Understanding the Federal Reserve: Predicting FOMC Decisions Using Machine Learning

Liam Chentoufi

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Abstract

This research aims to explore the relationship between public communication from Federal Reserve Officials and changes to the target range of the federal funds rate. Such changes to the target range, affect the real economy by altering the investment/savings decisions of households and businesses. To achieve the Federal Open Market Committee's (FOMC) goal of maximum employment and stable prices, forward guidance is another tool utilized. Economic theory suggests that future expectations are an important factor of monetary policy which highlights the importance of forward guidance due to its unique power to direct expectations. Sentiment analysis will be applied to text web-scraped from the Board of Governors speech archive to attempt at prediction of monetary policy decisions based on the preceding attitudes expressed in published communications. By closely analyzing FOMC statements, one may be able to better understand its "reaction function", namely, the committee's projections and the actions it feels are necessary to meet broader goals.

1. Introduction

The Federal Reserve System (Fed), its function, and image, has changed greatly since inception, and will likely continue to evolve in line with the broader economy. In only several decades, customs surrounding the communication of its efforts with the global public have been immensely transformed.

In 2011 on the 27th of April, then Chairman of the Board of Governors (BOG), Ben Bernanke, held the first press conference after a routine FOMC meeting to discuss the committee's deliberations. This tradition has been continued by the succeeding Chair, Janet Yellen, along with today's Chair, Jerome Powell. As Chair Bernanke expresses, "[a] more open Fed, in my view, is both a more effective and more democratically legitimate institution" (Bernanke, 2013). Today, transparency is not only used to stabilize or inform markets, but since the 2008 Global Financial Crisis, forward guidance has been used as a tool of monetary policy, to actively influence markets and financial conditions, providing additional economic stimulus by reaffirming the interest rate or balance sheet policy already adopted.

As recent as early 2022, language alone has proven it can prematurely tighten borrowing conditions. This is an indication of a highly credible Fed in the eyes of market participants. Decades of tenable forecasts has made FRO communications a reliable indicator of what is to come. As reference, prior to the hiking campaign adopted in March 2022, financial conditions showed signs of tightening months before material changes in the federal funds target range due to the signaling effect of forward guidance.

As recently as the 1990's this would have been oddly against the norm. In 1998, Chair Greenspan, who preceded Bernanke, stated, "[s]ince I've become a central banker, I've learned to mumble with great incoherence. If I seem unduly clear to you, you must have misunderstood what I said" (Greenspan, 1987). This ambiguity was intentional as Greenspan had preferred the Fed to remain unpredictable. The consensus at the time was that this would grant the Federal Open Market Committee (FOMC) more policy space to pursue their goals. In no way is this intended to discredit Chair Greenspan for he served a distinguished five-term tenure, during which, helped to facilitate the longest US economic expansion. All told, when considering the evolution of "Fedspeak", the difference between the ideals of Greenspan and Bernanke become pertinent.

This paper aims to explore Federal Reserve communication over the 2006-2023 period and serves as an attempt at quantifying the effect of forward guidance included the published speeches of Fed officials. Due to the FOMC structure in which District Presidents rotate voting powers, Board of Governors' speeches will be of particular focus, given their voting power permanence. A long short-term memory (LSTM) recurrent neural network (RNN) is employed – which is suitable for time-series datasets – to predict upcoming meeting decisions given current economic conditions and the BOG sentiment score over the intermeeting period. Further, a multinomial logistic regression is used to better understand the individual impact of sentiment on decision-making. This preliminary research has found a negative relationship between text of dovish sentiment and the probability of increasing rates, in line with expectations.

2. In the Literature

For long, it has been understood that the tone in which a speech or statement is given can have broader implications for markets. As a reference, Chair Powell's hawkish Jackson Hole speech outlined what may be necessary to get inflation down from its 2022 highs. "The speech was followed by more than $6 Trillion USD loss in equity valuation over the next 3 days" (Shah et al., 2023).

In previous research in which sentiment analysis is used to predict market movement, the text classification models utilized are made highly proprietary. In such cases, research outcomes are shared but the restricted nature of the tools used for analysis poses a barrier to reproduction of the study. This decision is understandable, considering models of the like are often used in to supplement decision making in the case of financial firms and investment managers. That said, many similar analyses have been conducted by public institutions such as the Bank for International Settlements and the Federal Reserve Bank of New York, among others.

In 2017, Martens et al. from within the Bank for International Settlements published their paper titled “Between hawks and doves: measuring Central Bank Communication”. In their approach, they analyze media reports to grasp the relative hawkish/dovish sentiment surrounding the economic environment. Authors utilize a support vector machine classifying model and prove its accuracy in predicting European Central Bank interest rate moves based on media sentiment. Their findings prove to be true the theorized impact of forward guidance.

Within the New York Fed, Adams et al. apply similar tools in the context of the Federal Reserve System. The authors utilize Twitter engagement data to judge social sentiment in the context of its implications for credit and financial market movements. Their findings hold that discussion on the Twitter platform were able to provide enough sentiment context to assist in predicting stock market returns for the following day. The analysis was even able to capture negative reactions to sentiment after the occurrence of an unexpected monetary policy tightening event. In order to grasp a text’s sentiment, authors use the fine-tuned machine learning model for financial sentiment analysis, FinBERT.

Turning to the private sector, Kan Chen from within BBVA Research, used text analysis to group FOMC statements into positive, negative, and neutral categories. The author finds that during the Great Recession, the share of positive words within a statement had fallen greatly. At the onset of the recession, specific statements went so far as holding a 0% share of positive words. As time passed, the share of positive words began to grow before peaking in the final months of the Great Recession. Interestingly, negative sentiment was highest when the Fed had set forth on its first round of quantitative easing in the midst of the recession. This finding relates heavily to the idea that expansionary actions are not necessarily met with positive sentiment. Expansionary measures may be occurring against a severe economic backdrop. Finally, Chen also uncovered the high correlation between negative sentiment and market uncertainty, using the VIX volatility index as a proxy for market uncertainty.

As of April 2023, Morgan Stanley has patented an AI powered tool to analyze FOMC statements and serve as a leading indicator for monetary policy actions. (Zhang et al., 2023) The authors have found that sentiment scores produced for FOMC statements can serve, on average, as a one-year leading indicator of FOMC decisions. In their research, sentiment scores were used to predict changes to interest rates, the yield-curve, and the US exchange rate.

The in recent "Trillion Dollar Words: A New Financial Dataset, Task & Market Analysis", Shah et al. formulate a classification model using the RoBERTa framework developed by Meta (Meta, 2019). The transformer architecture allows for the nuanced difference between hawkish, dovish, and neutral text to be uncovered. Shah et al. pre-train their classification model on Federal Reserve published press conference, meeting minutes, and speech textual data.

3. Data Collection

This paper has taken a slightly different approach to the aforementioned pieces of literature in the sense that BOG speeches are prioritized due to their permanent voting powers. The primary assumption being made is that speeches given by members whose vote is guaranteed at the approaching FOMC meeting will be scrutinized most heavily among the nineteen FOMC participants. That said, all FRO discission is rich in information regarding the committee's economic outlook and general policy tilt and will be explored in future analyses. Furthermore, speeches will be the only source of real-time opinions. As highlighted in Zhang et al., FOMC statements are published on a less frequent basis which reduces the amount of available data to be used during analysis. The exciting aspect of analyzing speech transcripts is that Fed officials publish speeches *within* intermeeting periods. An attempt will be made to relate the overall sentiment expressed in a meeting period to anticipate actions taken at the following committee meeting.

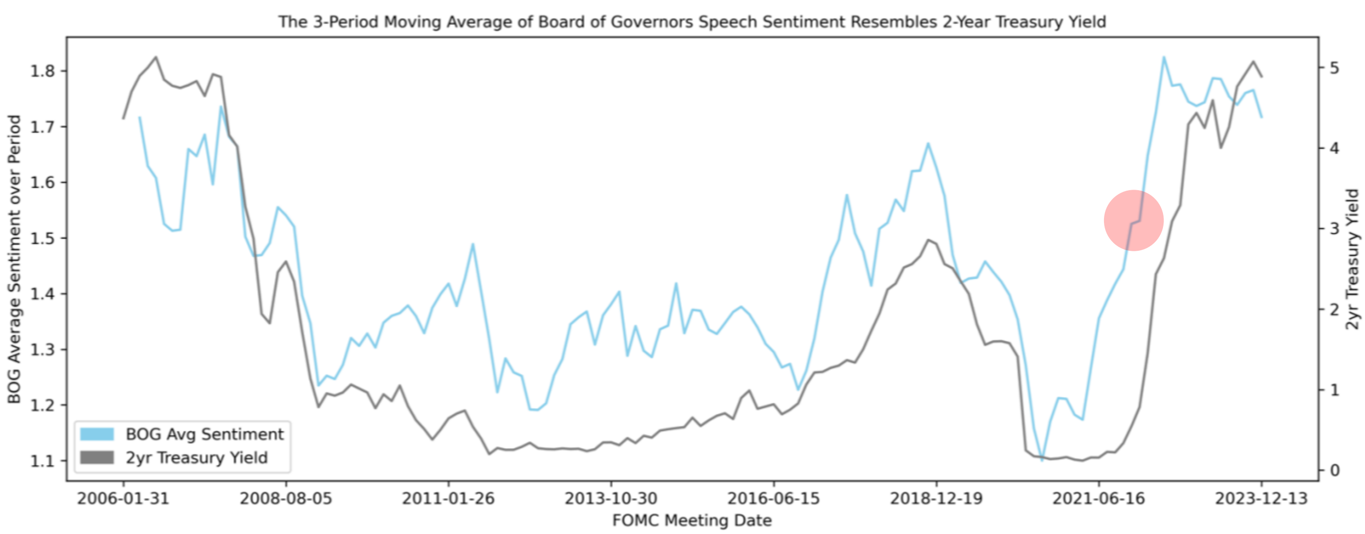
Speech data was obtained through the BOG speech archive found at (federalreserve.gov/newsevents/speeches.htm). Python's Selenium and BeautifulSoup packages were used to collect data ranging from January 2006 to December 2023. Additionally, meeting schedules for each year were web-scraped from the BOG calendar webpage. This calendar schedule will be useful for aggregating speech data and control variables by the official FOMC meeting period. It will be most helpful to separate speeches by the period they fall within as Fed official forward guidance is heavily context specific.

After obtaining raw text data from the BOG website, each speech is split into two sentence chunks. This was done primarily due to a restriction on text length that could be input into the text classification model. Also, by splitting the speech into smaller components, we enhance a singular statement's context. As noted by Shah et al., "the Fed is known to project a stance but often accompanies this with a moderating statement that serves as a counterweight to the original stance" (Shah et al., 2023). A consistent worry is that too much context would dilute any hawkish or dovish opinions expressed. On the other hand, too short of a string would leave little context for the model to base its sentiment prediction on.

After data cleaning and speech splitting, roughly 50,000 two sentence chunks were ready to be labeled. As referenced earlier, a pre-trained model created by Shah et al. in their recent research "Trillion Dollar Words: A New Financial Dataset, Task & Market Analysis" was utilized.

Prior to their model training, each statement was human annotated for its relative hawkish/dovish stance. Such data was then input into an open-source transformer-based machine learning model, RoBERTa-large, to accurately predict what makes a statement "hawkish" or "dovish" based on text similarities across the data provided. After their model was developed, it was ready to ingest unseen text and classify it as "hawkish", "dovish", or "neutral", based on the content of the statement.

Python's HuggingFace-Transformers package was used to load the Shah et al. *FOMC-RoBERTa* model to classify the scraped and split BOG speeches. Across the eighteen-year period, 6196 dovish, 7847 hawkish, and 36032 neutral statements were found. These sentence chunks and their sentiment were grouped based on the period each was spoken. While grouping by FOMC meeting period, the sentiment scores were averaged to summarize the BOG sentiment for the intermeeting period. Moving forward, all neutral statements will be excluded to extract purely the changes in hawkish versus dovish sentiment across a time frame. Neutral statements are useful in the traditional sense of a speech and forward guidance; however, it is expected that the primary driving force of policy decisions/market participant expectations are emotionally guided statements.



When plotting the average sentiment over time, it appears to track the two-year Treasury yield. The yield on the two-year Treasury is of particular interest because it is a short-term interest rate highly responsive to changes in the stance of monetary policy. A sentiment score closer to “2” is increasing in hawkishness and sentiment closer to “1” is increasing in dovishness. Hawkish sentiment is generally associated with the anticipation of less accommodative monetary policy whereas dovish discussion is generally given against a backdrop of economic weakness. As shown above, BOG hawkishness increases prior to the initial increase to the federal funds target range in March 2022, (first increase to federal funds target range approximated by red highlight) and falls drastically during recessions. As an example of the guiding power of language, the two-year Treasury yield steadily increased prior to March 2022’s actual rate increases in anticipation of tightened financial conditions in the near future. During this timeframe, officials were expressing an interest in raising the federal funds target range to begin the fight against increases in inflation. Markets scrutinize the committee's outlook in order to best position themselves for the future state of financing markets.

4. Fitting the Model

Once the average BOG sentiment for each meeting period is found, it is combined with economic indicators suggesting the conditions for the corresponding period. In total, forty-three economic indicators are used alongside BOG sentiment to guide predictions for the following meeting decision. A codebook with information on all economic control variables can be found here, which is also below the page of references. Such data was collected through the Federal Reserve Economic Database maintained by the St. Louis Fed (fred.stlouisfed.org/). In addition to variables indicating economic conditions, a single variable stating the FOMC's interest rate decision for that meeting period was included. The model will refer to the true decision by the FOMC to judge how accurate its prediction was when using information solely from the economic indicators/BOG sentiment. Below is a snippet of the format of such dataset:

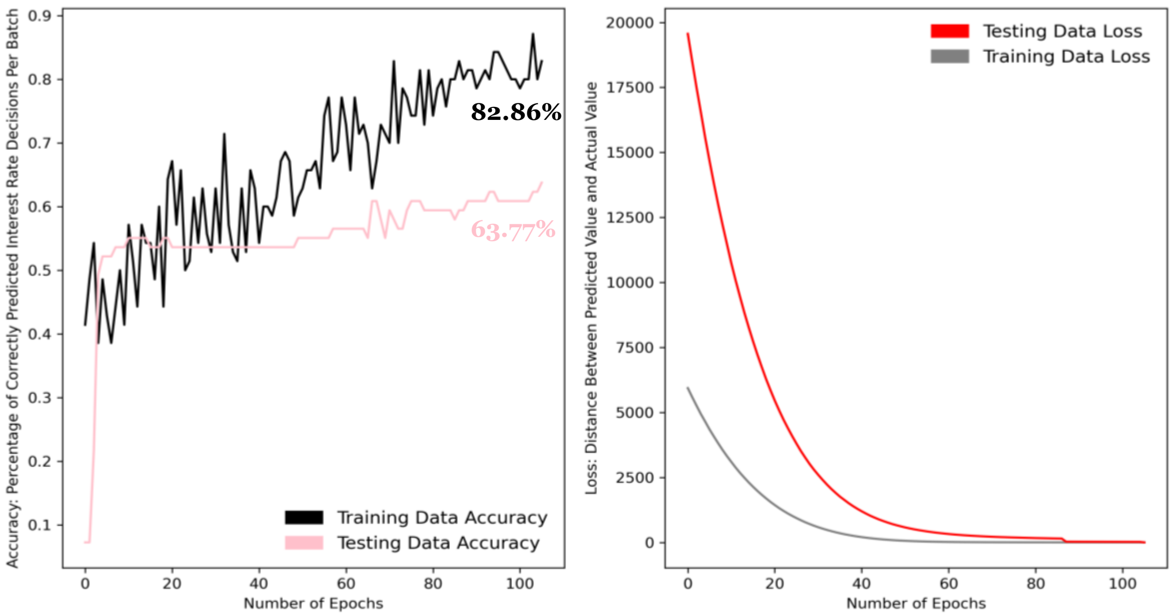
	period	avglabel_excludingneutral	PSAVERT	MORTGAGE30US	HOUST	PERMIT	UNRATE	U6RATE	CIVPART	LNS11300060	...	T10YIE	DFII5	DFII10
0	2006-01-31	1.916667	3.00	6.210	2273.0	2212.0	4.70	8.40	66.00	82.80	...	2.35	1.995	2.05
1	2006-03-28	1.619403	3.25	6.270	2044.0	2129.5	4.75	8.30	66.15	82.95	...	2.53	2.010	2.09
2	2006-05-10	1.611111	3.00	6.510	1881.5	1951.5	4.65	8.15	66.10	82.80	...	2.60	2.255	2.41
3	2006-06-29	1.656250	2.90	6.620	1802.0	1867.0	4.60	8.40	66.20	82.80	...	2.61	2.340	2.46
4	2006-08-08	1.555556	2.40	6.760	1693.5	1742.5	4.70	8.45	66.15	82.95	...	2.59	2.450	2.49
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
136	2023-06-14	1.696078	4.80	6.480	1418.0	1441.0	3.60	6.90	62.60	83.50	...	2.20	1.590	1.46
137	2023-07-26	1.805970	4.40	6.745	1451.0	1443.0	3.50	6.70	62.60	83.40	...	2.24	1.870	1.56
138	2023-09-20	1.777778	4.20	7.105	1330.5	1506.0	3.80	7.05	62.80	83.50	...	2.34	2.120	1.90
139	2023-11-01	1.712500	4.00	7.530	1376.0	1498.0	3.80	7.20	62.70	83.30	...	2.37	2.420	2.40
140	2023-12-13	1.660870	3.95	7.365	1539.0	1480.0	3.70	7.05	62.65	83.25	...	2.26	2.210	2.16

141 rows × 46 columns

A long short-term memory (LSTM) recurrent neural network (RNN) is created using the Keras Python library for deep learning (Keras, 2015). Given the nature of the data, and its low observation count, a relatively small network in terms of trainable parameters was used to reduce the likelihood of model overfitting, a scenario in which the RNN learns relationships within the training dataset to a high degree while being unable to generalize to unseen data. To test the model's generalization, the above dataset was split into a training and testing dataset. The model is only allowed to adjust its predictions based on learnings from the training set. The testing set serves as an examination of the general predictive power of the model as the testing data is "unseen" by the model in the sense it does not update its predictions based on information found within this subset of the data. This is akin to a student being tested on questions similar – but not identical – to those found within lecture. The student will learn from lecture problems but in order to test if concepts were internalized, exam questions may be permutations of problems familiar.

The final machine learning model consists of two LSTM layers of five nodes each, one dense layer of four nodes, and an output layer of three nodes, each node corresponding to a potential federal funds target range decision. The output of the network will display three probabilities; the probability of a federal funds target range hike, pause, and cut, given the data from a specific period.

The network cycled over the entire 141 meeting period dataset for 306 epochs. For each cycle, or "step", its predictions were adjusted to approach their actual values. Training was stopped at this point due to the testing loss increasing considerably in later epochs. Increasing testing dataset loss shows that the model's performance on unseen data began to fall, considering a low loss measure indicates a small difference between predicted and actual outcomes, a sign of accurate predictions.



The model's performance over time is shown above. The highest training accuracy was 82.86% per batch of four meeting period observations with a testing accuracy on unseen data approximately 63.77%.

In order to better understand the impact of BOG sentiment on the ultimate FOMC decision for each period, a multinomial logistic regression was utilized to allow for predicted probabilities of various interest rate outcomes. Given the nature of the dependent variable being able to take on three unique categories, the multinomial logistic model was well suited for the data. Only four control variables were used for the regression in comparison to the LSTM due to concerns of multicollinearity affecting our interpretation of the statistical significance of the variable of interest, BOG sentiment. A greater number of variables enhances predictive power, in the case of the LSTM neural network, however, when estimating the magnitude of effect of individual variables on a given dependent variable, including numerous highly correlated control variables could bias the standard errors of our estimates.

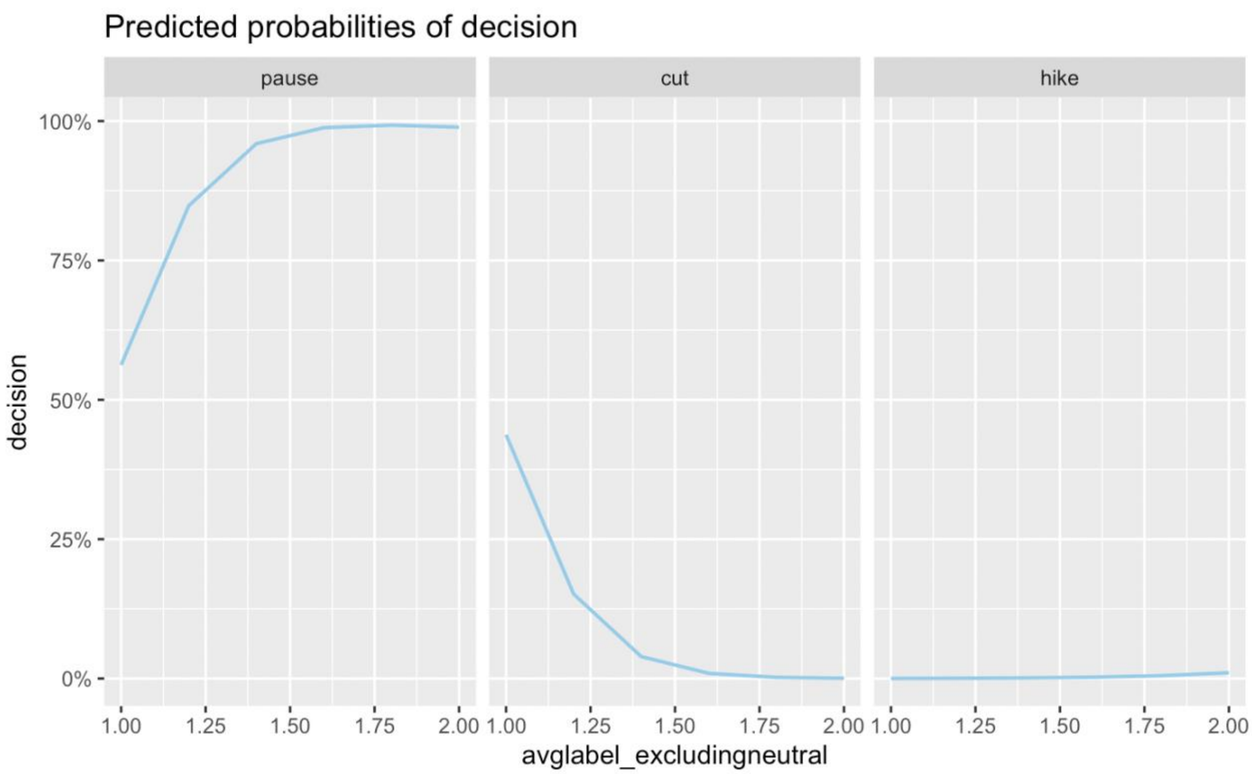
The model's control variables were selected based on what is understood to most heavily guide FOMC decision making in the pursuit of its goals of maximum employment and stable prices. Included is the effective federal funds rate (EFFR) for the period, the U3 unemployment rate, the twelve-month core PCE inflation rate and five-year inflation expectations produced by the Cleveland Fed. The unemployment rate was lagged by three meeting periods and the core PCE inflation rate was lagged by seven meeting periods. The statistical significance for these controls proved to be highest at these lag amounts. The effective federal funds rate was lagged by one period to represent the interest rate that prevailed in the period leading up to the day of a new decision. BOG average sentiment by period was not lagged due to its statistical significance being highest at the most recent time frame. This is plausible considering FOMC participants base their policy vote on their current sentiment and not necessarily their attitude at the previous meeting, given changes to the economy have likely occurred during the intermeeting period, altering the committee member's perspective.

More work must be done to fine-tune the most efficient number of lags. While the optimal count of lags remains slightly ambiguous, some amount of lag is expected to be necessary given the fact that FOMC participants use the culmination of recent data to formulate their monetary policy decision, not just the preceding month's data prints.

Variable of Interest

Group <chr>	Term <chr>	Contrast <chr>	Estimate <chr>	Std. Error <chr>	z <chr>	Pr(>|z|) <chr>	2.5 % <chr>	97.5 % <chr>
cut	avglabel_excludingneutral	mean(dY/dX)	-0.459	0.215	-2.139	0.0324	-0.880	-0.0385
hike	avglabel_excludingneutral	mean(dY/dX)	0.229	0.189	1.209	0.2268	-0.142	0.5996
pause	avglabel_excludingneutral	mean(dY/dX)	0.231	0.271	0.851	0.3945	-0.300	0.7619

The above regression results suggest that a more hawkish lean decreases the probability of a cut to the target range of the federal funds rate. This is statistically significant at the .05 level and is in line with expectations as hawkish language is generally present during periods of high inflation which calls for increases to the target range. However, the results show that, given our dataset, we cannot confidently say that there is a strong relationship between increases in BOG sentiment and the probability of a rate hike, a concerning find as one would expect a more hawkish committee to also be inclined to raise the target range. Below shows the relationship of various target range decisions, namely, a pause, cut, or hike, and changes to BOG sentiment (indicated by “avglabel_excludingneutral”).



The above plot suggests that as the BOG becomes more dovish, the probability of a cut to the target range of the federal funds rate increases, in line with expectations. However, there is no material change to the probability of a hike to the target range given more hawkish language from the Fed. One plausible argument for this is that the committee would rather wait on incoming data before conducting increases to the target range. In contrast, during an economic contraction, it may be more beneficial to make hastily policy moves, rather than wait on future data, given the immense hardship economic downturns cause. The risk of too accommodative policy outweighs the cost of a prolonged recession, hence the incentive to act on current sentiment rather than wait on incoming data.

However, during periods of high inflation, the penalty of raising interest rates too soon is likely high enough to warrant a measured approach to fighting inflation. In this case, the committee may choose to tolerate above target inflation for several periods before they can confidently conclude inflation will remain elevated for a prolonged period and require a policy response. In sum, BOG sentiment appears to be a useful predictor of FOMC changes to the target range, however, this asymmetry must not be ignored. Such regression results may suggest the committee relies more heavily on present day sentiment in their deliberations during downturns and takes a more data-dependent approach prior to costly hiking campaigns.

While the above is solely a hypothesis, it is still supported by their actions during the recovery from the 2020 pandemic lockdown shock. Following the sharp economic contraction of 2020, the FOMC had stated that, despite signals of rising inflation, it preferred to wait for indications of a robust recovery in the labor market before conducting increases to the target range. This decision is understandable given weak labor market conditions can have harsh effects on the economy's workers. A weak labor may also lead to slow output growth overall creating a feedback loop of economic contraction.

4. Conclusion

By analyzing all BOG published speeches since 2006, one is able to glean the changes in attitude expressed over time and how it relates to the committee's decision making. The two-year Treasury yield roughly tracks the committee's attitude over time which is a welcome finding given expectations of this short-term rate being highly sensitive to the stance of monetary policy. Discussion hidden within speeches hints at where the stance of policy may go. That said, there are time periods in which speech sentiment is a leading indicator of future financial conditions – such as during hiking campaigns as seen in 2022 – as well as periods in which speech sentiment appears to slightly lag markets, one example being the COVID-19 pandemic shock. It is understandable for this relationship to ebb and flow when considering that in the former case, the Fed is driving changes to financial conditions and the broader economy and in the latter, the Fed is reacting to events outside of their control.

When testing the effect of changes to sentiment on policy decisions, these findings suggest that FOMC committee members react more drastically to economic downturns than to gradual increases in inflation. This is supported by relatively low predicted probability of an interest rate hike for highly hawkish discussion which is in contrast to the high probability of an interest rate decrease for dovish discussion. While this is plausible and falls within lines of general expectations, scrutiny of these results is still needed. It may be useful to conduct the same tests on a longer time scale in order to provide the model more context. Additionally, this longer time scale should be separated into the various regimes, such as post-2008 and the pre-1990 transparency enhancements.

Furthermore, the FOMC was required to battle the zero lower bound (ZLB) for many years following the Great Recession. As a result, there may have been periods during the downturn in which officials would have preferred to provide additional stimulus to the economy through lower interest rates but were constrained by already near-zero financing costs. This may materialize in the regression results as an increased probability of interest rate pauses given a grouping of economic conditions. We are aware that in such cases, the FOMC did not deliberately choose to halt changes to their target range but were instead forced to, due to structural issues limiting the viability of negative nominal interest rates.

A solution to this constraint and its potential biasing of regression estimates is to employ a tobit model (Goldberger, Tobin, 1958). Further analysis of this research question will seek to build an in-house sentiment classification model using the findings from Shah et al. as a baseline and source of guidance. Results from the tobit regression architecture will be juxtaposed with the findings from the multinomial logit to decipher more robustly what is causing the immaterial effect of sentiment on rate hikes.

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Codebook

Federal Reserve Economic Data (FRED) Codes:

PSAVERT, Personal Saving Rate

MORTGAGE30US, 30-Year Fixed Rate Mortgage Average in the United States

HOUST, New Privately-Owned Housing Units Started: Total Units

PERMIT, New Privately-Owned Housing Units Authorized in Permit-Issuing Places: Total Units

UNRATE, Unemployment Rate

U6RATE, Total Unemployed, Plus All Persons Marginally Attached to the Labor Force, Plus Total Employed Part Time for Economic Reasons, as a Percent of the Civilian Labor Force Plus All Persons Marginally Attached to the Labor Force (U-6)

CIVPART, Labor Force Participation Rate

LNS11300060, Labor Force Participation Rate - 25-54 Yrs.

EMRATIO, Employment-Population Ratio

LNS12300060, Employment-Population Ratio - 25-54 Yrs.

PAYEMS, All Employees, Total Nonfarm

JTSQUR, Quits: Total Nonfarm

JTSJOL, Job Openings: Total Nonfarm

UNEMPLOY, Unemployment Level

FRBATLWGT3MMAWMHWGO, 3-Month Moving Average of Weighted Median Hourly Wage Growth: Overall

ICSA, Initial Claims

PCEPILFE, Personal Consumption Expenditures Excluding Food and Energy (Chain-Type Price Index)

PCEPI, Personal Consumption Expenditures: Chain-type Price Index

CPIAUCSL, Consumer Price Index for All Urban Consumers: All Items in U.S. City Average

CPILFESL, Consumer Price Index for All Urban Consumers: All Items Less Food and Energy in U.S. City Average

PCETRIM12M159SFRBDAL, Trimmed Mean PCE Inflation Rate

MEDCPIM158SFRBCLE, Median Consumer Price Index

EXPINF1YR, Cleveland Fed 1-Year Expected Inflation

EXPINF5YR, Cleveland Fed 5-Year Expected Inflation

EXPINF3YR, Cleveland Fed 3-Year Expected Inflation

EXPINF10YR, Cleveland Fed 10-Year Expected Inflation

T5YIFR, 5-Year, 5-Year Forward Inflation Expectation Rate

MICH, University of Michigan: Inflation Expectation

EFFR, Effective Federal Funds Rate

DGS1MO, Market Yield on U.S. Treasury Securities at 1-Month Constant Maturity, Quoted on an Investment Basis

DGS2, Market Yield on U.S. Treasury Securities at 2-Year Constant Maturity, Quoted on an Investment Basis

DGS5, Market Yield on U.S. Treasury Securities at 5-Year Constant Maturity, Quoted on an Investment Basis

DGS10, Market Yield on U.S. Treasury Securities at 10-Year Constant Maturity, Quoted on an Investment Basis

T5YIE, 5-Year Breakeven Inflation Rate

T10YIE, 10-Year Breakeven Inflation Rate

DFII5, Market Yield on U.S. Treasury Securities at 5-Year Constant Maturity, Quoted on an Investment Basis, Inflation-Indexed

DFII10, Market Yield on U.S. Treasury Securities at 10-Year Constant Maturity, Quoted on an Investment Basis, Inflation-Indexed

RBUSBIS, Real Broad Effective Exchange Rate for United States

BAMLH0A0HYM2, ICE BofA US High Yield Index Option-Adjusted Spread

BAA10Y, Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity

AAA10Y, Moody's Seasoned Aaa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity

T10Y3M, 10-Year Treasury Constant Maturity Minus 3-Month Treasury Constant Maturity

T10Y2Y, 10-Year Treasury Constant Maturity Minus 2-Year Treasury Constant Maturity