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# Using Sentiment Analysis to Understand Monetary Policy Uncertainty

By

LINGYUN XIAO

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Lingyun Xiao

Thesis Advisor: Professor Christopher Roark

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**Abstract**

This paper proposes a novel method to identify monetary policy surprises and analyze the impact of monetary policy uncertainty by applying aspect-based sentiment analysis in natural language processing on documents from Federal Open Market Committee (FOMC). With techniques in machine learning, I associate each document with a sentiment score and categorize monetary policy based on how hawkish/dovish it is. In particular, by assessing the difference in sentiment scores of FOMC statements and Minutes that are released weeks apart, I construct the monetary policy uncertainty index, and find that the reaction of long-term yields is higher/lower when uncertainty is low/high.

**Keywords:** FOMC, Monetary Policy, Uncertainty, Sentiment Analysis, Natural Language Processing

# 1 Introduction

Monetary policy has a profound impact on the economy through financial market. The effectiveness of monetary policy has been a central question in modern macroeconomics literature. Alongside the enactment of the monetary policy itself, *how* Federal Reserve communicates the information on monetary policy with the public is also critical to shaping the efficacy of such implementation. In the early 1990s, the public had to infer the decisions on monetary policy from the movement of interest rates. However, in late 1990s, Federal Open Market Committee (FOMC) began to make *public* announcements of the economic outlook and future economy forecast, which can influence the public assessment of the overall economy as well as their beliefs about future outcomes.

Despite the continuing efforts by Fed to improve its communications to the public, sometimes financial markets are *surprised* by FOMC announcements. For example, in the "taper tantrum" episode in 2013, as soon as investors learned that the Fed was considering slowing down the Quantitative Easing, the abrupt spike on the long-term treasury yields reflected both investor's overconfidence and misinterpretation of the policy intentions. As evident from the past, a discrepancy between the *intention* of FOMC announcements and the *interpretation* of the public has a strong impact on the effectiveness of monetary policy implementation. Therefore, the *uncertainty* of monetary policy plays a critical role in the transmission of monetary policy from the Fed to the market, as suggested by De Pooter et al. (2021).

While an abundant literature has focused on quantitative data presented in FOMC documents such as federal funds target rate and the forecast on inflation, much less attention is given to the qualitative nature of these announcements. In other words, each kind of FOMC statement, minute or transcript is fundamentally a text-based document rather than a table of numerical figures. On the other hand, the public not only reacts to plain numbers, but also reads through the documents in order to adjust their beliefs. Therefore, it is essential to include these "soft" data conveyed through Fed communications, which was pointed out for the first time in Jegadeesh and Wu (2017).

The current advancement in machine learning and text mining is reshaping the landscape of research in monetary policy by offering tools to obtain contextual meaning of a word. In particular, I am able to extract the essential information on FOMC documents by *sentiment analysis*, which is a text mining method that categorizes word-based files into different polarity. Specifically, in the context of monetary policy, a natural choice of the polarity is whether the policy is *hawkish* or *dovish*. If the Fed's aim is to raise interest rates aggressively and enacts a contractionary monetary policy in response to a high inflation rate (such as what we observe post-COVID), the delivered sentiment from the text is hawkish. On the contrary, if the Fed favors an expansionary monetary policy and targets lower unemployment rate, the sentiment now becomes more dovish. Therefore, through text mining, I am able to assign a proper sentiment score to each individual FOMC document that captures how hawkish or dovish an investor perceives it to be. Among all types of FOMC meeting documents, the more well-known FOMC statements are revealed shortly after the meetings. Most of the previous studies have exclusively concentrated on FOMC statements because of the relative short timing of release. Nevertheless, as Rosa (2013) has observed, FOMC *Minutes*, which are released weeks after each announcement, have not received as much attention due to their length and complexity. Again, tools in natural language processing make it possible to analyze these lengthy documents and extract the highly relevant information of how aggressive the proposed policy is.

However, because of the large difference in timing, influence by the previous meeting on FOMC Minutes are tenuous. This level of independence offers an ideal setting to obtain a separate sentiment score for each Minute, and I can *compare* the sentiments between each FOMC statement and its subsequent Minute. One of the key observation of this paper is the association between **monetary policy uncertainty** and **difference in sentiment scores**. Intuitively, if FOMC Minutes have fully and clearly conveyed *all* the information in FOMC statements, the monetary policy uncertainty would become *lower*. On the other hand, if any new information is included in the minutes, the uncertainty would rather *increase*, and we would expect the asset prices to react differently.

In this paper, I propose a novel method to assess monetary policy uncertainty by quantifying the difference in the sentiment scores of FOMC statements and FOMC minutes. In the next step, I follow a high frequency identification method proposed by Hanson and Stein (2015) to identify the monetary policy shocks. Specifically, I use the shift in the short-term (2-year) nominal Treasury yield in a 60-minute window around the release of FOMC *minutes* as the proxy of monetary policy shocks. Finally, I regress long-term (10-year) nominal Treasury yields on the monetary shocks, monetary uncertainty that I constructed, and the interaction between the two terms. My main findings suggest that, during periods of low monetary uncertainty, a hawkish monetary policy, or a "tightening" policy is positively correlated with an increase in nominal rates. However, if monetary uncertainty is high, the effect of the hawkish policy is significantly reduced. I conclude that sentiment analysis provides additional insight into understanding FOMC minutes, and *how* the Fed conveys the message clearly through FOMC statements and minutes has a strong impact on the efficacy of monetary policy.

My work is closely related to three different branches of studies of monetary policy. First, this paper fits in line with previous literature on monetary policy surprises and the long-term yields by Hanson and Stein (2015) and Nakamura and Steinsson (2018). Both papers point out that long-term yields are significantly affected by monetary policy surprises. While Hanson and Stein (2015) demonstrate that the changes in long-term yields is fundamentally driven by investor's risk-taking, Nakamura and Steinsson (2018) attributes the shifts in yields to the changes in private sector's belief about future economy, therefore results in a re-evaluation of the expected rates of long-term yields. This paper fundamentally differs from these works because of the inclusion of monetary policy uncertainty in the analysis of long-term yields responses, and the uncertainty arises from the possible discrepancy between sentiments communicated in FOMC statements and FOMC minutes.

Second, my work speaks to studies on quantifying the measure of monetary policy uncertainty. In summary, these measures can be categorized into three groups: (1) news-based, survey-based, and econometric; (2) asset market based; and (3) Knightian uncertainty, proposed by Cascaldi-Garcia et al. (2020). A model-free econometric estimate of macroeconomic uncertainty was created by Jurado et al. (2015), which bears minimal influence from the choice of theoretical models. Swanson (2006) exploits the probability distribution of federal funds rate implied by the prices of interest rates derivatives, and uses at-the-money eurodollar futures options to compute the width of the distribution of one-year fed funds rate as a measure of monetary policy uncertainty. The study finds that a decline in the monetary policy uncertainty and the enhancement of Fed communication transparency lead to an improvement of the forecasts of interest rates. De Pooter et al. (2021) continues to use the uncertainty measure and finds that monetary surprises also have a strong impact on medium-term and long-term nominal and real Treasury yields. Furthermore, by using monthly data on news-based uncertainty index, inter-quantile range of three-month Treasury Bills forecasts as well as discrepancies in the ten-year yields forecasts, Tillmann (2020) finds that when uncertainty is high, investors are more attracted to securities with longer maturities and ask for a lower premia.

While these previous research shed some light on quantifying the effect of monetary policy uncertainty, all of them have exclusively examined various numerical data sets to construct the uncertainty index. For the first time, my work incorporates *text* data from FOMC minutes into the study of monetary policy uncertainty. Moreover, instead of treating uncertainty as purely numerical, my paper integrates sentiments, or *emotions* communicated through FOMC documents into the analysis of variability in the delivery of monetary policy. After all, policies are enacted by humans, and human language serves a critical role in the understanding of the messages.

The third aspect of research that my paper contributes to is the increasing popular literature on using machine learning and text mining techniques to analyze actions by the

Federal Reserve. Aruoba and Drechsel (2022) uses sentiment analysis to identify monetary policy shocks, complementing the base-line identification method developed by Romer and Romer (2004). Moreover, Jegadeesh and Wu (2017) uses Latent Dirichlet Allocation (LDA) method to uncover the semantic underlying structure of FOMC documents, and find that FOMC minutes indeed contain additional information that is transmitted to the financial market. Similarly, Tadle (2022) develops a semi-automated method to perform sentiment analysis on FOMC statements and identifies significant association between sentiments and Fed funds futures rate. Nevertheless, my work is the first that links the monetary policy uncertainty with the degree of dissimilitude between FOMC statements and minutes, and examines how long-term yields respond to the level of uncertainty.

The structure of my paper is as follows. Section 2 summarizes the data source used in my paper, and elaborates on my method to extract monetary policy uncertainty using sentiment analysis in detail. Section 3 presents the empirical framework and results on the responses of long-term treasury yields to monetary policy uncertainty. Section 4 concludes.

# 2 Data

In this section, I will first present the source of data for subsequent analysis. Next, I will explain how to perform sentiment analysis and construct a sentiment score on FOMC statements and minutes.

## 2.1 FOMC statements and minutes

Starting from the early 1980s, the FOMC has been holding eight annual regularly scheduled meetings. Members propose future monetary policy and discuss the economic outlook during these meetings, and any shift in policy will be enacted through open market operations. In particular, before January 1994, the public had to infer policy changes from shifts in interest rates, which became evident after the announcements. Starting from 1994, however, FOMC meeting *statements* were released to the public shortly after each meeting. Various studies have investigated the market response based on these statements.

Furthermore, after a delay ranging from 3 to 6 weeks, a more detailed statement with summarized records from the staffs is made available, which is known as the FOMC *minutes*. In principle, FOMC minutes do not contain any additional information between the FOMC meeting and the date of release. Rather, the minutes provide internal discussions and potentially mixed staff reviews of the monetary policy, thereby adding more complexity to the *tone* it communicates. Overall, whether FOMC minutes are able to convey useful information to the public is subject to its content. Given the large state space of the data set, it naturally follows to use text mining to skim through the documents and use only the essential information to construct sentiment scores.

## 2.2 Constructing Sentiment Score

First, from the public data source on the website of Federal Reserve Board of Governors (FRB), I have selected historical FOMC statements and associated minutes for FOMC meetings from January 2000 to December 2021. In order to keep my construction of sentiment score consistent, I exclude periods before 1994 because FOMC statements were not made visible to the public, while FOMC minutes were instead released. Prior to the beginning of 2000, only FOMC statements were announced if there is a policy change. Due to the small number of samples available, I also excluded the time period between 1994 and 1999. Also, I do not include any unscheduled meetings because typically no new documents are written for these meetings. My choice of FOMC documents leads to a total of 346 pdf text files for 173 meetings.

In order to break down each individual file into relevant text-based information, I remove the introductory page in each Minute file because it mostly contains staff names and titles that are irrelevant to the sentiment calculation. Next, I eliminate all the stop words that make up a large proportion of the text (such as “a”, “is”, “on”, ...). I also preserve the cohesiveness of words within one paragraph by parsing each document by paragraphs instead of sentences or single words. The reason is that individual paragraphs are relatively independent from each other, and the start of a new paragraph usually marks a shift in the topics. However, each word or sentence is relatively dependent on the context it appears in. Simply ignoring the underlying semantic structure of the text could result in an inaccurate characterization of the sentiment score.

Moreover, following a similar approach by Gardner et al. (2021), I build a dictionary of key words and phrases that capture specific topics, or *aspects* of each document: labor, output, inflation, financial conditions. Table 1 shows the most frequent words associated with each category. Each phrase is associated with a *hawkish* (positive) or *dovish* (negative) sentiment. An increase in a hawkish key word would lead to a hawkish monetary policy. For example, "inflation" is hawkish because a rise in inflation triggers the incentive to implement a contractionary policy with rising interest rates. On the contrary, "unemployment" would be dovish because a spike in unemployment rate would likely give rise to an expansionary policy with fallen interest rates.

One important advantage of the dictionary approach is its ability to effectively identify the key words appeared in the text. Moreover, given that many phrases, such as "job losses" need to be viewed as a whole to avoid confusion, using a pre-selected dictionary is much more computationally efficient. Finally, each FOMC statement and minute is organized in a similar structure that does not change much over the years, the choice of a fixed dictionary is less vulnerable to heterogeneity in the phrasing across individual documents. If we were to analyze FOMC Green Books which have much more complicated structure that varies over years, the dictionary method will not work as well as a dynamic machine learning method that trains a subset of data and gradually learns the semantics of each document as suggested by Jegadeesh and Wu (2017).

Furthermore, I construct a list of *modifiers* based on a dictionary proposed by Loughran and Mcdonald (2011), which is the prevalent choice of dictionary used in economic and

| **Labor** | **Output** | **Inflation** | **Financial Conditions** |
|---|---|---|---|
| unemployment | GDP | inflation | credit |
| employment | income | prices | loans |
| job losses | export | price | financial |
| job gains | investment | cost | mortgage |
| labor market | spending | | |

Table 1: Most Frequent Words in Each Topic of FOMC documents

financial texts. After looping through the relevant FOMC documents, I find that most modifiers that appear in the documents consist of adjectives and verbs near each key topic, and the most frequent modifiers are summarized in Table 2. Each modifier can be labeled by either positive, negative, *multiplicative.* For the former two cases, I assign +1 sentiment score to a positive modifier, and -1 sentiment score to a negative modifier. Introducing multiplicative modifier is one of the improvements this paper has made to the calculation of sentiment score. I have noticed that some modifiers exert a much stronger impact on the related key words. For example, consider the following sentence that is particularly common in periods of financial distress:

"Financial markets remain under considerable stress, and credit has tightened further for some businesses and households." (FOMC statement, January 30, 2008)

In this sentence, the noun "stress" is dovish, and the verb "tightened" is negative. On the other hand, the words "considerable" and "further" are neutral by meaning, but if they are placed adjacent to another modifier, the sentiment score needs to be *multiplied.* In fact, these multiplicative modifiers are ignored as in previous studies, and *intensity* of sentiment conveyed in the sentence above would not be comparable to the true level. Therefore, I identify the cases where the multiplicative modifiers are adjacent to another positive/negative modifier, and accordingly multiply the sentiment score of the combined phrase to obtain +2 and -2. As a result, the sentiment of the sentence above would give rise to -4 sentiment instead of -2.

I can obtain the sentiment index for each paragraph of the FOMC statement or minute

| **Positive** | **Negative** | **Multiplicative** |
|---|---|---|
| increase | fell | further |
| high | decrease | significant |
| stronger | decline | considerable |
| raise | reduce | important |
| stable | weak | pronounced |

Table 2: Most Frequent Modifiers in FOMC documents

by summing up all sentiments of individual phrases. Finally, I compute the weighted sum of all sentiment scores by the length of the paragraph, and normalize the overall score to have variance 1. By performing sentiment analysis on both statements and minutes, I obtain the following time series by comparing their sentiment scores that range from -4 to 4:

It is evident that while both time series follow a similar trend, there are multiple periods where significant deviation exists between them. In general, sentiments from FOMC minutes are less volatile than sentiments from FOMC statements. It is likely to occur because while FOMC statements send more direct and clear-cut signals for monetary policy implementation, FOMC minutes are often filled with mixed opinions of staff members and contrasting reviews of the proposed change in policy. As a result, whether each FOMC statement delivers a hawkish or dovish policy, the subsequent Minute often dampens its magnitude.

I also find out that FOMC statements sometimes have very large deviation in sentiment from FOMC minutes, even with opposing sign at times. This phenomenon is conspicuous in 9-11 in 2001, 2008 financial crisis and 2020 COVID-19 outbreak where the Fed faced a frequent adjustment of monetary policy. Therefore, these are the moments where the monetary policy *uncertainty* is also high. Such correlation gives rise to my own construction of the monetary policy uncertainty measure based on the discrepancy in sentiment using FOMC statement and minute data.

## 2.3 Formulating Monetary Policy Uncertainty

As discussed in the review of literature, former efforts on defining monetary policy uncertainty has never focused on any of the text-based sentiments disclosed by FOMC documents. In order to capture the relationship between sentiment and uncertainty, I construct the following uncertainty index:

$$\text{uncertainty}_t = |Z_s - Z_m|$$

where $Z_s$ is the sentiment score of FOMC statement, and $Z_m$ is the sentiment score of FOMC minute.

The index captures the positive correlation between difference in sentiment and uncertainty level. If the dissimilitude between FOMC statement sentiment and FOMC minute sentiment is significant, an immediate implication is that the FOMC minute document contains a large amount of contrasting views on the proposed monetary policy, which reflects a heightened uncertainty in the effectiveness of such implementation. Furthermore, if the sentiments have opposite sign, the FOMC minutes would contain contrasting propensity that are at least comparable with the policy presented at the announcement, which also indicates a rise in uncertainty.

After standardizing the monetary policy uncertainty indices, I obtain the time series shown in Figure 1. It is evident that the sentiment scores of FOMC Statements fluctuate more than the FOMC minutes, which suggest that in general, compared to a fixed message delivered in statements, the messages conveyed in minutes are more nuanced. This phenomenon stems from the fact that FOMC minutes is often a comprehensive review of all discussions and staff opinions rather than a direct policy implementation. Such discrepancy demonstrates that FOMC minutes often contain essential information in the Fed's decision making that is unavailable in the short, concise statements.

Finally, Figure 2 reflects the implied monetary uncertainty index calculated from the sentiment scores. It is indeed notice that the monetary policy uncertainty spikes during a financial crisis, such as the Great Recession and COVID-19 outbreak. At other times, the movements of the two sentiments are more aligned.

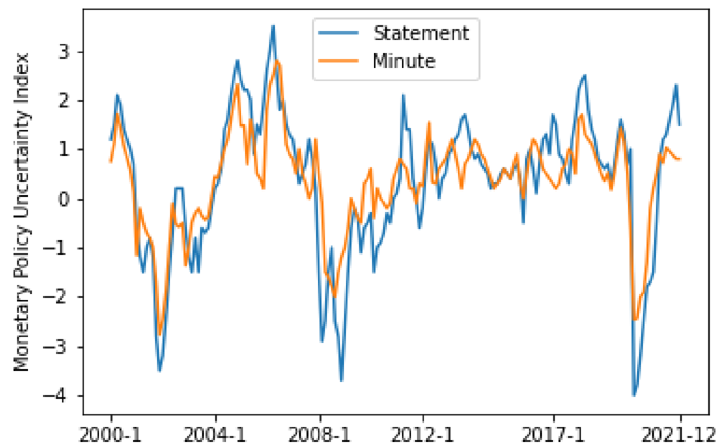


Figure 1: Sentiment Scores of FOMC statements and minutes

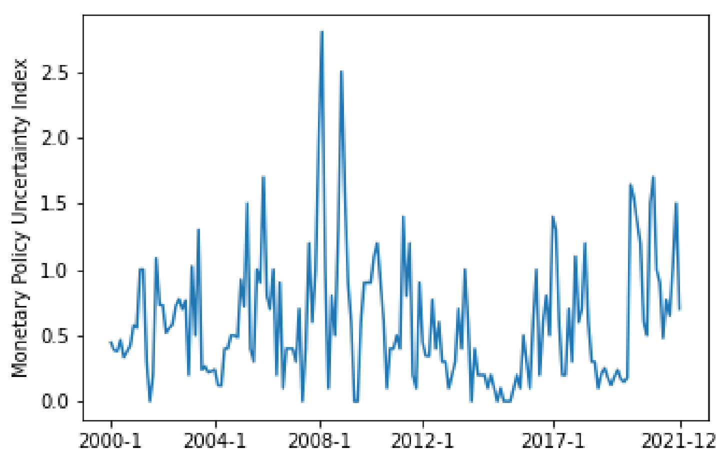


Figure 2: Monetary Policy Uncertainty Index

# 3 Empirical Studies

My empirical framework follows the high-frequency identification in the event studies proposed by Swanson (2006), Hanson and Stein (2015) and De Pooter et al. (2021). In particular, I estimate the following regression:

$$\Delta y_{t+1}^{m} = \alpha + \beta \Delta mp_{t+1} + \gamma \text{uncertainty}_t + \delta \Delta mp_{t+1} \times \text{uncertainty}_t + \epsilon_{t+1}$$

where time $t$ is the day that FOMC minute is released; $\Delta y_{t+1}^{m}$ represents the two-day shift in bond yields with maturity $m$ on day $t-1$ and day $t+1$; $\Delta mp_{t+1}$ is the monetary policy shock by the change in 2-year bond yields within a 60-minute window around the delivery of FOMC minute, typically at 2pm three weeks to six weeks after the FOMC announcement. The $\text{uncertainty}_t$ term is the implied monetary policy uncertainty index calculated from the sentiment scores defined in the previous section.

The underlying assumption of the empirical model is that monetary policy surprises directly influences yields in a linear relationship. Moreover, the effect of monetary policy surprises depend on the level of *uncertainty*, and its variation is captured by coefficient $\delta$. Finally, $\beta + \delta \text{uncertainty}_t$ identifies the overall monetary policy shock, *conditional* on the level of monetary policy uncertainty.

Table 3 summarizes the main result of my empirical framework to investigate the effect of monetary policy surprises on 5-year and 10-year nominal yields in column (1) and (2) respectively. Row (1) is the estimated coefficient $\beta$, which shows that an increase in the change of short-term bond yields, or a "tightening" monetary policy shock, is indeed positively correlated to long-term yields. This relationship agrees with the previous findings in Hanson and Stein (2015) and Nakamura and Steinsson (2018). However, Row (2) shows an interesting finding when I analyze the impact of monetary policy shock *under* the influence of monetary policy *uncertainty*: The negative coefficient $\delta$ indicates that the scale of a monetary policy shock diminishes with increasing uncertainty.

| | 5-year Nominal Yields | 10-year Nominal Yields |
|---|---|---|
| $\Delta mp_{t+1}$ | 0.857*** | 1.012*** |
| | (0.142) | (0.163) |
| $\Delta mp_{t+1} \times uncertainty_t$ | -0.369*** | -0.377*** |
| | (0.110) | (0.108) |
| low uncertainty | 0.737*** | 0.811*** |
| **bottom** 25% | (0.152) | (0.170) |
| high uncertainty | 0.277*** | 0.293*** |
| **top** 25% | (0.0471) | (0.0429) |
| Observations | 173 | 173 |

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3: Response of U.S. Treasury Nominal Yields to Monetary Policy Uncertainty with Fine-Grained, Aspect-Based Sentiment Analysis

Recall that the uncertainty index is constructed by the absolute difference in sentiment score of FOMC statement and minute. This result unveils an important underlying connection between the effect of monetary policy and the *delivery* of FOMC announcements based on their choice of texts. Row(3) and Row(4) evaluate $\beta + \delta \text{uncertainty}_t$ when the monetary policy uncertainty index is on bottom 25% and top 25% with respect to its distribution. During turbulent periods with heightened uncertainty, such as post-crisis phases in 2010 and 2021, monetary policy has a weakened impact on the market.

An implication of the result suggests that sentiments in the FOMC texts have significant influence on the implementation of monetary policy. If the messages conveyed in FOMC statements and minutes are similar, and minimal additional information is given to the public in the minutes, we would expect the monetary policy to be more effective. On the contrary, if minutes reveal *conflicting* messages and diversions from the statements, the market response to the policy is likely to be qualified. Therefore, both the numerical data on future economic forecasts and the actual texts of policy announcements have profound impact on the market outcomes.

Table 4 demonstrates the result using *simple* sentiment analysis as a robustness check. Instead of constructing the sentiment scores using the approach in Section 2.2, I simply count and sum up the number of words and modifiers with positive and negative sentiments, and normalize the scores to have variance 1. A similar trend still holds with a different choice of sentiment analysis I perform, which suggests that the effect of uncertainty on monetary policy surprises is evident regardless of the sentiment measures.

| | **5-year Nominal Yields** | **10-year Nominal Yields** |
|---|---|---|
| $\Delta mp_{t+1}$ | 0.903*** | 0.974*** |
| | (0.176) | (0.181) |
| $\Delta mp_{t+1} \times uncertainty_t$ | -0.238*** | -0.251*** |
| | (0.0566) | (0.0542) |
| low uncertainty | 0.801*** | 0.830*** |
| **bottom** 25% | (0.212) | (0.237) |
| high uncertainty | 0.652*** | 0.713*** |
| **top** 25% | (0.131) | (0.123) |
| Observations | 173 | 173 |

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 4: Response of U.S. Treasury Nominal Yields to Monetary Policy Surprises with Simple Sentiment Analysis

# 4 Conclusion

While substantial studies have concentrated on the identification of monetary policy surprises by numerical data in FOMC announcements, less attention is given to the *text* data of the documents themselves. In this paper, I propose a novel method to construct monetary policy uncertainty index with fine-grained, aspect-based sentiment analysis in text mining. In particular, I quantify the hawkishness of each FOMC statement and minute through the detection of positive, negative and multiplicative words and modifiers. Then, I construct the uncertainty index by calculating the difference between the sentiment scores of FOMC statements and FOMC minutes. Finally, the empirical results suggest that, given a monetary policy surprise, the reaction of long-term yields is more noticeable when the monetary policy uncertainty is low.

My findings demonstrate that *how* the Fed communicates to the public on future public policy and whether the communication is *consistent* in related FOMC documents are as essential as the policy itself. One possible extension of this paper is to find a more systematic way to construct sentiment scores in various types of FOMC documents, such as the Green Books and live transcriptions of each meeting. Another promising direction for further investigation is to study the impact of monetary policy uncertainty on a larger set of assets such as exchange rates.

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