The informational content of FOMC meeting transcripts

A textual analysis analyzing the relationship between the content of FOMC meetings and changes in the federal funds rate

I. Introduction

Textual analysis applied to economic research has undergone a renaissance of sorts in recent years. With significant advancements in machine learning and computing power, formerly qualitative data embedded in texts has now become available for economists to quantify, classify, and incorporate into their models. These developments have created an opportunity to answer questions from level of individual actors and their reactions, rather than summary statistics describing their interactions with markets. Through applying new machine learning methods, researchers can gain a more granular understanding of how individual reactions affect different economic outcomes.

In this paper, we explore the reactions of a small set of actors with outsized influence on economic policy: members of the Federal Open Market Committee (FOMC). We attempt to understand what concerns are the most important in determining a change in Federal Reserve policy regarding interest rates. Previous research analyzes quantitative measures, such as unemployment and inflation, to understand what prompts policymakers to change interest rates. In undergoing a textual analysis, we can answer this question by looking directly at qualitative data from these policymakers.

The Federal Reserve releases qualitative information in the form of meeting minutes, statements, press releases, reports and transcripts. Transcripts of meetings and conference calls are released to the public with a five-year lag. As FOMC members' comments are relatively protected from scrutiny by this lag, we can use these transcripts to understand which issues drive changes in interest rate policy.

Through textual analysis of transcripts of FOMC meetings, can we identify the primary concerns that cause the Federal Reserve to change the target federal funds rate? Can we do this by quantifying the content of the meeting? By answering these questions, we can take a closer look at our traditional economic understanding of the factors that influence the federal funds rate. We can attempt to understand if the FOMC members' words reflect the actions of the market.

To achieve this, we first collect, clean and transform data with the goal of isolating relevant word counts. Our outcome variable is the target federal funds rate. We focus on years 1982 – 2008, as pre-1982 there was no target rate and post-2008 the Federal Reserve switched to a target range. We began by scraping FOMC transcripts from this time period, in total amounting to nearly 18,741 pages. Each document is stripped of formatting, converted into text, removed of stop words, and passed to the Porter algorithm to reduce to stems. We then preselect a list of relevant word stems to observe, chosen by examining descriptive statistics and economic intuition. After pre-processing we count words, scale by size of document, and associate the words with the relevant change in federal funds rate.

We then examine the relationship between these words and our outcome variable. We use a linear model using least-squares penalty trained with an L1 prior (also known as Lasso), with iterative fitting along a regularization path to derive our regression coefficients. We select the best model using a 20-fold cross validation scheme fitted with coordinate descent and least angle regression. We also compile various summary statistics, examining how the weighted frequency of these words changes over time, and how they vary across positive and negative changes in interest rate.

We conduct two separate the regressions on reductions in federal funds rate and increases in federal funds rate. In both, we do not find no relevant word stems that are statistically significant in determining the federal funds rate. We test our regressions with t-statistics to confirm our model's result. We then conduct a textual analysis of our sample, revealing a lack of variability in our outcome variables with regard to reductions in federal funds rate, and additionally a lack of variability in proportions of word counts across transcripts associated with increases in federal funds rate. We are able to deduce that FOMC transcripts in our sample roughly touch the same topics in similar proportion regardless of the outcome of the meeting. This suggests that there may be unobserved factors that FOMC members do not reveal in meetings that determine their vote, and that FOMC meetings are more of a discussion of possibilities with few subtleties revealing voting decision.

The remainder of the paper is organized as follows. Section II outlines relevant work by other researchers. In Section III we present our methodology and data collection process. We present the results of our regression and textual analysis in Section IV, and interpret its significance. Section V concludes.

II. Literature Review

Economic literature attempting to incorporate qualitative data through textual analysis has evolved through developments in machine learning methods and open-source software programs that implement them. Prior to these advancements, researchers were limited to pre-scheduled public announcements with easily quantifiable impact. Methodology centered on variations of difference-in-differences analysis or manual interpretation of texts. As a result, analysis was conducted on small samples of data, with limited quantitative analysis.

Present day textual research uses classification and regression analysis, scaling to thousands of data points. Post-2000, with algorithmic advancements granting the ability to analyze large quantities of data on different types of informational events, the amount of published textual analysis research has skyrocketed.

The data analyzed has extended to unscheduled announcements, with data from supplementary texts, news and other media sources collected for analysis. Pre-processing of data varies across papers, but the most common identification strategies include sentiment analysis and word-frequency regressions.

This paper primarily builds on various methods used for pre-processing data to organize word counts, and borrows heavily from advances in word-frequency regressions. These methods vary by paper across the source of data examined, as each presents unique challenges to pre-processing. As methodology is fairly new, most research focuses on predicting prices of various securities.

Regarding stock price analysis, source data for textual analysis research generally originates from internet stock boards or firm specific news stories. Among research using internet stock board postings, there is a consensus that sentiment analysis using language-processing algorithms provide the best measure of stock price (Antweilier and Frank 2004; Das, Martinez-Jerez and Tufano 2005). There are a variety of modern day computational linguistics methods that can measure both intensity and dispersion of sentiment. A particular problem in classification is understanding which method works best. Recent research suggests a voting scheme between classifiers reduces the number of false positives and results in higher sentiment accuracy (Das and Chen 2007). This paper uses those insights by running a 20-fold cross validation scheme, using two different algorithms, least angle regression and coordinate descent, in each validation step and choosing the optimal.

Research using firm specific news stories is similar in that sentiment analysis algorithms are used, but because these documents are less polarized, hence making classification harder and limiting the amount of algorithms available. Most make use of bag of words or n-grams in pre-processing their words and compare them to pre-defined negative and positive classifications (Tetlock, Saar-Tsechansky, and Macskassy 2008; Fang and Peress 2009; Engelberg and Parsons 2011). A newer pre-processing strategy, developed in 2008 by Stanford's Natural Language Processing group, has recently been used to classify relationships between words in a tree structure (Engelberg 2008). This method was far too complex and costly for the data I was using, but applying this methodology could produce a more nuanced result to this research.

In research surrounding management statements to predict earnings reports, pre-defining words with positive and negative sentiment becomes tougher. Management statements are generally less sentimentally charged and use financial jargon. Therefore linguistic theory is heavily employed to measure sentiment (Davis, Piger and Sedor 2012). Recent scrutiny of existing papers' pre-defined sentiment classifications is leading to better methods, but none have emerged as the dominant method (Demers and Vega 2012; Loughran and McDonald 2011). In this paper, we choose the words most relevant beforehand, looking at descriptive statistics to try and optimize selection.

Textual analysis of macroeconomic announcements have not been explored in the same depth, and have generally been used to create treasury or relevant asset price predictions (Hafez and Xie 2013). However, a small subset of research examining FOMC minutes does exist using sentiment analysis to predict treasury yields and future interest rate predictions (Lucca and Trebbi 2009; Danker and Luecke 2005). Most notable among them is a paper authored by Federal Reserve Bank of New York economists Boukus and Rosenberg (2006), examining the relationship between themes in FOMC minutes and US Treasury yields. Using a process called latent semantic analysis, they categorize minutes into characteristic themes. Their methodology is mathematically complex, and applying it to FOMC transcripts would be a possibility to further explore. Our paper draws inspiration from their use of the Porter algorithm to stem words.

This paper adds to the existing corpus by considering FOMC transcript data. Most literature surrounds private sector documents, and even analysis of Federal Reserve documents is limited to FOMC minutes. Transcripts represent a considerably larger dataset. While meeting minutes average 8-10 pages in length, transcripts from meetings and conference calls average nearly 100 pages each and represent direct communication from economic actors, rather than edited statements. Through this paper, we attempt to more directly understand the motivations behind changes in the federal funds rate. Further research could endeavor the compare this paper's results with purely quantitative measures to understand which is a better predictor of changes in federal funds rate.

III. Model, Methods and Data

III.I Model and Methodology

The method we use to examine the relationship between our word count data and the change in federal funds rate is a Lasso linear model, using least-squares penalty trained with an L1 prior, with iterative fitting along a regularization path to derive our regression coefficients. I add several nuances to this general method, including cross validation for selection of the regularization parameter and different parameter fitting formulas.

Our final equation, shown below, predicts a change in federal funds rate given a vector of relevant word frequencies. $f_{\hat{\theta}}(\vec{x})$ represents the basis point change of the federal funds rate. It is defined by a coefficient matrix $\vec{\hat{\theta}}$, which this paper estimates. We will determine two functions, running our regression twice, separately considering decreases in federal funds rate and increases in federal funds rate. The function takes a vector of relevant word stem frequencies, $\vec{x}$, defined below. Each j represents a different word stem, x_j represents the frequency associated with that word stem, and β_j represents the derived coefficient parameter for that particular word stem:

$$f_{\hat{\theta}}(\vec{x}) = \vec{\hat{\theta}} \cdot \vec{x} = \sum_j (\beta_j x_j)$$

The relevant word stems that we use in our equation are as follows. These were chosen by compiling descriptive statistics and using economic intuition on our processed word stem counts per document:

inflat	save	continu	expect	stock	profit	gain	fund
resili	househol	indic	bear	distribu	custom	incom	bull
partici	oil	suppli	employ	confid	bank	forecas	price
foreign	tax	stagnat	headwin	debt	wage	growth	unemplo
workfor	weak	geopoli	dramat	demand	labor	consum	job
produc	risk	polici	strong	rate	global	energi	corpor
deficit	supplier	exchang	commod	wealth	recover	condit	capit
market	lend	economi	abroad	mortgag	percent	lack	crisi

We find the value of our coefficient matrix $\hat{\theta}$ by minimizing the following objective function. $\hat{\theta}$ is selected as the loss minimizing matrix of all possible coefficient matrix values θ.

$$\hat{\theta} = argmin_{\theta} \frac{1}{n} \sum_i Loss(y_i, f_{\theta}(x_i)) + \lambda R_{Lasso}(\theta)$$

In our loss function, y_i corresponds to the change in federal funds rate a particular row of data i. $f_\theta(x_i)$ is our estimate of the change in federal funds rate, defined by the coefficient matrix we are testing θ, given the input x_i representing the word frequencies for row *i* of our data.

$$Loss\big(y_i, f_\theta(x_i)\big) = (y_i - f_\theta(x_i))^2$$

Our objective function to minimize is comprised of two parts: least squares, shown above, and the L1 prior as a regularizer, shown below. Least squares minimizes in typical fashion, by fitting with more sensitivity to outliers as the squared term emphasizes larger deviations. The L1 prior is used to avoid overfitting, and is particularly useful in estimating sparse coefficients.

$$R_{Lasso}(\theta) = \sum_j |\theta_j|$$

We choose an L1 prior because has the ability to set coefficients to 0 if the word stem is not statistically significant in determining change in federal funds rate. We use it to select only the most informative word stems, giving our regression the ability to exclude unnecessary terms. As shown above, it is calculated by adding the sum of the absolute value of the selected weights corresponding to relevant word j. Because this is added to our loss function, our estimation method allows us to remove weights.

The Lasso estimate therefore solves the minimization of the least squares penalty with $\lambda R_{Lasso}(\theta)$ added to it, where λ is the regularization parameter, a constant defining the weight of the L1 prior. As the Lasso estimate does not have an analytical solution, we must use numerical methods to approximate. Our software package, scikit learn, uses both coordinate descent and least angle regression algorithms to fit the coefficient matrix θ, and chooses the best estimate as $\hat{\theta}$.

Lastly, we must find the proper value to assign our regularization parameter λ that determines what weight we give to our L1 prior. To compute the optimal value, we use a 20-fold cross a validation scheme on our training data. This means we randomly split our original training set into a new training set and validation set with a 70-30 split. We minimize our objective function on the new training set for a particular value of λ using both coordinate descent and least angle regression. We then test our coefficient matrix on the validation set with that λ, graph the result and repeat the process until we have generated a curve of mean square error over multiple values of λ. We repeat this process 20 times, selecting the value that minimizes our averaged error across our curves.

A possible complication in running this pipeline could be rank deficiency in our samples. In the case of encountering linear dependence or numerical instability due to rounding in our sample matrix, our coordinate descent and least angle regression fitting methods will result in two dramatically different answers. Fortunately, our scikit learn package automatically exclude the row of data if we encounter this problem.

Although incorporating regularization is intended as a robustness check, a potential weakness in using this methodology could be selection bias. Perhaps there are other word stems that are more critical to determining a change in federal funds rate that I have not included. To ensure the stems that are selected do contribute to determining basis point change, I test individual significance with a t-statistic on each selected coefficient. Further research could use our methodology but explore changing the relevant words. An interesting area of research could examine and improve the relevant word selection process.

In addition to our regressions, we perform a textual analysis by compiling various summary statistics. This includes averages of word counts grouped by associated interest rate, sample size grouped by interest rate, and overall orderings of word stems by the percentage of the transcript that they make up. We plot the terms with most variability in a time series to examine how the informational content of transcripts changes during business cycle. We use this analysis to gain insight on our regression results.

III.II Data

The underlying data used in this paper consists of transcripts from FOMC meetings, changes in the federal funds rate, and corresponding unemployment, real GDP, and inflation data. All the data was scraped using BeautifulSoup, requests and os python packages, and heavily pre-processed before applying it to the above model. The data collection and transforming process, final processed documents, results of textual analysis and python implementation of the above regression are open-sourced and available for further reference here.

III.II.I Independent Variables

Our FOMC transcripts containing our independent variables, relevant word counts, were taken from the Federal Reserve website. We conducted our study on transcripts from 1982 – 2008, as pre-1982 the federal reserve did not issue a target federal funds rate, and post 2008 the federal reserve switched to a target range. In total, we scraped 660MB, amounting to 230 documents or 18,741 pages of transcript data. This included all communication of FOMC members in conference calls before meetings and during the meetings. Each document averaged 81 pages long.

We pre-processed each document by the following procedure. We first removed stripped all the cover pages. We then passed each PDF into a text converter, using the PyPDF2 python package. We then removed extremely common functionally-neutral words that do not contribute to our analysis, commonly referred to in machine learning literature as *stop words*. This includes pronouns, articles, conjunctions and prepositions such as “I”, “the”, “he”, etc. The remaining terms are further processed by using the Porter algorithm to stem. We remove the suffixes such that words that share the same etymological root are mapped to the same stem. For example, our stemmer maps the terms *increase*, *increased*, *increases* and *increasing* to the stem *increas*. Finally, we count the relevant word stems in each document and weight them using term-frequency inverse document-frequency (tf-idf).

We choose tf-idf weighting as it is the most common, although a variety of different weighting schemes are available as noted by Sebastiani (2002). Under tf-idf, the more a term appears across all documents, the less important it is if it appears in a particular document. For example, if the word “president” is common among all of the FOMC transcripts, while “labor” is not, but in a particular document “president” is mentioned only slightly more than “labor”, tf-idf weighting will correctly reweight the counts such that “labor” is given far more significance in that particular document.

The tf-idf weighting of each term is done in accordance with the below equation. $tf(t,d)$ is the term frequency of the term t in document d. It is multiplied by $idf(t)$, which roughly represents the inverse of the total amount of mentions of the term t across all documents. In our paper, we use the following formula, with n_d representing the total number of documents and $df(t)$ representing the number of documents that contain term t.

$$tf - idf(t,d) = \quad tf(t,d) * idf(t)$$

$$idf(t) = \log \frac{1 + \ n_d}{1 + df(t)} + \ 1$$

We then normalize the resulting word vectors for each document.

$$v(d) = \begin{bmatrix} tf - idf(t_0, d) \\ tf - idf(t_1, d) \\ \dots \\ tf - idf(t_n, d) \end{bmatrix}$$

$$finalWordStemCounts(d) = \frac{v(d)}{\|v(d)\|} = \frac{v(d)}{\sqrt{v_0^2 + v_1^2 + \dots + \ v_n^2}}$$

Finally, we then group together all the final word stem counts in all documents leading up to the meeting before a change in federal funds rate and all the documents leading up to the meeting prior if during that prior meeting the FOMC voted to maintain interest rates. We add each term in the above normalized matrix together, and renormalize the vector. That final vector is associated with the appropriate change in federal funds rate.

III.II.II Outcome Variables

Our outcome data for the federal funds rate was taken directly from the Federal Reserve Bank of St. Louis' FRED portal. In addition to our outcome variables, we collected gross domestic product, unemployment, and inflation rate data correlated to changes in federal funds rate for cursory analysis and initial exploration. Our gross domestic product data was from the US Bureau of Economic Analysis. Unemployment and inflation rate calculated using the consumer price index were taken from the US Bureau of Labor Statistics.

We can identify potential shortcomings in the collection and pre-processing of our data. Our PDF to text is highly accurate upon cursory observations, but without manual inspection it is impossible to confirm. Lots of time was spent exploring different packages, many were too messy and obfuscated results. In addition, we are exploring single choices of words (in machine learning parlance, Bag of Words encoding). Our analysis might be improved by using n-gram encoding, where one examines the existence of combinations of words. For example, if choosing bi-gram encoding, we would count every combination of two words and continue our analysis. This method might retain valuable context and give different results, which further research could explore.

IV. Results and Discussion

We explore the relationship between the change in federal funds rate and words said during FOMC meetings by fitting our data to a Lasso linear model, using least-squares penalty trained with an L1 prior. Our independent variables are frequencies of relevant words stems, which we pre-selected based on descriptive statistics and economic intuition. Our outcome variable was basis point change in federal funds rate. When solving for the relevant estimators, we separated our sample by considering negative basis point changes (meetings that preceded a reduction in federal funds rate) separately from positive basis point changes (meetings that preceded an increase in federal funds rate). For each regression, we split our relevant data at random into training and test samples at a roughly 75 – 25 ratio respectively. We fitted our model using coordinate descent and least angle regression on our training data, and evaluated the accuracy of our model on the test set.

Estimators for Reduction in Federal Funds Rate

Word Stem	Coefficient	T-Statistic	STD
bank	-0.0004629	2.747 e-05	89.16
price	0.00048339011	3.085e-05	82.92
rate	-5.825e-05	-2.641e-06	116.72
percent	0.0001378	4.491e-06	162.35

Average Relevant Word STD: 35.26

Root Mean Squared Error: 0.17295

Here we see our regression results for estimators determining a reduction in federal funds rate. Of the 64 relevant words, our regression used four as determinants of a change in federal funds rate. However, as our t-statistics show, none are statistically significant and our root mean squared error on our test set is relatively high. We do note that the relevant variables left by our L1 prior do have a significantly higher standard deviation than the other relevant words.

Estimators for Increase in Federal Funds Rate

Word Stem	Coefficient	T-Statistic	STD
polici	7.766e-05	6.212e-06	76.04
inflat	2.626e-06	1.217e-07	131.27
percent	-5.544e-05	-2.165e-06	155.76

Average Relevant Word STD: 33.58

Root Mean Squared Error: 0.31653

In our regression results for estimators determining an increase in federal funds rate, we see a similar result. Our regression used three relevant words as determinants of a change in federal funds rate. Again, our t-statistics show that none of these variables are statistically significant. Again, our model selected variables with a notably larger standard deviation than other relevant words. We now use descriptive statistics and textual analysis of word frequencies to gain a deeper understanding our regression results.

The below graph gives us an idea of how our training data is distributed across outcome variables. We see that in our sample, reductions in federal funds rate succeeding FOMC meetings are rarely outside 0.5 or 0.25 basis points. We are therefore limited in the number of outcome variables considered in our reduction analysis. This suggests that our model did not have enough variability in outcome data to create significant estimators for our word frequencies.

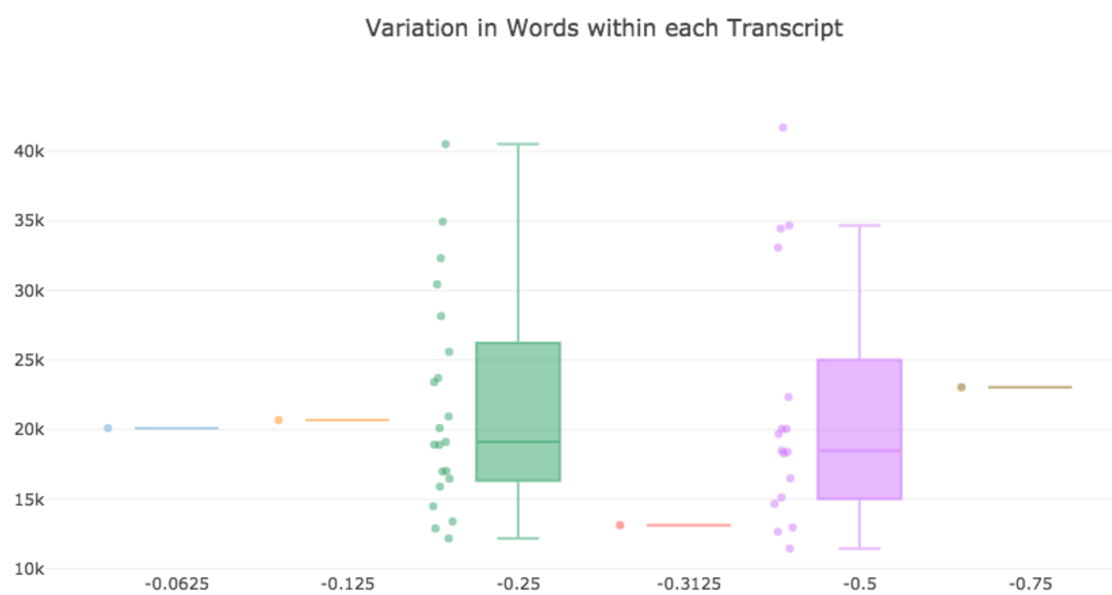

Figure 1: Variability in Words per Transcript Grouped by Interest Rate, corresponding to our reduction in federal funds rate analysis.

We again see a similar result when considering increases in federal funds in the graph on the following page. In our sample, increases in federal funds rate succeeding FOMC meetings are almost entirely 0.5 basis points. In fitting our regression, regardless of our input, our model would optimally predict a change of approximately 0.5 basis points as we lack variability in outcome data. We now take a closer look at our independent variables, word frequencies, and how their distribution within transcripts changes over time.

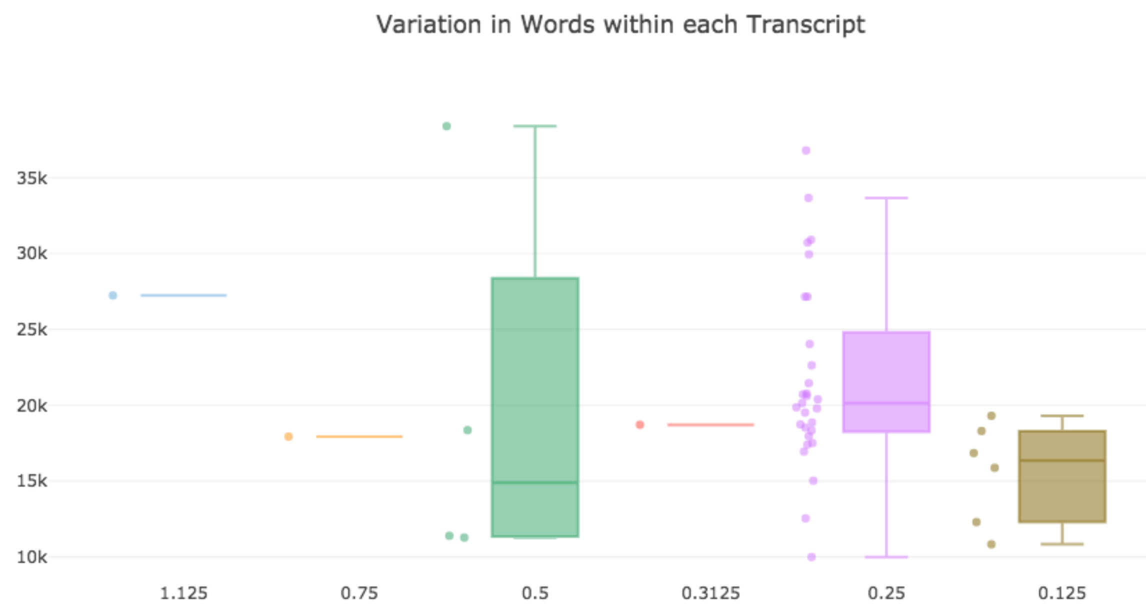

Figure 2: Variability in Words per Transcript Grouped by Interest Rate, corresponding to our increase in federal funds rate analysis.

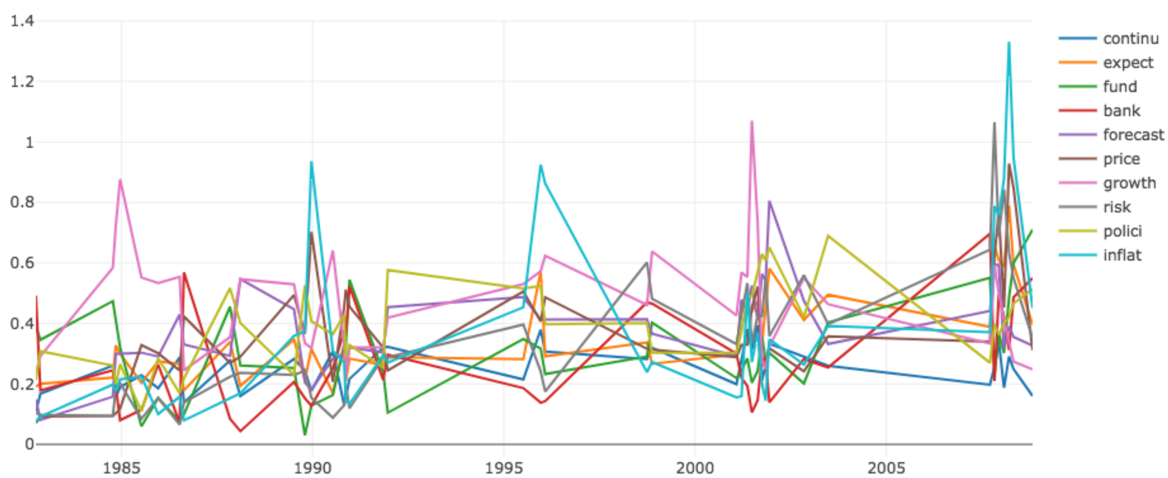

Figure 3: A selection of relevant words and their change in proportion of transcript over time. For reduction in rate analysis.

In the above graph, we observe several word stems and the relative proportions that they take in FOMC transcript. Although we have 64 relevant word stems, we show the stems with the most variability above. Upon close examination, we see that the differences in these proportions are variable. Of all relevant word stems, 'inflat', 'bank', 'growth' show the most variability. This suggests that in our reduction analysis, the primary cause of statistical insignificance regarding the estimators for model is related to lack of variability of our outcome variables.

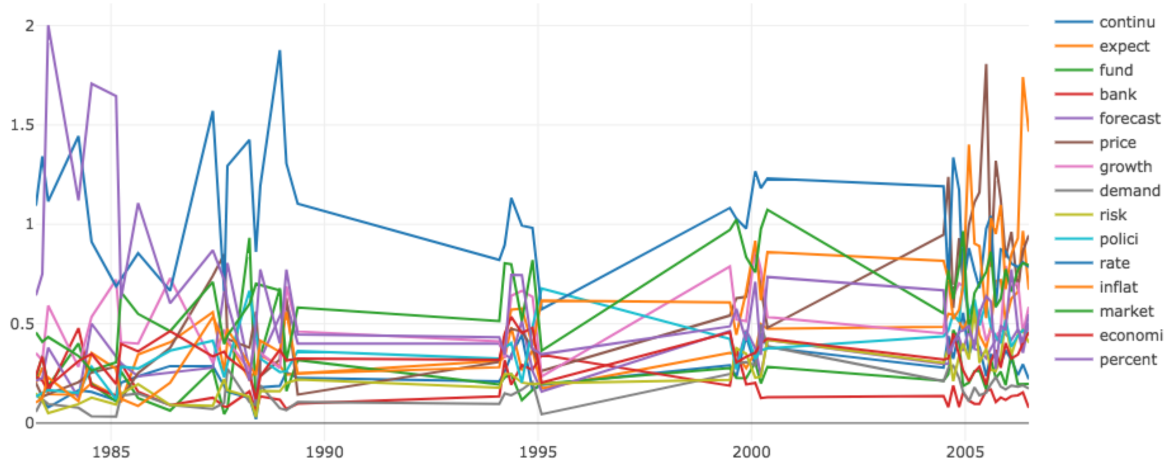

Figure 4: A selection of relevant words and their change in proportion of transcript over time. For increase in rate analysis.

In our analysis of increases in federal funds rate, we see a different result. We can observe that the differences in proportions are surprisingly constant with a few notable outliers, including 'polici, 'inflat, 'percent', which our model selected as determinants. This suggests that in our analysis of increases in federal funds rate, the lack of variation in our data for independent variables also contributed to statistical insignificance of our estimators. We also note that increases and decreases in federal funds rate are concentrated around certain periods, as all data points occur within close time proximity to each other. This reflects economic intuition, as changes in federal funds rate cluster in accordance with business cycle patterns.

Finally, we will make general observations about our data by examining proportions of word stems across federal funds rate changes.

-0.25	-0.50	0.5	0.25	0.125
1.054 rate	1.037 rate	0.865 rate	0.961 rate	0.996 rate
0.715 market	0.761 market	0.661 inflat	0.838 price	0.887 percent
0.527 growth	0.469 percent	0.612 market	0.778 inflat	0.5 growth
0.518 percent	0.404 risk	0.55 percent	0.713 market	0.413 market
0.491 inflat	0.402 growth	0.501 polici	0.599 percent	0.375forecast
0.479 price	0.391 economi	0.423 growth	0.568 growth	0.348 price
0.428 polici	0.379 polici	0.371 price	0.48 expect	0.295 economi
0.419 economi	0.365 expect	0.337 economi	0.452 polici	0.26 inflat
0.411 expect	0.359forecast	0.301 expect	0.385forecast	0.203 expect
0.405forecast	0.35 bank	0.293forecast	0.324 economi	0.194 fund
0.383 risk	0.341 fund	0.293 continu	0.307 risk	0.188 polici
0.313 fund	0.308 inflat	0.266 bank	0.3 continu	0.173 bank
0.27 bank	0.279 price	0.258 risk	0.254 fund	0.166 continu
0.265 continu	0.221 continu	0.213 fund	0.192 demand	0.15 risk
0.154 weak	0.175 weak	0.179 strong	0.171 labor	0.128 strong

Figure 5: Average appearances of word stem in percentage terms, grouped by change in federal funds rate

In the above table, we observe the average percent that a word stem appears in a FOMC transcript, grouped by the corresponding change in federal funds rate. We note the similarities in proportions and differences between proportions across our outcome variables. Similar word stems, regardless of decrease or increase in federal funds rate, appear in our transcript samples with nearly no difference in ordering. Although we use this table to make any inferences regarding our regression, as statistical significance relies on a variety of factors including variability of word stems that this table does not include, this does suggest the topics covered in FOMC meetings, regardless of basis point change, remain relatively constant over time. This initial exploration informed our decision of relevant word stems, as we added the stems with the highest proportion to our initial list generated using economic intuition, assuming that variability in the word stems that appear the most might play a role in determining rate changes.

Our regression results and textual analysis reveal that the words said during the content of FOMC meetings are statistically insignificant in determining federal funds rate changes. The implications of these results provide insight into the structure of FOMC meetings. As we observe the same words being used in similar frequencies, regardless of the outcome of the meeting, this suggests that FOMC meetings in this period could be more structured than we previously assumed, with discussion centering around the same topics. Rather than help, more transcript data simply showed similar word frequencies and outcomes, instead of uncovering subtleties that could signal oncoming changes in federal funds rate.

In addition, statistical insignificance of relevant word stems could suggest that changes in federal funds rate may be driven by internal bias or another unobserved factor inherent to FOMC members' backgrounds. Although our research assumed that transcripts would reveal these motivations, further research on the backgrounds of FOMC members' and their previous voting history could prove useful in understanding these factors and their significance in determining federal funds rate changes.

Alternative explanations of the statistical insignificance calculated in our regression results could include complications in our data collection. The period considered, 1982 – 2008, is unique in that Alan Greenspan presided as the Chairman of the Federal Reserve throughout most of this period (1987-). This could influence the discussion during meetings to be similar, and hence the content of FOMC transcripts to appear similar in word count, as staff and other members' could be like minded and therefore inclined to express similar opinions throughout this period, or meetings could be structured in a consistent fashion, covering the same topics without much deviation. In addition, as the economic climate was relatively favorable during this period, many meetings that resulted in a change in federal funds rate were only associated with a single transcript. Further research could increase the sample size by considering a larger range of years, under different chairmen or chairwoman. In particular, including the Volcker years could increase the number of different changes in federal funds rate, providing our model with more variable outcome data.

The scope research has been limited to FOMC transcript data and its relationship to changes in federal funds rate. As changes in federal funds rate are not as variable as other economic indicators, we cannot take the statistical insignificance that we calculated and extrapolate it to other economic indicators. Our results also do not suggest that other FOMC texts are insignificant in determining federal funds rate. Other research has shown high levels of autocorrelation between themes in FOMC meeting minutes, treasury yields and federal funds rates (Rosa 2013; Neely and Mizrach 2008).

Ultimately, our findings do not support our thesis that textual analysis of transcripts of FOMC meetings can reveal the primary concerns that cause the Federal Reserve to change the target federal funds rate. As none of our relevant words were statistically significant in predicting either an increase or decrease in federal funds rate in our sample, we conclude that the primary factors in determining these changes are not revealed during the meetings we observed. Instead, through textual analysis, we uncover that the same general themes are discussed during all meetings in our sample.

Related research analyzing the content of FOMC minutes suggests a higher correlation between federal funds rates and prepared FOMC remarks. This shows that contrary to intuition and despite transcripts having nearly ten times as many words as meeting minutes, prepared remarks summarizing the meeting after making a rate change decision differ more in tone and theme (Boukus and Rosenberg 2006). Our findings suggest that prepared post-decision remarks may be a better indicator of economic variables such as federal funds rate, rather than the meetings themselves that discuss broader aspects of the economy and lead to the decision.

V. Conclusion

Understanding how economic indicators move with regards to FOMC communications requires mapping complex, qualitative information into quantitative measures. Related research examining FOMC texts have either centered on meeting minutes, which represent a significantly smaller sample of data, or relied on indicator variables determined by manual analysis of documents.

In this paper, we apply pre-processing methods and transformations that lead to statistical analysis using machine learning methodology to interpret FOMC transcripts. Our model captures speech content, translates it into related word stem counts, and associates it with the appropriate change in federal funds rate. We interpret the impact of different frequencies of word stems by fitting our Lasso linear model using coordinate descent and least angle regression, performing 20 cross validation steps to determine our regularization parameter for our L1 prior, giving us the ability to exclude words that are insignificant determinants of federal funds rate.

After separating our regressions into positive and negative changes in federal funds rate, we discover no statistical significance. Limited by a lack of variability in our word stem frequency and changes in federal funds rate, our model cannot determine consistent estimators. However our textual analysis reveals insights on the relative frequencies of topics discussed during FOMC meetings and their change over time. Our research suggests that FOMC meetings are consistent, covering similar topics regardless of associated basis point change. Our evidence directs market participants to other forms of data or more comprehensive data collection, suggesting that motivations behind changing the federal funds rate run deeper than the information content of meeting transcripts.

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