Committees and Decision Making

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Abstract

We study the interactions and strategies of economic agents within a business committee to better understand how decisions are made in an important group setting. Specifically, we study the Federal Reserve's Federal Open Market Committee (FOMC) monetary policy actions and meeting transcripts to understand how the committee members' discussion impacts the chosen monetary policy. The results show that after controlling for the impact of macroeconomic factors related to the Federal Reserve's dual mandate and past policy actions, there exist variables that have a statistically significant effect on the FOMC meeting outcomes. These include members' efforts in *interpreting* the current economic data and *persuading* other members through cognitive and affective persuasion strategies. The implication is that for a business committee to arrive at a group decision, the members need to digest and interpret the relevant information, spend time persuading other members using logic and emotion in order to aggregate member viewpoints to a consensus decision. Thus, the interpretation processes and persuasion methods that are used during a committee discussion have a non-trivial impact on the final outcome that the committee makes.

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I. Introduction

Aggregating and synthesizing public and private information by economic agents is a critical function that is performed within many different facets of business and economics. The mechanisms that have evolved to perform this critical function are varied in their structure and approach; some are defined by a set of rigid rules, while others have few rules relying instead on interpretation of the available information and interpersonal persuasion methods to facilitate an efficient outcome.

One of the important entities to aggregate and synthesize information is a business committee. Examples of such entities abound, and include company board of directors, advisory boards, search committees, regulatory boards, etc. Like capital markets, the goal of a business committee is to aggregate the information sets of the committee members to arrive at a good business decision. Precisely how a business committee accomplishes this goal is unclear, and addressing this question empirically is the focus of our inquiry. Specifically, we study the interactions among committee members to see how the discussion during the meeting affects a final outcome, and the processes members use to arrive at a committee decision.

The empirical study of how committees work has traditionally been difficult for a number of reasons. First, it is often infeasible to obtain data on the interactions and decisions of economic agents within real business committees as many are private organizations. Second, even with available data it is often difficult to compare or relate decisions/strategies through time as many committees consider issues that have enormous variance with respect to their content, frequency and importance (e.g. the board of directors of a firm). We avoid these difficulties by analyzing the Federal Reserve's Federal Open Market Committee (FOMC) for which there is ample publicly available information in the form of a long time-series of comparable decisions along with detailed transcripts of the member's discussion. Furthermore, by analyzing the FOMC we provide a unique window into the inner workings of one of the most influential committees on the world economic stage.

The two primary research aims of this paper are: (1) To uncover the process level details in a committee's decision-making; and (2) To assess the impact of such process-level variables on the committee's final decision. For our specific empirical context our data are comprised of two main parts: macroeconomic variables and FOMC meeting transcripts. We use both these data corresponding to 379 meetings, from the years 1978 to 2013, to explain the FOMC's decision to stay, ease or tighten the target federal fund rate at each meeting. By doing so we also quantify the incremental role of the meeting discussions in explaining the committee's decision over and above the macroeconomic data in an econometric model. Our data exhibit significant variation on several dimensions that we utilize. During our sample period there were four FOMC chairs (Miller, Volcker, Greenspan, and Bernanke), and it spanned multiple recessions, presidencies, and economic crises. Further, during this time the target federal funds rate was set as high as 9.81% and as low as 0%.

Our specific discussion-process variables are chosen to test a simplified theoretical committee model adapted from Hinsz et al. (1997) which includes two hypothesized committee activities: interpretation of the data (or information processing) and inter-personal persuasion. Our analysis of the potential impact of the FOMC's meeting transcripts consist of a series of nested multinomial logit regressions of the FOMC monetary policy outcomes, wherein the transcript related variables are constructed by text-analyzing those data. As is typical in such text analyses, this results in a large number of variables (Berger et al. 2020, Netzer et al. 2019). To address the $p>n$ problem for our multinomial logit regressions, we use the penalized regression framework (Tibshirani 1996, Zou and Hastie 2005) to analyze these data.

The results show that including variables related to the FOMC meeting discussion improves the model fit of the monetary policy action between 4.4 and 10.7% after controlling for the macroeconomic data that is typically thought to make up the Federal Reserve's reaction function. Consistent with our hypothesized model, we find that the FOMC discussion which focuses on (1) understanding and internalizing information, and (2) cognitive (logical) and affective (emotional) persuasion strategies are both statistically and economically important in explaining the monetary policy decision. Of particular importance to the interpretation efforts are references to macroeconomic words, while cognitive and affective persuasion are important for aggregating member views and arriving at a committee decision. Importantly, we find evidence that during periods of disagreement, crisis and stress, when the risk of making a poor decision is elevated, committee members place more emphasis on interpreting relevant data and persuasion of other members is accomplished with an *affective*, person-focused narrative style; while during periods of calm, when the risk of making a poor decision is low, less time is spent on interpretive discussion and persuasion is more cognitive, and accomplished with more formal and precise language. Our descriptive evidence further suggests that the FOMC chairs, whose primary focus may be to build a consensus, exhibit more person-focused narrative; while district presidents, who have the responsibility to advocate for their specific districts, use stronger logical and categorical language.

The paper makes several significant contributions to the literature. First, we show that information processing, or interpretation, has a large impact on a business committee's decision that is not captured by key macroeconomic variables. To the best of our knowledge, we are the first to empirically demonstrate this finding that involves multiple decision makers. Second, we show that persuasion tactics employed by individuals within the group impact a committee's decision. These persuasion strategies take two forms: cognitive and affective. While the former is to be expected, the latter is also shown to impact committee decisions. We further find that the role of persuasion tactics in a business committee is moderated by economic conditions (e.g. crises, recession, and economic policy uncertainty) and amid disagreement between members. Finally, we demonstrate that the text data in the context of a business committee, when available, not only helps capture some of the process level aspects of the committee's decision, but also adds to an econometric model's ability to predict the committee's ultimate decision.

The rest of the paper is organized as follows. Section II provides some background on the Federal Open Market Committee. Section III reviews the relevant literature. Section IV details our theoretic motivation. Section V describes our data along with some summary statistics regarding our text variables. Section VI specifies our econometric model and text regressions and Section VII discusses our empirical results. Section VIII investigates our process-level variables, interpretation and persuasion and Section IX concludes.

II. The Federal Open Market Committee

The Board of Governors of the Federal Reserve System is the institution that is charged with setting and implementing U.S. monetary policy. Specifically, the U.S. Congress, through a 1977 amendment to the Federal Reserve Act, charged the Federal Reserve to "promote effectively the goals of maximum employment, stable prices and moderate long-term interest rates." The decision-making body within the Board of Governors that is responsible for carrying out the congressional mandate is the Federal Open Market Committee (FOMC). The committee is chaired by the Chairperson of the Board of Governors and populated by up to six standing Federal Reserve Governors and the twelve Federal Reserve District Bank Presidents.[1]

A number of tools are used by the FOMC to implement monetary policy. Specifically, to affect the level of reserves in the banking system, the FOMC has control of the discount window borrowing rate, the federal funds rate as well as open market operations. Within each meeting, participants are presented with the most recent macroeconomic data as well as the Board of Governor Staff's assessment of that data, after which members discuss possible courses of action lead by the FOMC chair. The meeting concludes with a vote of (voting) members to either accept

[1]At any one time 5 of the 12 Federal Reserve District Bank Presidents are voting members of the FOMC. The President of the Federal Reserve Bank of New York is a permanent voting member of the FOMC while the other 4 seats are rotated through the 11 other districts on an annual basis.

or reject the proposed course of action which could include doing nothing or easing (tightening) monetary policy by lowering (raising) the federal funds target rate and/or discount rate. The resulting action and associated vote are communicated to the public with varying time lags. For more information concerning the FOMC see, http://www.federalreserve.gov/fomc.

III. Related Literature

This paper is unique in that it spans a number of disparate literatures. Quite naturally, there is a great deal of interest by economists and market participants alike, in how the Federal Reserve conducts monetary policy, specifically as it relates to the voting behavior and reaction function of the Federal Open Market Committee. Work by Tootell (1996), Chappell and McGregor (2000), Meade (2005) and Meade and Sheets (2005), investigates the voting behavior of the FOMC as well as the forces that influence particular voting patterns such as regional effects and dissensions.[2] Hamilton and Jordà (2002), Hu and Phillips (2004), Jondeau et al. (2004) and Galbraith et al. (2007) provide an estimate of how the chosen FOMC policy decision is related to macroeconomic inputs, such as inflation, employment, GDP, etc., when making its monetary policy decisions. Clearly, our paper is related to these two sets of the literature as we too analyze the workings of the FOMC; however, our focus is on whether and how the *interactions* within the FOMC committee discussion impact the final outcome controlling for the most recent economic data.

The use of text analysis in research has increased substantially as of late, being used in a myriad of ways. Text analysis has been used to understand psychological and social processes (Tausczik and Pennebaker 2010), such as personality (Walker et al. 2007), social hierarchy (Kacewicz et al. 2014), deception (Newman et al. 2003) and motives (Schultheiss 2013). Also within economics and in other related fields, increasing number of research utilize text as sources of rich information (Gentzkow

[2]Harris et al. (2011) conduct a similar study of the voting behavior of the Bank of England.

et al. 2019), to understand, for example, how financial text impacts markets, prices and contracts as in Boudoukh et al. (2012), Kearney and Liu (2014), Loughran and McDonald (2016) and Netzer et al. (2019).[3] More closely aligned with our work are studies that focus on text associated with the Federal Reserve. Like our investigation, Boukus and Rosenberg (2006), Schonhardt-Bailey (2013), Jegadeesh and Wu (2017), Woolley and Gardner (2017) and Baerg and Lowe (2018) analyze the FOMC minutes/transcripts; however, their research questions are substantially different from this paper. Our contribution to this literature is our focus on whether, and how, a committee mechanism is able to aggregate members' information into a joint decision, rather than what might be gleaned about the economy from the FOMC discussion. More specifically, we study the role of information interpretation and persuasion tactics employed by individual members on the FOMC's decision, and show that such persuasion tactics are moderated by economic conditions (e.g. crises, recession, etc.) and disagreement within the committee. More broadly, we rely on the text data in the context of the FOMC to study some of the process level aspects of the committee's decision-making and test if it adds to an econometric model's ability to predict the committee's decision outcome.

Also related is work in the social psychology literature that studies the process by which a group of agents arrive at a joint decision. Papers by Loewenstein et al. (1989) and Hinsz et al. (1997) survey the existing research in this area and provide a theoretic framework to understand group behavior. Others investigate the specific role of variables such as fairness (Deutsch 1975, Albin 1993), influence (Corfman and Lehmann 1987, Corfman 1991), group polarization (Myers and Lamm 1976, Rao and Steckel 1991), power (Bottom et al. 1996, Komorita et al. 2006) and preference aggregation (Arora and Allenby 1999, Baucells and Shapley 2008) play in group decision-making. Our work differs significantly from this literature. Our empirical

[3]Relatedly, Malenko (2014), Marchisio (2013) and Schwartz-Ziv (2017) study how the decisions of corporate boards, shareholder votes and board activism respectively, are influenced by the communication between, and interaction among, members.

context involves a large committee; to the best of our knowledge large groups have not been studied in this literature because of the lack of good data. Our work adds to this literature by both measuring the nature and impact of committee activity on a group decision, and investigating the specific roles that information interpretation and cognitive/affective persuasion play within the context of an economically important applied setting—the Federal Reserve.

IV. Theoretical Motivation

Our two primary research aims are to uncover the process level details in a committee decision and assess the impact of such process-level variables on the committee's final decision. To help accomplish these two aims, we build upon the literature in economics and social psychology and construct a guiding framework described below. Economists have long sought a function of macroeconomic data that explains/predicts how the Federal Reserve would alter its policy in response to changes in the economy. These include papers by Orphanides (2001), Hamilton and Jordà (2002), Hu and Phillips (2004), Galbraith et al. (2007) and Eichler and Lähner (2018). Unfortunately, these models have met with limited success as few macroeconomic inputs appear consistently important and the results vary substantially across studies depending on the time periods and data definitions used. Consequently, more recently there has been a movement to estimate the Federal Reserve's reaction function based on the mandate imposed on it from the U.S. Congress, i.e. the Taylor Rule, examples include, Asso et al. (2011), Branch (2014) and Baerg and Lowe (2018).[4] These models focus more narrowly on price stability, employment and economic growth as the basis for the reaction function and have subsequently been more successful than the earlier models. Given the clear link to the Federal Reserve's mandate along with their consistently intuitive results, we adopt a version

[4]The Federal Reserve mandate is sometimes referred to as the "Dual Manadate" or the "Taylor Rule" after the work of John Taylor in Taylor (1993).

of the Taylor Rule as our benchmark model.

Key to our two research inquiries is Hinsz et al. (1997) which provides a compelling framework within social psychology to conceptualize a group as an information processor. Their model partitions group decision-making tasks into a number of components related to: an objective, relevant information, attention, encoding, storage, retrieval, processing space, response and feedback. The foundation for these specific components is a thorough integration of the psychology literature on these specific tasks. For purposes of studying the FOMC, we adapt (simplify) their standard model by combining a number of their processes. Specifically, in our setting the group objective is the FOMC's mandate, the information set is all current and past macroeconomic data and the response is the monetary policy action (ease, tighten or no change). The remaining components of the model, attention, encoding, storage, retrieval and processing components, are renamed or grouped within the context of the FOMC setting, see Figure I.

We conjecture that the most primitive process to arrive at a decision is the interpretation and internalization of relevant economic data. Hinsz et al. (1997) use the term encoding to describe this information processing stage of the committee's decision-making process. Encoding involves the process of how individual members combine the information available into a meaningful representation. It involves questions related to shared mental representations such that the macro data are meaningfully interpreted by the committee. Given the nature of a committee that meets regularly and has well established norms, the FOMC members likely share mental models and related collective cognitive representations. Such shared interpretations with well-established dimensions help the committee arrive at their final recommendation in an efficient manner. For the FOMC this involves a reflection on historical time series including, but not limited to, the federal funds rate, employment, inflation, and growth.

Once the relevant data are interpreted, we hypothesize that members engage in persuasion activities to arrive at a group decision. Furthermore, we contend that two of the important methods used to persuade or influence other members are cognitive and affective reasoning (Zajonc 1980, Fabrigar and Petty 1999).

Cognitive persuasion is based on facts (i.e. macro data in this decision-making context) and logical reasoning, which is likely a mechanism that members would rely on in a committee setting. The literature in social psychology views an individual's behavior to be guided by their beliefs and attitude towards a target object. For example, an individual FOMC member's beliefs about how the economy functions (e.g. the relation between unemployment and inflation) may impact their overall attitude towards the economy; this in turn may impact their decision on how to vote for the proposed federal fund rate target. One such well-known model, Fishbein and Ajzen (2011) assumes that individual attitudes are a function of the weighted sum of their beliefs where the subjective weights capture the relative importance of each belief. The underlying thinking here is that individuals rationally process the information they have available and such an approach is characterized as cognitive. In addition to the cognitive input, a large literature in social psychology shows the presence of affective aspects of decision making. Zajonc (1980) highlights the role of feelings and emotions in the decision-making process. In the FOMC context, it is reasonable to expect that individuals may also rely on affective persuasion strategies that are based on how an individual member feels about the state of the economy.

The joint impact of cognitive and affective factors has been studied in the legal context where the authors explore the social psychology of justice judgments (Harris et al. 2007). These authors argue that cognitive processes pertaining to the justice judgment process involve evaluation and weighting of the information available before a judgment is formed. In contrast, affective or intuition factors may play a significant role on the judgment where individual gut feelings guide moral judgment. Neuroscientists also study the interrelationship between cognition and emotion as it relates to decision making (LeDoux 1989) and both are well known to impact individual decisions.

In the FOMC context, data on macro variables fail to capture the critical interpretation and persuasion aspects of the committee decision making process. Beyond aligning with intuition and theory, from a practical perspective, we believe these basic processes to be measurable and distinct from each other. We develop relevant hypotheses that will be empirically tested in the forthcoming analysis.

V. Data

The central data we employ in this study are the transcripts of Federal Open Market Committee discussion at each regularly scheduled meeting and the resulting committee action (if any) of changing the target federal funds rate and/or discount rate or executing other monetary policy tools, e.g. quantitative easing (QE).[5] Our data begins on March 1978 and runs through December of 2013.[6] We supplement these historical FOMC data with macroeconomic data, first published where appropriate, from the Federal Reserve Bank of St. Louis FRED database. Consistent with a version of the Taylor rule as our benchmark model, we collect the consumer price index (CPI) and the civilian unemployment rate (CUE). Also pertinent to the model are the federal funds rate, the slope of the yield curve – measured as the difference between the 10-year and 1-year Treasury yields, and the return of the Wilshire 5000. We include these in our benchmark model as the federal fund rate provides an anchor to the current state of the money market. An inverted yield curve is a well known harbinger of recessions, and it has been increasingly argued that the Federal Reserve adjusts monetary policy to buoy the stock market (Cieslak and Vissing-Jorgensen

[5]We also include the transcripts of committee discussions at inter-meeting FOMC conference calls if a decision was made regarding monetary policy, i.e. not purely informational.

[6]The Federal Reserve has only relatively recently adopted a more transparent communication strategy regarding its actions, votes and discussion. In 2002, the Federal Reserve began disseminating a press release announcing the outcome of the vote/meeting, whereas prior to that, the FOMC policy decision was signaled through open market operations and transcripts were not made public. In 2011, the Chair began holding a press conference to announce the outcome of the meeting. Currently FOMC meeting transcripts are released to the public on a five year lag, although more recent data are available for the voting record and committee action.

2020).

It is important for the reader to appreciate the richness of our dataset. Over the time span of our study, there were 379 FOMC meetings made up of 294 regularly scheduled meetings and 85 intermeeting conference calls.[7] Over our sample period there have been four chairs (Miller, Volcker, Greenspan, and Bernanke), 38 different board members and 52 different district presidents who have participated (voted) in the FOMC meetings. From a historical perspective, these FOMC meetings include deliberations/discussion through multiple recessions, presidencies, and economic crises such as the oil crisis of the late 1970s, the 1987 stock market crash, the World Trade Center attack and the 2008 financial crisis. In addition, over this time span the Federal Reserve operated under a number of different monetary policy regimes, early on targeting borrowed reserves, then non-borrowed reserves, followed by the monetary aggregates and most recently targeting the federal funds rate. During the federal funds rate targeting regime, the target federal funds rate was set as high as 9.81% and as low as 0%, Figure II provides some context regarding the frequency and extent that the FOMC altered monetary policy over this period.

V.A Organization of the Text Data

Our empirical work begins by extracting information from the FOMC transcripts. The FOMC meeting is the unit of analysis for our study. We employ text analysis techniques to partition and quantify the individual member comments within each FOMC meeting transcript.[8] Specifically, the entire set of raw transcripts $\mathcal{D}$ is organized with tagged information about each meeting. As *Document* is a standard unit of analysis in text data, in our setting, each document $\{\mathcal{D}_i\}$ contains all the words spoken at meeting i, where i ranges from 1 (March, 1978) to 379 (December, 2013). The raw text data within the transcripts contain 13,219,743 total words and 43,597

[7]From 1981 onward, there have been 8 regularly scheduled FOMC meetings per year, prior to 1981, meetings were scheduled roughly monthly.

[8]Gentzkow et al. (2019) provide an excellent overview of the current practices and applications using text as data.

unique words. Words in a document are tokenized and summarized in a numerical row vector $\mathbf{c}_i$ recording the frequency of the occurrence of a specific token in document i. Note that the $\mathbf{c}_i$ are organized in a document-token matrix $\mathbf{C}$ which has very high dimensionality since the number of columns can be as large as the number of unique words and word combinations, spoken at each meeting; thus, some type of feature/variable selection is required.

V.B Text data stemming

Two common feature selection strategies are stemming and the removal of low content words, or *stop words*. Stemming is the process of reducing words to their root. For instance, "agreement", "agreeing", "agreed" and similar derivations are all reduced to the stem "agree". We employ the standard stemming tool, the Porter stemmer, from Porter (1980), to our corpus data. The removal of stop words such as articles ("a" and "the") and conjunctions ("and", "but" and "or") is the other common strategy to reduce the dimensionality. While this strategy would also reduce the number of features we consider, we refrain from eliminating these words given the nature of our research questions. The removal of stop words makes sense when *what* is discussed in the text is the focus of the analysis, but would be detrimental if interested in *how* things are said, as we are. It is well understood that *linguistic styles* are characterized by how one uses function words (pronouns, articles, prepositions, auxiliary verbs, common adverbs, conjunctions and negations), and these words can illuminate hidden cognitive and psychological processes (Pennebaker 2011). For example, leaders tend to have higher usage of "we" words ("we", "us", and "our") whereas followers tend to use "I" words ("I", "me", and "my"). Therefore, the more frequent use of first person plural pronouns over singular pronouns characterizes more of a leader than a follower role as in Kacewicz et al. (2014).

V.C Creating text dictionaries for analyses

We further reduce the dimensionality of the document-token matrix **C** by organizing the words into three dictionaries and corresponding word counts, where a dictionary is simply a predetermined set of relevant words that can be user-defined or borrowed from the extant literature. Dictionary-based analyses allow us to filter the text information into more targeted sets, leveraging the existing knowledge. A dictionary-based approach remains one of the most widely used methods in text analysis (Loughran and McDonald 2011, Humphreys and Wang 2018).

The first dictionary, the FOMC dictionary, is created by us to capture text information representing the content of each meeting. These include different permutations of words related to the FOMC mandate, i.e. the Taylor Rule, such as inflation, employment, growth, credit, equity and foreign exchange markets, monetary aggregates, reserves, federal funds and long/short horizons. We attribute these content words and phrases to represent more granular levels of discussions by the FOMC members surrounding the important themes. This dictionary contains 12 categories with 28 subcategories and 524 words, see the Appendix for the specific word list.

The second dictionary for the document-token matrix **C** that we use represents the words based on the LIWC (Linguistic Inquiry and Word Count) dictionary from Pennebaker et al. (2015). Originally created in 1993, the fourth and the most recent LIWC dictionary (2015 version) was constructed through rigorous processes involving multiple steps and judges, and extensive validation processes spanning over 80,000 sources and 231 million words. LIWC has an advantage over other existing dictionaries by providing the most comprehensive and psychologically valid measures, and has been used in hundreds of studies across multiple disciplines to investigate personal and social effects based on language. The LIWC dictionary is organized into 13 categories, 92 sub-categories and almost 6,400 words.[9] Unlike the

[9]For a complete list of the LIWC categories see https://liwc.wpengine.com/compare-

FOMC dictionary that measures the content of the meetings, the LIWC dictionary measures the social, emotional and psychological processes embedded in the use of language. The LIWC software provides the frequency of the word counts of each category and sub-category as a fraction of the total document word count.

Finally, in order to be as comprehensive and inclusive as possible, we also utilize a Frequency dictionary which is constructed simply by selecting the most frequently used tokens found within all the FOMC meetings. Specifically, we selected the most frequent uni-grams (single terms, such as "time"), bi-grams (combination of two words, such as "last_time") and tri-grams (combination of three words, such as "one_last_time") taken from the stemmed set of words. We remove punctuation, numbers (to remove page numbers and meeting dates (including names of the month, from the text), and stop words. These operations result in 25,714 unique terms; from this set we select those appearing at least 1,000 times thus resulting in 995 uni-grams. Similarly, of the 1,414,508 total bi-grams, we select the 796 that appear at least 300 times and among the 4,344,611 tri-grams, we select those appearing at least 100 times, which result in 382 terms. See Table I for a summary of the word libraries that we employ. In our forthcoming empirical analyses, we view the three classes of dictionary words as partitioned variable sets in matrix $\mathbf{c} = [\mathbf{c}_{FOMC}, \mathbf{c}_{LIWC}, \mathbf{c}_{FREQ}]$.

V.D Visualizing text data

Figures III, IV, V and VI display summary information regarding the text variables created from the FOMC transcripts. Figure III presents raw word counts over our sample periods which suggests that meeting word counts are increasing over time. Figure IV presents the fraction of total word count by FOMC member groups – chair, vice chair, board member and district presidents. Note that there are distinct periods over our sample where different FOMC member groups dominate the discussion. Recently, it appears that district presidents have been the most vocal

dictionaries.

in the meetings. Figure V presents fractional word counts related to the Federal Reserve's dual mandate of inflation control (Panel A) and full employment (Panel B). There appears to be increased attention/discussion to the dual mandate since 1995 as both panels show heightened activity later in the sample. Not surprisingly, there are distinct periods where the FOMC focused its discussion on inflation (1992 through 2002) and employment (2008 through 2010). Figure VI displays a comparison word cloud based on the relative word usage by monetary policy outcome of the meeting. Interestingly, the important topics of discussion are very different based on the ultimate monetary policy decision. For example, meetings where the FOMC decided to tighten, "inflation" and "prices" are a focus as one would expect, meetings resulting in an easier monetary policy had "financial" and "credit" as important words and meetings with no change in policy centered discussion on "unemployment."

VI. Text Regressions

Our investigation begins with testing whether the activities within the FOMC meeting have *any* meaningful impact on the committee's ultimate policy decision. Upon confirming the significant impact of meeting discussions, we then proceed to investigate *how* such discussions relate to the committee decisions using our theoretical model depicted in Figure I.

Our first analyses comprise a series of multinomial logit regressions to model the FOMC's monetary policy decisions to ease the federal funds rate, tighten it, or leave it unchanged. Sets of the meeting related text variables are sequentially added to a baseline model that includes important macroeconomic indicators. A comparison of model performance demonstrates whether the addition of text information explains the policy outcomes above and beyond the baseline model. In our empirical context, the selected text features can exceed 2,000, which is much larger than our sample size of 379 meetings. As a result, we employ the penalized regression model that is widely used in the machine learning literature (Tibshirani 1996). This model is particularly useful for contexts where the number of covariates is large, as is the commonly the case with text data (Marafino et al. 2015, Joshi et al. 2010, Gentzkow et al. 2019).

VI.A The General Setting

In the context of our empirical data, we denote the document-token matrix as $\mathbf{C}$, where each row of $\mathbf{C}$ represents a FOMC meeting resulting in the policy outcome $\mathbf{V}$. We are interested in predicting the policy outcome ($\hat{\mathbf{V}}$) as a function of text information contained in $\mathbf{C}$, as well as the augmented first published macroeconomic information $\mathbf{M}$ released before the meeting; $p(v_i|\mathbf{c}_i, \mathbf{m}_i)$. To do this, we set our econometric model as a text regression generally specified as:

$$p(v_i|\mathbf{c}_i, \mathbf{m}_i) = E[v_i|\mathbf{c}_i, \mathbf{m}_i] = f(\mathbf{x}_i'\beta) \quad (1)$$

where $\mathbf{x}_i$ contains the known transformation ($f(\cdot)$, e.g., standardization) of the explanatory variables containing feature counts ($\mathbf{c}_i$) and macro indicators ($\mathbf{m}_i$). The feature counts $\mathbf{c}_i$, as described above, consist of the frequency of FOMC words, LIWC categories, and frequent terms, $[\mathbf{c}_{FOMC}, \mathbf{c}_{LIWC}, \mathbf{c}_{FREQ}]$.

VI.B Baseline Macro Model

Following the economic literature on the Federal Reserve's reaction function, we begin by constructing a baseline macro model, i.e., set $\mathbf{c}_i$=0 for the model in (1). Included in our baseline model are the lagged federal funds rate, the most recent first-published percent change in the consumer price index (CPI) and civilian unemployment rate, the spread between the 10-year and 1-year U.S. Treasury notes, and the return of the Wilshire 5000 over the past 3-months. In addition, we include two lags of each of these variables to capture any state dependence and lagged effects that may exist.

VI.C Penalized Regression with Text Variables

For the multinomial logit model, penalized regression solves the following general maximization problem:

$$\max_{\{\beta\}} \left[\sum_{i=1}^{N} logPr(g_i|\mathbf{x}_i) - \lambda J(\beta) \right] \tag{2}$$

where $Pr(v_i|\mathbf{x}_i)$ is the familiar logit probability function for the outcome v_i, and $J(\beta)$ is the regularization function.

In penalized regression (also called regularized regression), complex models are penalized through the tuning parameter λ and the regularization function $J(\beta)$. The two common regularization functions are denoted as $L_1 = \sum_{j=1}^{p} |\beta_j|$ and $L_2 = \sum_{j=1}^{p} \beta_j^2$, wherein the regularization through L_1 represents the Lasso and L_2 the Ridge regression. Elastic-net (Zou and Hastie 2005) is the mixture of the two regularization terms, by setting an additional parameter α in the penalty term $\sum_{j=1}^{p}(\alpha\beta_j^2 + (1-\alpha)|\beta_j|)$. Due to its flexibility of combining the strength of the two regularization terms, we estimate elastic-net regressions. The parameters α and λ are obtained via grid search.

The standardized variables are grouped within their respective libraries denoted $[\mathbf{c}_{FOMC}, \mathbf{c}_{LIWC}, \mathbf{c}_{FREQ}]$ and placed within matrix $\mathbf{c}$.[10] After the macro-only model, our strategy is to run elastic net estimation sequentially. The second regression includes macro variables and the FOMC dictionary, which adds specific contextual information to the regression. Third, we add the LIWC dictionary into this model,

[10] Variables are standardized in a regularized regression as per Friedman et al. (2010); thus, we adopt two variable standardizations for this purpose. First, a word count for term j in meeting i (wc_{ij}) is converted into a fraction relative to the total word count for the meeting, $w_{ij} = \frac{wc_{ij}}{\sum_{m=1}^{M_j} wc_{mj}}$, where M_j is the number of tokens for the meeting. Second, the word count fractions are normalized by scaling them within the range of word count fractions for that meeting, $x_{i,m} = \frac{w_{ij} - min(w_{\cdot,j})}{[max(w_{\cdot,j}) - min(w_{\cdot,j})]}$. These standardizations control for differences in total word counts across meetings as well as differences in the frequency that specific words are used, thereby placing all variables on similar measurement scales. Note that this standardization process corresponds to the operation $f(\cdot)$ in equation (1), and is a critical procedure for the regularized regression. We also note that macro indicators are normalized, as well, in order to be included in the same elastic net estimation as the other text variables.

to investigate if linguistic style variables have explanatory power beyond the content-related words. Finally, we add the Frequency dictionary to the model, capturing any information not covered by FOMC and LIWC words.

VI.D Model Fit

The model performance is assessed by an out-of-sample predictive test using the Area Under the Curve (AUC) metric for each model specification. The baseline for assessing the AUC is 0.5 (random classification) and the perfect prediction is where the AUC equals one. Although the AUC measure typically assesses the classification accuracy in binary outcomes, we extend its use to the multinomial cases by using Hand and Till (2001). We use the first 70 percent of the meeting data (past) to estimate the model and predict the outcomes of the subsequent 30 percent of the (future) meetings to accommodate the time series nature of the data.[11]

VII. Empirical Results

VII.A Baseline Macro Multinomial Logit Estimation

The baseline macro model discussed in the previous section has three possible policy outcomes: ease, tighten and stay. During our sample period, there are 74 ease, 71 tighten and 234 stay outcomes.

The results for our baseline model are displayed in Table II. The coefficients and their standard errors are presented relative to the "stay" policy outcome, such that positive (negative) estimates are to be interpreted as increasing (decreasing) the likelihood of the respective ease or tighten policy decision. A review of the results shows that they are largely in line with economic intuition. In particular, the federal funds rate exhibits positive (negative) autocorrelation at the one (two) month lag(s)

[11] The usual practice in the machine learning literature is to run K-fold cross-validation. However, this will treat each data point as an independent observation, which is not the case given the time-series nature of our data.

respectively, which is consistent with step-wise, and measured, policy moves with few reversals. The dual mandate variables of inflation and unemployment display the requisite sign and significance - higher inflation (CPI) lowers (raises) the likelihood of easing (tightening) and higher unemployment (CUE) lowers the likelihood of tightening. Interestingly, the impact of the mandate variables are largely concentrated in the current period suggesting that lagged values are already incorporated into the policy assessment. Consistent with being a harbinger of a recession, a flattening (inversion) of the yield curve slope sharply reduces the likelihood of tightening; however, the opposite does not appear to hold for the ease case suggesting an asymmetric impact from the bond market signal. Lastly, the return to the Wilshire 5000 appears to have little impact on the policy outcome, perhaps suggesting that the performance of the equity markets are only recently of interest in forming monetary policy. The baseline model produces results which are largely in line with previous studies (Hamilton and Jordà 2002, Hu and Phillips 2004) and a provides a legitimate point of comparison for our forthcoming analysis.

VII.B Elastic Net Estimations

Upon confirming that our parsimonious baseline macro model performs reasonably well, we now proceed to estimate the penalized text regressions. Table III compares the performance of our models.[12] The first model (Model A) is the same model as the baseline macro shown in Table II, but estimated via elastic net. Model B adds the FOMC dictionary words ($\mathbf{c}_{FOMC}$) to the baseline model. The FOMC dictionary consists of counts of author-selected words grouped into 20 categories/variables relating to the Taylor Rule and other economic and market related words; thereby increasing the number of variables from 13 to 33.[13] Similarly, Model C adds the

[12]Estimations are done in software R. Elastic net models are estimated using *glmnet* package (https://cran.r-project.org/web/packages/glmnet/index.html)

[13]Due to the high sparsity of the feature counts (i.e., large number of zero entries), all the upward inflation variables (inflation up, price up, etc.) are aggregated further into a variable *inflation up*. Similar aggregations were performed to obtain *inflation down*, *employment up*, *employment down*,

LIWC dictionary words in $\mathbf{c}_{LIWC}$. As both the categories and subcategories are included the total explanatory variable count rises to 125. Lastly, Model D adds the $\mathbf{c}_{FREQ}$, which includes the most frequent 1,2,3 grams.

The baseline macro model has an AUC equal to 0.765, which is substantially higher than 0.5 (random guessing). The fit increases to 0.799 (4.4% increase compared to Model A) when FOMC dictionary words are added. This is consistent with the existence of important information within the FOMC deliberation not being picked up by the basic macro indicators, but captured by the FOMC dictionary words. This suggests that knowing only the history of the federal funds rate, employment, inflation, etc. offers a partial understanding of the FOMC's decisions, instead requiring the nuance of the discourse during the committee meetings to appreciate it fully. The fit increases again to 0.847 (an incremental increase of 10.7%), with the addition of LIWC library words, which is particularly interesting given the LIWC dictionary does not contain words that are directly related to the economy or markets. Finally, adding the frequency library (including all the library words) results in an AUC of 0.811 with an improvement relative to the macro model of 6%. Considering that the model includes over 2,000 additional covariates, we note a relatively moderate improvement over the baseline model and the FOMC topic model (Model B), and it has a poorer fit relative to the LIWC model (Model C). We interpret this result as reflective of an over-fitted model.[14]

growth up and *growth down*. As a result, a number of FOMC topic variables is reduced to 20.

[14]We run several other cross-validation specifications to check the sensitivity of the AUC. First, we used 60-40 percent split and estimate the same models. The overall pattern of results are largely similar to those of 70-30 split. Next, we split the sample into 5 sequential blocks (first block is the first 1/5 of the meetings, and so forth) and applied forward chaining; in the first fold, the first block was used to estimate the model to predict the outcomes of the second block. In the second fold, the first two blocks are use for the estimation to predict the outcomes of the third block, and so forth. The resulted AUCs show the similar patters, with the only exception that Model D had a very small increase in AUC (by 0.04) than Model C. In these specifications, the time order is preserved in a sense that the future outcomes are not used to predict the past outcomes. They can be seen as modified cross-validation approaches, while in the standard K-fold cross-validation, time order is ignored and each observation is treated as independent. With the standard cross-validation with K=5 or 10, we still obtain the similar patterns such that Models B and C incrementally improve the fit. However, AUC for Model D increases substantially, to over 0.95. The implication is that, knowing the granular details of the discussions of meetings (represented by over 2,000 variables) would help predicting the outcomes of the in-between meetings, but not so much in predicting the

Overall, these results demonstrate an economically and statistically significant improvement in the goodness-of-fit measure (AUC) over the baseline macro model when sets of text variables are used to explain the FOMC monetary policy decision. As the three libraries are constructed with words related to economic theory (FOMC dictionary), linguistic styles and psychological processes (LIWC), and frequent use (Frequency library), these broad word groups are likely to form the basis for understanding which activities help formulate the committee's decision, a question we turn to next.

VIII. Process-Level Analysis

While it is clear that the FOMC discussion is important for the monetary policy decision, our goal is to understand precisely what within the FOMC discussion is impacting the committee's decision. Our analysis thus far uncovered two sets of terms, the FOMC and LIWC dictionaries, that significantly improve the predictive power of the model. Using our adapted theoretical model discussed in section IV and Figure I, we hypothesize that the two distinct processes related to the FOMC and LIWC words are interpretation and persuasion, respectively.

VIII.A Interpretation Process

Hinsz et al. (1997) describe information processing as a key component of the group decision making process that includes "encoding information in terms of shared mental models and related collective cognitive representation." We hypothesize that a significant fraction of the meeting discussion is meant to help individual members take in and digest relevant data as each member brings with them their own abilities, experiences, biases, etc. In the context of the FOMC, this process centers quite naturally on the use of the FOMC dictionary as those words are directly related to

outcomes of the meetings outside the estimation time range.

their congressional mandate. In addition, as the members look to determine the best course of action they try to anticipate the future state of the economy; thus, forecasts are key to the interpretation process. And of course, *how* the monetary policy decision is implemented is a necessary component in understanding the ramifications of various policy paths.

VIII.B Persuasion Processes

We hypothesize that, in addition to interpretation, the process of persuasion is key to the *aggregation* of individual member information. While the persuasion process can take many forms: influence, debate, consensus building, coercion, etc., drawing on past research relating psychological constructs and language use, we postulate there are two distinct processes represented in the FOMC discussion that are mechanisms to impact the committee's decision-making, namely, cognitive and affective persuasion.

In the process of persuading others within group decision-making, particularly in the context of the FOMC, it is likely that agents appeal to logical reasoning to make one's point. For instance, referencing recent macroeconomic indicators, statements made by important leaders, notable political and economic incidents, and the Fed's mandate. There are multiple linguistic styles associated with cognitive persuasion. Pennebaker et al. (2014) define cognitive linguistic styles by the use of function words. Function words, which include pronouns, articles, prepositions, conjunctions, auxiliary verbs, negations, and common adverbs, reflect cognitive processing by connecting, shaping, and organizing content. One linguistic style is analytical which is characterized by a formal and precise language. This style is identified by the frequent use of articles and prepositions, since referencing precise objects (e.g., data, facts, events, organizations and statistics) requires articles and prepositions. Another linguistic style is storytelling which is characterized by time-based stories and a person-focused narrative language. This style is identified by the frequent use of pronouns, conjunctions, auxiliary verbs, and adverbs.

Pennebaker et al. (2014) construct a Categorical-Dynamic Index (CDI) based on these two linguistic styles. Categorical language reflects the analytical linguistic style and Dynamic language reflects the linguistic style of storytelling. CDI has a high value when categorical language dominates and a low value when dynamic language dominates. We adopt the CDI by Pennebaker et al. (2014) to measure cognitive persuasion. Thus, a high CDI reflects a persuasion style that is formal and precise with a high usage of articles and prepositions (categorical/analytical), whereas a low CDI reflects a persuasion style that is a person-focused narrative with a high usage of pronouns, auxiliary verbs, conjunction, adverbs and negations (dynamic/storytelling).[15] Accordingly, our *cognitive persuasion* variable is measured by CDI, which is computed for each meeting i as

$$CognitivePersuasion_i = 0.3 + (Prepositions_i + Articles_i - Pronouns_i - Aux.verbs_i - Conjunction_i - Adverbs_i - Negations_i) \tag{3}$$

where each linguistic dimension corresponds to a LIWC category, normalized by the meeting word count.[16]

Even though the process of cognitive persuasion would be key in the FOMC meeting discussion, not all the situations can be handled effectively by utilizing logic. For example, it is possible that opposing sides of an issue have their own logical justifications based on their interpretation of the facts and/or their monetary policy preferences. In such instances, it may be effective for agents to appeal to emotional

[15] We note that LIWC provides summary variable *Analytical thinking* based on the CDI measure but is factor-analytically derived rather than summed. The analytical thinking is used to capture the logical vs. narrative language styles in various studies, e.g., see Markowitz (2019) and Barfar (2019). However, the factor weights to compute the Analytical thinking score are proprietary, so we employ the original CDI scale, for which the exact formula is available. We confirm that the correlation between the CDI and the Analytical thinking is almost perfect (0.995).

[16] Following the original CDI composition in Pennebaker et al. (2014), we add 0.3 adjustment to make the score positive. However, this is without loss of generality as it does not affect the following estimation given we standardize the measure and convert it to a z-score.

or affective persuasion which is our second persuasion process. To capture the emotion words, we use the LIWC category *affective processes*, which is obtained by aggregating positive and negative emotions. Examples of affective words in the LIWC library are happy, hate, nervous, afraid, tense, grief, good, sad, and bitter.[17] In addition, we also include the frequency of swear words and exclamations, as they also represent strong emotion. Thus, our *affective persuasion* variable is measured by the sum of LIWC categories affective processes, swear words and exclamation marks, normalized by the total meeting word counts.

$$AffectivePersuasion_i = Affect_i + Swearing_i + Exclamations_i \tag{4}$$

VIII.C Model Fit with Interpretation and Persuasion Variables

To test our adopted theoretical model in Figure I, we ran an additional elastic net estimation with the FOMC dictionary and LIWC categories that are included in equations (3) and (4). This model produced the AUC of 0.802, exhibiting an improvement over the baseline macro model of 4.8 percent and a moderate improvement over the FOMC model. Thus, these variables representing interpretation and persuasion processes impact the meeting outcomes. Given the success of the interpretation and persuasion variables in explaining the FOMC monetary policy decision, we turn our attention to better understanding how these committee processes vary over time and by committee member.

VIII.D Interpretation and Persuasion: A Deeper Investigation

To begin investigating the variation of the two persuasion process variables, we collapse our interpretation variable into an aggregate series by simply summing

[17] This is distinct from sentiment, which seeks to find the *net* position of positive and negative emotions. Instead, our objective is to measure the degree to which emotion words are utilized, regardless the sentiment it represents.

(and normalizing) the individual component counts by meeting. The time series comparison of the three process variables (aggregate interpretation and the two persuasion variables) shown in Figure VII reveals important insights. Notice that the interpretation variable (Panel a) is particularly high in the early part of the sample (1980s and 1990s) and has a downward trend in both level and volatility over time. In contrast, the cognitive persuasion variable (Panel b) is relatively low in the first half of the sample and higher in the later half. The affective persuasion variable (Panel c) displays no time trend, but has much more volatility than the other two variables. Visually, Figure VII demonstrates clear differences in these discussion variables, both between FOMC meetings, and across the entire sample period. These figures suggest that FOMC members devote varying amounts of effort interpreting information and persuading others using cognitive and affective language.

Given the evidence that the mix of the FOMC meeting discussion changes by meeting and over time, it is quite natural to ask whether the mix of time spent persuading is similar or different across *FOMC members groups*. In particular, one might conjecture that some FOMC members utilize different language styles trying to persuade others to their way of thinking, which we caution, is importantly different than how much time is spent persuading and whether the efforts are successful. We investigate this possibility by obtaining the individual chair and FOMC position level process variables using Equations (3) and (4) and averaging over all the meetings.

Figure VIII displays the results (mean and standard errors) partitioned by the individual FOMC chair (Panel a) and by FOMC position (chair, vice-chair, board member, district presidents) (Panel b). Of the five chairs, Burns and Bernanke have distinctly higher affective language counts relative to Miller, Volcker and Greenspan. From a cognitive language perspective, Bernanke and Greenspan display relatively more categorical and analytic language while Volcker and Miller display dynamic storytelling. The results are an interesting complement to the differing styles of the recent Federal Reserve chairs: Bernanke—academic, Greenspan and Volcker—authoritative. The results by FOMC position groups displays much less variation, likely because of the averaging of individuals. All groups have relatively low counts for affective language; however, in a relative comparison of cognitive language, district presidents have the highest measure and chairs have the lowest. We conjecture that these cognitive linguistic style differences may be due to a chair's need to formulate a consensus among the members and district president's mandate to advocate/argue for the needs of their specific district.

VIII.E Factors Influencing Processes

Given the variation in interpretation and persuasion over time illustrated in Figure VII, we now turn our attention to how these processes may be adapted in different situations. First, we investigate whether FOMC members alter their level of interpretation and persuasion tactics in periods of high economic uncertainty and in crisis periods. We employ the economic policy uncertainty (EPU) indices from Baker et al. (2016) to identify periods of high uncertainty. For crisis periods, we employ a dummy variable to capture the 2008 financial crisis, 9/11, the 1987 stock market crash, and the stagflation and Iran-US hostage crisis in 1979-81. To study the effects of a recession, we employ the NBER recession indicator. Second, we investigate whether FOMC members alter their level of interpretation and nature of persuasion tactics in meetings with high disagreement, measured by the number of ex-post dissensions in a meeting. Third, we investigate whether FOMC members alter their behavior when their accountability and public scrutiny increases. We do this by comparing the committee members' efforts to interpret information and their persuasion styles before and after the shift to more transparency in 1993 when it was determined that the FOMC meeting transcripts would be published with a five-year lag (see Hansen et al. (2018) for more discussion).

Tables IV and V display our results. All models include chairperson fixed effects to account for any "style" differences. Table IV presents the results for periods of stress, crisis and disagreement. Column 1 displays the results employing the broader EPU index, EPU_3, based on three components; (1) the frequency of newspaper references to economic uncertainty, (2) the number of federal tax code provisions set to expire, and (3) the extent of forecaster disagreement over future inflation and government expenditures. Column 2 displays the results for the narrower EPU index including the news component only. Columns 1 and 2 show that committee members use significantly more affective persuasion methods during periods of economic uncertainty; however, We do not detect any significant differences on the interpretation variable that is attributable to economic uncertainty.

Consistent with our conjecture, column 3 reveals that during a crisis, FOMC members appear to devote more time interpreting information compared to non-crisis periods. Column 3 also shows that during a crisis, FOMC members use more affective persuasion and less analytical persuasion styles. Please recall that a lower cognitive persuasion reflects a storytelling approach, versus analytical arguments, to convince others. Column 4 further reinforces this result by showing that during a recession as well, FOMC members use more affective persuasion and more storytelling to influence others. Finally, column 5 displays results for periods with high disagreement, measured ex post. These are periods where the FOMC vote contained at least one dissension in the final vote on the committee decision. Column 5 reveals that committee members engage in more storytelling (lower Categorical-Dynamic Index), and employ more affective persuasion than during periods of consensus. They also exert greater effort in processing the available information during periods of disagreement as shown by the positive coefficient for the interpretation variable.

Next, we investigate whether FOMC members alter their behavior when their accountability and public scrutiny increases. We do this by comparing the committee members' efforts to interpret information and their persuasion styles before and after the shift to more transparency of the meeting transcripts in 1993. Previous literature finds more stylized (scripted) discussions, less dialogue, and more objective discussion as transparency increased in 1993. For the constructs we are investigating, we can expect more cognitive persuasion and less affective persuasion as transparency increases.

To test the effect of transparency in our empirical context, we limit the meetings from 1989 to 1997 to match Hansen et al. (2018). Table V presents the results of models 1a, 2a, and 3a, where the three meeting process variables are regressed on the transparency variable only. Models 1b, 2b, and 3b, include other control variables that can potentially influence our three meeting processes, following the Hansen et al. (2018) specification. The results reveal that committee members changed the nature of persuasion tactics after they were made aware that meeting transcripts would be publicly available in the future. Members spend less time on affective persuasion in the new "transparency" regime and adapt their cognitive persuasion style to become more analytical. Figure IX supports our results by illustrating that members use a more formal and precise language and less storytelling after the shift to more transparency, consistent with Hansen et al. (2018).

In all, the results in this section show that FOMC committee members adapt their persuasion methods and efforts to interpret information to different challenges that arise over time. When uncertainty is high, recession is looming, or disagreement dominates, members tend to shift their cognitive persuasion style from analytical to storytelling, and they resort to more affective persuasion. In times of crisis and periods of high disagreement in the committee, members spend more time interpreting the available information. Finally, committee members appear to adapt to more accountability and public scrutiny by employing a more analytical cognitive persuasion style and avoiding the affective persuasion style.

IX. Summary and Conclusion

This paper sets out to better understand a committee as a mechanism to aggregate information, by asking whether, and how, the activities/discussion of a committee contributes to the ultimate group decision. Specifically, we study transcribed discussions within the Federal Reserve's Federal Open Market Committee, one of the most influential committees on the world economic stage, to address the following two questions, (1) does the discussion within a committee help to explain the policy choice, and (2) what are the processes at play that contribute to aggregating information and formulating a group decision?

Our two primary research aims are to uncover the process level details in a committee decision; and to assess the impact of such process-level variables on the committee's final decision. The FOMC serves as a unique empirical context to answer these questions because it offers ample publicly available information in the form of a long time-series of comparable decisions (setting the federal fund rate) along with detailed transcripts of the members's discussion that lead up those decisions. We utilize two main data sources: macroeconomic indicators and unstructured meeting transcripts, corresponding to 379 meetings, from the years 1978 to 2013, to explain FOMC's decision to stay, ease or tighten the target federal fund rate at each meeting. To shed light on the committee's processes through which the decisions are reached, we exploit the fact that our data include deliberations/discussion through multiple recessions, presidencies, and economic crises. To help answer our research questions, we study the underlying decision-making processes for the FOMC. By doing so we also quantify the incremental role of the text data in explaining the committee's decision over and above the macroeconomic data in an econometric model.

Our theoretical guiding structure is adopted from the committee model of Hinsz et al. (1997) from social psychology literature, which includes two hypothesized committee activities: interpretation of the data (or information processing) and inter-personal persuasion. We show that these two dimensions, interpretation and persuasion, improve the model fit of the monetary policy action between 4.4 and 10.7% after controlling for the macroeconomic data that is typically thought to make up the Federal Reserve's reaction function. We provide new insights by showing that FOMC discussion which focuses on understanding and internalizing information, as well as both cognitive (logical) and affective (emotional) persuasion strategies, are statistically and economically important in explaining the monetary policy decision. The interpretation efforts reference macroeconomic topic words, while cognitive and affective persuasion are important for aggregating member views and arriving at a committee decision. Our empirical results also demonstrate how these tactics are utilized by the committee members during periods of disagreement, crisis and stress. Specifically, when the risk of making a poor decision is elevated, committee members place more emphasis on interpreting relevant data and persuasion of other members is accomplished with an *affective* persuasion style; while during periods of calm, when the risk of making a poor decision is low, less time is spent on interpretive discussion and persuasion is more cognitive, and accomplished with more formal, precise and logical language.

The paper makes several significant contributions to the literature. First, we show that information processing, or interpretation, has a large impact on a business committee's decision that is not captured by key contextual (macroeconomic) variables. Second, we show that persuasion tactics in both cognitive and affective forms employed by individuals within the group impact a committee's decision. While the usage of cognitive persuasion is to be expected, we also show that affective persuasion also impacts committee decisions. We further find that the role and the form of persuasion tactics in a business committee is moderated by economic conditions (e.g. crises, recession and economic uncertainty). To the best of our knowledge, we are the first to empirically demonstrate these detailed process-level mechanisms in a relevant business setting involving multiple agents. Finally, we demonstrate a way that text data can be utilized to gain insights in important economic contexts by exploiting the established linkage between language and social/psychological processes. This is particularly relevant as availability of large amount of text data increases, widening the opportunities to explore hidden processes that typical numerical data would not be able to uncover. As our investigation demonstrates, the text data in the context of a business committee, when available, not only helps capture some of the process level aspects of the committee's decision, but also adds to an econometric model's ability to predict the committee's decision outcome.

Our results imply that the discussion within a committee is a critical component of aggregating information into a group decision. Moreover, actions to enhance the ability of committee members to interpret data and persuade others via cognitive and affective processes should be encouraged for the committee's effectiveness. Key to these activities is for all members to have access to common information, the opportunity to ask questions, and the ability to reference other members. Nonetheless questions remain to be answered. For example, do individual FOMC member discussion/comments have an impact on the monetary policy decision? What determines which members, and when, are persuaded to revise their opinion, view or preference? We leave this to future work.

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Table I

Dictionaries

Dictionary	Source	Number of Categories	Number of Terms
FOMC	Authors	12 categories, 28 subcategories	524
LIWC	Pennebaker et al. (2015)	13 categories, 92 subcategories	6,400
Frequent	Authors	Most frequent 1, 2, & 3 grams	2,173

The table lists the dictionaries utilized in the text analysis along with the source and number of categories, subcategories and word terms.

Table II

Baseline Macro Multinomial Logit Regression

	Ease	Tighten
Federal Funds lag 1	-0.621*	0.080
	(0.318)	(0.368)
Federal Funds lag 2	0.920***	-0.070
	(0.343)	(0.378)
Unemployment	1.170	-1.459*
	(0.810)	(0.834)
Unemployment lag 1	-0.114	0.190
	(1.127)	(1.107)
Unemployment lag 2	-1.590	0.924
	(0.990)	(0.877)
CPI	-1.067*	1.829***
	(0.576)	(0.528)
CPI lag 1	0.071	-0.060***
	(0.444)	(0.018)
CPI lag 2	-0.033	-0.073*
	(0.053)	(0.040)
Yield Spread lag 1	0.319	-2.039**
	(0.645)	(0.824)
Yield Spread lag 2	-0.016	1.911**
	(0.651)	(0.808)
Wilshire	-0.032	0.039
	(0.025)	(0.027)
Wilshire lag 1	-0.041	0.004
	(0.032)	(0.031)
Wilshire lag 2	-0.002	0.004
	(0.025)	(0.026)
Constant	0.151	0.002
	(0.767)	(0.854)
N		379
Pseudo R^2		0.222
AIC		604.731
BIC		714.982

The federal funds rate is the market rate, the CPI is the consumer price index, unemployment is the civilian unemployment rate, yield spread is measured by the difference between the 10-year and 1-year Treasury yields and the Wilshire 5000 is return over the previous month. AUC is assessed in-sample. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table III

Elastic Net Estimation: Area Under the Curve (AUC)

Model	Dictionary (see Table I)	Number of Variables	AUC	Change over Baseline
A	None (baseline)	13	0.765	–
B	FOMC	33	0.799	4.4%
C	FOMC + LIWC	125	0.847	10.7%
D	FOMC + LIWC + Frequent	2,298	0.811	6.0%

The table displays the performance of a sequence of models using the elastic net estimation technique. The baseline model (Model A) includes macro variables only (Table II). Successive models (Models B to D) are defined by incrementally adding text library variables from the FOMC, LIWC and Frequency dictionaries. The Area Under the Curve (AUC) results detail the goodness-of-fit for each model is based on the estimation on the first 70% of the meetings in the sample period, used to predict the hold-out sample of the last 30% of the meetings.

Table IV

Interpretation and Persuasion Processes in Various Situations

Dependent Var	EPU_3	EPU_news	Crisis	Recession	Dissents
Regression Model	OLS	OLS	Logit	Logit	Poisson
Interpretation	-1.776	-4.038	0.529**	0.323	0.252***
	(2.177)	(3.336)	(0.258)	(0.207)	(0.067)
Cognitive Persuasion	-3.247*	1.762	-0.837*	-0.395*	-0.406***
	(1.854)	(2.694)	(0.498)	(0.212)	(0.103)
Affective Persuasion	5.004**	10.620***	0.554*	0.727***	0.174**
	(2.451)	(3.720)	(0.332)	(0.244)	(0.075)
Chair Dummy	Yes	Yes	Yes	Yes	Yes
Observations	305	305	361	361	379
R^2/Pseudo R^2	0.259	0.162	0.338	0.135	0.186

EPU_3 is taken from Baker et al (2016) including (i) the frequency of newspaper references to economic uncertainty, (ii) the number of federal tax code provisions set to expire, and (iii) the extent of forecaster disagreement over future inflation and government expenditures. EPU_news is the narrower EPU index including the news component only. Our crisis periods include the stagflation and Iran-US hostage crisis - November 1979 to January 1981; 1987 stock market crash - October 1987 to November 1987; World Trade Center attack - September 2001 to October 2001; and 2008 financial crisis - August 2007 to February 2009, and our recession periods are taken from the NBER recession indicator. Dissents are the number of dissenting votes at the FOMC meeting. Interpretation is the standardized total FOMC Topic word counts. Robust standard error are in parentheses. ***, ** and * indicates significant at 1%, 5% and 10% level, respectively.

Table V

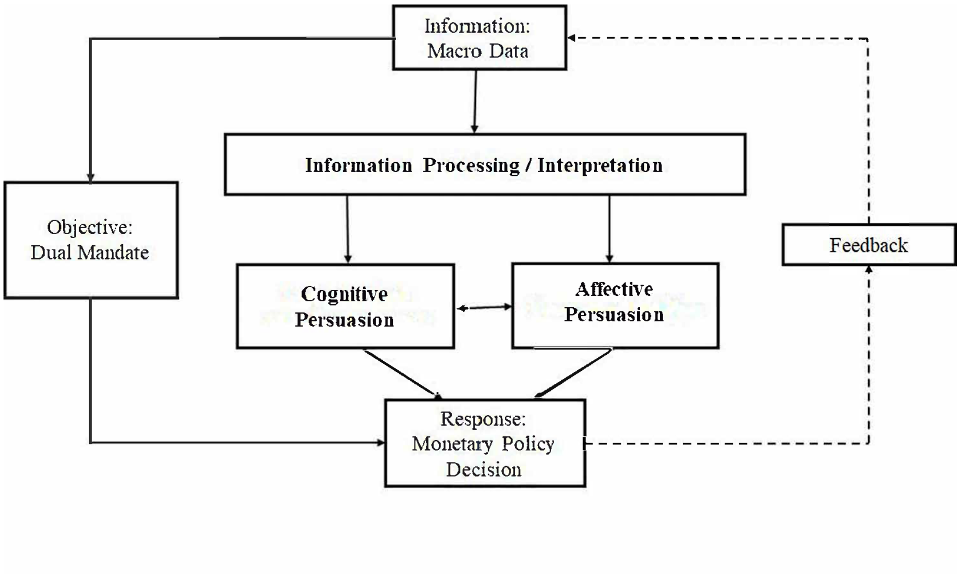
Effect of Transparency in Interpretation and Persuasion Processes

	Dependent Variables					
	Interpretation		Cognitive		Affective	
Models	1(a)	1(b)	2(a)	2(b)	3(a)	3(b)
Transparency	-0.021	-0.182	0.997***	0.889***	-0.635***	-0.468***
	(0.160)	(0.189)	-0.124	(0.146)	(0.115)	(0.133)
EPU_news		-0.005		-0.005*		0.007**
		(0.004)		(0.003)		(0.003)
Recession		-0.181		0.233		-0.084
		(0.315)		(0.242)		(0.221)
Constant	0.138	0.696	-0.611***	-0.069	0.488***	-0.218
	(0.110)	(0.427)	(0.085)	(0.328)	(0.079)	(0.300)
Observations	72	72	72	72	72	72
R^2	0.0003	0.037	0.482	0.506	0.304	0.360

Transparency is an indicator variable for after the transparency. EPU_news and Recession are the economic policy uncertainty scores and U.S. recession indicators. Using EPU_3, instead of EPU_news, does not alter the main results. Sample period is January 1987 to December 1997 to match Hansen et al. (2018). Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Figure I

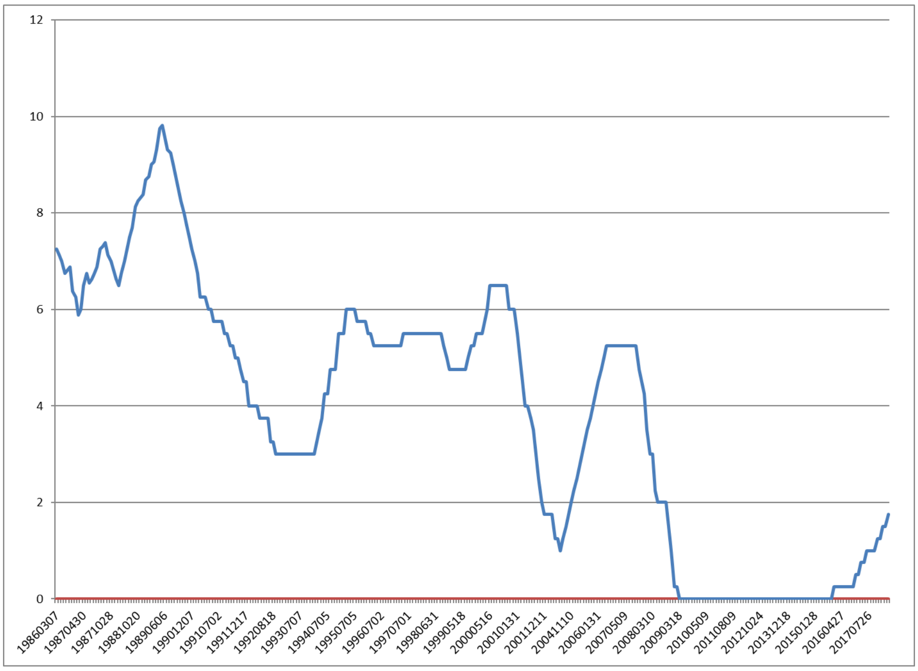
Simplified Hinsz et al. (1997) Model



This figure is a simplified model of figure 1 in Hinsz, Tindale and Vollrath. (1997) The emerging conceptualization of groups as information processors. *Psychological bulletin*, 121(1):43-64

Figure II

Target Federal Funds Rate



The figure displays the federal funds rate target the FOMC adopted over the period March 1986 through December 2018.

Figure III

FOMC Regular Meeting Word Count over Time

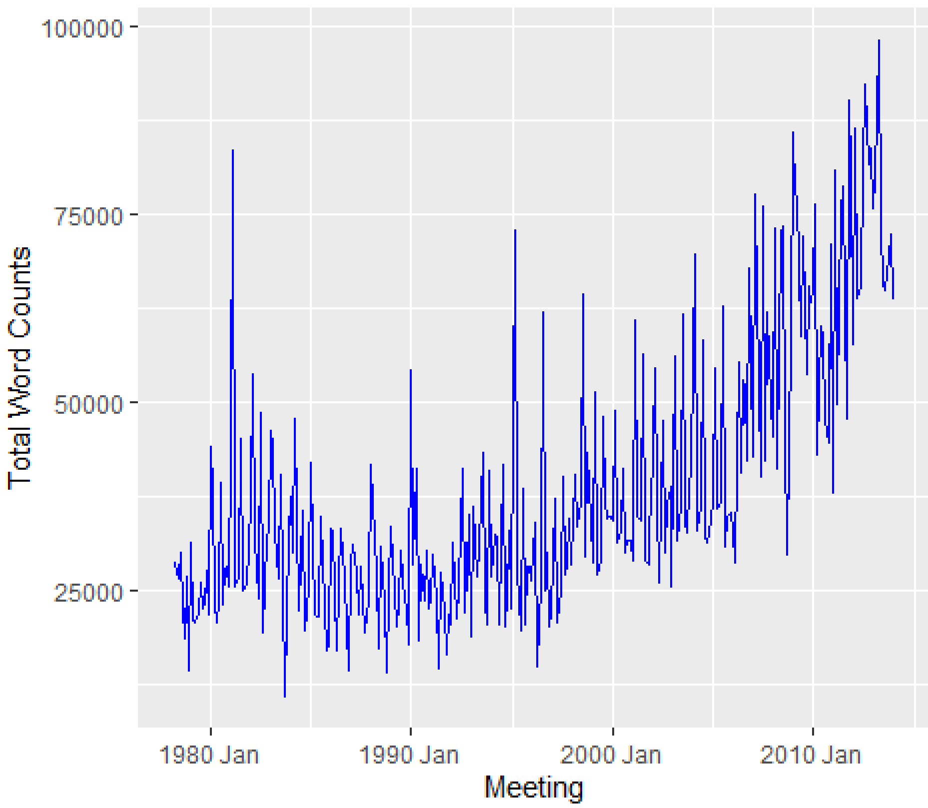
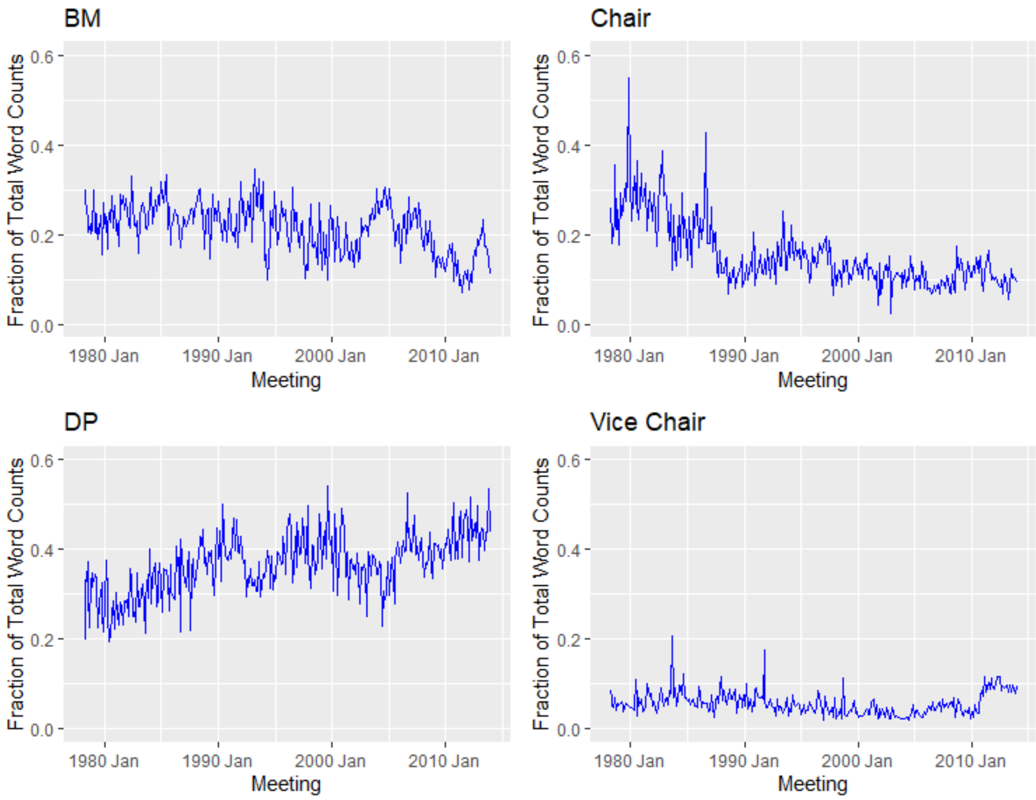


Figure IV

Fraction of Meeting Words by FOMC Member Groups



Total word counts by Board Members (BM), chairpersons, District Presidents (DP) and vice chairs, normalized by the total meeting word counts.

Figure V

FOMC Dual Mandate Topic Words

Inflation word counts are the aggregate counts of all the inflation-related FOMC topic words (inflation up, prices up, etc.) normalized by the meeting word counts. Likewise, employment word counts are the aggregate counts of all the employment-related topic words (employ up, unemploy up, etc.) normalized by the meeting word counts.

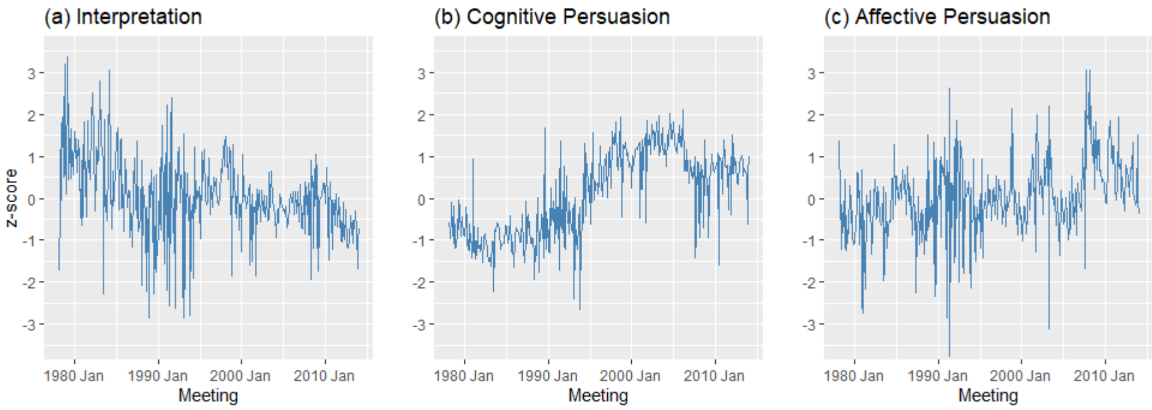
Figure VI

Comparison Word Cloud Partitioned by FOMC Monetary Policy Actions

Comparison word cloud displays term frequencies compared to other outcomes. Thus, terms with larger display are the ones spoken more frequently in that outcome and less in other outcomes. Terms spoken frequently in all meetings do not appear in comparison cloud.

Figure VII

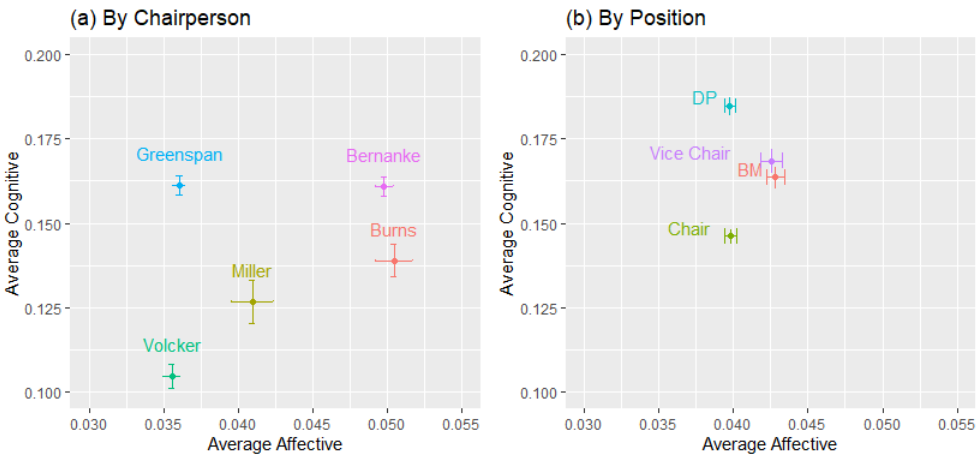
Interpretation, Cognitive Persuasion and Affective Persuasion over Time



Interpretation variable is obtained as the sum of word counts of interpretation words (from the FOMC Topic dictionary). Cognitive and affective persuasion variables are as explained in the texts. All variables are converted to the ratio to the total meeting word count, then standardized (to zero mean and one standard deviation). For example, z-score of one indicates that, in that meeting, the counts of respective variable is one standard deviation more than the typical usage of the respective type of words in all the meetings.

Figure VIII

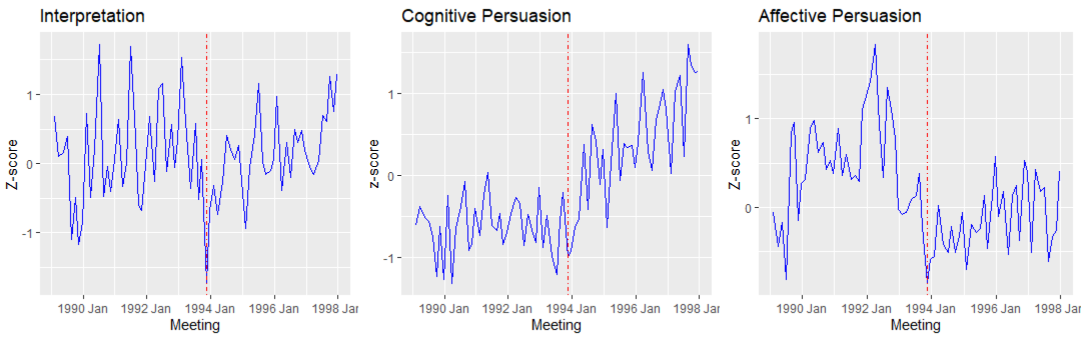
Cognitive and Affective Persuasion by FOMC Member Groups



Mean (points) and standard error (arms) of the cognitive and affective persuasion z-scores by (a) chairperson and (b) position. Including earlier transcripts (from June 1976) for a comparison purpose.

Figure IX

Interpretation and Persuasion Variables Before and After Transparency



Red line represents the date (November 1993) when the fact that individual statements during the FOMC will be in public record became known by all the participating members.

Appendix

Table A.1: FOMC Dictionary Words

Group	Category	Variable	Terms
Taylor Rule	Inflation	Inflation up	inflation up, inflation increases, increasing inflation, increases in inflation, inflation rate to increase, accelerate inflation, accelerating inflation, inflation rises, rising inflation, Inflation rate to rise, high inflation, higher inflation, inflation above, more inflation, upward pressure on inflation, increased risk of inflation, inflation risks, upside risk to inflation, risk of higher inflation, pick up in inflation, strong inflationary, wages up, increase in wages, wage increases, higher wages
		Inflation down	inflation down, inflation decreases, decreasing inflation, decreases in inflation, inflation rate to decrease, decelerate inflation, decelerating inflation, inflation falls, falling inflation, inflation rate to fall, low inflation, lower inflation, inflation below, less inflation, downward pressure on inflation, decreased risk of inflation, contained inflation, downside risk to inflation, deflation, wages down, decrease in wages, wage decreases, lower wages

Table A.1: FOMC Dictionary Words

Group	Category	Variable	Terms
		prices up	prices up, price increases, increasing prices, increases in prices, prices to increase, rising prices, prices to rise, high prices, higher prices, upward pressure on prices, upside risk to prices, risk of higher prices
		prices down	prices down, price decreases, decreasing prices, decreases in prices, prices to decrease, falling prices, prices to fall, low prices, lower prices, downward pressure on prices, downside risk to prices
		wages up	wages up, wage increases, increasing wages, increases in wages, wages to increase, rising wages, wages to rise, high wages, higher wages, upward pressure on wages, upside risk to wages, pick up in wages
		wages down	wages down, wages decreases, decreasing wages, decreases in wages, wages to decrease, falling wages, wages to fall, low wages, lower wages, downward pressure on wages, downside risk to wages
		Inflation neutral	inflation expectations, inflation projections, actual inflation, inflation threshold, inflation outlook, price inflation

Table A.1: FOMC Dictionary Words

Group	Category	Variable	Terms
	Employment	Employ up	employment up, employment increases, increasing employment, increases in employment, employment rate to increase, employment rises, rising employment, employment rate to rise, high employment, higher employment, employment above, more employment, is more than employment, upside risk to employment, pick up in employment, employment strength, employment growth
		Employ down	employment down, employment decreases, decreasing employment, decreases in employment, employment rate to decrease, employment falls, falling employment, employment rate to fall, low employment, lower employment, employment below, less employment, is less than employment, downside risk to employment, employment weakness, employment shrinks

Table A.1: FOMC Dictionary Words

Group	Category	Variable	Terms
		Unemployment up	unemployment up, unemployment increases, increasing unemployment, increases in unemployment, unemployment rate to increase, unemployment rises, rising unemployment, unemployment rate to rise, high unemployment, higher unemployment, unemployment above, more unemployment, is more than unemployment, increased risk of unemployment, unemployment risk, upside risk to unemployment, risk of higher unemployment, unemployment growth
		Unemployment down	unemployment down, unemployment decreases, decreasing unemployment, decreases in unemployment, unemployment rate to decrease, unemployment falls, falling unemployment, unemployment rate to fall, low unemployment, lower unemployment, unemployment below, less unemployment, is less than unemployment, decreased risk of unemployment, downside risk to unemployment, unemployment contraction
		Employment neutral	employment report, payroll, employment, private employment, employment statistics, full employment, maximum employment mandate

Table A.1: FOMC Dictionary Words

Group	Category	Variable	Terms
	Growth	Growth up	economic growth up, economic growth increases, increasing economic growth, increases in economic growth, economic growth to increase, accelerate economic growth, accelerating economic growth, economic growth rises, rising economic growth, economic growth to rise, high economic growth, higher economic growth, economic growth above, more economic growth, upward pressure on economic growth, upside risk to economic growth, pick up in economic growth
		Growth down	economic growth down, economic growth decreases, decreasing economic growth, decreases in economic growth, economic growth to decrease, decelerate economic growth, decelerating economic growth, economic growth falls, falling economic growth, economic growth to fall, low economic growth, lower economic growth, economic growth below, less economic growth, downward pressure on economic growth, downside risk to economic growth, risk of lower economic growth, drag on economic growth

Table A.1: FOMC Dictionary Words

Group	Category	Variable	Terms
		Production up	production up, production increases, increasing production, increases in production, production to increase, accelerate production, accelerating production, production rises, rising production, production to rise, high production, higher production, production above, more production, upward pressure on production, upside risk to production, pick up in production
		Production down	production down, production decreases, decreasing production, decreases in production, production to decrease, decelerate production, decelerating production, production falls, falling production, production to fall, low production, lower production, production below, less production, downward pressure on production, downside risk to production, risk of lower production, drag on production
Markets	Credit	Growth neutral	GDP growth, economic growth, sustainable economic growth, production
	Equity	Credit Markets	credit, bond, market yield curve
	Currency	Equity Markets	equity, stock market, S&P, NYSE, Dow Jones, Russell

Table A.1: FOMC Dictionary Words

Group	Category	Variable	Terms
		FX Dollar Up	dollar up, dollar increases, increasing dollar, increases in the dollar, strong dollar, strengthening dollar, dollar appreciation, appreciating dollar, dollar to appreciate, higher dollar, upward pressure on the dollar
		FX Dollar Down	dollar down, dollar decreases, decreasing dollar, declines in the dollar, weak dollar, weakening dollar, dollar depreciation, depreciating dollar, dollar to depreciate, lower dollar, downward pressure on the dollar
		Foreign Currencies	euro, pound, yen, yuan, Canadian dollar, peso, lira, guilders, kroner, marks, schillings, currency, currencies
Target Tools	Monetary	Monetary Aggregates	monetary aggregates, money, M1, M1A, M1B, M2, M3, monetary base, velocity, cones, ranges
	Reserve	Reserves	reserves
	FFR	Federal Funds Rate	federal funds, fed funds
Time Frame	Long	Long Run	long run
	Short	Short Run	short run, short-term, near-term, immediate
Prediction			greenbook, bluebook, tealbook, beigebook, redbook, teal, green, blue, beige