# The Effects of the Content of FOMC Communications on US Treasury Rates

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## Abstract

This study measures the effects of Federal Open Market Committee text content on the direction of short- and medium-term interest rate movements. Because the words relevant to short- and medium-term interest rates differ, we apply a supervised approach to learn distinct sets of topics for each dependent variable being examined. We generate predictions with and without controlling for factors relevant to interest rate movements, and our prediction results average across multiple training-test splits. Using data from 1999-2016, we achieve 93% and 64% accuracy in predicting Target and Effective Federal Funds Rate movements and 38%-40% accuracy in predicting longer term Treasury Rate movements. We obtain lower but comparable accuracies after controlling for other macroeconomic and market factors.

## 1 Introduction

This study uses the verbal content of Federal Open Market Committee (FOMC) public communications to predict the directions of interest rate movements on the days those communications are released. The FOMC, who determines government policies relevant to interest rates, meets roughly eight times a year and releases a statement after each meeting. The FOMC is known to be an important mover of markets, and economic research has found that equity and interest rate markets tend to move when FOMC communications are released (Farka and Fleissig, 2012; Gürkaynak et al., 2005; Mueller, 2015; Rosa, 2011) that the policy actions alone do not explain these responses (and thus the content of the text must be responsible) (Gürkaynak et al., 2005), and that the directions of market movements coincide with a human-coded measure of the sentiment expressed in the texts (Rosa, 2011). Writers in the finance industry and in the popular press have also examined word clouds of FOMC minutes (Cofnas, 2010; Durden, 2011) and have discussed the market implications of the total number of words included in FOMC minutes (Fitz-gerald, 2014; Kennedy, 2014; Wynne, 2013).

A growing body of research applies NLP methods to understand the market effects from the contents of these texts. Researchers have applied Latent Semantic Analysis (LSA) to describe the key topics covered in FOMC minutes, obtaining insights into the FOMC's deliberation process (Hansen et al., 2015; Fligstein et al., 2014; Schonhardt, 2013). Additionally, researchers have used NLP-derived measures of the content of FOMC minutes to predict equity and interest rate volatilities; (Boukus and Rosenberg, 2006) use LSA-defined topics in a regression context, and (Zadeh and Zollman, 2009) apply a dependency-based measure of text content to an expert-classified set of financially relevant words and then use both regression and SVM to predict volatility. Papers have found temporary effects of the sentiments from company-specific news articles and message board postings on stock prices and volatility, company earnings, and trading volumes, using dictionary-based sentiment measures (Davis et al., 2012; Tetlock, 2007; Tetlock et al., 2007; Tetlock, 2011) as well as sentiment measures that are trained on a human-classified subsample (Antweiler

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and Frank, 2004, 2006; Das and Chen, 2007).[1] Studies have found temporary effects even when information is "stale" (Tetlock, 2011) and also that short-sales precede negative news (Fox *et al.*, 2009/2010). Researchers also find that the readability of corporate filings is positively associated with earnings and the precision of analysts' forecasts about the company (Li, 2008; Lehavy *et al.*, 2011).

The current study builds upon this literature by examining a somewhat different question than previous researchers do and by applying a different set of techniques that are particularly well-suited for measuring the market effects of texts. Rather than examine the texts' effects on *volatility*, which increases in response to both positive and negative sentiments, we predict the *direction* in which interest rates move, which is the focus of market participants as well as the FOMC texts themselves.[2] The question we ask is also somewhat different than that examined in the literature because we analyze the relatively short FOMC statements that are released immediately following the meetings—and contain the key market-moving content (Gürkaynak *et al.*, 2005; Mueller, 2015)—rather than on the lengthier minutes that have more text to analyze but are only released after the key information from the statements has been available for three weeks.

In addition to making contributions specific to our application, this study highlights methods that are particularly useful for measuring the market effects of text content. FOMC communications are known to provide distinct information about short- versus medium- or long-term policies (Gürkaynak *et al.*, 2005). We consequently use MedLDA (Zhu *et al*, 2009), a supervised topic model, to learn separately the sets of words that are most predictive of movements in short- and medium-term interest rates[3] Through this supervised topic model, we generate

topics, based upon context (which words appear together) as well as co-movement with the outcome variables being studied. Hence, the varies depending upon which dependent variable is being considered. Second, we address possible bias from one important set of omitted variables—releases of macroeconomic data, as discussed by (Rosa, 2011)—by estimating specifications in which we control for those factors separately and predict whether interest rates moved more or less than would be expected based upon the latest data on the macroeconomic environment. By examining an immediate market response to the publication of text and controlling for potential confounding factors, this study demonstrates one way in which NLP approaches, in addition to their value in classifying text content, can be applied to estimate statements' causal effects. We control for the effects of macroeconomic data and time-specific factors like day-of-week effects and time trends using only observations from non-FOMC dates, so that we do not lose degrees of freedom in our estimation. Third, unlike Boukus and Rosenberg (2006) and Hendry and Madeley (2010) but similarly to Zadeh and Zollman (2009), we split the sample into training and test sets in order to limit overfitting in our predicted values. Zadeh and Zollman (2009) use data from 1967-2000 as a training set, and then they test their model on data from 2001-2008. Given the importance of context in predicting interest rate movements, we instead restrict our sample to observations from meetings from May 1999 to May 2016[4]. Because autocorrelation in our dependent variables is relatively limited, we treat the observations as independent and, among observations in our sample, average our test performance across multiple training-test splits.

## 2 Market Effects of Text Content

### 2.1 Overview of Text Content

FOMC statements contain information about many aspects of the economy, including interest rates, the money supply, inflation, unemployment, and economic growth. These communications are highly repetitive, often containing nearly identical sentences and sentence structures from previous meet-

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[1]While not examining market data, (Chua *et al.*, 2009) also examines the problem of classifying sentiment in message board postings.

[2]A related study has applied LDA to measure the impacts on returns and volatility of communications from the Bank of Canada (Hendry and Madeley, 2010).

[3]Other classification methods that we attempted but found to be less effective include regression of rate movements on word count, logit estimation on the frequencies of the most common words, and k-nearest neighbor estimation using a word2vec similarity measure (Mikolov, 2013).

[4]May 1999 was the date of the last major redesign of the FOMC statements

ings. Slight changes in the wordings are known to have major effects on markets (Gürkaynak *et al.*, 2005).

**Pre-processing of text:** In order to convert the text into a format that can be easily processed, we perform several cleaning operations to the texts. Non-alphabetic characters are removed, and the texts are converted to lower case. Each document is separated into a bag of words, and common words (*e.g.,* mr and federal) and stop words are deleted using the stopwords list from nltk.corpus in Python. Words are stemmed using the Porter stemming algorithm (stem from stemming.porter2 in Python), and one-letter words are dropped.

## 2.2 MedLDA

LDA (Latent Dirichlet Allocation) (Blei *et al.*, 2003) is an unsupervised model, whereas supervised topic model (sLDA) (Blei and McAuliffe, 2007) introduces a response variable to LDA for each document. Max-Entropy Discrimination LDA (MedLDA) (Zhu *et al*, 2009) is max-margin variant of the supervised topic models. MedLDA can be built for both regression and classification prediction tasks. In this study we employed the model built for classification task. For classification, the response variables $y$ are discrete having values $\{1, 0, -1\}$ denoting the movements of the interest rates. Hence, we consider the multi-class classification version of the MedLDA. It is defined based on a Support Vector Machine (SVM), which integrates the max-margin principle with an underlying LDA model for topics. Formally, the probabiltiies associated with max-entropy discrimination topic models (MedTM) can be generally defined as:

$$min_d \mathcal{L}(q(H)) + KL(q(\Gamma)||p_p(\Gamma)) + U(\xi) \quad (1)$$

where $H$ are hidden variables (e.g., $(\theta, z)$ in LDA); are the parameters of the model pertaining to the prediction task (e.g., $\eta$ in sLDA); $\Gamma$ are the parameters of the underlying topic model (e.g., the Dirichlet parameter $\alpha$); and $L$ is a variational upper bound of the negative log likelihood associated with the underlying topic model. $U$ is a convex function over slack variables. For the general MedTM model, we can develop a similar variational EM-algorithm as for the MedLDA.

We apply the MedLDA model on the FOMC documents and considering the interest rates as the response variables ($y$) to compute topics that are closely related to variations in the interest rates. Eventually these topics are used to classify changes in the rates using the max-margin classifier embedded in the MedLDA model.

## 2.3 Controlling for Macroeconomic Information

In addition to these text-based data, we supply our classifier with "control" variables describing the latest releases of macroeconomic variables. The macroeconomic data considered in this analysis are three of the most important measures of US economic health: the Consumer Price Index (CPI) used to measure inflation, Unemployment, and real annualized growth in the US Gross Domestic Product (GDP). The values for all three of these statistics are publicly released on a monthly basis. The CPI and Unemployment numbers are measured on a monthly basis and are typically not updated from their initially released values. The CPI data are typically released between 15 and 20 days after the end of the month, and the Unemployment data are typically released 6 to 10 days after the end of the month. GDP is measured on a quarterly basis, and three estimates are provided: "advance," "preliminary" or "second," and "final" or "third," which are released about one, two, and three months after the end of the quarter, respectively. The final GDP numbers are occasionally revised in later releases. Our release date data and some of the macroeconomic statistics were obtained from direct requests to the U.S. Bureau of Economic Analysis (B. of Econ. An. (a), 2015; B. of Econ. An. (b), 2015) and the U.S. Bureau of Labor Stats (B. of Lab. Stat. (a), 2015; B. of Lab. Stat. (d), 2009). Additional data on the GDP and unemployment numbers released were obtained from public sources (Econ. Anal. (c), 1989; Fed. Res. (a), 15).

If macroeconomic information is released on the same day as an FOMC communication, it is possible that this release could influence both the content of the FOMC statement as well as the interest rate movements that day. To avoid that possibility, we implement a modified MedLDA approach using a dependent variable that is "purged" of these potentially confounding influences. In some of our speci-

**Table 1:** Accuracy of Medlda Classifier after purging out of control for statements between 1999 and May, 2016 [K (topics) = 20]

| Outcome variable | MedLDA | | | Baseline (Random Chance)[5] | | |
|---|---|---|---|---|---|---|
| | None | Linear | Interactions | None | Linear | Interactions |
| Target Fed Funds Rate | 0.9321 | 0.9160 | 0.8954 | 0.6849 | 0.6849 | 0.6849 |
| Effective Fed Funds Rate | 0.6421 | 0.4479 | 0.5112 | 0.4589 | 0.4658 | 0.4658 |
| Median Treasury Rate | 0.4209 | 0.3803 | 0.4012 | 0.4589 | 0.4247 | 0.4247 |
| Average Treasury Rate | 0.3803 | 0.4611 | 0.3924 | 0.4726 | 0.4041 | 0.4041 |

fications, we first regress the interest rate movements of interest on these macroeconomic indicators. Our main set of controls includes the latest values for the most recent two values of the unemployment rate, GDP growth rate, and CPI inflation rate and their changes, a daily time trend, and year, month, and day-of-the-week dummies. Some specifications use this set, and others add the full set of two-way interactions across these different variables. For both the main and the interacted set, we regress the change in the rate of interest on the full set of controls for the full set of non-FOMC dates from May 1999 through May 2016. Hence, we estimate the relationship between interest rate movements and the releases of macroeconomic data using dates in which FOMC statements or minutes were not released. Using the coefficients from these regressions, we generate residuals of interest rate movements for the FOMC dates and then create indicators for whether the residual was positive or negative for that interest rate movement on that FOMC date.

## 3    Empirical Results

We randomly split the data, containing 146 data points (FOMC statements and corresponding movements in the interest rates from May 1999 through May 2016) into a a 80-20% train-test set split to compute the accuracy of the model to predict the movement. For each experiment, we varied the number of topics ($K$) to see which value of $K$ is giving the best accuracy. In most cases, the best accuracy is given by $K = 20$. The results presented in Table 1 shows the average accuracies of predicting the movements of the interest rates after purging the outcome variables out of control. The presented accuracies are the results of 20 fold validation. When no controls are used, our accuracy is 93% and 64%

for the Target and Effective Federal Funds Rates (both better than random chance) and 42% and 38% for the Median and Average Treasury Rates[6] The specifications with control variables have similar but somewhat lower accuracy rates. Hence, our text-mining approach is comparable in effectiveness at measuring whether interest rates moved more or less than expected, after controlling for the economic environment, than it is at predicting the raw directions of movement. MedLDA model is compared against a simple baseline. The baseline is the accuracy, if the interest rate movements are randomly guessed from the prior distribution of each of the interest rates under the different controls. For the Target and Effective rates, the MedLDA model outperforms the baseline with a great margin and for the Median and Average rate, the performance is slightly poorer.

The high target rate prediction accuracy suggests that the MedLDA model can effectively associate the text contents of the meetings with the movements in the rate, even though the numeric values are dropped from the text. Similar arguments can be applied to the effective rate prediction. On the other hand, treasury rates are not directly connected to the text of the FOMC statements, so the factors influencing these rates are not present or mentioned in the text. Thus, to have a better prediction accuracies for these variables information from other sources are necessary which is beyond the scope of this paper. However, the present FOMC meeting might give an indication to future FOMC plans and thus, to the

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[5]Our random chance baseline is a classifier that always selects the most likely of the three outcomes (increase, decrease, or no change) based upon their frequencies in the full dataset.

[6]Median Treasury Rate is the median of the -1, 0, and 1 classifications among the movements of the 3m, 1y, 3y, 5y, and 10y Treasury Rates. Average Treasury Rate is the -1/0/1 classification of the average of those rates.

treasury rates. Hence, the prediction accuracies are not much worse than the baseline.

## 4 Conclusion

This study measures the effects of text-based information released by the FOMC on daily interest rate movements. We used the medLDA model on a set of 146 docs and obtain accuracies of 93% and 64% in predicting the Federal Funds Target Rate and the Effective Rate.

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