learning Research*(13), 2063-2067.

Frankel, M. (2019, January 30). *Here's Why Stocks are Soaring After the January Federal Reserve Meeting.* Retrieved from The Motley Fool: https://www.fool.com/investing/2019/01/30/heres-why-stocks-are-soaring-after-the-january-fed.aspx

Ito, R., Izumi, K., Sakaji, H., & Suda, S. (2017). Lexicon Creation for Financial Sentiment. *Journal of Mathematical Finance*(7), 896-907.

Loria, S. (2019, April 19). *TextBlob: Simplified Text Processing - TextBlob 0.15.2 documentation*. Retrieved from TextBlob: Simplified Text Processing: https://textblob.readthedocs.io/en/dev/index.html

Loughran, T., & McDonald, B. (2011, February). When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks. *The Journal of Finance, 66*(1), 35-65.

Lucca, D. O., & Moench, E. (2015, February). The Pre-FOMC Announcement Drift. *The Journal of Finance, 70*(1), 329-371.

Neuhierl, A., & Weber, M. (2018, August 31). *VOX*. Retrieved from Predictable movements in asset prices around FOMC meetings : https://voxeu.org/article/predictable-movements-asset-prices-around-fomc-meetings

Ren, R., Wu, D. D., & Liu, T. (2019, March). Forecasting Stock Market Movement Direction Using Sentiment Analysis and Support Vector Machine. *IEEE Systems Journal*, *13*(1), 760-770.

Rosa, C. (2018, December). The Financial MarketEffect of FOMC Minutes. *FRBNY Economic Policy Review*, 67-81.

S&P Dow Jones Indices. (2019, April 20). *S&P 500® - S&P Dow Jones Indices.* Retrieved from S&P Dow Jones Indices: https://us.spindices.com/documents/methodologies/methodology-sp-us-indices.pdf

S&P Dow Jones Indices. (2019, April 20). *S&P 500® S&P Dow Jones Indices*. Retrieved from S&P Dow Jones Indices: https://us.spindices.com/indices/equity/sp-500

Sarhan, A. (2018, September 26). *What Does The Fed Meeting Mean For Stocks?* Retrieved from Forbes: https://www.forbes.com/sites/adamsarhan/2018/09/26/what-does-the-fed-meeting-mean-for-stocks/#68d60ae02a8b

Smales, L., & Apergis, N. (2017). Does more complex language in FOMC decisions impact financial markets? *Journal of International Financial Markets, Institutions & Money, 51*, 171-189.

Zhang, G., Xu, L., & Xue, Y. (2017, March). Model and forecast stock market behavior integrating investor sentiment analysis and transaction data. *Cluster Computing*, *20*(1), 789-803.