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

By MICHAEL MAK*

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 S&P 500 Index. I generate sentiment using several sentiment dictionaries, financial and otherwise from previous bodies of work. I find the 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.

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Sentiment analysis is branch of textual analysis where a piece of text is given a quantitative number, usually representing the text's polarity. As applied uses of sentiment analysis in Economics and Finance is still growing, there is opportunity to apply this method of analysis to statements from the Central Bank. In the stock market, movements and policy changes from the Federal Reserve, the United States' central bank is closely watched. However, there is a gap in research in studying the sentiment of key press releases and statements. In this paper, I take a 19-year period of Federal Reserve statements, following policy meetings, and generate a quantitative proxy for sentiment, and study its short-term effects on the United States stock market. To generate sentiment, I take three differing sentiment dictionaries from previous bodies of work and compare the results. One dictionary is generated from non-Economic or Finance related context (De Smedt & Daelemans, 2012). Another dictionary is based off Financial specific terms and meanings (Loughran & McDonald, 2011). The last sentiment dictionary was created from a collection of Central Bank statements throughout 63 different monetary bodies (Correa, Garud, Londono, & Mislang, 2017). In this paper, I describe the parts of the United States monetary system relevant to this study, and I also look at previous literature in researching central bank public statements and text-based analysis. After retrieving and parsing the relevant statements, I use Python to convert the text data in to variables such as polarity, subjectivity, and positive and negative word counts. I find that sentiment dictionaries that were created for general use are not effective in use in economic of financial 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. FOMC, Meetings, and Statements.

The FOMC (Federal Open Market Committee) is a group within the United States' Federal Reserve that meet and set the monetary policy of the United States Central Bank. In this case, monetary policy is the Federal Reserve's actions to affect the nation's money supply and interest rates. The main goal of monetary policy is to promote optimal and steady economic growth, while balancing variables such as employment, wage growth, inflation rate, and gross domestic product. Currently, the Federal Reserve conducts monetary policy using three tools, the ability to set the discount rate, reserve requirements, 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 each other within the Federal Reserve. Reserve requirements are the requirements for banks and similar institutions to hold a portion of their total capital in Federal Reserve banks. This requirement serves to not only ensure there is sufficient capital on hand for banks, but to also control money liquidity and supply. Open market operations are the ability for the Federal Reserve 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 cashflows.

The FOMC meets regularly to discuss and determine the current and future economic state, and how to set policy. Since 1981, there are eight scheduled meetings each year, with varied unscheduled meetings and conference calls (Lucca & Moench, 2015). Whether or not any action is taken, since May 1999, a public statement is always released after the meeting (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 are released roughly around 2:15pm Eastern Standard Time from September 1994 to March 2011 (2015). However, they note that release time has fluctuated since April 2011, with release time ranging between 12:30 to 2:00 pm. Generally, FOMC statements will include the Committee's view on the economy, projections in to the future, and changes in monetary policy, all of which will affect an investor's expectations of future cash flows. Changes between statements are watched very closely by investors and capital market participants in judging 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 United States 500 publicly traded firms 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 as of February 20th, 2019 (S&P Dow Jones Indices, 2019). However, as it 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 market open takes place at 9:30 am and market is closed at 4:30 pm. Eastern Time.

III. Related Literature

The idea of examining FOMC statements and subsequent reactions from the stock market is widely discussed in business media, and widely watched by participants in capital markets. Every time an FOMC meeting nears, there is a flurry of articles and commentary trying to predict the Federal Reserve's tone and how it will affect the markets. For example, a *Forbes* article published in September 2018, suggests the Federal Reserve will almost definitely raise Federal Fund rates next meeting, and that "The stock-market could get more challenging and volatile" (Sarhan, 2018). More recently, an article on *The Motley Fool* discusses why and how the recent FOMC statement has led to the stock market to gain (Frankel, 2019). An analysis on *The Street* suggest that there is a connection between market volatility, FOMC policy decisions, and subsequent response by the markets

(Beeson, 2018). The research discusses the possibility of market volatility being a factor in rate hike probabilities (Beeson, 2018). The article also suggests that recent market volatility may influence the strength of the reaction post-statement (Beeson, 2018). Research conducted by Neuhierl and Weber indicate that the equity markets may have a predictable effect post policy decision announcement (Neuhierl & Weber, 2018). Their research analysis notes a shock in prices that may continue for 15 days, averaging returns of 4.5% (Neuhierl & Weber, 2018). Carlo Rosa, an economist in the Federal Reserve Bank of New York, has authored an article on the effect of FOMC minutes to 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 nonfarm payroll (Rosa, 2018). Rosa also indicated a weakening response to the minutes since 2008, suggesting increased transparency of the Federal Reserve as an explainer (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 advent of natural language processing and computational sentiment analysis techniques, research has been conducted modeling stock market returns to various sources of sentiment. A commonly cited 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 using a networked machine learning approach, created 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).

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, in part due change in 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 variables that I create from the S&P 500 Index are the future percentage changes over an n-period of days. The formula for calculating the n-day percentage change is

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

where y_t is the value closing value of the index at time t and n is the number of days forward, looking ahead. 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.

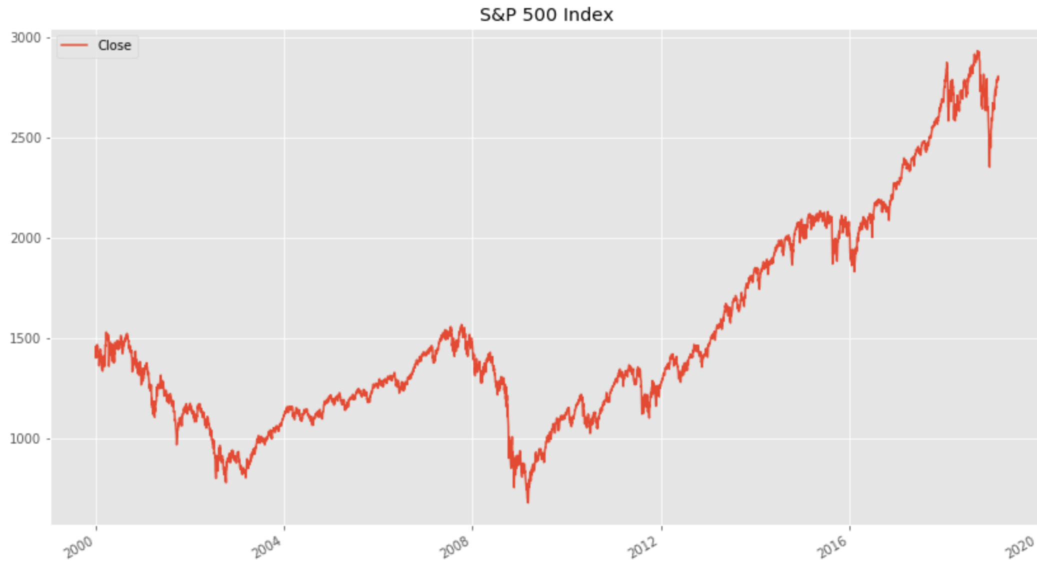

FIGURE 1. S&P 500 INDEX, DAILY CLOSE, JANUARY 2000 TO MARCH 2019

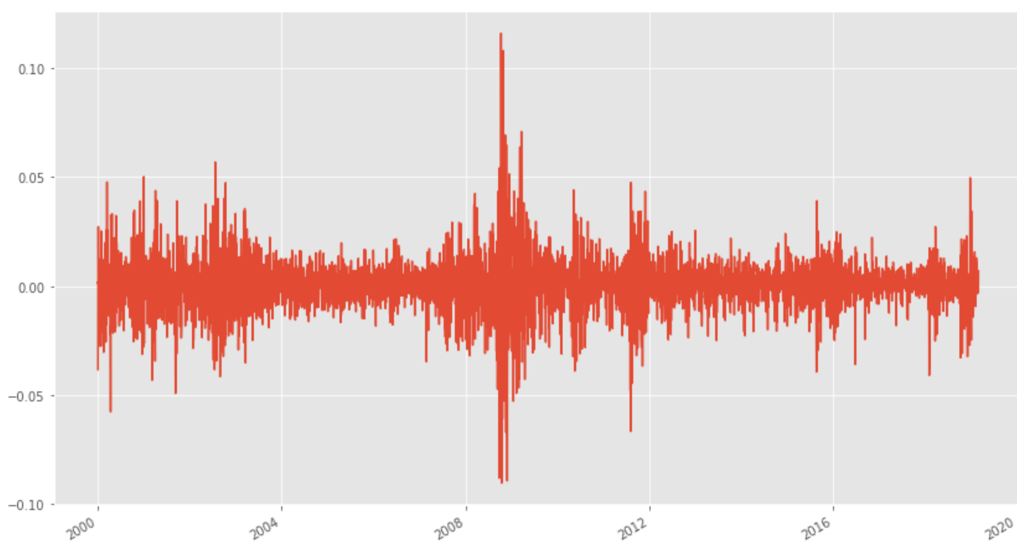

FIGURE 2. S&P 500 INDEX, DAILY PERCENTAGE CHANGE ON CLOSE,
JANUARY 2000 TO MARCH 2019

B. Sentiment Data

FOMC statements were acquired from the Federal Reserve Board website, (https://www.federalreserve.gov/monetarypolicy.htm). This was done by a Python-based web crawler program that I programmed 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 only text cleaning that the program does is removing escape characters from the text data (\n, \r, \t, \xa0, \u2003, \u2011) this is deemed unnecessary as its 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 a FOMC meeting statement was released. This was done by another web crawler that I wrote, which parsed the relevant dates from the calendars available on the Federal Reserve Board website. The retrieved dates were then used 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 it using several methods and returns 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.

Polarity and Subjectivity. — The polarity and subjectivity variables are generated by means of a Python package known as *TextBlob* (Loria, 2019). This package itself is a wrapper of several natural language processing libraries in written 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 negativity represents a more negative sentiment from the text, and a positive number is more positive. 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, LM_neg. — LM_POS and LM_neg are both counts of words from the passed text data and matching 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, CB_neg. — CB_POS and CB_neg positive and negative word counts generated using the same method as the LM_POS and LM_neg counts. In this case, the difference is the positive and negative word lists that are passed in to the function. The dictionary used for these values was from the work of Correa et al. in *Sentiment in Central Banks' Financial Stability Reports*, where words used and context is derived from central bank reports (Correa, Garud, Londono, & Mislang, 2017). The methodology used to retrieve positive and negative word count is the same as the previous Loughran and McDonald sentiment word counts. The method of negation words is also applied.

Word_count. — 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 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.

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

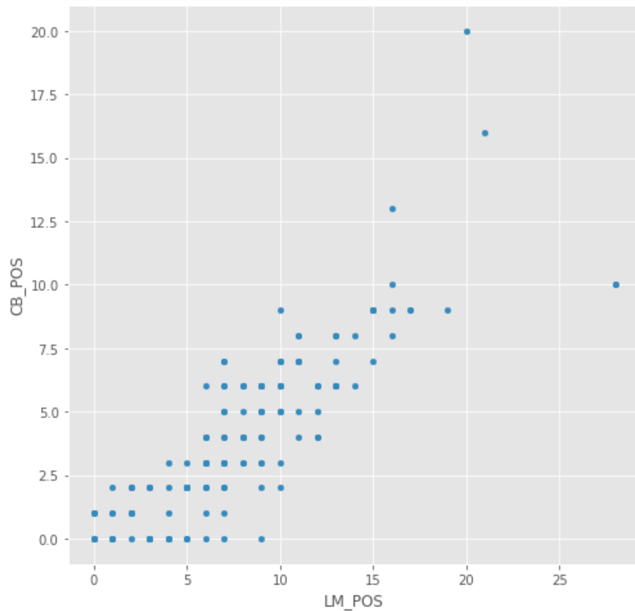

FIGURE 3. POSITIVE WORD COUNTS BETWEEN LOUGHRAN AND MCDONALD DICTIONARY AND THE CENTRAL BANK SENTIMENT DICTIONARY

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

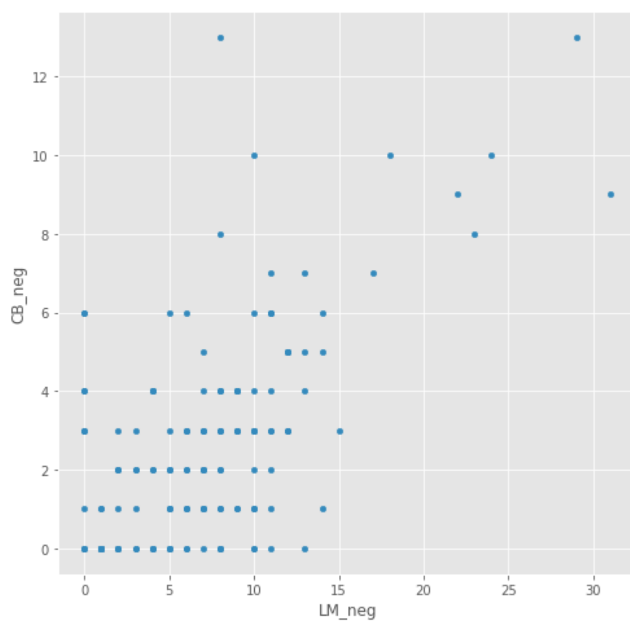

FIGURE 4. NEGATIVE WORD COUNTS BETWEEN LOUGHRAN AND MCDONALD DICTIONARY AND THE CENTRAL BANK SENTIMENT DICTIONARY

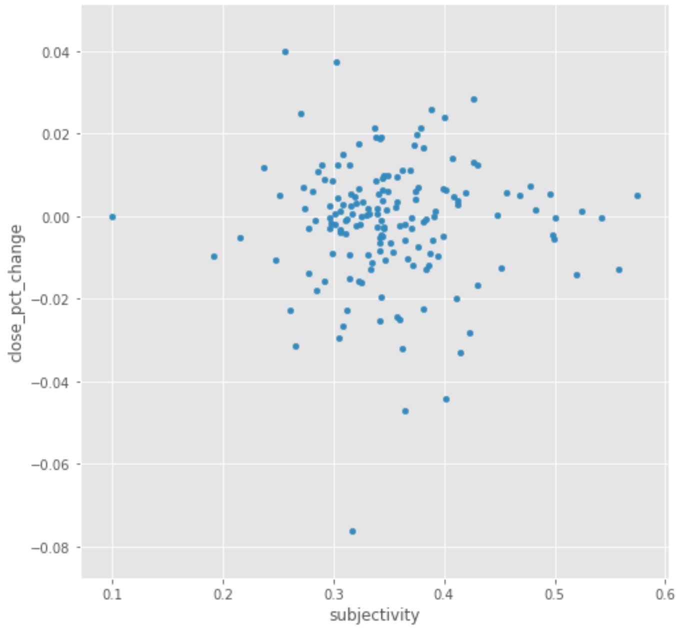

FIGURE 5. RELATIONSHIP BETWEEN SUBJECTIVITY AND THE 1 DAY PERCENTAGE CHANGE

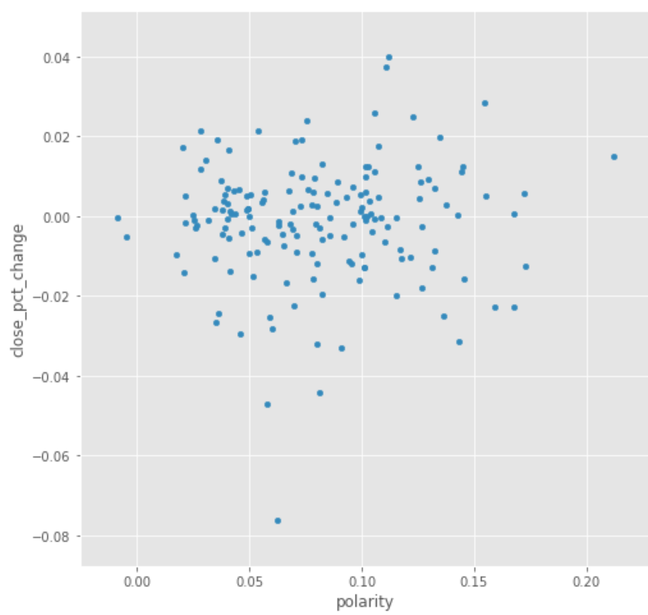

FIGURE 6. RELATIONSHIP BETWEEN POLARITY AND THE 1 DAY PERCENTAGE CHANGE

Finally, a look at the absolute 1 Day percentage change with polarity and subjectivity show a slight negative correlation between subjectivity and absolute return, and a more muddled relationship between polarity and the absolute change.

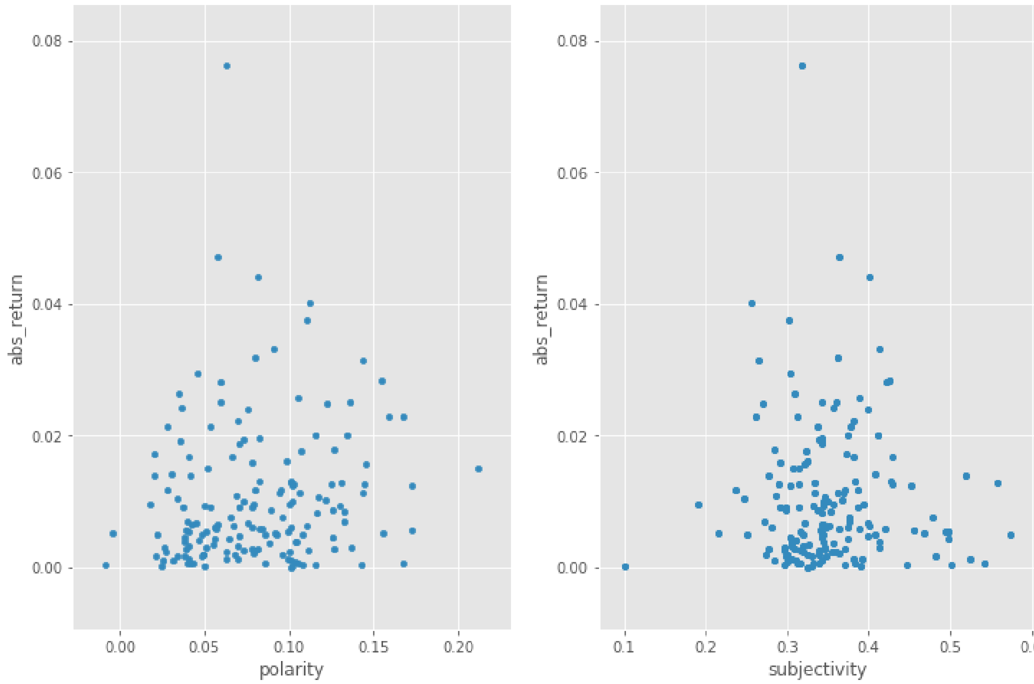

FIGURE 7. POLARITY, SENTIMENT AND THE ABSOLUTE 1-DAY PERCENTAGE CHANGE

C. Political and Policy Leaders

I also 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 a 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 is needed in order to examine the baseline effect of a statement itself.

The next three models will be using 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 are only when there is only a statement release. This is 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.

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

where Polarity is the measure of polarity from each statement, and Subjectivity is each statement's subjectivity. y_1 is the one-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 as an effect on future stock index prices.

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

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

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 relation 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 its raw form to not lose 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, show a small but significant at the 10% level estimate, which can be explained by the price change of the previous day. Interestingly, when Presidents and Fed Chairs are controlled for, Mr. Obama’s coefficient returns a more significant, positive number. However, little can be drawn from this as equities were in an uptrend for most of Mr. 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). Where I measure the change from previous close to current close, and their study is 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 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. When I do so, Polarity returns a positive coefficient, with subjectivity also returning a positive coefficient. However, 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 a direction of future returns. When the percentage change value is converted to an absolute number, significance appears amongst the polarity and subjectivity variables. While I am wary of the result's polarity significance, as mentioned previously, the significance of the negative subjectivity coefficient is interesting. This implies that a higher subjectivity measure, where subjectivity is close to 1, the lower the absolute value of the one-day future return is. As the subjectivity variable exists between 0 and 1, where 0 is objective and 1 is subjective, this would possibly mean that a more objective statement would lead to a higher magnitude 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 for the most part hold similar meanings across different context.

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, I examine the results of both the LM sentiment dictionary model, as well as the CB (Central Bank) sentiment dictionary model. For the Loughran – McDonald dictionary, there seems to be little, if at all any relationship between the number of positive and negative words as described by the dictionary. Again, in this case, I propose that Loughran and McDonald's idea that only contextual sentiment dictionaries should have relatable effects to be the main reason.

TABLE 6—REGRESSION RESULTS: LM, CB SENTIMENT

	LM 1-Day Percentage Change Model All Dummies	CB 1-Day Percentage Change Model All Dummies
Intercept	-0.0031	-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	-0.0090	-0.009534
	(0.005629)	(0.005565)
Obama	0.0021	-0.000063
	(0.004599)	(0.004094)
Trump	-0.0014	-0.001687
	(0.006378)	(0.006227)
Greenspan	0.0097 **	0.009934**
	(0.004294)	(0.003946)
Powell	0.0013	-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 the one period future price change. That is, the more negative words there are in the statement, the larger the effect, as multiplied by the negative coefficient, on following prices. Conversely, positive words have a positive coefficient, as expected, but does not have a statistically significant result.

VII. Discussion and Conclusion

There are three results of note from the previous section. First, it appears that polarity sentiment created by a non-contextual sentiment dictionary will not be effective in financial applications. Second, the subjectivity of a statement has a negative, but limited correlation on the magnitude of the future one-day returns. While this may be a result of using non-contextual subjectivity values, it could also mean that market participants view subjective statements from the Federal Reserve to be clearer on the direction the Committee is taking. Higher subjectivity giving clear signals, resulting in smaller price movements. Third, the amount of negative sentiment words as defined in a financial stability, central banking context as a significant effect on the immediate one-day returns. Positive words as defined in the same context, do not have the same significance in effect. An explanation to this effect is that market participants may not be looking at FOMC meetings for significant good news. As markets price off 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 where risk is increasing, as financial stability is decreasing, market participants may be engaged to liquidate positions in the market. Whereas if risk is decreasing in the economic environment, market participants look toward individual corporate earnings for a further direction. From a Central Bank perspective, if the goal was to not spark declines and 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.

As the study of natural language processing is still growing, there is more work to be done with deciphering sentiment. As found in my research, the idea of sentiment does not hold across multiple disciplines, even ones that are similar in nature, in this case Finance and Economics. Further non-lexicon-based analyses can be done on this work, such as using machine learning techniques to determine actual 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. This led to the only dependent variables available to study being changes from one day to another. As many stock market participants know, large changes and fortunes happen in the span of minutes. An intraday study of FOMC meeting statement sentiment effects might prove fruitful.

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