Deliberation in Collective Decision-Making: The Case of the FOMC

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Abstract

A process of deliberation, in which policymakers exchange information prior to formal voting procedures, precedes almost every collective decision. Yet, beyond scarce evidence coming from field and laboratory experiments, few studies have analyzed the role played by deliberation in policy-relevant decision-making bodies. To fill this gap, this dissertation provides an empirical analysis of the process of deliberation within the Federal Open Market Committee (FOMC), which is the body in charge of implementing monetary policy in the United States. I study the deliberation records from FOMC meetings to quantify the extent to which allowing participants to communicate with one another results in decisions that pool the information of individual members. In the first chapter, I empirically assess whether the information FOMC members provide in their economic forecasts is truthfully reported. I provide evidence that their predictions are systematically biased and fail to incorporate publicly available information. I exploit the variation among FOMC members’ appointment process and career experiences to show that the biased nature of these forecasts is consistent with members’ heterogeneity in preferences. In the second chapter, I explore the systematic biases in the verbal content of FOMC members’ deliberation process. I estimate a probabilistic topic model that allows me to extract the time FOMC members spend deliberating different aspects of monetary policy-making and its relationship with members’ characteristics and forecast biases. In the third chapter, I show that there is a substantial amount of information transmitted through the sequential deliberation of policy recommendations. I estimate an empirical model of policy-making that incorporates social learning via deliberation. In the model, committee members speak in sequence, allowing them to weight their own information and biases against recommendations made by others. I find the process of deliberation significantly changes members’ policy recommendations compared to the case where members follow their private information. Incorporating sequential learning explains the pattern of individual recommendations and collective choices extremely well and improves the fit over behavioral models that ignore deliberation.
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Chapter 1

Introduction

In almost all relevant decision-making bodies such as courts, juries, legislative committees, governmental agencies, corporate board of directors, academic committees, and international organizations, among others, decisions are commonly preceded by some form of communication among individual members. In all these cases, deliberation provides a unique opportunity for participants to arrive at more reasoned judgments (Habermas [1996]; Macedo 2010), enhance the legitimacy of the collective decision (Gutmann and Thompson [1996]), encourage the cooperation among participants (Goeree and Yariv 2011), and affect collective decision-making by influencing others (Landa and Meirowitz 2009). Thus, along with voting, deliberation is the most relevant political mechanism to ensure that policy decisions reflect the preferences of individual members (Fishkin 1991).

The potential impact of communication on decision-making has contributed to the emergence of an important theoretical literature that explains under what conditions deliberation leads to collective choices in which individual information is efficiently aggregated. These conditions arise mainly in the form of differences in preferences -whether participants share a common goal (Austen-Smith and Feddersen 2005; Austen-Smith and Feddersen 2006; Coughlan 2000; Doraszelski, Gerardi and Squintani 2003; Gerardi and Yariv 2007; Van Weelden 2008) or have private values (Meirowitz 2006; Meirowitz 2007)- and on the
type -public vs private- and quality of available information. Yet, empirically quantifying the effect of deliberation on policy-making has faced important limitations which prevent us from giving clear-cut answers to fundamental questions, such as: how well deliberation works, by what mechanisms, and under what circumstances (Page and Shapiro [1999]). One relevant limitation faced by previous empirical work on deliberation is that communication among real-world policy-makers is usually unstructured. This feature makes it harder to disentangle the influence of individual participants throughout the deliberation process, as well as the extent to which members learn from others. A more practical limitation is that the conversation protocols of policy-making bodies are rarely obtainable. These reasons explain why an overwhelming portion of the existing empirical literature on deliberation has to rely on field and laboratory experiments (Dickson, Hafer and Landa [2008]; Dickson, Hafer and Landa [2015]; Goeree and Yariv [2011]; Karpowitz and Mendelberg [2011]; Humphreys, Masters and Sandbu [2006]) or on evidence from citizens’ deliberative forums (Ban, Jha and Rao [2012]; Barabas [2004]; Luskin, Fishkin and Jowell [2002]) to assess whether the presence of deliberation has an effect on policy attitudes and choices. An exception is provided by Iaryczower, Shi and Shum [2014] who, under a structural approach, quantify the effects of deliberation on decision-making at policy-relevant bodies such as appellate courts. Overall, these studies have been successful in showing that exposure to different components of deliberative institutions has significant consequences for both aggregate opinion change and collective choices. Nevertheless, previous literature has been silent about the potential mechanisms through which deliberation affects both participants’ beliefs and choices. In particular, past studies have been agnostic regarding the relevance of different communication protocols for policy-relevant decision-making bodies. Thus, for these policy-making institutions we still do not know to what extent individual members learn from each other, whether they act upon this information, and how much this learning process affects policy outcomes.
In this dissertation, I seek to overcome these limitations by providing an empirical analysis of the process of deliberation in the Federal Open Market Committee (FOMC henceforth), which is the body in charge of implementing monetary policy in the United States. The FOMC is an ideal case to analyze the role of communication in collective decision-making for several reasons. First, the decisions that the FOMC implements have relevant policy implications, as they regulate the economy and affect households’ and firms’ expectations. Second, historical FOMC deliberation transcripts and economic projections are publicly available, allowing me to extract members’ actual communication protocols including their economic predictions, policy recommendations, and the verbal content of their deliberation process. Finally, real-time data at the time of the meetings is also readily available in the form of staff forecasts and economic indicators.

I study the deliberation records from FOMC meetings to quantify the extent to which allowing participants to communicate with one another results in decisions that pool the information of individual members. The majority of studies that have tried to analyze the dynamics within monetary policy committees use dissenting votes in an attempt to infer policy preferences from members’ voting behavior (e.g., Belden [1989], Krause [1994], McGregor [1996], Gerlach-Kristen and Meade [2010]). However, explaining the behavior of individual members out of voting records has missed a fundamental component of monetary policy making, embodied in the deliberation process, in which committee members discuss their own views and potentially solicit privately held information that might help in overcoming conflicts of interest (Coughlan [2000]). As Bailey and Schonhardt-Bailey observe for the case of the Federal Reserve, “the deliberative process that underpins monetary policymaking is important not only for the policy outcome but also for the reputations of the committee members, and the Fed as an institution” (Bailey and Schonhardt-Bailey [2008], pp. 409). In order to capture the different dimensions of monetary policy-making in the FOMC, as well as the heterogeneity among committee members regarding both their preferences and infor-
I leverage the information contained in the history of FOMC deliberation records.

In chapter 2, I analyze the economic expectations that each individual member of the FOMC presented in monetary policy meetings during the period 1992-2005. The information contained in these forecasts reflect the privately held views of FOMC members about the future state of the economy regarding the value of inflation, output growth, and unemployment, which are exchanged and discussed at FOMC meetings before any formal vote is cast and the final policy decision is reached. With these expectations at hand, it is possible to compute a finer proxy of the disagreement among committee members regarding their policy preferences, as well as the uncertain consequences of their policy choices.

I implement a test to assess whether FOMC members truthfully reported the information contained in these forecasts. The results from this exercise provide evidence for three related findings that account for the heterogeneity observed in members’ forecasting behavior. First, I find substantial dispersion across individual forecasts, which contrasts with the united front appearance that the FOMC shows to the public in voting records. Second, I show that the dispersion in members’ behavior cannot be explained by differences in available information. In fact, these individual forecasts are systematically biased and fail to incorporate information contained in publicly available indicators. Third, these biases can be reconciled with the presence of heterogeneity in members’ policy preferences given by their costs for under and over-predicting the state of the economy. These biases are consistent with policymakers’ characteristics in the form of political appointment, career background, and regional influences.

In chapter 3, I analyze how FOMC members’ characteristics captured in their appointment process affect the verbal content of monetary policy deliberations and its relationship to members forecasting behavior. I explore this issue using the verbatim transcripts of everything that was said at FOMC meetings during the Greenspan chairmanship (1987-2006). To quantify members’ behavior with text data I use a probabilistic topic model, which is
a class of machine learning algorithm, that allows me to infer the time FOMC members spend deliberating different topics of monetary policy-making and its relationship to their individual characteristics and forecast biases. Overall, I find significant differences in the behavior of FOMC members that vary with their appointment process and their regional influences. In addition, the evidence indicates that the time FOMC members spend deliberating certain economic topics over others is closely related to their forecasting behavior. For instance, as members spend more time discussing topics related to inflationary pressures and economic growth, they are more likely to exaggerate their inflation and output growth predictions while under-predicting unemployment. In general, the results from this chapter show that the manner and content of members’ deliberation shapes their behavior, at least in their role as forecasters. The systematic differences in the behavior of members by appointment is additional evidence of the relevance of preference heterogeneity in shaping the monetary policy debate within the FOMC.

In chapter 4, I show that there is a substantial amount of information transmitted through the sequential deliberation of policy recommendations. For this purpose, I estimate an empirical model of policy-making that incorporates social learning via deliberation. In the model, committee members speak in sequence, allowing them to weight their own information and biases against recommendations made by others. The results from the estimation using the history of policy recommendations for the period 1970-2008 suggest substantial effects of deliberation as an information-sharing mechanism that were omitted in previous empirical literature. First, with the model estimates at hand, I assess the relative weight that members assign to deliberation against their private information when providing policy recommendations. Second, under given counterfactual scenarios, I find large effects of previous recommendations on the behavior of FOMC members. The effect of deliberation in this context is given by the probability that a FOMC member would switch her behavior after listening to previous recommendations.
I compare the predictions and performance of the empirical model (sequential deliberation model) with respect to two available explanations of committee decision-making: the spatial ideological model (Clinton, Jackman and Rivers [2004]; Jackman [2000]; Poole and Rosenthal [2000]) and the simultaneous deliberation model (Iaryczower and Shum [2012]). The former characterizes members’ behavior according to their preference divergence, which has been the most common explanation to account for members’ heterogeneity within the FOMC (Chang [2003]; Chappell, McGregor and Vermilyea [2005]; Tootell [1991]), as well as in other decision-making bodies such as courts (Martin and Quinn [2002]). The latter, as the building block of the sequential deliberation model, incorporates heterogeneity in the quality of information across members. Nonetheless, it assumes that members give their recommendations in a vacuum, ruling out the possibility of information transmission through sequential deliberation.

An evaluation of the efficacy of the abovementioned behavioral models to account for the actual patterns of policy recommendations clearly indicates that the sequential deliberation model outperforms both the spatial ideological and simultaneous quality models according to a variety of goodness-of-fit measures previously employed in the literature. In fact, incorporating sequential deliberation explains 91% of observed policy recommendations versus 85% and 75% for the spatial ideological and simultaneous models, respectively. Compared to the spatial ideological model, the better performance of the sequential deliberation model comes from the fact that it allows ideology to interact with the value of information contained in member’s private signals and in the previous recommendations made by other FOMC members. The sequential deliberation model substantially improves the fit of the simultaneous model because it is able to disentangle the effect of private information from that of the history of previous recommendations, providing expertise estimates that discount learning.

In the remainder of this introduction I provide the institutional context under which collective decision-making within the FOMC takes place.
1.1 FOMC Institutional Background

By the Banking Act of 1935, monetary policy decisions in the U.S. are the sole responsibility of the FOMC, which usually meets around eight times a year to set the short-term rate (i.e., Federal Funds rate) for open market operations - sales and purchases of government securities.\(^1\) The current structure of the FOMC is depicted in Figure 1.1 and consists of seven members of the Board of Governors, including the Chairman of the committee, and the twelve presidents of district Reserve Banks located throughout the country. All board members along with five of the twelve district presidents have voting rights at any given meeting.\(^2\) Nevertheless, the remaining seven non-voting district presidents attend committee meetings, participate in the discussions, and contribute to the committee’s assessment of the economy and policy options.\(^3\)

The institutional appointment process of FOMC members differs between board governors and district presidents. The former are appointed by the President of the United States and ratified by the Senate to serve staggered fourteen-year terms.\(^4\) The latter are chosen to serve five-years renewable terms by their own boards of directors with the consent of the Board of Governors. The board of directors of each district’s Bank consists of nine members representing three different sectors: banking, agriculture and commerce, and a mix of academia and other members of the general public.

FOMC meetings throughout the period under study follow a standard protocol with four main stages. First, the staff offers an outline of economic conditions and forecasts regarding the current state of the economy nationwide. The presentation on the current

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1. The Federal Funds rate is the rate at which commercial banks lend funds overnight with one another and is a crucial determinant of other rates with longer maturity.
2. From the latter group, the district president of the Federal Reserve Bank of New York has a right to vote at every meeting, and four of the remaining district presidents serve one-year terms as voting members on a rotating basis.
3. For the purposes of this paper, the term “member” is used for both voting and non-voting presidents. The rotating voting seats are filled from the following four groups of Banks, one district president from each: Boston, Philadelphia, and Richmond; Cleveland and Chicago; Atlanta, St. Louis, and Dallas; and Minneapolis, Kansas City, and San Francisco.
4. One of the seven governors is appointed chairman by the U.S. President for a four-year term subject to a Senate confirmation.
state of the economy prepared by the staff is contained in a report that members receive before each meeting labeled the *Greenbook*, which includes data on the national economy, as well as the staff projections for the U.S. economy in the short and medium term. After the staff’s presentations, individual members discuss their own impressions of the state of the economy, emphasizing first regional economic conditions in the case of district presidents, and then, the national and international economic situation. The discussion of economic conditions is usually followed by the policy go-around. At this stage, the staff presents possible policy alternatives and their consequences to inform the committee as it proceeds to select a policy directive. Then, individual members verbally express their preferred policy position sequentially, with an order that varies across meetings. Finally, the chairman crafts a directive that is brought to a formal vote by majority rule. In this stage, members can only agree or disagree with respect to the directive. In the case of disagreement, FOMC includes a brief statement in the minutes indicating the direction of the disagreement, from which it can be inferred whether members dissent because they want “easier” (i.e., higher policy rate) or “tighter” (i.e., lower policy rate) monetary policy.

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5The *Beigebook* contains a summary of the economic conditions pertaining each of the twelve districts as organized by district presidents.
Figure 1.1: Structure of the FOMC.
Chapter 2

Biases in FOMC Forecasts

2.1 Introduction

Less than 20 years ago, monetary policy in most central banks relied on a single person whose career prospects were tied to the fate of the government. Nowadays, in almost all central banks, monetary policy is set by an independent committee of members with heterogeneous skills and biases (Mahadeva and Sterne [2000]).

Among the reasons in favor of committee decision making, it has been argued that it can provide insurance against the potential extreme preferences of individual central bankers. In addition, it can lead to better decisions by pooling the knowledge, in the form of economic models and forecasts, of individual members. Finally, diverse committee members might bring different decision-making heuristics that may outperform individual central bankers (Blinder [2008]).

However, the extent to which aggregating information from individual committee members enhances the quality of the decision-making process hinges on members’ ability to provide advice that truthfully reveals their available information. Theoretically, it has been shown that honest revelation of information can arise whenever members share similar preferences, so that everyone agrees on which course of action is the most desirable (Coughlan...
Hence, under homogenous preferences, accounting for variation in individual behavior is straightforward, as it can be rationalized by differences in the amount and quality of the information observed by policy makers.

Yet, from an empirical standpoint, quantifying whether differences in observed behavior comes from information heterogeneity, preference divergence, reputational concerns, or other sources of information misrepresentation, represents a difficult endeavor. This is because the actual process of communication in real-world deliberative bodies is usually concealed from the public, which leaves us inferring members’ choices at the deliberation stage out of the incomplete information provided by voting decisions and actual policy outcomes (Iaryczower, Shi and Shum [2014]). To overcome this limitation, in this chapter I exploit the information contained in the forecasts FOMC members provide about the future state of the economy with respect to the value of inflation, output growth, and unemployment, which are exchanged and discussed at FOMC meetings before any formal vote is cast and the final policy decision is reached.

The advantage of using these individual forecasts to assess whether FOMC members report information truthfully comes from the fact that, during the available period, FOMC members believed that these forecasts would not be publicly available (i.e., outside the FOMC), allowing me to abstract from potential misrepresentation of information due to the presence of reputational concerns with respect to an outside audience, which might influence FOMC members to shade or exaggerate their forecasts in order to earn good publicity, just like professional forecasters appear to do (Ottaviani and Sørensen [2006a]; Ottaviani and Sørensen [2006b]).

First, I implement a test to assess whether FOMC members truthfully reported the information contained in these forecasts under the assumption of homogeneous preferences. The evidence from this exercise indicates that these individual forecasts are systematically biased and fail to incorporate information contained in publicly available indicators.

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1 A key feature of the model necessary for this result to hold is that preferences are common knowledge. See Meirowitz [2007] for an alternative communication equilibria with private beliefs and values.
Second, I rationalize members’ systematic biases with differences in their costs for under and over-predicting the state of the economy. In particular, forecast biases are consistent with policy-makers’ characteristics in the form of political appointment, career background, policy-making experience and regional influences.

On the one hand, district presidents, who are appointed by regional economic interests, are systematically more “hawkish” in terms of their inflation-aversion than board governors, who are appointed by the Executive. Moreover, district presidents tend to submit their forecasts with a regional bias. They provide a more “dovish” inflation forecast and put forward a more pessimistic output and unemployment outlook whenever the local economic conditions in their districts are relatively worse than the national economy.

On the other hand, board governors, who are appointed by the Executive, tend to submit a more “dovish” inflation forecast whenever they are appointed by a Democrat President.

In terms of members’ career experience, the evidence indicates significant effects of the type of job members held prior to joining the FOMC in explaining forecast biases. In particular, more experience in the private banking sector is associated with members exaggerating inflation and unemployment and under-estimating output growth.

The remaining of this chapter is organized as follows. Section 2.2 places the contribution of this chapter in the context of related literature that analyzes the influence of appointment in shaping FOMC members’ voting behavior, as well as other uses of FOMC individual forecasts to explain members’ disagreement. Section 2.3 explains in detail the available dataset on FOMC individual economic projections. Section 2.4 implements the empirical test of truthful reporting on FOMC individual forecasts. Section 2.5 rationalizes members’ systematic biases to differences in members’ characteristics in the form of political appointment, career background, and regional influence. Section 2.6 assess whether the forecasts members produce shape their policy-making behavior. Finally, section 2.7 summarizes the chapter and concludes.
2.2 Related Literature

This paper extends previous literature that has identified the existence of political influence on the FOMC decision-making process. Following the literature on political business cycles (e.g., Hibbs Jr [1977], Alesina [1987]), these studies have tried to identify systematic patterns on voting data regarding the political appointment process (e.g., Chappell, Havrilesky and McGregor [1993]), the uncertainty about the economic environment, or other personal characteristics of committee members (e.g., Belden [1989]; Meade [2005]; Gerlach-Kristen and Meade [2010]).

Although these papers provide interesting voting patterns suggesting the presence of partisan influence in monetary policy through the appointment process, they are limited by the fact that the policy proposal they vote on is a consequence of the recommendations they provide in the deliberation process. Thus, from these studies it is not possible to disentangle whether the degree of consensus observed from voting records is due to preference heterogeneity, learning, or strategic behavior.

Given the recent publication of individual projections analyzed in this paper, few other papers have examined the behavior of FOMC members out of these economic forecasts. For instance, Romer and Romer [2008] studied the central tendency of these forecasts across members and compared the relative value of these predictions with respect to those prepared by the FOMC staff. The authors conclude that individual projections are of lesser quality than those presented by the FOMC staff. Unlike this paper, Romer and Romer [2008] cannot say anything about the diversity of committee members’ projections and their relative quality vis-à-vis the staff or the private sector.

Previous to this paper, Banerghansa and McCracken [2009] and Tillmann [2011] analyzed the individual forecasts of FOMC members. The first authors document patterns of disagreement according to whether members are district presidents or board governors. Tillmann [2011] extend this analysis correlating members’ disagreement to voting status. Their findings suggest that disagreement across members is larger for non-voters with respect to
voters. I extend these papers by providing an analysis of their efficiency and a connection of members’ forecasts and their policy recommendations. In addition, I provide an explanation for the differential behavior of FOMC members by looking into their appointment process, regional biases, and career experience.

2.3 Data

Individual economic projections presented by FOMC members in the economy go-around are drawn from the dataset collected by Romer and Romer [2008] and currently maintained by the Federal Reserve of Philadelphia. The data contains the forecasts of output growth, inflation, and unemployment provided by individual FOMC members for the period 1992-2005, covering a portion of the Greenspan’s chairmanship.

FOMC members submit these forecasts for the record before the meetings of January-February and June-July preceding the Chairman’s semi-annual testimony to Congress. Members discuss and exchange these expectations based on information available at the time of each meeting, which includes staff projections reported in the Greenbook, as well as members’ individual assessments about potential relevant factors likely to affect economic outcomes, such as their assessments on the appropriate stance of monetary policy.

In May 2009, the Federal Reserve published these projections for the period 1992-2000 and agreed to subsequently release more on a regular basis with a 10-year lag. As of today, the individual expectations of 38 committee members are available from the January-February meeting of 1992 to the June-July meeting of 2005. Individual FOMC members provide their forecasts of inflation, output growth and unemployment for the end of the current and following years.

There are two subtleties of the data as noted in Romer [2010] that are worth mentioning. First, after each meeting, members had approximately a week to revise their forecasts before the final publication and only the final revisions are publicly available. Thus, no systematic
information on the amount of these revisions can be extracted with certainty. Fortunately, the extent of forecast revisions after each meeting does not compromise the results of the empirical estimation below. This is because, any forecast revision that include relevant information to improve forecast accuracy would go against the presence of biased and inefficient forecasts that I am testing for in the empirical analysis. The second issue with this dataset is that, unfortunately, the Chairman of the FOMC did not submit any individual projection as part of this process.

Figure 2.1 presents, as an example, the distribution of current-year inflation forecasts made at the January-February meeting of each year over the period 1992-2005, when this data is available. This value is calculated using real-time data as observed by FOMC members roughly three months after its first release.

Overall, there is a wide range of dispersion across FOMC members’ forecasts. Consider as an example the inflation forecasts made by FOMC members for the January-February meeting of 1994, when inflation at the end of the year was 2.6%. The mean forecast across members at that meeting was 2.98%. Thus, the mean forecast laid very close to the actual outcome released 10 months later. At the same meeting, however, there was a huge dispersion of forecasts across FOMC members driven by extreme predictions, such as the one submitted by district president Tom Melzer from the St. Louis Fed, who forecasted inflation as high as 4%, which was 34% larger than that of the committee consensus.

### 2.4 A Test of Truthful Reporting

#### 2.4.1 Identification Strategy

To identify whether members truthfully reported the available information contained in FOMC forecasts, I test for departures from the benchmark case of honest forecasting, where members share the same preferences and their forecasts minimize the mean of any symmetric
function of the forecast error, such as the mean squared error (MSE) (Bhattacharya and Pfleiderer [1985]).

Suppose that at any given meeting $t = 1, \ldots, T$, member $i = 1, \ldots, N$ receives a signal, that is normally distributed, and informative about the unobserved state of the economy in the form of the macroeconomic variable $y_t$ (either inflation, output growth, or unemployment). Let $q_{it} \sim N(y_t, \tau_i)$ denote this signal. Under MSE, $L(y_t - f_{it}) = (y_t - f_{it})^2$, the honest forecast, $f^*_{it}$, solves

\[
    f^*_{it} \equiv \arg\min_{f_{it}} E \left[ (y_t - f_{it})^2 | q_{it} \right],
\]

with a solution that is given by the conditional expectation of $y_t$, $f^*_{it} = E[y_t | q_{it}]$. Notice that this benchmark model is equivalent to members reporting their Bayesian posterior expectation of the true state of the economy under the assumption that the prior distribution of the state is uniform on the real line\(^2\).

\(^2\)For instance, in the case where $y_t$ is also normally distributed with some mean $\mu$ and variance $\nu$, the honest forecast would be given instead by $f^*_{it} = E[y_t | q_{it}] = \frac{\nu}{\tau_i + \nu} q_{it} + \frac{\tau_i}{\tau_i + \nu} \mu$. Although this specification is
An important implication of this benchmark case is that the dispersion we observe in FOMC forecasts in Figure 2.1 should be explained exclusively from differences in members’ information $q_{it}$. This is because members, under this benchmark, share the same symmetric loss function.

I define the ex-post forecast error of this projection as $e_{it} = y_t - f_{it}$. Thus, under honest forecasting, the conditional mean of this error should be zero, $E[e^*_{it}|q_{it}] = 0$, where $e^*_{it} = y_t - E[y_t|q_{it}]$. Applying the law of iterated expectations to the above optimality condition, it must be the case that

$$E[E[e^*_{it}|q_{it}]|q_{it}] = E[e^*_{it}|q_{it}] = 0. \quad (2.2)$$

### 2.4.2 Empirical Estimation

Using a sample counterpart of the above moment condition, I can empirically validate whether FOMC members adhered to truthful reporting of information in their economic projections. In particular, $E[e^*_{it}|q_{it}] = 0$ implies that:

1. FOMC members’ predictions should be unbiased, $E[e^*_{it}] = 0$.

2. FOMC members’ predictions should incorporate all available information contained in $q_{it}$. Equivalently, the honest error, $e^*_{it}$ should not be related to available information known by FOMC member $i$ at meeting $t$.

One relevant point to notice regarding the optimal moment condition above is that in order to assess whether FOMC members fully adhered to the definition of honest forecasting, one would need to observe, for every FOMC member, the realization of $q_{it}$, which incorporates private information unobserved to the analyst. Fortunately, if the purpose of the empirical exercise is to reject the hypothesis of honest forecasting, it is sufficient to show that some relevant available information was not incorporated when FOMC members submitted their feasible to estimate empirically with a Bayesian linear model, the observable implications of this test would be less straightforward to interpret, as they depend on the estimates for the state prior $\mu$. 17
predictions. Thus, the empirical test should include variables that were part of FOMC members’ information set at the time they reported their economic projections. For this reason, I extract relevant information from FOMC records that are available to individual members before each meeting takes place in the form of staff estimates of relevant macroeconomic variables reported in the Greenbook. In particular, I include the board staff’s estimate of the output gap \((\text{gap}_{t}^{GB})\), defined as the difference between actual output growth and the output growth that is consistent with full employment. This variable has been used throughout the history of FOMC meetings to gauge future inflationary pressures, and is regularly discussed in committee deliberations as a fundamental variable of interest to FOMC members. From the Greenbook, I also include two-quarter ahead staff forecasts of inflation \((\text{inf}_{t}^{GB})\) and GDP growth \((\text{output}_{t}^{GB})\).

In addition, I include members’ past forecast errors \((e_{i,t-1})\), given the most recent publication of data available to FOMC members at the time of each meeting. This variable is surely known by FOMC members at the time they submit new predictions, and I use it to assess whether FOMC members learn from their previous mistakes.

Finally, I account for the cross-sectional average of a sample of private sector forecasts \((f_{C,t}^{C})\) obtained from Consensus Economics, which is a private firm that polls professional forecasters regarding their expectations on relevant macroeconomic variables. This measure represents a proxy of market expectations regarding the same outcomes FOMC members are trying to predict. These forecasts are collected at least two weeks in advance of FOMC meetings and, as such, can be considered as available information by the time deliberations take place.

As suggested in Capistran [2008], I implement a single regression to evaluate members’ forecasts under a MSE loss function that has the forecast error as its dependent variable:

\[
e_{it} = \beta_0 + \beta_1 \text{gap}_t + \beta_2 \text{inf}_t^{GB} + \beta_3 \text{output}_t^{GB} + \beta_4 e_{i,t-1} + \beta_5 (f_t^{C} - f_{it}) + \epsilon_{it}. \tag{2.3}
\]

\(^{3}\)The information of the survey can be found at www.consensuseconomics.com
In this manner, under the null hypothesis of *honest forecasting*, it must hold that $e_{it}$ should be uncorrelated with available information on the right-hand side of equation (2.3). This null hypothesis can be expressed as $H_o: \beta_0 = \ldots = \beta_5 = 0$. Moreover, the parameter $\beta_5$ in this equation can be interpreted as the relative weight assigned to $f_t^c$ under *honest forecasting*. To see this, ignore for the moment $\beta_0, \ldots, \beta_4$ and notice that $e_{it} = y_t - f_{it} = \beta_5(f_t^c - f_{it}) + \epsilon_{it}$ is equivalent to estimating $y_t = \beta_5 f_t^c + (1 - \beta_5)f_{it} + \epsilon_{it}$. 

Point estimates of the coefficients in equation (2.3) can be computed consistently through OLS by pooling members and forecast horizons. However, as initially noted by Keane and Runkle [1990], under the hypothesis of *honest forecasting*, the error term, $\epsilon_{it}$, shows both spatial and serial correlation. Therefore, OLS would yield inconsistent standard errors in the presence of aggregate shocks. For this reason, I exploit the structure of forecast errors under the null hypothesis to construct a consistent covariance estimator in the presence of serial and spatial correlation. In particular, this variance covariance matrix takes into account: 

1) different error variances across FOMC members (i.e., within homoskedasticity and between heteroskedasticity), 
2) correlation of contemporaneous shocks across members, 
3) contemporaneous shocks for consecutive years for each member and 
4) across members.

The procedure to provide the consistent covariance estimator can be found in Appendix A.1.

2.4.3 Results

The results of testing the null hypothesis of *honest forecasting* on FOMC individual forecasts of inflation, output growth, and unemployment are graphically displayed in Figure 2.2 and presented in Table A.2. In terms of the aggregate behavior of FOMC members, I reject (with a 95% confidence level) the joint null hypothesis of *honest forecasting* for the three variables analyzed.

In particular, FOMC members significantly over-estimated the true value of inflation and unemployment whenever the staff expected higher inflationary pressures in the form of increases in expected inflation and output gap. In addition, they under-estimated inflation
Figure 2.2: **Honest Forecasting for FOMC Members under MSE.** The estimated equation is: $e_{it} = \beta_0 + \beta_1 \text{gap}_t + \beta_2 \text{inf}_{GB}^{GB} + \beta_3 \text{output}_{GB}^{GB} + \beta_4 e_{i,t-1} + \beta_5 (f^C_t - f^t_t) + \epsilon_{it}$. $f^C$ denotes the cross-section mean forecast of the private sector Consensus Forecast survey. $\text{gap}_t$ denotes the estimate of current quarterly output gap (i.e., actual output growth - potential output growth) collected from the Greenbook. $\text{inf}_{GB}^{GB}$ denotes the two-quarter ahead Greenbook inflation forecast. $\text{output}_{GB}^{GB}$ denotes the two-quarter ahead Greenbook real GDP growth forecast. Pooled OLS estimates with confidence intervals calculated using standard errors consistent with heteroskedasticity, serial, and spatial correlation.

and unemployment whenever the staff expected higher GDP growth. Conversely, for the case of output growth forecasts.

Notice as well that members’ inflation forecasts failed to efficiently incorporate information contained in private sector predictions ($f^C_t$) and in their own past forecast errors ($e_{i,t-1}$). With respect to private sector forecasts, I cannot reject the null hypothesis that $\beta_5 = 1$. This result implies that if one were trying to predict inflation as accurately as possible and had access to both forecasts, one could confidently discard FOMC members’ projections and keep only the private sector forecasts.

To disaggregate the forecast biases at the individual level, Figure 2.3 presents the ranking of FOMC members according to their individual forecast biases. As can be seen, there is significant variation across members in the direction and magnitude of these biases. With respect to inflation forecasts, 26% of FOMC members systematically over-estimated the actual outcome and 40% significantly under-estimated it. In the case of output growth, 12% of FOMC members over-predicted the actual value while 43% of them under-predicted it.
Finally, in terms of unemployment 63% of members tended to bias their forecasts, all of them over-predicting the actual outcome.

2.5 Explaining Forecast Biases

One important limitation regarding the interpretation of the results presented above is that the test of honest forecasting implemented in the previous section involves a joint hypothesis of preference homogeneity with MSE loss along with an efficient use of available information. Thus, rejection of the null hypothesis can be driven by the violations of any of these two assumptions, or both of them. Thus, faced with this evidence, one could still argue that departures from honest forecasting could be the consequence of members’ myopic behavior, in a world in which they share the same preferences.

To refute this potential alternative hypothesis, I exploit the variation among FOMC members’ characteristics to show that the biased nature of these forecasts cannot be rationalized by members’ myopic behavior but, instead, is consistent with members’ heterogeneity in preferences as influenced by their appointment process and career experience.
In terms of appointment, I compare the forecasting behavior between district presidents and board governors. In this manner, I am able to assess whether board governors, as appointees of the President, have a preference bias towards output stabilization and, therefore, are less inflation-averse than district presidents.

For the group of board governors, I further split their forecast biases by the party of the Executive that appointed them. In this way, I test whether Republican-appointed governors shared the preferences of Republican Presidents, who have been associated with more conservative anti-inflation monetary preferences compared to Democrats, who are said to put more weight on the real side of the economy (output growth and unemployment) than on taming inflation.

For the group of district presidents, who are appointed by regional economic interest groups, I test whether they are biased towards regional economic interests when predicting the state of the economy nationwide. Specifically, I assess whether the local economic conditions they face are correlated with their forecast biases. To measure regional economic pressures, I construct a measure of the gap between regional and national unemployment (e.g., Meade and Sheets [2005]). The regional unemployment rate is calculated as a population-weighted mean of unemployment data at the county level for each specific district geographic region. The regional unemployment rate at each meeting is a moving average of the unemployment in the preceding three months4.

Figure 2.4 shows the evolution of the regional unemployment gap for five selected Federal Reserve Banks. The variation across regional economies is significant, with a variety of economic cycles faced by district presidents at any given policy meeting.

With respect to the heterogeneity in career experiences of FOMC members, I test the hypothesis laid out in the literature on monetary policy delegation by which financial sector experience makes central bankers more inflation-averse (e.g., Belden [1989]; Havrilesky and Gilders [1991]; Woolley [1985]; Adolphi [2013]). To measure career experience of FOMC

4County-level data of unemployment can be found at data.bls.gov
members, I employ and expand the measure of career backgrounds created by [Adolph 2013] which partitions central bankers’ past jobs into seven mutually exclusive categories, namely: financial (i.e., private banking jobs), government (i.e, bureaucrats outside the Federal Reserve and the Treasury Department), finance ministry (i.e., bureaucrats in the Treasury Department), central bank (i.e., staffers within the Federal Reserve System), economics (i.e, academic economists), business (i.e, private sector excluding banks), and other (e.g., international organization officials). The career experience for each category is computed as the fraction of the FOMC member’s career spent in that job category up to the date of her most recent appointment as a FOMC member.

Figure 2.5 shows the average career experience of FOMC members for the sample under study. On the one hand, FOMC members have spent most of their career as bureaucrats (around 47%), either in the finance ministry, central bank, or in other governmental jobs. Past jobs as private bankers, on the other hand, account for 18% of FOMC members’ career experience.

To explain forecast biases by FOMC member characteristics I run regressions of the form:

\[ e_{it} = X_{it} \Gamma' + \nu_{it}, \]  

(2.4)

where \( X_{it} \) is a vector of members’ characteristics such as appointment, party of the Executive, regional unemployment and career experience. All the regressions are estimated with standard errors robust to spatial and serial correlation (Appendix A.1).

Figure 2.6 presents the differences in forecast biases by appointment for each outcome variable under study. In the case of inflation forecasts, the left panel shows evidence that district presidents had a significantly lower bias than board governors. Whereas board governors under-predicted inflation in 0.4%, district presidents under-predicted it by 0.2%. No significant differences were found in the case of output growth forecasts. In contrast, the right panel shows that board governors over-estimated unemployment in a larger magnitude.
Figure 2.4: **Regional Unemployment Gap for Selected Federal Reserve Banks.** The figure shows, for each period, the difference between the regional unemployment rate and the national unemployment rate for the Federal Reserve Banks of Boston, New York, Philadelphia, Cleveland and Richmond. The regional unemployment rate is constructed as a population-weighted mean of unemployment data at the county level for each Federal Reserve Bank geographic region. The regional unemployment figure at each meeting is a three-month moving average. Unemployment at the county-level is collected from the Bureau of Labor Statistics at [data.bls.gov](http://data.bls.gov).

(i.e., around 0.05%) than district presidents. Overall, this evidence is consistent with district presidents being more inflation-averse than Presidential-appointed board governors who, instead, exaggerated more unemployment concerns.

Looking at the sample of board governors, Figure 2.7 indicate significant differences in the forecasting behavior according to the party of the President who appoints them. The left panel shows that Republican-appointees are more conservative in forecasting inflation with a bias 0.2% smaller than that of Democrat-appointees. No differences were found for the case
Figure 2.5: **Average Career Experience by Job Category.** The figure shows the mean career experience score for each job category. Career experience is the fraction of a member’s career prior to FOMC membership.

of output growth forecasts. Surprisingly, as shown in the right panel, Republican-appointees significantly over-estimate unemployment around 0.1% more than Democrat-appointees.

The results of testing for regional bias in FOMC predictions are presented in Figure 2.8, which shows the expected bias of a hypothetical district president as a function of the gap between regional and national unemployment. The takeaway point of this figure is that district presidents’ biases are systematically correlated to the regional economic conditions they face when predicting the national economy. In particular, in the face of an increase in their regional unemployment with respect to the national average, district presidents tend to put less weight on inflationary pressures, and instead report a more pessimistic scenario on the real side of the economy at the national level. For instance, when the regional unemployment rate goes from 1% below to 2% above the national average, a typical district
Figure 2.6: **Forecast Biases of Fed Presidents and Board Governors.** The Figure shows the estimated forecast bias aggregated by appointment and the difference between district presidents and board governors. Solid circles denote point estimates and solid lines denote 90% confidence intervals.

Figure 2.7: **Forecast Biases of Democrat- and Republican-Appointed Governors.** The Figure shows the estimated forecast bias aggregated by appointment and the difference between district presidents and board governors. Solid circles denote point estimates and solid lines denote 90% confidence intervals.

President under-predicts inflation and output growth in around 0.3% and 0.2%, respectively, while over-predicting unemployment in approximately 0.3%.

Figure 2.9 shows the results of regressing FOMC members’ biases on their career experiences in finance, government (the sum of experience at the Department of the Treasury and other branches of government), and economics. I present the results in terms of coun-
The figure simulates the effect of moving from the minimum to the maximum observed values of regional unemployment gap on the expected forecast bias for inflation, output growth and unemployment. A 90% confidence interval is shown in light blue.

The left panel of this Figure shows that increasing a members’ experience in finance one standard deviation from 18% to 49%, would imply a change in the inflation bias of $-0.18\%$, which is indicative of FOMC members with more experience as private bankers exaggerating inflation to a larger degree. In contrast, increasing government experience one standard deviation from 8% to 21%, does not have any effect on members’ inflation bias. More experience as a central banker is associated with a more “hawkish” bias on average, but is not precisely estimated, as can be seen from its wide confidence interval.

The results for output growth and unemployment forecasts do not seem to show a higher degree of monetary conservatism for FOMC members with more experience in finance. This is because an increment in finance experience is significantly associated with members exaggerating bad economic conditions (i.e., under-estimating growth and over-estimating unemployment).

In general, these results show significant effects of career experience in explaining forecast biases. The results for inflation forecasts are in line with the hypothesis of career effects that
emphasizes a higher degree of inflation aversion for FOMC members with more experience in the private banking sector. However, more experience in finance is also associated with a higher emphasis on bad economic conditions, which seems at odds with a higher monetary conservatism of finance types.

Figure 2.9: Forecast Biases and Career Experience. The figure presents the change in forecast bias following a one standard deviation increase in career type: Finance, Central Banking and Government. In performing the counterfactual, when one career experience is increased, all other career experiences are reduced proportionately from their means to maintain a sum of one. Solid points denote median changes and solid lines depict 90% confidence level.

2.6 The Effect of FOMC Members’ Forecasts on Policy Recommendations

Given the significant relationship between forecast biases and FOMC members’ characteristics has been established, I assess whether FOMC members’ biases translate into their monetary policy decisions. To do this, I test whether FOMC members use these biased forecasts as inputs to express their policy recommendations relative to additional available information.

The voiced policy recommendations shared by FOMC members in the policy go-around are obtained from the verbatim transcripts of FOMC meetings collected by Chappell, Mc-

I estimate the weight that FOMC members assign to their own forecasts in determining their policy recommendations relative to private sector forecasts from Consensus Forecasts and staff forecasts from Greenbook, both of them available to FOMC members prior to each meeting.\(^5\) The results are presented in Figure 2.10 as counterfactual changes in individual preferred rates from increasing each covariate of interest from the 25th to the 75th percentile in the sample, while setting all remaining covariates at their median sample values. The results indicate that, with the exception of private and staff unemployment forecasts, the only significant predictors of FOMC members’ policy recommendations are their own individual forecasts.\(^6\) This is the case even when FOMC staff forecasts are, at least for inflation, more accurate than members’ forecasts. (Romer and Romer [2008]). This is evidence that difference in preferences for under- and over-predicting the state of the economy can help in explaining the heterogeneity in policy decisions across FOMC members.

2.7 Conclusions

One of the argued benefits of committee decision-making compared to decisions made by individuals is that a committee pools the knowledge, information, and forecasts of its members, leading to better decisions (Blinder [2009]). However, this assertion does not consider the fact that this information may not be the most accurate and instead could be biased in a direction that may not be consistent with a homogenous committee. The fact that policy makers act based on this distorted information suggests a connection between the forecasts they put forward in the deliberation process and monetary policy choices, that goes beyond the degree of consensus that can be observed in the voting stage, where committee members

\(^5\) I also control for the previous week level of the Federal Funds Rate and FOMC Members’ fixed-effects.

\(^6\) The direction of the effects are in the expected direction, with the exception of members’ unemployment forecasts. However when I exclude the staff’s unemployment forecast, the sign of this effect is negative, as expected.
Figure 2.10: **Relative Weight of FOMC Members' Forecasts on Voiced Policy Preferences.** The figure shows the change in individual preferred rates from increasing the covariate of interest from the 25th to the 75th percentile in the sample. For each estimate, all other covariates are set at their median sample values. All simulated effects are estimated controlling for members’ fixed-effects and clustered standard errors at the member level. The level of Fed Funds rate is used as a control but not shown.

usually speak with one voice. In fact, the evidence presented in this chapter points out that the information put forward by committee members is biased in a direction that represents the policy preferences of the people who appoints them.
Chapter 3

Verbal Content of FOMC Deliberations

3.1 Introduction

FOMC members spend most of their time at monetary policy meetings discussing, arguing, giving reasons and providing information regarding a wide set of economic topics in order to justify both their views about the future state of the economy and their policy positions. Therefore, examining how members’ characteristics influence their deliberative process, as well as assessing whether these arguments and opinions shape their policy decisions is a step forward to understand the mechanisms through which deliberation ultimately affect policy outcomes. In chapter 2 I show how members’ characteristics determine their forecasting behavior and in turn, their policy choices. However, members’ economic expectations and policy recommendations comprise a minimal portion of the decision-making process within the FOMC. In reality, members produce their economic projections and policy recommendations together with a set of qualitative arguments that paint a more detailed picture of their economic views and policy preferences. Thus, in this chapter I investigate whether members’ arguments at monetary policy meetings are consistent with their actions, as measured by
the forecasts they produce. I explore this issue using the verbatim transcripts of everything that was said at FOMC meetings during the Greenspan chairmanship (1987-2006). To quantify members’ behavior with text data I use a probabilistic topic model, which is a class of machine learning algorithm, that allows me to infer the time FOMC members spend deliberating different topics of monetary policy-making and its relationship to their individual characteristics and forecast biases. First, I assess whether FOMC deliberations are related to members’ biases given by their appointment process and regional influences. On the one hand, I explore whether board governors, as Presidential appointees, deliberate monetary policy with a relative “dovish” bias compared to district presidents, with the former potentially emphasizing and even exaggerating output and unemployment concerns and the latter putting more emphasis on inflationary pressures. Moreover, given the appointment of district presidents by local economic interest groups, I explore the extent to which district presidents are influenced by regional economic conditions in the way they communicate at FOMC meetings.

Second, I examine the connection between the verbal content of FOMC deliberations and members’ forecasting behavior. In particular, I explore whether and to what extent the proportion of time members spend discussing certain economic topics over others leads to systematic biases in their economic forecasts.

In general, the objective of this chapter is to show that that the content of members’ deliberation ultimately shapes their behavior, at least in their role as forecasters. The systematic differences in members’ behavior by appointment is additional evidence of the relevance of preference heterogeneity in shaping the monetary policy debate within the FOMC.

1I choose this sample period because individual forecasts are only available for a portion of the Greenspan years (1992-2005).
3.2 Related Literature

To the best of my knowledge, this is the first study that systematically analyzes the relationship between the verbal content of FOMC members’ deliberations and members’ behavior. However, I build on a large literature that analyzes differences in members’ behavior by appointment using data on dissenting votes (e.g., Chappell, Havrilesky and McGregor [1993], Krause [1994], McGregor [1996], Chang [2003]). Overall, these studies suggest significant differences in the behavior of board governors with respect to district presidents, with the latter being systematically more “hawkish” in their monetary policy stance than the former. This heterogeneity in members’ behavior by appointment is also present using data on individual monetary policy recommendations taken from verbatim transcripts, as originally collected by Chappell, McGregor and Vermilyea [2005]. Here, I extend the evidence presented in the abovementioned studies by assessing whether political appointment also determines the way FOMC members communicate with one another at monetary policy meetings.

This chapter also complements several studies that examine the presence of regional biases in monetary policy-making at the FOMC by looking at both voting records and policy recommendations (e.g., Tootell [1991], Gildea [1992], Meade and Sheets [2005], Jung and Latsos [2015]). Using a measure of local unemployment relative to the national rate, the majority of these papers find a significant regional bias in the monetary policy-making of district presidents, with “dovish” policies associated with high local unemployment relative to the national average. In this chapter I assess whether regional economic developments, as found in previous literature, also influence the content of district presidents’ internal communication at FOMC meetings. Related to the presence of regional biases on FOMC communication, Hayo and Neuenkirch [2013] show that the tone of district presidents’ speeches in their regions is influenced by regional macroeconomic variables. The authors read every transcripts and subjectively code speeches based on whether they indicate likely increases or decreases in the policy rate. Although this manual coding is able to capture the tone of FOMC speeches in those cases where they directly address changes in the monetary policy
rate, it is unclear how to code other statements that do not explicitly talk about the policy instrument. Instead, using text analysis to examine FOMC transcripts allows me to systematically consider every single term included in members’ interjections at FOMC meetings and recover from the data, in the form of clusters of words, the variety of economic topics that members talk about.

As implemented in this chapter, other studies use automated content analysis to examine the record of FOMC deliberations. Bailey and Schonhardt-Bailey [2008] analyze the ideas and arguments introduced by Volcker at FOMC meetings to bring inflation down during the period 1979-1980. Schonhardt-Bailey [2013] extends this analysis to the deliberation at the FOMC during the Greenspan years and examines the relationship between Congress and the FOMC via a text analysis of Congressional Oversight Hearings. Hansen, McMahon and Prat [2014] and Egesdal, Gill and Rotemberg [2015] model FOMC transcripts using variants of probabilistic topic models to assess the effect of increased transparency, given by the public release of FOMC transcripts in 1993, on monetary policy deliberations.

3.3 Data

To measure deliberation I use the verbatim transcripts of everything that was said by FOMC members at monetary policy meetings during the Greenspan chairmanship from August 1987 to January 2006, for a total of 148 meetings. I identify all members’ interjections within any of the two main sections of committee meetings: the economic situation discussion and the policy go-around, as described in section 1.1 in the introduction. A document \( d = 1, \ldots, D \) is constituted by the list of words uttered by member \( i = 1, \ldots, N \) in section \( s \in \{ \text{Economic Discussion, Policy Discussion} \} \) at meeting \( t = 1, \ldots, T \), \( w_d = \{ w_{d,1}, \ldots, w_{d,N_d} \} \).

For the period under study this gives a total of 5645 documents so defined. The documents are preprocessed following standard practice (e.g., Quinn et al. [2010]). First, I remove...
punctuation, capitalization, numbers and stopwords. Second, I standardize key paired words that are frequently used in FOMC deliberations into single terms (e.g., “federal funds rate”, “fed funds rate” and “funds rate” all become “ffr”). In addition, to account for frequently paired words, I consider all bigrams and trigrams. Third, all the words are stemmed, which allows me to leverage the shared topical meaning of words with the same linguistic root. I refer to unigrams, bigrams, and trigrams after stemming as “terms”.

There are 881,622 terms in the vocabulary of FOMC members, with a large proportion of them being unique to a specific document or infrequent enough to contain relevant information. For the empirical analysis, I remove sparse terms defined as those that appear in less than 0.1% of all documents. This procedure leaves a total of 869,446 terms to analyze.

3.4 Quantifying Deliberation at the FOMC

To quantify members’ behavior with text data, I focus on the use of a probabilistic topic model known as the Structural Topic Model (Roberts et al. [2014]; Roberts, Stewart and Tingley [2016]), which is a class of machine learning algorithm that infers latent topics from clusters of words that occur together. Specifically, this statistical model of text defines topics as probability distributions over a vocabulary of words that express the same underlying themes. Under this framework, a document is represented as a mixture of topics, with each word within a given document representing exactly one topic.

The main innovation of the Structural Topic Model with respect to other well known probabilistic topic models, such as the latent Dirichlet allocation model (Blei, Ng and Jordan [2003]), is that it allows for information about individual documents (i.e., meta-data) to inform the distribution of both topics across documents and words within topics.

For each document $d$, a distribution over topics $k = 1, \ldots, K$, $\theta_d$ is drawn from

$$
\theta_d \sim \text{LogisticNormal}(X_d \gamma, \Sigma),
$$

(3.1)

---

4I use the SMART information retrieval system at Cornell University that contains 571 words.
where $\mathbf{X}_d$ is a matrix of document-level covariates that includes: the estimate of the output gap from the Greenbook ($\text{gap}_t^{GB}$), the level of the Federal Funds Rate the week prior to each meeting ($\text{previous policy}$), the voiced policy recommendation of member $i$ at meeting $t$ ($r_{it}$), a binary indicator that takes the value of one if member $i$ is a district president ($\text{pres}_i$), a binary indicator that takes the value of one if member $i$ is a Democrat-appointed governor ($\text{dem}_i$). I include member $i$’s experience at meeting $t$ in the form of a binary indicator ($\text{Rookie}$) that takes the value of one if member $i$ served in less than 34 meetings. Here, 34 meeting represents the 25th percentile of term length in the sample. I include career experience scores in finance, government, finance ministry, and economics, as introduced in chapter 2. I account for a switch in the transparency of FOMC deliberations, since prior to November 1993 FOMC members were not aware that meeting deliberations were being recorded and eventually published. After November 1993, meeting discussions took place under the assumption that every individual statement and comment would be publicly available within five years after each meeting. Thus, to measure this transparency change, I include an indicator variable ($\text{transparency}$) that takes the value of one after November 1993. I include a binary indicator ($\text{section}$) that takes the value of one if the speech of member $i$ at meeting $t$ is given in the economic discussion section of the FOMC meeting. Finally, I include a flexible spline for meeting effects.

By including these covariates in the document-topic proportions, the model allows topics to be correlated and permits each document to have its own prior defined by the linear functional form $\mathbf{X}_d \gamma$. In this way, I can infer the time FOMC members allot deliberating different monetary policy topics as a function of both meeting and member characteristics.

Then, for each word $w_{d,n}$ in document $d$, a topic for that word is drawn from a multinomial distribution based on the distribution over topics $\theta_d$:

$$z_{d,n} \sim \text{Multinomial}(\theta_d).$$  \hspace{1cm} (3.2)
The document-specific distribution over words is given by

$$\beta_{zd,n} \propto \exp(m + \kappa_k), \quad (3.3)$$

where \(m\) is the common word distribution and \(\kappa_k\) is a topic-specific effect.

Finally, conditional on the topic selected, the observed word \(w_{d,n}\) is drawn from a multinomial distribution over the vocabulary:

$$w_{d,n} \sim \text{Multinomial}(\beta_{zd,n}), \quad (3.4)$$

where \(\beta_{k,v}\) denotes the probability of drawing the \(v\)th word in the vocabulary for topic \(k\).

The number of topics \(K\) that is estimated by the Structural Topic Model has to be set in advance. Fixing the number of topics to be large, provides a fine-grained summary of the deliberation process at the cost of estimating very narrow conversational patterns. Setting the number of topics to be small gives a general overview of the verbal content of FOMC meetings at the cost of estimating topics that reflect more than one relevant aspect of monetary policy. I estimate the model setting the number of topics at \(K = 40\). Modifying the number of topics in the range of 25 – 50 topics produce similar results in terms of the themes of FOMC deliberation that I analyze in the empirical estimation.

The model is estimated with an initialization based on the spectral method of moments estimator of Arora et al. [2013]. As explained in Roberts, Stewart and Tingley [2014], this initialization method guarantees to recover globally optimal parameters, which is a crucial advantage in the presence of multi-modal posterior distributions such as the ones that plague clustering models in general and topic models in particular.
3.5 Identification of FOMC Deliberation Topics

The estimated topics from the Structural Topic Models have no pre-assigned labels. In order to attribute meaning to any given topic, I look at the collection of words that are highly associated with each topic using two different metrics: the highest probability words and words that are both highly frequent and exclusive.\[^{5}\] In addition, I read and examine those documents that have the highest proportion of words drawn from each topic given by the estimates of $\theta_d^k$.

Figure 3.1 displays the estimated proportion of FOMC deliberations spent in the top ten topics. For instance, the topic that consumes most of the discussion at FOMC meetings (about 9%) consists of terms reflecting uncertainty about economic outcomes (Uncertainty). Next, FOMC members spent around 7% of FOMC meetings discussing one of the topics associated to inflation (Inflation Target).

I examine the estimated topics in detail to identify the main themes of monetary policy deliberation at the FOMC related to inflation, economic growth and regional economies, for which I expect differential levels of attention among district presidents and board governors.

Figure 3.2 displays the top words associated with two inflation topics: Price Stability (Topic 45) and Inflation Expectations (Topic 35). For each topic, I present a “wordcloud” representation, with larger words being more highly associated with the topic, given the estimates of $\beta_{z_d,n}$. Terms such as “goal”, “price”, and “achieve” are the most prominent and exclusive in the Price Stability topic, whereas terms like “energyprice”, “coreinfl”, and “inflationexpect” differentiate the topic I label Inflation Expectations. The attributed meaning to each of these topics can also be seen from their representative documents. For instance, the document most highly associated to the Price Stability topic is a commentary provided by district president Broaddus during the economic discussion at the July meeting in 1995:

\[^{5}\] The highest probability words are inferred directly from the topic-word distribution, given the estimates of $\beta_{z_d,n}$. The words that are both frequent and exclusive are calculated with the FREX score (Roberts et al. [2014]) that computes the harmonic mean of rank from the topic-word distribution and from the distribution of topics given words.
“[…] we should commit ourselves publicly and firmly to the price stability objective put forward in the Neal Amendment—both its definition of price stability, whose language I think was negotiated at the time, and also importantly its 5-year longer-term horizon. It is that specific time horizon that I think would make it meaningful.”

Beyond the discussion on inflation, I identify a series of topics related to economic growth, which I exemplify in Figures 3.3 and 3.4 with the labels Productivity Growth, Labor Market/Wages, Economic Risk, and Consumption and Investment. For the Productivity Growth topic the top terms are “earn”, “acceler”, “product”. For the Labor Markets/Wages topic,
the most likely terms are “wage”, “labormarket”, “demand”. The Productivity Growth topic is highly associated to the discussion initiated by Alan Greenspan in the 1990’s to explain, via productivity improvements, the sustained economic growth of the US economy from the beginning of that decade. This can be seen from the following quote of Alan Greenspan taken from the policy discussion made at the March, 1993 meeting:

“For quite a while our Greenbook and indeed all models have been projecting slower economic growth and higher inflation than actually have materialized. Looking back, it is conceivable and perhaps likely that the major explanation for these projection errors is that the models have missed the extent of the acceleration in productivity.”

Regarding the Economic Risks topic, the highest probability terms are “uncertainty”, “chang”, and “polic”. The fact that this topic captures uncertainty in both the economic
Productivity Growth

Labor Market/Wages

Figure 3.3: **Productivity and Labor Market Topics.** Each panel shows a word cloud for an estimated topic taking the 70 words with highest probability of being drawn from the particular topic. The size of each word in the cloud is proportional to the probability conditional that the word comes from that particular topic.

... environment and in the consequences of monetary policy is better exemplified in the following quote from Governor Ferguson at the December, 2000 meeting in the midst of the “Dotcom Bubble Burst”:

“We are in a period, I believe, of great uncertainty. And I think it’s not illegitimate for us to recognize some uncertainty by saying that we tend to think the risks are in one direction.”

For the *Consumption and Investment* topic, terms like “recoveri”, “stimulus”, and “invest” are the most frequent ones.

Another set of topics of interest, which will be analyzed in detail in section 3.6, is related to the economic conditions at the geographical regions supervised by district presidents. In this regard, Figure 3.5 shows as an example two of these topics. The most distinctive words for these regional topics are “district”, “agricultur”, “region”, “businessoutlook”, and...
“local”. These discussion themes are mainly brought about by district presidents during the economic discussion section of FOMC meetings. The main content of these topics as can be inferred from the following quote attributed to district president Hoening in November 1992:

“[..] our district continues to show some modest improvement and considerably more optimism looking forward. Our agricultural sector is really trading off between improvement in our livestock business and some deterioration in our grain business, so that overall we have flat prospects for that sector this year and into next year. The manufacturing sector is a bit mixed.”

A particular way to assess the predictive validity of the estimated topic model and its corresponding topic labels, is evaluating the extent to which estimated topics are related to events uninvolved in the measurement process [Quinn et al. 2010]. One clear example of the correlation between external events and the attention FOMC members pay to particular topics is presented in Figure 3.6. In this Figure I plot the fraction of FOMC meetings that committee members spend discussing the Labor Markets/Wages topic against the evolution
Regional Economy I

Figure 3.5: **Regional Economy Topics.** Each panel shows a word cloud for an estimated topic taking the 70 words with highest probability of being drawn from the particular topic. The size of each word in the cloud is proportional to the probability conditional that the word comes from that particular topic.

... of the expected output gap published in the *Greenbook*. There are large increases in the discussion of the topic associated with labor demand, productivity and wages that coincide with increments of observed output relative to potential growth, particularly in the second half of the 1990’s, when labor productivity was at the center of the debate within the FOMC.

### 3.6 Differences in Deliberation by Appointment

The main quantity of interest I explore in the empirical analysis is given by $\theta_{ik}$, which is an estimate of the proportion of words in document $d$ attributable to topic $k$. In other words, this is an estimate of the fraction of time that member $i$ in section $s$ at meeting $t$ spends deliberating topic $k$.

To assess whether there exists potential differences in the deliberation process within the FOMC by appointment, I compute the difference between district presidents and board
Figure 3.6: **Output Gap and Time Spent Deliberating Labor Markets/Wages Topic.**
The figure show the value of the output gap at each FOMC meeting during the Greenspan Chairmanship (1987-2006) along with the expected fraction of time spent on Topic 42: Labor Markets/Wages.

governors in the proportion of time they spend discussing the set of economic topics related to regional economies, inflationary concerns, and economic growth.

Figure 3.7 displays the words associated with each of the seven topics that I relate to the discussion of regional economies, as well as the topic proportions by appointment. As expected given the time allotted in FOMC meetings to the regional economic situation of Federal Reserve Banks, district presidents systematically spend more time discussing the economic situation at the regional level with respect to board governors. This difference is statistically significant at the 5% level for 4 out of 7 estimated topics, with district presidents spending around 4.25% more time in these topics than board governors.
Figure 3.7: **Presidents vs Governors on Regional Economy Topics**. The left panel shows the words that are highly associated and exclusive to each topic according to the FREX score. The right panel presents the difference in topic proportion between district presidents and board governors. Other covariates are set to their median values. Solid lines represent 95% confidence intervals calculated with the method of composition that accounts for the uncertainty in the dependent variable.

Figure 3.8 shows that district presidents not only spend disproportionately more time discussing the economic situation in their own districts but, consistent with their systematic bias towards inflation aversion, they put relatively more emphasis on inflation topics than board governors. This is the case for all three topics that I associate with the discussion on inflation (i.e, *Inflation Expectations*, *Inflation Target*, and *Price Stability*).

In clear contrast and consistent with the bias of board governors towards output concerns, district presidents spend relatively less time (around 3% on average) discussing topics related to economic growth than board governors. This is the case for the topics labeled *Industrial Production*, *Productivity Growth*, and *Consumption and Investment*.

I find no significant difference in the topic proportion between district presidents and board governors for the *Economic Risks* and *Labor Markets/Wages* topics. This is noteworthy given that, from the set of economic growth themes, these topics are associated with
Figure 3.8: Presidents vs Governors on Inflation Growth Topics. The left panel shows the words that are highly associated and exclusive to each topic according to the FREX score. The right panel presents the difference in topic proportion between district presidents and board governors. Other covariates are set to their median values. Solid lines represent 95% confidence intervals calculated with the method of composition that accounts for the uncertainty in the dependent variable.

terms related to both output concerns, which board governors emphasize more in FOMC deliberations, and inflationary pressures, which district presidents systematically talk more about at FOMC meetings, consistent with their respective biases. To explore this issue further I examine the vocabulary used by board governors and district presidents when discussing the Labor Markets/Wages topic. Figure 3.10 shows the “wordcloud” representation of this topic allowing the vocabulary to vary by appointment. This is done by expanding the document-specific distribution over words, $\beta_{zd,n}$, in equation 3.3 to be a function of an appointment binary indicator. As can be seen in the left hand side of the plot, board governors talk more about employment and firm performance issues with terms like “employment”, “unemployment”, “jobs”, and “report”, whereas district presidents, although they use the term “inflat” less frequently than board governors, they speak more often about price increases and labor costs with terms that include “pressur”, “increas”, “price”, “cost”, “wage”
Figure 3.9: Presidents vs Governors on Output Growth Topics. The left panel shows the words that are highly associated and exclusive to each topic according to the FREX score. The right panel presents the difference in topic proportion between district presidents and board governors. Other covariates are set to their median values. Solid lines represent 95% confidence intervals calculated with the method of composition that accounts for the uncertainty in the dependent variable.

and “labor”. This is evidence that, although both groups of members spend a similar amount of time talking about Labor Markets/Wages, they do so with a different substantive vocabulary, with board governors emphasizing terms more related to output concerns and district presidents using terms more related to inflationary pressures.
Figure 3.10: Differences in Vocabulary by Appointment for the Labor Market/Wages Topic. The figure shows a wordcloud of the Labor Market/Wages topic where the word size is proportional to the frequency with which a word is used. On the left side of the dashed line are words that board governors use more frequently given the topic. On the right side of the dashed line are words that are used more frequently by district presidents. The differences in topical content are estimated by allowing the document-specific distribution over words, $\beta_{z,d,n}$, to vary by appointment.

3.6.1 Regional Bias in FOMC Deliberations

In chapter 2 I show that district presidents are more prone to exaggerate bad economic conditions and downplay inflationary concerns at the national level, whenever their regional unemployment is relatively larger than the national average. To assess whether district presidents, consistent with their forecasting behavior, also have a regional bias in the attention they give to different aspects of the monetary policy debate, I re-estimated the Structural Topic Model to allow the topic proportion across district presidents to vary as a function of the regional unemployment gap in their districts. This is in addition to the set of controls I present in section 3.4 to inform topic proportions across documents. I identify estimated
topics related to inflation, economic growth and regional economies, as in the case of the analysis by appointment.

Figure 3.11 presents the topic proportions as a function of the regional unemployment gap. The top row presents the words that are highly associated to each topic. In the bottom row, I display the linear relationship between regional unemployment and each topic. Overall, the evidence indicates a clear regional bias in the behavior of district presidents while deliberating different aspects of monetary policy. First, district presidents significantly increase their attention on the discussion of regional economic conditions as their unemployment rate deteriorates with respect to the national average (right panel). At the same time, as the economic conditions in their regions worsen relative to national unemployment, district presidents significantly reduce the time allocated to discuss topics related to inflation, irrespective of the actual level of inflationary pressures nationwide (left panel), as measured by the output gap. In terms of the focus on economic growth topics, the middle panel indicates that, on average, district presidents seem to focus relatively more on topics related to output concerns as their regional unemployment increases, although the difference in topic proportion is small in magnitude and not statistically significant at the 5% significance level. In Appendix B.1 I show that the relationship between regional unemployment gap and topic proportions does not depend on the selected topics presented in Figure 3.11. In fact, when we choose other estimated topics that appear to be related to the discussion of regional economies, economic growth, and inflation, the overall evidence is consistent with a regional bias in the deliberation process of district presidents.
to each topic. The bottom row displays the linear relationship between topic proportion and regional unemployment gap. Other variables included in the model are held at their sample median. Results are presented with 95% confidence intervals. Confidence intervals are calculated with the method of composition that accounts for the uncertainty in the dependent variable.

### 3.6.2 Connecting Forecast Biases and Deliberation

The evidence presented so far points to the presence of systematic differences in the deliberation process of FOMC members according to their appointment process and regional biases. However, up to this point, it is unclear whether the heterogeneity in the way they deliberate monetary policy is also directly related to members’ biases, as found in their forecasting behavior. To explore this issue, I investigate whether FOMC members who increase the attention paid to topics that deal with either inflationary pressures, economic growth and unemployment, tend to provide more exaggerated forecasts of these variables. For this purpose, I regress members’ forecast biases, defined as actual minus forecasted value...
\( e_{it} = y_{it} - f_{it} \), on the topics related to both the discussion on inflationary pressures and output concerns, Labor Markets/Wages and Economic Risk, respectively. I include one of the topics that is closer to the discussion of inflation, Inflation Target, as well as one of the topics mostly related to economic growth, Productivity Growth. In addition, I include one of the topics that include terms related to procedural discussions and conversational patterns as a placebo test. As this topic is not related to members’ economic discussion, it should not be related to members’ forecast biases. The top terms of this topic are shown in Figure B.4 in Appendix B. Highly associated terms to this topic are “accept”, “fine”, “speech”, as well as names of FOMC members (e.g., ”bob” and ”parri”). I include a set of control variables given by the level of the Federal Funds rate in the week prior to each meeting \( (f_{frt}) \), staff estimates of the output gap \( (gap_{t}) \), as well as two-quarter ahead inflation \( (inf_{t}^{GB}) \) and output growth \( (output_{t}^{GB}) \) forecasts. Finally, the estimated regression include member fixed-effects. In this way, any significant correlation between forecast biases and topic proportions is conditional on available information to FOMC members, as well as on members’ individual characteristics, such as mean individual biases.

Table 3.1 presents the results of the estimated models for each outcome variable. With the exception of the topic Inflation Target, there is a significant relationship between the time FOMC members spend deliberating the selected monetary policy topics and the extent to which they exaggerate their economic predictions. More importantly, the direction of this relationship is consistent with the content of each topic and the biases of FOMC members. First, as FOMC members increase the amount of time they spend deliberating the Labor Markets/Wages topic, they tend to systematically under-predict output growth. For instance, increasing in 8% the amount of time spent discussing this topic is associated with an under-prediction of output growth of 0.48%. This significant effect goes in the same direction as the impact of the output gap estimate \( (gap_{t}) \) on output growth forecasts. Thus, FOMC members upon observing actual output increasing over potential one, they allot more
time to discuss issues related to labor demand and labor costs, and tend to under-predict economic growth for the current and following years.

Second, I find that spending more time discussing the topic labeled *Economic Risk*, is related to members significantly exaggerating inflation and under-predicting output growth, painting a more negative picture about the future state of the economy in both fronts than what is actually observed. The magnitude of these effects are substantial, an increase of 13% in the fraction of time FOMC members allot to talk about economic uncertainty is associated to a 0.71% inflation over-prediction and to a 0.93% output growth under-prediction.

Third, talking about the *Productivity Growth* topic is related to significant forecast biases in all three outcome variables analyzed. Consistent with the content of this estimated topic, as FOMC members talk more about productivity increases, wage increments and accelerating inflation, they systematically over-estimate inflation. In the same sense, talking more about higher labor productivity and falling unemployment is significantly associated to members over-estimating output growth and under-estimating unemployment. In particular, a 2% increment in the amount of time members spend talking about this topic is related to over-estimating inflation and output growth in 0.47% and 1.33%, respectively, while under-estimating unemployment in 1%.

Finally, changes in the amount of time members spend talking about terms unrelated to the economic discussion, as exemplified in the *Procedural Discussion* topic, is uncorrelated to members’ forecasting behavior, which further validates the estimated topics and their assigned labels.

### 3.7 Conclusions

For some observers and participants, monetary policy deliberation at the FOMC has been regarded as a highly technical affair, where members and the technical staff read crafted statements about objective economic indicators that are already incorporated in members’
<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Inflation</th>
<th>GDP Growth</th>
<th>Unemployment</th>
</tr>
</thead>
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<tr>
<td>Fed Funds Rate</td>
<td>−0.126**</td>
<td>−0.349**</td>
<td>0.084</td>
</tr>
<tr>
<td></td>
<td>(0.057)</td>
<td>(0.155)</td>
<td>(0.071)</td>
</tr>
<tr>
<td>Output Gap (Staff)</td>
<td>−0.381***</td>
<td>0.887***</td>
<td>−0.356***</td>
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<tr>
<td></td>
<td>(0.075)</td>
<td>(0.182)</td>
<td>(0.076)</td>
</tr>
<tr>
<td>Inflation Forecast (Staff)</td>
<td>−1.695***</td>
<td>3.149***</td>
<td>−1.426***</td>
</tr>
<tr>
<td></td>
<td>(0.154)</td>
<td>(0.377)</td>
<td>(0.169)</td>
</tr>
<tr>
<td>Output Growth Forecast (Staff)</td>
<td>1.279***</td>
<td>−2.117***</td>
<td>0.664***</td>
</tr>
<tr>
<td></td>
<td>(0.155)</td>
<td>(0.344)</td>
<td>(0.161)</td>
</tr>
<tr>
<td>Labor Markets/ Wages:</td>
<td>−0.223</td>
<td>5.848***</td>
<td>−0.107</td>
</tr>
<tr>
<td></td>
<td>(0.852)</td>
<td>(1.812)</td>
<td>(0.805)</td>
</tr>
<tr>
<td>Inflation Target:</td>
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<td>−2.748</td>
<td>0.521</td>
</tr>
<tr>
<td></td>
<td>(0.669)</td>
<td>(1.681)</td>
<td>(0.789)</td>
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<tr>
<td>Economic Risk:</td>
<td>−5.505***</td>
<td>7.224**</td>
<td>0.528</td>
</tr>
<tr>
<td></td>
<td>(2.006)</td>
<td>(3.588)</td>
<td>(1.523)</td>
</tr>
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<td>Productivity Growth:</td>
<td>−1.807**</td>
<td>−5.137*</td>
<td>3.914***</td>
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<tr>
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<td>(1.115)</td>
</tr>
<tr>
<td>Procedural Discussion:</td>
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<td>37.974</td>
<td>0.356</td>
</tr>
<tr>
<td></td>
<td>(16.658)</td>
<td>(30.066)</td>
<td>(12.338)</td>
</tr>
</tbody>
</table>

| Observations        | 601       | 601        | 601          |
| Adjusted $R^2$      | 0.421     | 0.308      | 0.307        |
| Member Fixed Effects| Yes       | Yes        | Yes          |
| FOMC Members        | 35        | 35         | 35           |
| Meetings            | 40        | 40         | 40           |

*p<0.1; **p<0.05; ***p<0.01
Note: GMM standard errors in parentheses

Table 3.1: Topic Prevalence and Forecast Biases. The table shows, for each outcome of interest, the results of an OLS regression of forecast bias on economic topics and a set control of variables. Standard errors consistent with heteroskedasticity, serial, and spatial correlation in parentheses.
choices, turning the deliberation process irrelevant to policy-making (e.g., Meyer [2004]). The evidence presented in this chapter, nevertheless, paints a different picture. Using both the verbal content of FOMC meetings and members’ economic forecasts, I show that the arguments made by FOMC members at monetary policy meetings are predictive of their behavior, with members putting more emphasis in the discussion of topics that are consistent with their forecast biases. Moreover, the process through which policy-makers incorporate objective economic indicators that lead to a particular policy stance is shifted in the direction of members’ characteristics, as exemplified in this chapter by their appointment process and regional biases.

The evidence presented so far is just a first step in understanding the relationship between deliberation and policymaking. For a better understanding of the effect of deliberation on policy outcomes, it would be necessary to assess how the aggregate policy choice is influenced by the discussion of individual FOMC members at monetary policy meetings. This analysis would need to account, not only for the time FOMC members spend deliberating certain topics over others, but for the tone in which they discuss these topics, which could be mapped into observed changes in the direction of the monetary policy instrument.
Chapter 4

Sequential Deliberation of FOMC Policy Recommendations

In chapters 2 and 3 I argue that FOMC members tend to report biased information contained in both their economic predictions and their verbal communication during monetary policy meetings. These biases reflect members’ policy preferences and expertise, which are in turn influenced by their appointment process, past careers, and policy-making experience.

In spite of members’ biases, this chapter shows evidence that there is ample opportunity for information transmission through the deliberation process of policy recommendations. I propose the sequential deliberation model to explain the heterogeneity in individual policy recommendations and assess the extent of social learning within the FOMC. This model extends the framework developed by Iaryczower and Shum [2012], that incorporate differences in the quality of private information into the purely spatial ideological model to explain decision-making in the U.S. Supreme Court. In the context of monetary policy, Hansen, McMahon and Velasco-Rivera [2014] estimated this model to the voting patterns of Bank of England’s monetary policy committee to explain differences in ideological biases and expertise between internal and external committee members.
The presence of both preferences and private information in the model captures relevant features of monetary policy making that have been emphasized in the empirical literature (Blinder [2007]; Gerlach-Kristen [2006]). As in the framework presented in chapter 2, the ideological biases can be interpreted as the relative costs of over- or under-predicting the true state of the economy, which is consistent with the different views of committee members regarding the tradeoff between inflation and unemployment. The quality of private information captures the expertise of committee members to gauge inflationary pressures. This expertise can be a function of the privileged data that members oftentimes use to discuss monetary policy. This private information can be acquired through business contacts in members’ regions or through early access to certain economic indicators. Moreover, the heterogeneity in private information can capture differences in the amount of resources that members possess regarding each committee member’s staff and the forecasts they produce.

Conditional on members’ ideology and expertise, I incorporate the process of deliberation as a key feature of collective decision-making. In the model, the structure of debate can have important consequences, as it shapes members’ inferences about the uncertain state of the economy. This feature arises because members, after listening to early speakers, weight the information and the potential for bias contained in previous recommendations against their own according to Bayes rule. This behavioral model incorporates Bayes-rational individuals as first introduced by Banerjee [1992] and Bikhchandani, Hirshleifer and Welch [1992] in the social learning literature, and later extended by Smith and Sørensen [2000] to allow for a continuum of signals and for heterogeneity in preferences.

There is a sizable empirical literature applying the social learning framework in economics. In a political economy application, Knight and Schiff [2010] include social learning in an empirical model of sequential voting in primary elections. In the particular case of FOMC deliberations, Chappell, McGregor and Vermilyea [2012] use the policy recommendations for the period under Arthur Burns as chairman to investigate the presence of

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1 For a literature review see Bikhchandani, Hirshleifer and Welch [1998].

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Bayesian-updating in a “reduced-form” framework. The main limitations of their study, which prevents them to find any evidence of learning, is the assumption that members have the same quality of information, so that the value of previous recommendations is assumed away in their framework. Second, policy recommendations are assumed to have a particular linear functional form in which preferences do not interact either with the value of private information or with the history of previous recommendations.

To notice the relevance of the sequential deliberation process, consider the FOMC meeting of March 1994 under Greenspan as chairman. For the policy go-around, Philadelphia district president Ed Boehne was the first FOMC member to speak and stated a recommendation in favor of tightening the policy rate 50 basis points, which was 25 basis points higher than the median policy the staff proposed and the one chairman Greenspan previously stated as his preferred one. After him in the speaking order came district presidents Parry and Broaddus from San Francisco and Richmond district banks, respectively. Both members followed Boehne in his recommendations. More importantly, in making the case for his proposal, president Broaddus stated:

“Let me just say that I agree 100 percent with Ed Boehne. He said it very well; he really reflected my position completely[...]. But my own feeling is the same as Ed Bohne’s—that the risks are at least as great in not taking this action; I think there is a good chance that we would be seen as too cautious and too tentative.”

By accounting for the information contained in previous recommendations such as the one just quoted, the model introduced in this chapter is able to assess whether Broaddus’ recommendation would have been different under the counterfactual scenario where he did not learn about Boehne’s statement. More importantly, in the case that his recommendation contains additional information about the state of the economy, the sequential deliberation model is able to attribute this effect to social learning and not to the quality of Broaddus’ private information, giving a more precise assessment of his ability as policymaker.
4.1 Data

In principle, given the structure of FOMC meetings, I can analyze the information contained in both policy recommendations and voting records. In practice, FOMC voting records are not very informative to explain members’ behavior. This is because dissenting votes are extremely rare in the policy-making history of the FOMC, as can be observed in Figure 4.1. The light blue bars in this figure show the yearly evolution of the number of dissenting votes with respect to the chairman’s policy proposal for the period 1966-2008, which covers five different chairmen. For the period under study, dissents represent, on average, only 5.8% of the total number of votes cast. The rare instances of dissent within the FOMC are also comparatively low with respect to those in other central banks. For example, Riboni and Ruge-Murcia 2014 find that dissents are significantly more frequent in the monetary policy committees of the Bank of England and the Sveriges Riksbank than at the Federal Reserve. Moreover, there has not been a single instance in FOMC’s history where the chairman’s policy directive is on the losing side of the vote. Therefore, the chairman’s policy directive invariably coincides with the implemented policy rate at any given meeting. This feature has been noted by Swank and Visser 2007, among others, who argue that the FOMC as a whole is known to appreciate showing a united front to the market observers regarding the voting decision that is immediately released to the public after each meeting. This consensus-seeking desire constraints chairmen to offer policy proposals that can obtain at least a majority of votes. Nevertheless, as has been shown by Chappell, McGregor and Vermilyea 2005, the agreement of the chairman’s proposal and that of the FOMC median and mean voter is consistent with a policy directive that is influenced by FOMC members.

The limitation of voting records to characterize the FOMC has been noted since the 1960’s, despite the fact that all the work that followed on the topic well into the 2000’s, focused precisely on these records, as this quote from Yohe 1966 summarizes:

3In addition, dissenting voting records do not provide information about the behavior of non-voting committee members, who nevertheless, attend FOMC meetings, discuss monetary policy, and ultimately express their desired policy in front of the rest of the committee at the deliberation stage.
Figure 4.1: History of Dissents at the FOMC. This figure presents the yearly counts of dissents across committee members and meetings for both voting records (light blue) and policy recommendations expressed during the pre-vote deliberation stage (dark blue) for the period 1966-2008 encompassing five FOMC chairmanships. Policy recommendations are unavailable for the chairmanships of Martin (1966-1970) and Volcker (1980-1986) highlighted in gray.

*The reasons are not at all clear for the almost uncanny record of the chairman in never having been on the losing side of a vote on the policy directive. While there is no evidence to support the view that the directive always voted upon and passed on the first ballot merely reflects the chairman’s own preference, there is also no evidence to refute the view that the chairman adroitly detects the consensus of the committee, with which he persistently, in the interest of System harmony aligns himself.*
Fortunately, records of FOMC deliberations contained in FOMC transcripts provide us with the discussion that leads to a policy adoption, in which FOMC members share their views about the future state of the economy and voice their preference for a particular policy rate. All of this, before votes are cast and officially recorded.

The amount of information one can extract from the deliberation process can also be seen in Figure 4.1 where the dark blue bars show the yearly evolution of the amount of voiced dissent, measured as differences in the voiced policy recommendation of each member with respect to the chairman’s directive during the policy go-around. Just by looking at the discrepancies in dissent between deliberation and voting stages, one can draw a different picture of members’ behavior than the one that can be extracted solely from voting patterns. For instance, the proportion of voiced dissent with respect to the chairman’s proposal reaches an average of 33% over the period under study. This increase represents almost a fivefold jump in dissent with respect to what can be found from looking at voting records.

The voiced policy recommendations shared by FOMC members in the policy go-around, as well as the record of their order of speech at every meeting under study, are obtained from the verbatim transcripts of FOMC meetings. To systematically code the recommendations and speaking order of each committee member from textual records, I followed the efforts of Chappell, McGregor and Vermilyea [2012] who collected these voiced interest rate recommendations and a record of the speaking order for the period under Arthur Burns as a chairman between 1970 and 1978. I complemented and extended these data myself by collecting, whenever possible, the desired policy rate and speaking order of every FOMC committee member during the chairmanship of G. William Miller (1978-1979), the Greenspan years (1987-2006), and the Bernanke period (2006-2008).

From the available transcripts, I excluded the period under Volcker (1979-1986) because, during his tenure as Chairman, the FOMC changed its main policy instrument from a Fed
Funds rate to a borrowed reserves instrument that directly targeted the money supply, making the coding and comparison across periods infeasible. I also excluded the available meetings held during 2009 under Bernanke given that, as a consequence of the economic crisis of 2008, the Fed Funds rate reached the zero lower bound in December 2008 and remained at this level throughout the following year.\footnote{In addition, since the financial crisis monetary policy has taken a turn towards unconventional instruments that target the balance sheet of the central bank through the purchase of mortgage-backed securities and other securitized assets.}

I classify members’ desired policy rates into binary (low vs high rate) recommendations, by first establishing a benchmark policy with which members’ preferred rates could be compared. For this purpose, I rely on the policy scenarios suggested and distributed by the staff to FOMC members in advance of each meeting and then summarized just before the policy go-around takes place.\footnote{This data is contained in the Blue Book provided to members around a week in advance of FOMC meetings.}

I quantify a composite benchmark from these different alternatives by computing the median proposed policy offered by the staff at each meeting. Then, based on the textual records of deliberations, I code members as recommending a high policy rate whenever their desired Fed funds rate target is equal or higher than the staff median proposal and a low policy rate, otherwise. In those instances in which desired rates are not observable, I imputed a binary recommendation if members expressed a leaning direction or assenting preference with respect to the staff proposal, or to the recommendation of other members who explicitly expressed a desired rate.

I examine the policy recommendations of all members who sat on the FOMC for the period under study, excluding from the analysis those who participated in less than 10% of all meetings under consideration. In total, the sample comprises 265 monetary policy decisions made by 57 voting and nonvoting FOMC members for a total of 3,490 policy recommendations. Table\ref{table:policy_recommendations} presents the distribution of policy recommendations, along with the average macroeconomic conditions during each of the chairmanships under consideration.
As can be seen from this table, the sample of policy recommendations analyzed here were made under very diverse economic conditions, which coincide with changes in the identity of the FOMC chairman. On the one hand, the Burns and Miller regimes were characterized by high and increasing levels of inflation, paired with a strong slowdown in economic growth; whereas the Greenspan years coincide with a period of sustained growth with low and stable inflation, a prosperous period that ended abruptly during the Bernanke regime, with the largest economic crisis since the Great Depression, albeit under a period where inflation remained anchored at low levels.

<table>
<thead>
<tr>
<th>Period</th>
<th>Meet</th>
<th>Rec</th>
<th>Size</th>
<th>Unan %</th>
<th>( r_{it} = 0 )</th>
<th>( r_{it} = 1 )</th>
<th>Fed Funds</th>
<th>Inf</th>
<th>GDP</th>
<th>Unem</th>
<th>M1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Burns ('70-'78)</td>
<td>99</td>
<td>1203</td>
<td>12</td>
<td>44.44</td>
<td>27.18</td>
<td>72.82</td>
<td>6.44</td>
<td>5.55</td>
<td>6.32</td>
<td>5.79</td>
<td></td>
</tr>
<tr>
<td>Miller ('78-'79)</td>
<td>11</td>
<td>138</td>
<td>13</td>
<td>18.18</td>
<td>34.78</td>
<td>65.22</td>
<td>7.97</td>
<td>7.35</td>
<td>5.93</td>
<td>5.87</td>
<td></td>
</tr>
<tr>
<td>Greenspan ('87-'06)</td>
<td>132</td>
<td>1917</td>
<td>15</td>
<td>62.12</td>
<td>28.12</td>
<td>71.88</td>
<td>4.93</td>
<td>4.06</td>
<td>2.48</td>
<td>5.63</td>
<td></td>
</tr>
<tr>
<td>Bernanke ('06-'08)</td>
<td>23</td>
<td>232</td>
<td>10</td>
<td>39.13</td>
<td>50.43</td>
<td>49.57</td>
<td>4.05</td>
<td>3.33</td>
<td>1.59</td>
<td>5.07</td>
<td></td>
</tr>
<tr>
<td>All data ('70-'08)</td>
<td>265</td>
<td>3490</td>
<td>13</td>
<td>51.70</td>
<td>29.98</td>
<td>70.02</td>
<td>5.54</td>
<td>4.69</td>
<td>2.92</td>
<td>5.85</td>
<td></td>
</tr>
</tbody>
</table>

Note: Author’s calculations. Meet denotes the total number of meetings per period. Rec denotes the number of recommendations per period. Size refers to the median size of the committee for each period. Unan % is the percentage of unanimous recommendations per period. \( r_{it} = 0(1) \) refers to the percentage of low (high) rate recommendation per period. Fed Funds, Inf, GDP, and Unem refer to period averages for the Fed Funds rate, quarterly forecasts for inflation, real GDP growth, and civilian unemployment, as presented in the Greenbook by the staff of the Board of Governors. M1 denotes the three-month moving average money growth around the date of FOMC meetings, also provided in the Greenbook.

Table 4.1: Policy Recommendations by Chairmanship, 1970-2008

4.2 The Model

There are \( T \) monetary policy meetings, \( t = 1, \ldots, T \), in which each committee member \( i = 1, \ldots, N \) offers a policy recommendation \( r_{it} \in \{0, 1\} \) to the committee chairman \( C \), who proposes a policy directive \( d_t \in \{0, 1\} \), where 0 represents the lowest of two possible rate changes and 1 the highest. In the context of the FOMC, \( d_t \) can be thought of as the policy proposal that the chairman puts to a formal vote in the voting stage, which historically, has also been the implemented policy in every meeting of the FOMC under consideration.
This is because, even in the presence of dissents, the chairman’s final proposal in the voting stage has always been accepted by a majority of members. Therefore, by abstracting us from modeling the final voting stage, we do not lose much in terms of explaining the actual influence of individual members in the policy-making process.  

Member $i$’s preferences over the policy directive ($d_t$) depends on the state of the economy, $\omega_t \in \{0, 1\}$, that encompasses unknown inflationary pressures, where $\omega_t = 1$ represents the high inflation state (consistent with a high interest rate) and $\omega_t = 0$ is the low inflation state (consistent with a low interest rate).

With full information, members want the directive to match the state, $d_t = \omega_t$.

The payoffs of $d_t = \omega_t = 0$ and $d_t = \omega_t = 1$ are normalized to zero. However, members disagree on the costs of implementing the incorrect directive (i.e., mismatching the state). Member $i$ suffers a cost $\pi_i \in (0, 1)$ when the proposed directive is the low policy rate in a high inflation state ($d_t = 0$ when $\omega_t = 1$) and of $1 - \pi_i$ when the policy directive is a high rate in a low inflation state ($d_t = 1$ when $\omega_t = 0$). Accordingly, $1 - \pi_i$ can be thought of as member $i$’s threshold of evidence above which she is willing to recommend the higher rate. Thus, $\pi_i > \frac{1}{2}$ reflects her bias towards the higher policy rate (i.e., member $i$ is an inflation “hawk”), while $\pi_i < \frac{1}{2}$ reflects a bias towards the lower policy rate (i.e., member $i$ is an inflation “dove”).

I model the sequence of deliberation from the policy go-around, as follows:

1. The inflation state $\omega_t$ is released but unobserved to committee members. In addition, the sequential order of speech is exogenously given to FOMC members. Members of the committee are ordered according to that sequence: member $i$ offers her preferred policy option in rank $n(i)_t$, according to a given permutation $p_t : N \rightarrow N$.

2. Prior to giving a policy recommendation, member $i$ forms beliefs on $\omega_t$ by relying on four sources of information. First, there is public available information captured in

\[\text{[Riboni and Ruge-Murcia 2014].}\]
members’ common prior beliefs about the state of the economy, \( \rho_t \equiv Pr[\omega_t = 1] \). Second, member \( i \) observes an informative private signal \( s_{it} | \omega_t \sim \mathcal{N}(\omega_t, \sigma_i^2) \). Conditional on the state \( \omega_t \), these signals are statistically independent, with \( \sigma_i \) as a measure of the informativeness or precision of member \( i \)'s information, which I label member \( i \)'s expertise or ability interchangeably (i.e., lower \( \sigma_i \) denotes higher expertise or ability). Third, member \( i \) observes the history of recommendations when it is her turn to speak. We denote the relevant history for member \( i \) at meeting \( t \), \( x_{n(i),t} = (r_{1,t}, \ldots, r_{(n(i)-1),t}) \in \{0, 1\}^{(n(i)-1)} \). The history for the member who speaks first is empty, \( x_{1,t} = \emptyset \). In this way, member \( i \) can potentially weight previous recommendations against her private information to update her prior belief on the state of the world \( \omega_t \). Fourth, as FOMC members care about the chairman’s policy proposal, they act as if their recommendations are pivotal in the chairman’s decision. Therefore, in providing their recommendations, FOMC members incorporate the information contained in the pivotal event, \( PIV^i_t \), into consideration when providing their recommendations.

3. With this information at hand, the strategy for member \( i \) is defined by a map \( \gamma_{it} : \mathbb{R} \rightarrow (0, 1) \), where \( \gamma(s_{it}) \equiv Pr(r_{it} = 1 | s_{it}) \). I assume that when a member speaks, her recommendation is immediately heard by the chairman and all other members. In addition, it is assumed that member \( i \)'s type \( (\pi_i, \sigma_i) \) is known by all other members and the chairman.

4. The only difference between the chairman (\( C \)) and the rest of the committee, is that the former observes both her private signal \( s_{Ct} \), and the full vector of reports of the \( N \) committee members \( x_{Ct} = (r_{1t}, \ldots, r_{Nt}) \) when choosing the policy directive \( d_t \) at the end of the policy go-around.
Note that by the normality assumption on $s_{it}$, the likelihood ratio

$$L(s_{it}) \equiv \frac{Pr[s_{it}|\omega_t = 1]}{Pr[s_{it}|\omega_t = 0]} = \frac{\phi(s_{it}-1)}{\phi(s_{it})} = e^{\frac{2s_{it}-1}{2\sigma^2}}. \quad (4.1)$$

is increasing in $s_{it}$. This Monotone Likelihood Ratio Property implies that the equilibrium strategies are in cutoff points, where $\gamma(s_{it}) = 1$ if $s_{it} > s^*_it$ and $\gamma(s_{it}) = 0$, otherwise [Duggan and Martinelli 2001]. In particular, given the information contained in $s_{it}$, member $i$ recommends the higher rate change, $r_{it} = 1$, whenever $Pr[\omega_t = 1|s_{it}, x_{n(i),t}, PIV_i^t] \geq 1 - \pi_i$ and $r_{it} = 0$, otherwise. By basic manipulation of Bayes’ rule, this condition can be written as

$$Pr[\omega_t = 1|s_{it}, x_{n(i),t}, PIV_i^t] = \frac{Pr[\omega_t = 1] \prod_{j=1}^{n(i)-1} Pr[r_{jt}|x_{n(j),t}, \omega_t = 1] Pr[PIV_i^t|\omega_t = 1]}{\sum_{\omega} Pr[\omega_t] \prod_{j=1}^{n(i)-1} Pr[r_{jt}|x_{n(j),t}, \omega_t] Pr[PIV_i^t|\omega_t]}$$

$$= \frac{1}{1 + (\frac{1-\rho_t}{\rho_t}) \left( \frac{Pr[PIV_i^t|\omega_t = 0]}{Pr[PIV_i^t|\omega_t = 1]} \right) L(s_{it})^{-1} \prod_{j=1}^{n(i)-1} \Psi(s^*_jt)} \geq 1 - \pi_i;$$

Manipulating the normal density and solving for $s_{it}$, $r_{it} = 1$ whenever

$$s_{it} \geq \frac{1}{2} + \sigma_i^2 \left[ \log \left( \frac{1 - \pi_i}{\pi_i} \right) + \log \left( \frac{1 - \rho_t}{\rho_t} \right) + \sum_{j=1}^{n(i)-1} \log (\Psi(x_{jt})) + \log \left( \frac{Pr[PIV_i^t|\omega_t = 0]}{Pr[PIV_i^t|\omega_t = 1]} \right) \right] \quad (4.2)$$

Let $s^*_it$ denote the value of $s_{it}$ such that $s_{it} = s^*(\pi_i, \sigma_i, x_{it}, PIV_i^t, \rho_t)$. Then, the value of deliberation in member $i$’s equilibrium behavior, $\Psi(x_{jt})$, is defined as

$$\Psi(x_{jt}) \equiv \left[ \frac{\gamma_{jt,0}(s^*_jt)}{\gamma_{jt,1}(s^*_jt)} \right]^{r_{jt}} \left[ 1 - \frac{\gamma_{jt,0}(s^*_jt)}{1 - \gamma_{jt,1}(s^*_jt)} \right]^{-r_{jt}}. \quad (4.3)$$
The effect of pivotality on $s_{it}^*$ given in equation 4.2 depends on the strategy profile of subsequent speakers and its effect on the chairman equilibrium cutoff. The analytical expression for the pivotal event becomes convoluted for earlier speaking positions, as it needs to account not only for how member $i$’s recommendation affects the chairman’ cutoff directly, but also indirectly through her effect on subsequent speakers. Both of these pieces of information are incorporated into the chairman’s posterior update on the state $\omega_t$.

For example, consider the pivotality effect of member $i$ at meeting $t$ if she were the last speaker in the policy go-around (i.e., $n(i)_t = N$), which is illustrated in figure 4.2. The solid line denotes the chairman’s signal space, $\mathbb{R}$. The pivotal event is depicted in the red region where $s_{Ct} \in [s_{Ct}^*(r_{it} = 1), s_{Ct}^*(r_{it} = 0)]$. In this region, member $i$ needs to account only for the effect of her recommendation on the chairman’s cutoff. Therefore, we can write the probability that member $i$ is pivotal given $\omega_t$ as

$$\Pr[PIV_i^t|\omega_t] = \Phi\left(\frac{s_{Ct}^*(r_{it} = 0) - \omega_t}{\sigma_C}\right) - \Phi\left(\frac{s_{Ct}^*(r_{it} = 1) - \omega_t}{\sigma_C}\right)$$

(4.4)

Figure 4.2: Pivotal Event for the Last Member in the Order of Speech.

With the equilibrium cutoff pinned down, the probability of $r_{it} = 1$ in state $\omega_t$ can be written as

$$\gamma_{it,\omega_t}(s_{it}^*(x_{it})) \equiv 1 - \Phi\left(\frac{s_{it}^*(x_{it}) - \omega_t}{\sigma_i}\right).$$

(4.5)

Equation C.2 in Appendix C.3 contains the analytical expression for the pivotality effect if member $i$ were the next-to-the-last speaker in the policy go-around.
Notice how the signal cutoff, \( s_{i}^{\ast t} \), varies across both members and meetings. First, differences in cutoffs across FOMC members can be explained by members’ heterogeneity in both preferences, \( \{\pi_{i}\}_{1}^{N} \), and expertise, \( \{\sigma_{i}\}_{1}^{N} \). Moreover, movements over time in the cutoff are captured by changes in both the common prior (\( \rho_{t} \)) and the histories of policy recommendations.

Since behavior in this model is completely characterized by the signal cutoff, \( s_{i}^{\ast t} \), I can write the likelihood of observing the vector of recommendations and the chairman decision at meeting \( t \), \( r_{t} = (r_{1t}, \ldots, r_{Nt}, d_{t}) \), as

\[
Pr[r_{t}] = \sum_{\omega} \rho_{t}^{\omega t} (1 - \rho_{t})^{1-\omega t} \prod_{i=1}^{N+1} \gamma_{i,\omega_{t}}(s_{i}^{\ast t})^{r_{it}}[1 - \gamma_{i,\omega_{t}}(s_{i}^{\ast t})]^{1-r_{it}}. \tag{4.6}
\]

The likelihood in equation (4.6) as a function of equilibrium cutoffs, implicitly accounts for the history of previous recommendations in the sequential deliberation process given in equation (4.3). To better understand the role of this relevant parameter, consider the case where member \( i \) takes a policy decision (\( n(i)_{t} = 2 \)), right after member \( j \) (\( n(j)_{t} = 1 \)) provides her policy recommendation. Under this scenario, the influence of member \( j \) on the equilibrium cutoff \( s_{i}^{d t} \) can be written as

\[
\log(\Psi(s_{j}^{d t})) = \begin{cases} 
\log(\gamma_{jt,0}) - \log(\gamma_{jt,1}) & \text{if } r_{jt} = 1 \\
\log(1 - \gamma_{jt,0}) - \log(1 - \gamma_{jt,1}) & \text{if } r_{jt} = 0
\end{cases}
\]

Suppose, for instance, that member \( j \) recommends a high policy rate (i.e., \( r_{jt} = 1 \)). The value of information for member \( i \) given by this action will depend on the relative likelihood that member \( j \)’s recommendation matches the high state inflation (i.e., \( \log(\gamma_{jt,0}) - \log(\gamma_{jt,1}) \)). If member \( j \)’s probability of matching the state is equal to the probability of mismatching it, then deliberation would provide no informational value (i.e., \( \log(\gamma_{jt,0}) - \log(\gamma_{jt,1}) = 0 \)).

Suppose instead that after listening to member \( j \) recommending the high rate (\( r_{jt} = 1 \)), her probability of correctly matching the high state is larger than the probability of
incorrectly recommending $r_{jt} = 1$ when $\omega_t = 0$ (i.e., $\log(\gamma_{jt,0}) - \log(\gamma_{jt,1}) < 0$). The additional information embedded in this recommendation will reduce member $i$’s equilibrium cutoff in equation (4.2), making her more prone to follow member $j$’s recommendation (i.e., $r_{it} = 1$). \footnote{Notice also that the value of information of member $j$’s recommendation can also work in the other direction: if $\log(\gamma_{jt,0}) - \log(\gamma_{jt,1}) > 0$, this would also provide member $i$ with more information about the true state of the economy, increasing the probability that member $i$ goes against member $j$ by recommending the low policy rate $r_{it} = 0$.}

It is important to emphasize that the magnitude of the shift in $s^*_{it}$ after listening to member $j$’s recommendation hinges on member $j$’s expertise ($\sigma_j$) and bias ($\pi_j$). In particular, $s^*_{it}$ is monotonic in both $\sigma_j$ and $\pi_j$, but with different behavioral implications given their effect on member $i$’s recommendation probabilities. Consider the upper panels of Figure 4.3, which display the effect of varying the expertise of member $j$ on member $i$’s optimal cutoff, $s^*_{it}$, and on its respective probabilities, $\gamma_{it,0}$ and $\gamma_{it,1}$. Notice that, as $s_{jt}$ becomes more informative, the probability that member $i$ mismatches both inflation states diminishes, which makes her recommendation more influential on member $i$, reducing her cutoff, $s^*_{it}$, and increasing her probability of recommending the high rate, irrespective of the actual inflation state, $\omega_t$.

Regarding the case of the effect of member $j$’s ideological bias ($\pi_j$), notice that, as member $j$ becomes more “hawkish”, she increasingly discounts member $j$’s recommendation ($r_{jt} = 1$) and increases the probability of recommending the opposite policy $r_{it} = 0$. The lower right panel of Figure 4.3 shows that this effect is higher when the recommendation of member $j$ is consistent with her bias. This is because, as the bias of member $j$ becomes more “hawkish”, she will be more likely to match the high state while mismatching the low state.
Figure 4.3: Potential Effect of Policy Recommendations on Subsequent Speakers. This figure presents the effect of varying a committee member j’s expertise, $\sigma_j$ (top panel), and ideological bias, $\pi_j$ (bottom panel), on subsequent speaker i’s equilibrium cutoff, $s_{it}$, and probability of following j’s recommendation, $\gamma_{it}$. The changes in both expertise (from 0.25 to 1.4) and bias (from 0.1 to 0.7) come from the estimated parameters’ distribution of the empirical model below.

4.3 Estimation and Identification

I describe the procedure to estimate the sequential deliberation model outlined above and then discuss identification issues.

I directly recover both preference and expertise parameters from the likelihood function in equation (4.6). This contrasts with the two-step approach developed by Iaryczower and Shum 2012 that first estimates a flexible “reduced-form” version of individual choice probabilities.
while controlling for individual and time-varying covariates. Then, it recovers the structural parameters by solving for the equilibrium conditions of the voting game they analyze.

The benefit from the “direct” approach in this context is that it does not rely on estimates from reduced-form voting probabilities, which makes it insensitive to the robustness of “first-stage” parameters. I implement a Bayesian estimation of the structural parameters that easily incorporates a hierarchical structure that exploits variation across members and meetings. Finally, it allows me to directly estimate parameter uncertainty, as it approximates the full posterior distribution, instead of relying on modal approximations, such as the Delta method, or quasi-Bayesian simulations.

The “direct” estimation approach comes at a cost, as it calculates the recommendation probabilities across committee members over different meetings for every trial value of the parameters, which can be computationally intensive. For this reason, I implement the approximation of the posterior distribution with an efficient Markov chain Monte Carlo (MCMC) algorithm, via the Hamiltonian Monte Carlo method [Homan and Gelman 2014].

This technique includes ancillary parameters that allow the algorithm to move further in the parameter space at each iteration, providing faster mixing, even in high dimensions.

The estimation algorithm of the empirical model requires two main related steps: first, the computation of the equilibrium condition, and the subsequent construction of the likelihood (“the inner loop”), and second, the estimation of the parameter vector (“the outer loop”). The estimation of the model is done sequentially at every meeting \( t \) using the observed speaking order of committee members. In this way, I am able to incorporate both the value of deliberation and the effect of pivotality, \( \sum_{j=1}^{n(i)_t-1} \log (\Psi(x_{jt})) \) and \( \log \left( \frac{Pr[PIV|\omega=0]}{Pr[PIV|\omega=1]} \right) \), respectively, when updating the optimal cutoff.

Equilibrium Condition (Inner Loop): Fix a parameter vector \( \theta \equiv \{\{\pi_i, \sigma_i\}_{i=1}^{N+1}, \rho_t\} \). For member in order \( n(i)_t = 1, \ldots, N \):

1. Solve for the equilibrium condition in equation (4.2).
2. Given $s_{it}^*$, compute $\gamma_{it,0}(s_{it}^*)$ and $\gamma_{it,1}(s_{it}^*)$ using equation (4.5).

3. Compute $\sum_{j=1}^{(i)} \log (\Psi(x_{jt}))$ using equation (4.3).

4. Compute the increment of the likelihood at every time period $t$ from equation (4.6).

Approximation of the Joint Posterior Distribution (Outer Loop): Given the likelihood function in equation (4.6), I write the posterior distribution of the vector of parameters $(\theta)$ as a proportion of the product of the likelihood and its prior distribution

$$Pr[(\theta, \lambda)|r_t] \propto Pr(\theta, \lambda)Pr[r_t|\theta]$$

$$= Pr(\lambda)Pr(\theta|\lambda) \prod_{t=1}^{T} \sum_{\omega} \rho_t^{\omega_t}(1 - \rho_t)^{1-\omega_t} \prod_{i=1}^{N+1} \gamma_{it,\omega_t}(s_{it}^*)^{r_{it}}[1 - \gamma_{it,\omega_t}(s_{it}^*)]^{1-r_{it}},$$

where I aggregate the increments to the likelihood over FOMC meetings and $\lambda$ denotes the vector of hyperparameters in the model.

1. I allow for heterogeneity in the common prior beliefs by estimating $\rho_t$ to vary as a function of meeting characteristics $X_t$ that were available to committee members before the sequential deliberation process:

$$\rho(X_t) = \frac{exp(X_t^T\delta)}{1 + exp(X_t^T\delta)}; \quad \delta \sim N(0, (9/4)I),$$

(4.7)

where $\delta$ is a fixed coefficient that is normally distributed. The value imposed on the variance is consistent with an uninformative prior for $\rho_t \approx \frac{1}{2}$. $X_t$ is a matrix of meeting-level predictors that includes the lagged level of the policy rate (previous policy), recent money growth, M1, and two-quarter ahead staff forecasts of inflation rate, $E(\text{Inflation})$, unemployment, $E(\text{Unemployment})$, and GDP growth, $E(\text{RGDP Growth})$. 

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I account for the switch in the transparency of FOMC deliberations via an indicator variable that takes the value of one after November 1993 and zero before.

To fully control for changes in the composition of the FOMC over time and for the different agenda-setting power across chairmen, I include an indicator variable for the identity of the FOMC chairman at the time of each meeting (Burns, Miller, Greenspan, or Bernanke). These chairman effects are relevant in this context because they capture differences in the deliberation protocol across FOMC regimes, specifically regarding the intervention of the chairman in the policy go-around. Burns sometimes spoke early, stating a preference for a particular policy rate while Greenspan routinely spoke right after the staff, suggesting a specific proposal. Bernanke, did not intervened during the policy go-around, waiting after all members spoke to craft a policy directive. This informal influence from the chairman to the rest of the FOMC is an important component of agenda setting power that shaped not only the voting stage of the decision-making process within the FOMC, but also the flow of the debate, which is accounted for in the empirical model.

2. For the estimation of pivotality effects on the equilibrium threshold, I let $Pr[PIV_i^t|\omega_t]$ be a function of covariates for member $i$ at meeting $t$ and for the subset of members who speak after her (i.e., $\{n(i)_t+1, \ldots, N+1\}$). I choose a functional form to constrain $Pr[PIV_i^t|\omega_t] \in [0, 1]$ as follows:

$$\log \left( \frac{Pr[PIV_i^t|\omega_t = 0]}{Pr[PIV_i^t|\omega_t = 1]} \right) = \alpha_1 Early_{it} + \alpha_2 Late_{it} + X_{it}\beta'. \quad (4.8)$$

The matrix $X_{it}$ of member-meeting level covariates includes member $i$’s experience at meeting $t$ (Rookie). For the covariates of remaining members speaking after member

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9See chapter 3 for an explanation.

10In the empirical estimation I allow chairmen Burns and Greenspan to speak more than once at any given meeting whenever they voiced a policy recommendation during the policy go-around in addition to their policy directive at the end of each meeting.

11See the definition in chapter 3.
i, I include the fraction of them who are rookies \((\text{Experience}_{\text{remain}})\), who are district presidents \((\text{Pres}_{\text{remain}})\), and who are Democrat-appointed governors \((\text{Dem}_{\text{remain}})\). I also include the average fraction of remaining members’ past career (i.e., before the FOMC) in private financial institutions \((\text{Fin}_{\text{remain}})\), as economists \((\text{Eco}_{\text{remain}})\), within the ranks of the Federal Reserve \((\text{CB}_{\text{remain}})\). Finally, this specification includes random effects for the order of speech of member \(i\) \((\alpha_0, 1, \alpha_2)\) where \text{Early} (\text{Late}) takes the value of one (zero) if member \(i\) speaks in the first (second) half of the policy go-around and zero otherwise.

3. For the remaining structural parameters and their respective hyperparameters, I use the following distributional assumptions based on their constrained scale in the model:

\[
\pi_i \sim \text{Beta}(\alpha_\pi, \beta_\pi), \text{ for } i = 1, \ldots, 57.
\]

\[
\sigma_i \sim \text{Cauchy}(0, \tau_\sigma) \text{ for } i = 1, \ldots, 57.
\]

\[
\alpha_\pi \beta_\pi \sim \text{U}(0, 10),
\]

\[
\tau_\sigma \sim \text{Cauchy}(0, 2).
\]

4. I obtain posterior samples of the vector of parameters from its posterior marginal density at each iteration \(m = 1, \ldots, M\). I run three parallel chains with dispersed initial values for 10,000 iterations each with an initial warm-up period of 5,000 iterations and thinning of 100. I assess convergence for each parameter based on the potential scale reduction factor, \(\hat{R}\) \cite{Gelman1992} and through a visual inspection of the trace plots. Appendix C.5 contains the traceplots for the model hyperparameters and the main parameters of interest, as well as a set of sampling statistics relevant for the diagnosis of the Hamiltonian Monte Carlo sampler.

Having laid out the estimation procedure, the formal identification of the parameters \(\rho_t\) and of the equilibrium probabilities \(\gamma_{it, \omega_t}\) in the likelihood function of equation (4.6)
is given by the fact that, conditional on the unobserved state $\omega_t$, the observed vector of recommendations, $r_t$, is drawn from a finite mixture distribution with mixing parameter equal to the common prior ($\rho_t$). Under the Bayesian framework, the estimation of mixture models transforms its complex structure by simpler conditional ones using latent variables or unobserved indicators, as given in this case by the state of the economy, $\omega_t$, that specifies the mixture component from which policy recommendations are drawn. The identification is solved by imposing distributional assumptions on prior parameters and sampling $\omega_t$ from its full conditional distribution.$^{12}$

The identification of the structural parameters contained in equilibrium cutoffs $s_{it}$ is as follows. In the case of the common prior, $\rho_t$, the identification comes from the presence of a common value $\omega_t$ in the empirical model. In particular, the prior is identified from the frequency with which the majority of FOMC members recommend the high rate. This is due to the fact that high values of the common prior induce higher signals for all FOMC members at any single meeting. Thus, as the instances where the majority of members choosing the high rate increase, the estimated value of $\rho_t$ also increases.

For the preference parameter $\pi_i$, the identification comes from the assumption on preference differences. Changes in the common prior, $\rho_t$, induce increases in the probability of voting for the high rate, but to a larger degree for members with a high value of $\pi_i$. Therefore, low variability in the pattern of recommendations over meetings for a particular FOMC member will be estimated as more extreme preference biases.

The identification of members’ expertise ($\sigma_i$) comes from the “common value” feature of the model. This is because increases in the common prior, keeping preferences ($\pi_i$) fixed, will induce a higher signal correlation in which members with higher ability will be better able to predict the true state of the economy. In the data, a member with an observed pattern of recommendations that follows the majority over time, will be estimated as having a high

$^{12}$As can be seen from the visual inspection of the traceplots for each parameter of interest in appendix C.5 there does not seem to be evidence of label-switching, which is a common problem of other Bayesian mixture models.
expertise (i.e., low $\sigma_i$). Analogously, a member whose pattern of recommendations tends to disagree with this majority will be estimated as having a low quality of information (i.e., high $\sigma_i$).

In order to separately identify the value of deliberation and the pivotality effect, I exploit the variation of the speaking order across meetings, as well as the properties of the structural parameters in the equilibrium cutoff. As can be seen in equation (4.2), the value of deliberation is directly identified from the nonlinear function $\Psi$ that maps both individual and time specific parameters into a social learning parameter that varies both across members and over meetings.

For the pivotality effect, I treat $\log \left( \frac{\Pr[PIV_i^t | \omega_t = 0]}{\Pr[PIV_i^t | \omega_t = 1]} \right)$ as a primitive to be identified and estimated directly from the data instead of directly computing it from the equilibrium strategy profile of subsequent speakers. This strategy is made possible by exploiting the changes in the speaking order across meetings, which is a source of variation in recommendation histories beyond the one induced by members’ biases, expertise and prior information. In this way, I am able to estimate, via the flexible specification in equation (4.8), the remaining variation in the equilibrium cutoffs coming from changes in the pivotal probability.

To clarify this strategy, consider the equilibrium cutoff in the extreme case where the speaking order is the same across meetings. Under this scenario, it would not be possible to estimate changes in the pivotality effect via covariates of remaining members, as these would be fix over time and not separable from the effect of members’ biases and expertise.

Fortunately for the empirical identification, FOMC speaking order varied substantially across members and meetings. In this way, I observe FOMC members sharing their policy recommendation in different speaking positions along their tenure. According to anecdotal evidence, there was no prescribed order to speak before each meeting’s policy go-around took place. Laurence Meyer, former board governor, labeled the order assignment as “the wink system”, in which each FOMC member would wink at the FOMC deputy secretary her ideal position on the policy go-around at any given meeting. However, the FOMC secretary, who
is a member of the staff of the Board of Governors, would decide the final speaking order at his discretion. Then, the chairman would call upon the FOMC in the order of that list without members knowing in advance which exact speaking position they were going to be called upon (Meyer [1998]).

Figure 4.4: Speaking Order across Meetings for Six Selected Members’ Tenure. This figure shows, for each member’s tenure (Hayes, Melzer, Stern, McDonough, McTeer, Boehne), the speaking order in which they provided their policy recommendations during the policy go-around, along with the distribution of speaking positions along their tenure.

Figure 4.4 shows, as an example, the variation in speaking order of six FOMC members over time. The first panel shows the two members with the smallest variation in the data: New York district presidents Hayes (1956-1975) and McDonough (1993-2003). The reason behind these small movements comes from the fact that, during the Burns and early Greenspan years, the New York district president, who also serves as the FOMC vicechairman was usually granted the informal right to speak first in the sequence. Still, even for these members, we can find meetings where they provided their recommendations late in the policy go-around. The other four plots in the Figure display FOMC members speaking...
at different position across meetings with no systematic pattern, which is also the case for the rest of FOMC members. Overall, it can be seen that, with the exception of members McDonough and Hayes who spoke first at 80% of the meetings they were part of, there was a substantial variation in the speaking order across meetings. In fact, members spoke, on average, just 8% of their tenure at any given speaking order (with a 6% standard deviation).

Figure 4.5: Speaking Order Across FOMC Members. This figure shows the mean speaking order during the policy go-around of each FOMC member along their tenure. Solid lines depict 95% confidence intervals. Dots depict the distribution of speaking positions for each FOMC member across meetings. Darker colors denote a higher relative frequency for a particular speaking position. For instance, a black point depicts a speaking position where a member spoke 100% of their time along their tenure. Members highlighted in red are FOMC vice-chairmen. Vice-chairmen Hayes, McDonough and Volcker usually were granted the right to provide their policy recommendations early during the policy go-around.
4.4 Results

I begin by describing the results for the effect of meeting-level covariates, $X_t$, to predict the common prior ($\rho_t$) which tracks the evolution of the unobserved state $\omega_t$. Figure 4.6 displays the expected prior estimated from equation (4.7), under hypothetical values of the explanatory variables. In particular, these counterfactual scenarios are constructed by changing each covariate from its 10th percentile value to its 90th percentile value in the sample, while keeping the rest of explanators at their median. The main takeaway point from these results is that the economic indicators included in the specification have a large and significant influence in predicting the common prior, $\rho_t$. These effects go in the expected direction given the importance of some of these indicators as proxies of inflationary pressures and economic growth. For instance, increments in expected output growth, $E(\text{RGDP Growth})$ and expected inflation $E(\text{RGDP Growth})$, are associated with larger inflationary pressures and therefore, with predicted increments of the common prior $\rho_t$. On the other hand, increments in expected unemployment, $E(\text{Unemployment})$ are perceived by FOMC members as diminishing inflationary pressures, while increasing the negative risks for economic growth. Consistent with a reversion to the mean effect, high levels of the prevailing policy rate ($\text{Previous Policy (FFR)}$) are negatively associated to larger inflationary states.

The effect of chairman individual effects are calculated with respect to the Burns chairmanship (1970-1978), which is the omitted category. The Greenspan years up to the transparency reform of 1993 were more prone to higher inflationary states, while the post-transparency years (1994-2008) have reversed this trend, as they have been a period where inflation has been well anchored at low levels.

The effect of both meeting-level covariates and chairman individual effects ultimately map into a predicted common prior about the state of the economy that captures both the effect of objective economic indicators, as well as the interpretation of FOMC members about these effects. Figure 4.7 shows the evolution of the predicted common prior ($\rho_t$) over the period under study. The first thing to notice is that the estimated common prior
Figure 4.6: **Determinants of the Prior** \( \rho_t \) **on the Unobserved State of Inflation** \( \omega_t = 1 \). The figure provides the effect of increasing each of the displayed covariates on the common prior \( \rho_t \equiv Pr(\omega_t = 1) \). Solid circles give the posterior median, with vertical solid lines corresponding to the interquartile range of the posterior distribution and dashed lines corresponding to 95% posterior credible intervals. The counterfactual increase in the covariate of interest is a change from the 10th to the 90th percentile in the sample. For each estimate, all other covariates are set at their median sample values.

follows the actual tradeoff between inflation and output remarkably close. For instance, the estimated \( \rho_t \) sharply decreases in periods with deteriorating output and unemployment, while increasing following economic expansions and higher inflation risks. In fact, the gray shades in this Figure are evidence that sustained declines in the estimated common prior \( \rho_t \) are closely associated with the presence and duration of all four economic recessions that hit the U.S. economy in the sample under study, as measured by the National Bureau of Economic Research (NBER). In addition, the common prior closely followed fluctuations in
Figure 4.7: Evolution of Prior $\rho_t$ Over Time. The figure provides the estimated value of the common prior $\rho_t \equiv Pr(\omega_t = 1)$ across meetings. Solid circles give the posterior median, with horizontal solid lines corresponding to the interquartile range of the posterior distribution. Gray areas correspond to economic recessions in the sample measured as the period from peak to trough of a business cycle according to the National Bureau of Economic Research. The blue dashed line on the secondary right axis depicts the monthly industrial production growth during the same period obtained from real-time data series collected at the Philadelphia Federal Reserve (www.philadelphiafed.org).

Figure 4.8 summarizes the findings related to the posterior estimates of ideological biases $(\{\pi_i\}_{1}^{N})$. The top panel provides the ranking of members according to the magnitude of these biases. Solid circles give the posterior median, with horizontal lines corresponding to the interquartile range of the posterior distribution. The posterior median of ideological biases across members range between 0.19 for Dallas district president Robert McTeer to 0.76 for Darryl Francis, district president of the Saint Louis Fed during the Burns period. The

\[\textit{output growth, as captured by monthly changes in industrial production, an indicator that is not part of the covariates employed to estimate } \rho_t.\]

\[\textit{In fact, the data on monthly industrial production is not part of the information set of FOMC members, as it published after each meeting takes place.}\]
Figure 4.8: **Ideological Bias Estimates, \( \pi_i \).** The top panel provides posterior summaries of the ideological bias, \( \pi_i \) for each FOMC member during the periods 1970-1979 and 1987-2008. Solid circles give the posterior median, with horizontal lines corresponding to the interquartile range of the posterior distribution. Committee members who participated in more than 30 meetings are included. The bottom left panel of the Figure provides the result of a linear fit along with 95% confidence intervals between ideological biases \( \pi_i \), as recovered by the *sequential deliberation model* and ideal points, \( z_i \), as recovered by the *spatial ideological model*. The bottom right panel of the figure provides posterior summaries of the ideological bias of FOMC committee members, \( \pi_i \), aggregated by appointment, where a member is either a district president or board governor.
distribution of estimated ideological biases shows a high degree of polarization, with 46% of them being statistically different from 0.5, which captures ideologically neutral members.

So far throughout the chapter, I have given members’ biases, \( \{\pi_i\}_{1}^{N} \), an ideological interpretation in terms of the “hawk/dove” dimension that has been popularly used to classify central bankers and FOMC members in particular. Formally, however, it is defined as member \( i \)’s threshold of evidence above which she is willing to recommend the higher rate, which potentially could be related to factors other than members’ degree of inflation aversion. To check this issue, the lower left panel of Figure 4.8 plots the correlation between members’ biases according to the sequential deliberation model and the ideal points of FOMC members that are obtained from fitting a spatial ideological model to the pattern of policy recommendations. The estimation of the spatial ideological model is a Bayesian version of a multilevel IRT model fitted to the policy recommendations of FOMC members. The details of the estimation can be found in appendix C.1. The fact that members’ biases, \( \pi_i \), are extremely similar to the rank order of ideal points (with a Pearson (Spearman) correlation of 0.9 (0.91)) indicates that this ideological interpretation fits well the profile of FOMC members.

Consider district president Tom Melzer, who is placed on the highest tail of the distribution of members’ biases. He has been recognized by the press and other central bankers as one of the most “hawkish” members in the history of the FOMC. In fact, at almost every opportunity he had, he stated his views on monetary policy that can be summarized in the following quote from one of his speeches: “In my opinion, the main contribution the Fed can make to the economy in the long run is to keep inflation low and inflation uncertainty to a minimum. This means maintaining a consistent policy over a long period of time with a credible commitment to low inflation.” (Melzer [1994]). In contrast, on the “dovish” extreme, the spatial model places former governor and current chairwoman of the FOMC Janet Yellen, who has been characterized as a “dovish” member by the media, given her policy views that can be summarized in the following extract from one of her interventions at a FOMC meeting, “...I would agree that the Fed probably cannot achieve permanent gains in
the level of unemployment by living with higher inflation. But the Federal Reserve can, I think, make a contribution on the employment side by mitigating economic fluctuations—by stabilizing real activity.” (Yellen [1995]).

The difference between a board governor, such as Janet Yellen and a district president like Francis or Melzer in terms of their bias differences goes beyond the anecdotal. In fact, the relative ordering of members’ preferences is systematically correlated with their appointment process, as can be confirmed from the evidence depicted in the lower right panel of Figure 4.8. This figure provides posterior summaries of the ideal points of FOMC members aggregated by appointment.

I find that board governors, who are appointed by the President, are 19% more “dovish” than Federal Reserve presidents, who are appointed by district boards of directors comprised of regional banking and industry interests. As shown in Table 4.4, this finding is robust to controlling for both the party of the President who appointed board governors and the career experience of FOMC members as introduced in chapter 2. In this table, I also replicate the same exercise using the ideal points, \( z_i \), from the spatial ideological model, as well as those biases obtained from a model I label the simultaneous model, which incorporates members’ private information, but assumes that recommendations are given in a vacuum, ruling out the possibility of information transmission through sequential deliberation (i.e., ignores learning from previous speakers as well as pivotality effects) \(^{14}\).

These results confirm previous studies on the FOMC that have explained this differences between board governors and district presidents in terms of the political pressure through appointment that the Executive exerts on board governors (Chang [2003]). According to this argument, U.S. presidents, who are presumed as having biased preferences towards the real side of the economy, appoint central bankers with similar preferences to implement “dovish” policies.

\(^{14}\) The details and posterior estimates of the model without deliberation can be found in appendix C.2.
### Table 4.2: Bias Correlates for Different Behavioral Models

In this table I estimate a regression of the ideological biases for three different behavioral models (i.e., sequential deliberation model, spatial ideological model, and simultaneous model), controlling for the party of the Executive who appointed the board governor and for the career experience of FOMC members given by the fraction of their career spent in Finance, Treasury, Government, within the ranks of the Federal Reserve, and working as an economist. The omitted categories are Business and Other.
Figure 4.9: **Expertise Estimates**, $\sigma_i$. The left panel of the figure provides posterior summaries of the measure of expertise of FOMC committee members, $\sigma_i$. Solid circles give the posterior median, with horizontal lines corresponding to the interquartile range of the posterior distribution. Committee members who participated in more than 30 meetings are included. The right panel of the figure provides the results of a linear fit, along with 95% confidence intervals between the estimated posterior median ideological biases, $\pi_i$, and individual expertise, $\sigma_i$, as recovered by the *sequential deliberation model*.

The observed behavior of FOMC members while deliberating monetary policy cannot be characterized exclusively as a mere reflection of members’ ideology. At best, this characterization is incomplete, unless two important features of monetary policy deliberation are considered: first, the notion that monetary policy entails implementing a policy that seeks to match the true state of the economy, an issue that hinges on efficiently interpreting current economic conditions in an environment of pervasive uncertainty; second the important feature of deliberative committees, such as the FOMC, in which the structure of debate itself can have important consequences in the decision-making process, mainly in shaping members’ inferences about the uncertain state of the world.

The estimates of FOMC members’ expertise in gauging the state of the economy are depicted in in the left panel of Figure 4.9. From this plot, it can be observed a sizable...
amount of heterogeneity across FOMC members, with an interquartile range that goes from a signal quality ($\sigma_i$) of 0.5 for Chairman Miller to 1.76 for New York district president Corrigan. The dispersion in members’ expertise is a fundamental component to expand our understanding of committee decision-making and of the FOMC in particular, which was missing in previous empirical work on the topic. Mainly, it places the ideological divisions in perspective, showing that preference differences cannot account for the total variation in the behavior of committee members. In fact, members’ ideological biases are not systematically related to their expertise, as can be seen in the right panel of Figure 4.9. This null relationship between biases and ability comes from the observed behavior of FOMC members and not from modeling assumptions, as the theoretical framework does not impose any covariance structure between members’ preferences and their information structure.

When I split the sample of FOMC members by appointment, and in contrast to the preference biases, there does not seem to be any statistically significant difference between board governors and district presidents as shown in Table 4.4. Moreover, and in contrast to the simultaneous model, under the sequential deliberation model, none of the career experience variables seem to be associated with differences in expertise. This is due to the fact that the latter uses the information on members’ experience to estimate the effect of pivotality, whereas the former attributes differences in career experience to members’ expertise.

One interesting result from these expertise estimates is that three out of four FOMC chairmen in the data, except Bernanke, ranked at the top of the expertise distribution. This is relevant from a policy perspective given that the policy directive that is selected in FOMC meetings is ultimately crafted by the Chairman and as such, his expertise to track the evolution of economic conditions and to incorporate the information that other members bring to the discussion is crucial in determining the quality of the policy implemented. To quantify this last implication, I estimate the probability that chairman Greenspan gives a correct policy directive under the scenario where he only follows his private information. In the notation of the model, this means computing $\gamma_{it,1}$, when $\omega_t = 1$ and $1 - \gamma_{it,0}$, when $\omega_t = 0$. 

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### Table 4.3: Expertise Correlates for Different Behavioral Models

In this table I estimate a regression of the expertise estimates for two different behavioral models (i.e., sequential deliberation model and the simultaneous model), controlling for the party of the Executive who appointed the board governor and for the career experience of FOMC members given by the fraction of their career spent in Finance, Treasury, Government, within the ranks of the Federal Reserve, and as economists. The omitted categories are Business and Other.

**Dependent variable:**

<table>
<thead>
<tr>
<th></th>
<th>Simultaneous</th>
<th>Sequential Deliberation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Fed President</td>
<td>0.059</td>
<td>-0.040</td>
</tr>
<tr>
<td></td>
<td>(0.090)</td>
<td>(0.083)</td>
</tr>
<tr>
<td>Democrat Appointment</td>
<td>0.047</td>
<td>0.011</td>
</tr>
<tr>
<td></td>
<td>(0.088)</td>
<td>(0.080)</td>
</tr>
<tr>
<td>Financial Experience</td>
<td>-0.159</td>
<td>0.038</td>
</tr>
<tr>
<td></td>
<td>(0.187)</td>
<td>(0.171)</td>
</tr>
<tr>
<td>Government Experience</td>
<td>-0.798*</td>
<td>-0.073</td>
</tr>
<tr>
<td></td>
<td>(0.455)</td>
<td>(0.416)</td>
</tr>
<tr>
<td>Treasury Experience</td>
<td>-0.276</td>
<td>0.241</td>
</tr>
<tr>
<td></td>
<td>(0.340)</td>
<td>(0.311)</td>
</tr>
<tr>
<td>Central Bank Experience</td>
<td>-0.163</td>
<td>-0.019</td>
</tr>
<tr>
<td></td>
<td>(0.177)</td>
<td>(0.161)</td>
</tr>
<tr>
<td>Economics Experience</td>
<td>-0.370*</td>
<td>0.054</td>
</tr>
<tr>
<td></td>
<td>(0.185)</td>
<td>(0.169)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.639***</td>
<td>1.311***</td>
</tr>
<tr>
<td></td>
<td>(0.161)</td>
<td>(0.147)</td>
</tr>
</tbody>
</table>

Observations: 56  56  

R\(^2\): 0.153  0.034  

Adjusted R\(^2\): 0.029  -0.107  

F Statistic (df = 7; 48): 1.234  0.238

*p<0.1; **p<0.05; ***p<0.01

Note: Standard errors in parentheses
For this exercise, I assume that the common prior \( \rho_t = 0.5 \). Given Greenspan’s posterior estimates, \( \pi_i = 0.44 \) and \( \sigma_i = 0.84 \), his probability of correctly predicting both high and low inflation states is \( \gamma_{it,1} = 0.65 \) and \( 1 - \gamma_{it,0} = 0.79 \), respectively. Therefore, his total probability of correctly predicting the true state of the world is \( (0.5 \times 0.65) + (0.5 \times 0.79) = 0.72 \)\(^{15}\).

The above counterfactual calculation assumes that the Chairman submits his policy directives in isolation, without taking into consideration the deliberation process of policy recommendations. Suppose instead, that before taking a decision, he decides to listen to a couple of FOMC members’ recommendations in sequence: vicechairman William McDonough (\( \sigma_i = 1.74, \pi_i = .42 \)) speaking first followed by a typical “hawk” member, such as Alfred Broaddus (\( \sigma_i = 1.03, \pi_i = 0.68 \)). Faced with both McDonough and Broaddus recommending the low rate, Greenspan would reduce the probability of recommending a high rate from 0.43 in isolation to 0.34. In contrast, faced with McDonough proposing a high rate and Broaddus recommending a low rate, Greenspan implicitly weights both members’ biases and expertise. As Broaddus has a higher degree of expertise than McDonough, his recommendation is weighted more heavily leading to an increase in the probability of proposing a high rate of \( Pr[r_{Ct} = 1] = 0.84 \). When the contradictory advice comes from Broaddus recommending a low rate (i.e., a history \((1, 0)\)), Greenspan infers that Broaddus must have been received a very low signal that overcame his “hawkish” bias and thus, adjusts accordingly the probability of recommending a high rate to \( Pr[r_{Ct} = 1] = 0.5 \).

There are plausible scenarios where members significantly change their behavior after incorporating previous recommendations compared to the scenario in which they ignore the deliberation process and follow their own information. Moreover, assessing the expertise of committee members is drastically changed once members are allowed to learn from each other. Compared to the simultaneous model where expertise parameters are recovered without accounting for the deliberation process, there is a substantial difference in members’ expertise estimates, from an average of 0.48 for the simultaneous model to 1.3 sequential

\(^{15}\)The estimates employed for the counterfactual exercises correspond to the posterior median distribution of the parameters of interest.
Figure 4.10: **Expertise under the Sequential Deliberation and Simultaneous Models.**
The figure provides the distribution of expertise ($\sigma_i$) estimates under the two different behavioral models. Under the **simultaneous model**, members provide their recommendations taking into account their bias and private information. Under the **sequential deliberation model**, members also take into consideration the recommendations of previous speakers and the probability of being pivotal on the Chairman’s proposal.

In addition, the rank order of members’ expertise estimates changes drastically when members are allowed to learn from previous recommendations compared to the case without learning. This is shown in Figure 4.10, which compares the expertise estimates for both behavioral models. The reason behind these discrepancies arises from the relevance of deliberation as an information-sharing mechanism. The **simultaneous model** interprets any potential value of information contained in the history of recommendations of early speakers as a better quality of their private information. By explicitly accounting for the presence of information complementarities through sequential deliberation, the role

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16 The estimation results for the simultaneous model can be found in Appendix C.2
of private information in the quality of members’ recommendations is attenuated and, more importantly, disentangled from the social learning embedded in the deliberation process.

4.5 The Value of Deliberation

With the structural estimates at hand, I present a measure of the value of deliberation within the FOMC. This measure is defined as the frequency with which a member would change her policy recommendation after incorporating previous recommendations, compared to the scenario where she follows her private information.

To compute the value of deliberation, I generate two policy recommendations for each of the $N$ members across the $T$ meetings analyzed, $r^D_{it}$ under the actual sequential deliberation model and $r^S_{it}$ for the counterfactual committee without deliberation. The procedure is as follows:

For each posterior draw $m = 1, \ldots, M$ from the parameter distribution:

1. Draw the state of the economy $\omega_t$ given $\rho_t$.

2. Draw a signal for each member from $N \sim (\omega_t, \sigma_i^2)$.

3. Draw a policy recommendation for each member:
   - $r^D_{it} = 1$ if $s_{it} \geq s^*_{it} \equiv (\pi_i, \sigma_i, PIV^t_i, \rho_t)$.
   - $r^S_{it} = 1$ if $s_{it} \geq s^{**}_{it} \equiv (\pi_i, \sigma_i, \rho_t)$.

4. The value of deliberation by member is given by $\frac{1}{T} \sum_{t=1}^{T} 1_{r^S_{it} \neq r^D_{it}}$.

5. The value of deliberation by meeting is given by $\frac{1}{N} \sum_{i=1}^{N} 1_{r^S_{it} \neq r^D_{it}}$.

Given the Bayesian estimation framework, I am able to analyze the posterior distribution of the value of deliberation and estimate its uncertainty by computing $p_{th}$ percentiles from the $M$ posterior random draws.
The estimated value of deliberation takes a value of zero whenever members’ policy recommendations are identical with or without deliberation. The value of deliberation takes a value of one whenever members’ policy recommendations differ from the one without deliberation.

The left panel of Figure 4.11 presents the average value of deliberation in the FOMC for each member across meetings. The average value of deliberation across FOMC members is 36% with a significant variation across members. On one extreme, an inflation hawk such as president Francis would switch his recommendations after listening to other members only 6% of the time. On the other side, board governors Phillips and Chairman Bernanke would change their recommendations after incorporating previous recommendations 48% of the time.

Notice that from the group of chairmen, Bernanke and Miller are in the top 5 of members with the highest value of deliberation, whereas Greenspan and Burns rank in the middle of the distribution. In fact, Greenspan is the chairman with the lowest value of deliberation (39%), which is consistent with previous accounts of Greenspan’s dominance over the FOMC and the strong role he played during FOMC deliberations by steering the policy directive closer to his initial leanings and expertise rather than to the opinion of other FOMC members. A clear example of this behavior comes from the February 1994 meeting, as former FOMC member Alan Blinder noted “[…] when the Fed began a cycle of interest rate increases by moving the Federal funds rate up 25 basis points. The transcript of that meeting (which is now public) shows that a clear majority of the committee favored moving up by 50 basis points. Greenspan, however, insisted not just on 25 basis points, but on a unanimous vote for that decision. He got both.” (Blinder 2008)

The right panel of Figure 4.11 partially confirms the dominance of Greenspan over the FOMC as a whole during his early years as Chairman. This plot shows the time trend of the value of deliberation across FOMC members. From Greenspan’s appointment up to the transparency reform of FOMC communications in 1993, the average value of deliberation
decreased to its lowest point historically, from 35% during the Burns/Miller period to 22%. However, from 1990 onwards there has been an upward trend in the value of deliberation that peaked in the late Greenspan’s years around 2004.

Figure 4.11: The Value of Deliberation in the FOMC. The left panel shows the posterior distribution of the value of deliberation aggregated by member, with points corresponding to the median and solid lines to the interquartile range of the posterior distribution. The right panel of the figure plots the smoothed (by 2nd degree local polynomial) time trend of the value of deliberation by meeting. The shaded area corresponds to the posterior interquartile range. The value of deliberation is defined as the probability that a member \( i \) in meeting \( t \) change her policy recommendation after incorporating the recommendations made by previous speakers, as well as her pivotality effect compared to the scenario where she follows her private information.

Figures 4.12 and 4.13 present the correlates of the value of deliberation by member and meeting, respectively. Figures 4.12 shows that the variation of the value of deliberation across members can be systematically explained by differences in members’ biases and expertise. The left panel of this figure indicates that inflation “hawks” tend to rely more on their private information than “neutral” and “dove” members. Moving from the most “dovish” member (i.e., McTeer) to the most “hawkish” one (i.e., Francis), reduces the value of deliberation from 43% to 13%. The right panel of this figure is evidence that FOMC members with a
high degree of expertise tend to incorporate others' recommendations more often than those with less expertise. Moving from the member with highest expertise (i.e., Miller) to the member with the lowest expertise (i.e., Corrigan) decreases the value of deliberation from 45% to 29%.

In terms of the variation of the value of deliberation over time, Figure 4.13 shows that beyond differences across chairmen, the value of deliberation is higher during low inflationary states as can be seen from the fact that an increased in expected inflation reduced the value of deliberation around 11%, whereas an increase in expected unemployment increase the value of deliberation around 12%.

![Graphs showing the relationship between Value of Deliberation and Ideological Bias, Expertise](image)

Figure 4.12: Covariates of Value of Deliberation by Member. The left panel shows the relationship between members' value of deliberation and their ideological biases, $\pi_i$. The right panel shows the relationship between members' value of deliberation and their expertise, $\sigma_i$. 
Figure 4.13: **Covariates of Value of Deliberation by Meeting.** The figure shows the relationship between the estimated value of deliberation by meeting and time-varying covariates. Solid circles give the posterior median, with horizontal solid lines corresponding to the interquartile range of the posterior distribution and dashed lines corresponding to 95% posterior credible intervals. The counterfactual increase in the covariate of interest is a change from its minimum to its maximum in the sample. For each estimate, all other covariates are set at their median sample values.

### 4.5.1 Social Learning vs Pivotality

The value of deliberation shown above is calculated under a model where policymakers weight their own information against the recommendation of previous speakers, as in a pure social learning framework. In addition, they also account for the potential effect that their decision might have on the chairman’s proposal, as it is included in their pivotality effect. Thus, up to this point it is unknown whether the information they obtain from the deliberation process comes mainly from social learning or from strategic considerations. To shed light on this issue, I compute the relative weights that both considerations have on members’ equilibrium cutoffs, $s_{it}$. For each member’s cutoff given by equation (4.2), I calculate the average magnitude of social learning and pivotality given by the absolute value of $\sum_{j=1}^{n(i)} \log (\Psi(x_{jt}))$ and $\log \left( \frac{Pr[PIV_i | \omega_j = 0]}{Pr[PIV_i | \omega_j = 1]} \right)$, respectively as a proportion of the total
cutoff’s magnitude

$$\left| \log \left( \frac{1 - \pi_i}{\pi_i} \right) \right| + \left| \log \left( \frac{1 - \rho_t}{\rho_t} \right) \right| + \sum_{j=1}^{n(i) - 1} \left| \log (\Psi(x_{jt})) \right| + \left| \log \left( \frac{Pr[PIV_i t | \omega_t = 0]}{Pr[PIV_i t | \omega_t = 1]} \right) \right|.$$

Figure 4.14 presents the results of this exercise. The top panel compares the densities of the relative weights of social learning and pivotality in members’ equilibrium cutoffs. The lower panel disaggregates these relative weights by member. Overall, it can be seen that FOMC members assign a very small weight to strategic considerations and instead, place a larger emphasis on the information provided by previous speakers when providing their own recommendations.

The average weight that FOMC members put on pivotality considerations when providing policy recommendations is 10%. Not only the pivotality effect is small on average, but also the variation across FOMC members is small, from a minimum weight of 4% for chairman Burns to a maximum of only 14% for governor Mitchell. On the other hand, the relative weight of social learning on FOMC members’ behavior is four times larger than that of pivotality, as it accounts for 41% of the total magnitude of member’s cutoffs. Moreover, there is a significant dispersion of the weight members put on social learning. Consistent with the value of deliberation presented above, the weight that inflation “hawks”, such as presidents Francis and Hayes assign to social learning is less than 20%, which contrasts to the weights of 58% and 69% that Governor Meyer and Chairman Bernanke assign to previous recommendations, respectively.\footnote{Figure C.9 shows that, for the last and next-to-the-last speakers, estimating pivotality effects using specification 4.8 with covariates provides similar results to those that would be obtained by exactly computing the posterior updates of the Chairman as given by equation 4.4 and C.2}

4.5.2 Order of Speech and Correct Decisions

In any given policy go-around, the FOMC chairman, after listening to the sequence of policy recommendations of individual members, arrives at a policy directive that is officially voted
by majority rule. As this directive has obtained at least a majority of votes at every meeting in the history of the FOMC, I compute a measure of the quality of decision-making given by the probability that the chairman proposes a policy directive that is consistent with the true state of the economy. A natural question to ask given this measure of performance is how this quality is affected by the deliberation process in place at the FOMC? Then, I ask whether the performance of the FOMC decision-making process would have been different if deliberation is modified according to members’ characteristics. In particular, I modify the speaking order according to members’ biases, expertise and experience. The counterfactual speaking orders are given as follows: from the least to the most biased member and vice versa, from the least to the most expert member and vice versa, and by their experience as central bankers, where members with a longer career within the ranks of the Federal Reserve speak first.\footnote{18Members with no experience at the Fed are ranked alphabetically in the counterfactual simulation.}

As before, the probability that the chairman proposes a correct policy directive can be expressed as $\rho_t \gamma_{Cl,1}(s_{Ct}^*) + (1 - \rho_t)(1 - \gamma_{Cl,0}(s_{Ct}^*))$. This measure can be computed under any committee composition and history of recommendations observed by the chairman, $x_{Ct} = (r_{1t}, \ldots, r_{Nt})$.

Notice that for each of the counterfactual scenarios under consideration, the computation of the probability of the correct decision needs to account for changes, not only in the value of social learning from previous recommendations, but also in the pivotality considerations of FOMC members, as this is a function of the order of speech and of the characteristics of subsequent speakers. Therefore, given the estimated coefficients recovered from the covariate specification in (4.4), I recalculate the pivotality effects at the counterfactual value of each covariate in the pivotality specification.

The Figure 4.15 indicates that, compared to the case where the Chairman takes the decision in isolation (No Deliberation), the observed order of speech increases the probability of a correct policy decision by 6%. Moreover, from the counterfactual rankings considered,
ordering members by either their ideological biases (from most neutral to most biased), their expertise (from most expert to least expert), or their experience as central bankers, improves the decision-making quality of the FOMC by 9% on average, with respect to the case of no deliberation.

The small gains in precision from the best counterfactual rankings (i.e., by Fed experience and least biased member first) with respect to the observed speaking order, can be explained by the fact that the actual order of speech in the data partially incorporates these counterfactual scenarios. Table 4.4 estimates the correlation between the observed order of speech, categorized into Early, Middle and Late speaking positions, and members’ characteristics such as bias magnitude, expertise, career experience within the Fed, and experience as FOMC members. As can be seen from this Table, it is the case that more neutral members systematically speak early compared to more biased FOMC members. In particular, reducing the bias from 0.19 to 0.02 increases the probability of speaking early around 5%. In terms of members’ experience as central bankers, it is the case that going from a member with no past central bank experience to one with a entire career within the Fed is associated with an increase of 6% in the probability of speaking early. In the same sense, FOMC members with longer tenure tend to speak 8% more in early positions than rookie members.
<table>
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<th>Dependent variable:</th>
<th>Order of Speech</th>
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<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Ideological Bias</td>
<td>1.661***</td>
<td>1.511***</td>
<td>1.568***</td>
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<tr>
<td></td>
<td>(0.451)</td>
<td>(0.452)</td>
<td>(0.454)</td>
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<tr>
<td>Expertise</td>
<td>−0.031</td>
<td>−0.077</td>
<td>−0.071</td>
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<tr>
<td></td>
<td>(0.138)</td>
<td>(0.139)</td>
<td>(0.139)</td>
</tr>
<tr>
<td>Experience at the Fed</td>
<td>−0.301***</td>
<td>−0.296***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.071)</td>
<td>(0.071)</td>
<td></td>
</tr>
<tr>
<td>Rookie FOMC Member</td>
<td>0.390***</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>(0.071)</td>
<td></td>
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<tr>
<td>Observations</td>
<td>3,621</td>
<td>3,621</td>
<td>3,621</td>
</tr>
</tbody>
</table>

*p<0.1; **p<0.05; ***p<0.01

Note: Standard errors in parentheses

Table 4.4: Order of Speech Correlates. The dependent variable is a multinomial indicator that takes the value of 1 if the speaking position is in the first third of the policy go-around, takes the value of 2 if the speaking position is in the second third of the policy go-around and takes the value of 3 if the speaking position is in the last third of the policy go-around. Ideological Bias is given by |\(\pi_i - 0.5\)|. Expertise is given by the value of \(\sigma_i\). Experience at the Fed is the fraction of a member’s career before joining the FOMC spent within the ranks of the Federal Reserve.
Figure 4.14: Relative Weights of Social Learning and Pivotality in Committee Members’ Optimal Cutoffs. The top panel of the figure shows the distribution across committee members of the median weight of both pivotality and sequential learning in member’s optimal cutoffs. The bottom panel shows these relative weights by committee member. For each member, solid points denote the median of the posterior distribution with lines depicting the interquartile range of the posterior distribution. The relative weight of social learning and pivotality are computed as the absolute value of

\[
\frac{\sum_{j=1}^{n(i)} \log(\Psi(x_{jt}))}{\log\left(\frac{\text{Pr}[\text{PIV}_{i} | \omega_{t}=0]}{\text{Pr}[\text{PIV}_{i} | \omega_{t}=1]}\right)}
\]

and

\[
\frac{\sum_{j=1}^{n(i)} \log(\Psi(x_{jt}))}{\log\left(\frac{\text{Pr}[\text{PIV}_{i} | \omega_{t}=0]}{\text{Pr}[\text{PIV}_{i} | \omega_{t}=1]}\right)}
\]

respectively as a proportion of

\[
\log\left(\frac{1-\pi_{i}}{\pi_{i}}\right) + \log\left(\frac{1-\rho_{i}}{\rho_{i}}\right) + \sum_{j=1}^{n(i)-1} \log(\Psi(x_{jt})) + \log\left(\frac{\text{Pr}[\text{PIV}_{i} | \omega_{t}=0]}{\text{Pr}[\text{PIV}_{i} | \omega_{t}=1]}\right).
\]
Figure 4.15: Observed vs Counterfactual Committees. This figure shows the estimated posterior probability that the chairman proposes a policy directive consistent with the true state of the economy for different speaking orderings of committee members. Solid points denote the median of the posterior distribution and lines depict the interquartile range of the posterior distribution. The scenario of No Deliberation corresponds to the case where the chairman only takes into account his private information. The scenarios Most (Least) Biased First ranks committee members in descending (ascending) order given by $|\pi_i - 0.5|$. The scenario Most (Least) Expert First ranks committee members by expertise in ascending (descending) order given by $\sigma_i$. The scenario By Fed Experience rank members according to the proportion of their career spent within the ranks of the Federal Reserve in descending order.
4.6 Model Fit Comparison

In the previous section I show that the *sequential deliberation model* provides a framework to disentangle the value of private information from social learning. In addition, I find that the value of information transmitted through the sequential deliberation process is substantial. However, the relevance of incorporating social learning should be based also on whether it improves our understanding of the actual pattern of recommendations of committee members better than competing accounts available in the literature. For this purpose, I evaluate the explanatory power of the *sequential deliberation model* based on goodness-of-fit metrics that can provide a comprehensive picture of the ability the model has to account for the observed heterogeneity in behavior. For comparison purposes I use both the *spatial ideological model* and the *simultaneous model*. The former is the most common characterization of the FOMC in the empirical monetary literature. The latter incorporates the quality of private information into the spatial ideological model, but ignores the information coming from the sequential deliberation process. In this way, I can evaluate the power of sequential deliberation to explain the pattern of recommendations compared to behavioral models where members with different ideologies and expertise ignore the deliberation process and follow their biases and private information.

I take advantage of the fact that, under the Bayesian framework, the goodness-of-fit indicators are a function of the model parameters and as such, inherit the uncertainty coming from random sampling, which allows me to provide credibility intervals to performance measures. The first indicator I use is the percent of (in)correctly classified recommendations (*Error*). The second indicator is the excess error rate (*excess error*) proposed by Bafumi et al. [2005], defined as the proportion of error beyond what would be expected, given the model’s predicted values. The third indicator is the expected percent of correctly predicted recommendations (*EPCP*), which was proposed by Herron [1999] to alleviate the coarse

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19 The estimation details of this model are given in Appendix C.1.
20 Details and additional results of the estimation of this model can be found in Appendix C.2.
classification rule in fitted probabilities of binary outcomes, which can over-estimate the true fit of the model.

The left panel of Figure 4.16 presents a summary of the posterior distribution of each of the three goodness-of-fit measures. The fit of the *sequential deliberation model* is significantly better than any of the other two models in explaining the observed patterns of recommendations, irrespective of the performance metric used. The differences in explanatory power are substantial. The *sequential deliberation model* is able to correctly predict 92% of the individual recommendations in the sample, compared to 76% for the *simultaneous model* and 86% for the *spatial ideological model*. Also, using the expected proportion of correctly predicted recommendations (EPCP) as metric, we have that the *sequential deliberation model* correctly predicts 82% of recommendations, whereas the *spatial ideological* and the *simultaneous* models correctly predict 73% and 63% of recommendations, respectively.

![Goodness-of-Fit Statistics](image1.png)  
**Sequential Model**  
**Simultaneous Model**  
**Ideological Model**  

**Proportion of correctly classified 1’s**  
**Proportion of incorrectly classified 0’s**

![ROC Curves](image2.png)  
**Sequential Model**  
**Simultaneous Model**  
**Ideological Model**

**Proportion of correctly classified 1’s**  
**Proportion of incorrectly classified 0’s**

**Figure 4.16:** *Fit Measures Across Models.* The left panel presents goodness-of-fit statistics for the *sequential deliberation*, *spatial ideological* and *simultaneous* models. I estimate Bayesian versions of the percentage of Error (Error), the Excess Error Rate (Excess Error) and the expected proportion of correctly predicted recommendations (EPC), averaged by both committee member and meeting. The right panel shows a model comparison based on ROC curves, where the 45-degree line corresponds to a random prediction model.
The absolute excess error rates are also considerably lower under the \textit{sequential deliberation model} than under the other two behavioral models. In particular, they are around 7 and 20 percentage points lower than those for the \textit{spatial ideological} and the \textit{simultaneous} models, respectively.

Another way to compare the performance across models is by plotting their receiver operating characteristic (\textit{ROC}) curves, which are a graphical summary of the correctly classified recommendation rates against the incorrectly classified ones, for different cutoffs $c$ for which $r_{it} = 1$ if $\hat{Pr}(r_{it} = 1) > c$. As can be seen in the right panel of Figure 4.16, the curve for the \textit{sequential deliberation model} dominates the other two curves for any given cutoff $c$. The area under the ROC curve can also be used to assess the accuracy of each model. In this respect, the \textit{sequential deliberation model} dominates as well the other two with an area of 93\%, \textit{versus} 90\% and 66\% for the \textit{ideological} and \textit{simultaneous} models, respectively.

The comparison across models presented above focuses on in-sample fit, in which I contrast observed \textit{versus} classified policy recommendations using the entire data to estimate parameters. However, to assess the predictive accuracy across competing models it is necessary to estimate out-of-sample predictions using within-sample fits. This exercise of predictive accuracy is infeasible for the \textit{spatial ideological model} because an estimate of the location of policy alternatives is needed in order to fit it. Nevertheless, I can provide out-of-sample prediction accuracy for both the \textit{simultaneous} and \textit{sequential deliberation} models. Figure C.10 in Appendix C.4 shows the results from this exercise \textit{via} leave-one-out cross-validation (LOO), which compares observed recommendations across meetings and members with respect to predicted recommendations based on a training sample that excludes the data from member $i$ at meeting $t$. To avoid computing an exact LOO, which would require re-fitting the model a total of 3490 times (i.e., the total number of observations in the sample), I estimate an approximate LOO using Pareto smoothed importance sampling (PSIS) (Vehtari, Gelman and Gabry [2015]). This approach provides a computationally feasible and reliable estimate of LOO by resampling the joint posterior density with importance weights that
are smoothed with a Pareto distribution to minimize their instability. The results from this exercise show that, similar to the in-sample results, out-of-sample predictive rates are 92% and 76% for the sequential deliberation and simultaneous models, respectively.

In conclusion, the sequential deliberation model fits the observed patterns of FOMC recommendations really well both in and out-of-sample. The accuracy of this model is substantially better than alternative frameworks that ignore learning associated with the structure of debate.

4.7 Conclusion

Deliberation is a fundamental component of collective decision-making. Policymakers invest a huge portion of their time and effort expressing their own views and listening to others’ arguments regarding the appropriate policy that should be implemented. The relevance and potential consequences of deliberation on collective choices have been explored in previous theoretical and empirical work. However, less is known regarding the particular mechanisms that affect the behavior of policymakers throughout the deliberation process. I quantify the role of social learning as a fundamental mechanism of deliberation in policy-relevant institutions. In particular, I measure the influence that individual participants exert on others throughout the deliberation process. To do this, I estimate an empirical model of policy-making that incorporates the role of learning by exploiting the sequential nature of deliberation. This approach allows me to estimate changes in the behavior of committee members as they listen other members advocating for policies under different speaking orders. Moreover, this approach provides, for any given committee composition, the optimal order of speech that maximizes the quality of information transmission.

Explaining the patterns of recommendations from deliberation is particularly important in policy-making institutions where voting records and implemented policies are not informative of the underlying heterogeneity in members’ behavior. This is the case of the FOMC,
where the policy proposal that is put to a vote reflects the policy recommendations that members provide at the deliberation stage. The results of the empirical model using deliberation records of FOMC meetings change the common characterization of this committee in terms of ideological differences and, instead, emphasize the role of information acquisition as a key determinant of members’ heterogeneity. Second, it quantifies the value of deliberation in terms of the information it provides to committee members vis-à-vis their own private information. Third, it accounts for the observed pattern of behavior better than alternative explanations.

The empirical results presented in this chapter, by quantifying social learning effects from sequential deliberation, should inform future research on the relevance of learning as an information-transmission mechanism behind real-world deliberation. This empirical model can be used to explain the behavior of members in other deliberative policy-making bodies such as legislative committees, courts, and international organizations, where members are asked to speak in order to the issue in turn.

This analysis can be extended in several directions. One avenue of further research would be to incorporate reputational concerns into the current framework of sequential deliberation, where individuals would care not only about matching their actions to the state of the world, but also about being considered well informed. With this additional dimension I would be able to incorporate a dynamic component to the deliberation process and incorporate additional counterfactual exercises related to changes in the publicity of debate and transparency of information that have drawn attention in both theoretical and empirical literature (Meade and Stasavage 2008; Ottaviani and Sorensen 2001, Visser and Swank 2007), but that have not focused on the learning mechanism embedded in the deliberation process.
Appendix A

Biases in FOMC Forecasts

A.1 Estimation of the Robust Variance-Covariance Matrix

The elements of $\Omega$ are estimated using the OLS residuals of equation (2.3), $\hat{\epsilon}_{t,h,i}$, by subtracting means and averaging through time (Isiklar, Lahiri and Loungani 2006). All other covariances $E[\epsilon_{t,h,i}\epsilon_{t,m,j}]$ are assumed to be zero under the null of honest forecasting. In particular:

i) The error variance for each FOMC member $i$, $\sigma_i^2$ is estimated as

$$\sigma_i^2 = \frac{1}{TH} \sum_{h \in \{5,10,17\}} \sum_{t=1992}^{2005} \hat{\epsilon}_{t,h,i}^2.$$

ii) The covariances across members $i$ and $j$, $\gamma_{ij}$, are given by

$$\gamma_{ij} = \frac{1}{TH} \sum_{h \in \{5,10,17\}} \sum_{t=1992}^{2005} \hat{\epsilon}_{t,h,i}\hat{\epsilon}_{t,h,j}, \forall \ i \neq j.$$
iii) The contemporaneous covariances for consecutive years for each member $i$ when $h = 5$ (i.e., at the July meetings), $\omega_i$, are given by

$$\omega_i = \frac{1}{11} \sum_{t=1992}^{2005} \hat{\epsilon}_{t,5,i} \hat{\epsilon}_{t,17,i}. $$

iv) The contemporaneous covariances for consecutive years across members $i$ and $j$ when $h \in \{5, 17\}$ (i.e., at the July meetings), $s_{ij}$, are given by

$$s_{ij} = \frac{1}{11} \sum_{t=1992}^{2005} \hat{\epsilon}_{t,5,i} \hat{\epsilon}_{t,17,j} + \hat{\epsilon}_{t,5,j} \hat{\epsilon}_{t,17,i}, \forall \ i \neq j. $$

Given $\hat{\Omega}$, the covariance matrix of $\theta = (\alpha, \beta_0, \beta_1, \beta_2)$ can be written as

$$\hat{\text{Var}}(\hat{\theta}) = (X^T X)^{-1} X^T \hat{\Omega} X (X^T X)^{-1},$$

(A.1)

where $X = (1, \text{gap}_{t,h}, e_{t-j,h}, (f_{t,h} - f_{t,0}))$ is stacked by member $i$.

The standard errors corresponding to the elements of $\hat{\theta}$ are obtained by taking the square roots of the elements of the main diagonal of $\hat{\text{Var}}(\hat{\theta})$. Under the null hypothesis, usual $t$ and Wald statistics asymptotically follow a normal and $\chi^2$ distribution, respectively.

### A.2 Additional Tables

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**Dependent variable:**

<table>
<thead>
<tr>
<th></th>
<th>Inflation</th>
<th>GDP Growth</th>
<th>Unemployment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Output Gap (Actual - Potential)</td>
<td>−0.681***</td>
<td>0.644**</td>
<td>−0.200**</td>
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<td>(0.095)</td>
<td>(0.283)</td>
<td>(0.085)</td>
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<td>Inflation Forecast (Staff)</td>
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<td>−1.166***</td>
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<td>(0.354)</td>
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<td>Output Growth Forecast (Staff)</td>
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<td>−1.630***</td>
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<td>(0.133)</td>
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<td>Lagged Error</td>
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<td>(0.256)</td>
<td>(0.244)</td>
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<td>Mean Private Forecast</td>
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<td>(0.252)</td>
<td>(0.242)</td>
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<td>3.166***</td>
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<tr>
<td></td>
<td>(0.979)</td>
<td>(3.149)</td>
<td>(0.824)</td>
</tr>
</tbody>
</table>

\[ H_0 : \beta_0 = \ldots = \beta_5 = 0 \]

\[ (p\text{-value}) \]

\[ H_0 : \beta_1 = 1 \]

\[ (p\text{-value}) \]

| FOMC Members | 37 | 37 | 37 |
| Meetings     | 38 | 38 | 38 |
| Observations | 583| 583| 583|
| Adjusted R\textsuperscript{2} | 0.669 | 0.277 | 0.331 |

*\textsuperscript{p}<0.1; **\textsuperscript{p}<0.05; ***\textsuperscript{p}<0.01

Note: Heteroskedastic standard errors for serial and spatial correlation in parenthesis.

**Table A.1: Honest Forecasting for FOMC members under MSE.** The estimated equation is:
\[ \epsilon_{t+h,t,i} = \beta_0 + \beta_1(f_{t+h,t,i}^{C} - f_{t+h,t,i}) + \beta_2 gap_t + \beta_3 inf_{t}^{GB} + \beta_4 output_{t}^{GB} + \beta_5 \epsilon_{t-j,h,i} + \epsilon_{t+h,i}. \]

\( f^C \) denotes the cross-section mean forecast of the private sector Consensus Forecast survey. \( gap_t \) denotes the estimate of the output gap (i.e., actual output growth - potential output growth) collected from the Greenbook. \( inf_{t}^{GB} \) denotes the current-year Greenbook inflation forecast. \( output_{t}^{GB} \) denotes the current-year Greenbook real GDP growth forecast. Pooled OLS estimates with confidence intervals calculated using standard errors consistent with heteroskedasticity, serial, and spatial correlation.
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<th>GDP Growth</th>
<th>Unemployment</th>
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<td>(0.147)</td>
<td>(0.174)</td>
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FOMC Members
Meetings
Observations
Adjusted R²

Note: *p<0.1; **p<0.05; ***p<0.01
Note: GMM standard errors in parentheses

Table A.2: Relationship Between Forecast Biases and Career Experience
### Table A.3: Relative Weight of FOMC Members’ Forecasts on Voiced Policy Preferences

<table>
<thead>
<tr>
<th>Dependent variable:</th>
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</tr>
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<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
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<tr>
<td>Federal Funds Rate</td>
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<td>0.860***</td>
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<td></td>
<td>(0.026)</td>
<td>(0.029)</td>
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<tr>
<td>Inflation (CF)</td>
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<td>-0.048</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.038)</td>
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<tr>
<td>Output Growth (CF)</td>
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<tr>
<td></td>
<td>(0.024)</td>
<td>(0.027)</td>
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<tr>
<td>Unemployment (CF)</td>
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<td>-0.131**</td>
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<tr>
<td></td>
<td>(0.052)</td>
<td>(0.061)</td>
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<tr>
<td>Output Gap (GB)</td>
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<td>0.021</td>
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<tr>
<td></td>
<td>(0.013)</td>
<td>(0.019)</td>
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<tr>
<td>Output Growth (GB)</td>
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<td>0.028</td>
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<tr>
<td></td>
<td>(0.032)</td>
<td>(0.035)</td>
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<tr>
<td>Unemployment (GB)</td>
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<td>-0.365***</td>
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<td>(0.081)</td>
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<tr>
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<td>17</td>
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</tbody>
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*p<0.1; **p<0.05; ***p<0.01
Note: Standard errors clustered at the member level in parentheses
Appendix B

The Case of FOMC Transcripts

B.1 Regional Unemployment and Topic Proportions
Figure B.1: **Effect of Regional Unemployment on Regional Economy Topics** The top row shows the top words associated to each topic, with the size of each word being more highly associated to each topic. The bottom row displays the linear relationship between topic proportion and regional unemployment gap. Other variables included in the model are held at their sample median. Results are presented with 95% confidence intervals. Confidence intervals are calculated with the method of composition that accounts for the uncertainty in the dependent variable.
Figure B.2: Effect of Regional Unemployment on Economic Growth Topics The top row shows the top words associated to each topic, with the size of each word being more highly associated to each topic. The bottom row displays the linear relationship between topic proportion and regional unemployment gap. Other variables included in the model are held at their sample median. Results are presented with 95% confidence intervals. Confidence intervals are calculated with the method of composition that accounts for the uncertainty in the dependent variable.
Figure B.3: Effect of Regional Unemployment on Inflation Topics The top row shows the top words associated to each topic, with the size of each word being more highly associated to each topic. The bottom row displays the linear relationship between topic proportion and regional unemployment gap. Other variables included in the model are held at their sample median. Results are presented with 95% confidence intervals. Confidence intervals are calculated with the method of composition that accounts for the uncertainty in the dependent variable.
Figure B.4: **Procedural Discussion Topic.** The figure shows a word cloud taking the 70 words with highest probability of being drawn from the topic. The size of each word in the cloud is proportional to the probability conditional that the word comes from that particular topic.
Appendix C

Appendix for FOMC Policy Recommendations

C.1 Spatial Ideological Model

Under the spatial model, committee members are perfectly informed about the characteristics of the alternatives under consideration and have Euclidean preferences that can be represented in a one-dimensional space by points on the real line. Each committee member has an ideal point or preferred outcome $z_i \in \mathbb{R}$ and, for any two available policy rates in meeting $t$, $d_0^t = 0$ and $d_1^t = 1$, she prefers $d_1^t = 1$ if and only if $d_1^t = 1$ is closer to $z_i$ than $d_0^t = 0$. Conditional on this behavioral assumption, one only needs the ideal policy of committee members and the ideological location of the policy choice under consideration to confidently predict the observed pattern of policy recommendations across members and meetings.

I estimate the spatial model following a standard operationalization in the literature that assumes committee members have quadratic utility functions over the policy space with an additive idiosyncratic shock, $U(d) = -(z_i - r)^2 + \eta_i r$ (Clinton, Jackman and Rivers [2004]). Given this functional form, a committee member recommends the high policy rate, $r_{it} = 1$. 
whenever $U(1) > U(0)$ and recommends the lower rate, $r_{it} = 0$, otherwise. Assuming that the errors $\eta_{i0}$ and $\eta_{i1}$ are jointly normal, with $\eta_{i1} - \eta_{i0} \sim N(0, \tau_i^2)$, we can write $Pr(r_{it} = 1) = Pr(U(1) > U(0)) = \Phi(\lambda_t [z_i - \kappa_t])$, where $\lambda_t \equiv \frac{r_1^t - r_0^t}{\tau_t}$ and $\kappa_t \equiv \frac{r_1^t + r_0^t}{2}$.

I estimate the structural parameters of interest, $z_i$, $\kappa_t$, and $\lambda_t$, for $i = 1 \ldots, 57$ and $t = 1, \ldots, 265$, by fitting a Bayesian version of a multilevel ideal point model (Bafumi et al. [2005]). In particular I assume $z_i \sim N(0, 1)$, $\kappa_t \sim N(X_t \beta_{ideol}', \sigma^2_{\kappa})$, $\lambda_t \sim LN(0, \sigma^2_{\lambda})$, $\sigma^2_{\kappa}$, $\sigma^2_{\lambda} \sim Cauchy(0, 1)$ for $i = 1, \ldots, 57$, and $t = 1, \ldots, 265$.

![Determinants of the Policy Midpoint at each meeting \( \kappa_t \)](image)

Figure C.1: **Determinants of the Midpoint parameter \((\beta_t)\) (Ideological Model).** This figure provides the effect of increasing each of the displayed covariates on the midpoint $\beta_t$. Solid circles give the posterior median, with horizontal solid lines corresponding to the interquartile range of the posterior distribution and dashed lines corresponding to 95% posterior credible intervals. The counterfactual increase in the covariate of interest is a change from the 10th to the 90th percentile in the sample. For each estimate, all other covariates are set at their median sample values.

Notice that all the model parameters are globally identified, as we are constraining the ideal points $(z_i)$ to have mean zero and standard deviation one. In addition, I solve for the reflection invariance problem that plagues ideal point models by constraining the average gap parameter $\lambda_t$ to be positive, which is a reasonable assumption for the FOMC decision-making process, because it is clear that a positive recommendation corresponds to higher interest
Figure C.2: Ideal Point Estimates. The left panel of the figure provides posterior summaries of the ideal points recovered from the spatial ideological model for each FOMC committee member, $z_i$, during the periods 1970-1979 and 1987-2008. Solid circles give the posterior median, with horizontal lines corresponding to the interquartile range of the posterior distribution. Committee members who participated in more than 30 meetings are included. The right panel figure provides posterior summaries of the ideal points of FOMC committee members, $z_i$, aggregated by appointment, where a member is either a president of a regional Federal Reserve Bank or a member of the Board of Governors.

Finally notice that the midpoint of the policy location $\kappa_t$ is a function of covariates, as in the case of the estimation of the prior $\rho_t$ in the sequential deliberation model. Therefore, the number of parameter estimates of the spatial ideological model

I approximated the posterior distribution of the parameters of interest,

$$\{z_i\}_{i=1}^{57}, \{\kappa_t, \lambda_t\}_{t=1}^{265}, \sigma^2_\kappa, \sigma^2_\lambda,$$

with an application of Markov Chain Monte Carlo (MCMC) via the Hamiltonian Monte Carlo method as in Homan and Gelman [2014]. I obtained posterior samples of the parameters from their posterior marginal density at each iteration $m = 1, \ldots, M$. I ran three parallel chains with dispersed initial values for 10,000 iterations with an initial warm-up period of 5,000 iterations. I assessed convergence for each parameter based on the potential scale reduction factor, $\hat{R}$ (Gelman and Rubin [1992]).
C.2 Simultaneous Model

The main difference of the *simultaneous model* with respect to the *sequential deliberation model* comes in the optimal cutoff $s^*_t$, which in the latter case does not consider the value of sequential deliberation:

$$s^*(\pi_t, \sigma_t, \rho_t) \equiv \frac{1}{2} + \sigma_t^2 \left[ \log \left( \frac{1 - \pi_t}{\pi_t} \right) + \log \left( \frac{1 - \rho_t}{\rho_t} \right) \right]. \quad (C.1)$$

I estimate the model following the same algorithm as in the case of the *sequential deliberation model*.

Figure C.3: **Determinants and Evolution of the Prior ($\rho_t$) on the unobserved state of inflation $\omega_t = 1$ at each meeting $t$ (Simultaneous Model).** The left panel of the figure provides the effect of increasing each of the displayed covariates on the common prior $\rho_t \equiv Pr(\omega_t = 1)$. Solid circles give the posterior median, with horizontal solid lines corresponding to the interquartile range of the posterior distribution and dashed lines corresponding to 95% posterior credible intervals. The counterfactual increase in the covariate of interest is a change from the 10th to the 90th percentile in the sample. For each estimate, all other covariates are set at their median sample values. The right panel of the figure provides the estimated value of the common prior $\rho_t \equiv Pr(\omega_t = 1)$ across meetings. Solid circles give the posterior median, with horizontal solid lines corresponding to the interquartile range of the posterior distribution. Gray areas correspond to economic recessions in the sample measured as the period from peak to through of a business cycle according to the National Bureau of Economic Research.

As the equilibrium behavior of committee members in the *simultaneous model* is driven by common information, ideological biases, and private signals, assessing the value that the
latter have in members’ pattern of recommendations, would imply isolating its contribution from that of the rest of the parameters. For this purpose, Iaryczower and Shum [2012] quantified a measure of the value of private information by computing the probability that member $i$ gives a different policy recommendation from the one she would have given in a counterfactual scenario, had she only weighted the common prior against her signal. This “FLEX” score for member $i$ at meeting $t$ can be written as

$$FLEX_{it} = \begin{cases} 
\rho_t(1 - \gamma_{it,1}) + (1 - \rho_t)(1 - \gamma_{it,0}) & \text{if } \rho_t > 1 - \pi_i \\
\rho_t \gamma_{it,1} + (1 - \rho_t) \gamma_{it,0} & \text{if } \rho_t \leq 1 - \pi_i 
\end{cases}$$

I compute the posterior median distribution of $FLEX$ scores for each member and meeting of the FOMC, and present a summary of the results in Figure C.6.

In terms of the variation across members, the left panel of Figure C.6 shows that, on average, FOMC members have tended to follow their initial leanings when giving a policy recommendation, motivated solely by their preference biases and the common prior they observe. This is the result of estimating an average “FLEX” across FOMC members around 0.3, which implies that an FOMC member would have reverted his recommendation 30% of the time due to the information contained in their private information. Nonetheless, the dispersion on the value of information across members is sizable. On the one hand, we can see district president Francis, an extreme “hawk” ($\pi_i = 0.8$) with a very low ability ($\sigma_i = 1.2$), who obtains almost no value out of his private signal ($FLEX_i = 0.02$). On the other hand, district president McTeer, who is estimated as the second most “dovish” member in the committee ($\pi_i = 0.15$), with a medium level of expertise ($\sigma_i = 0.40$), has a median “FLEX” score of 0.58, which implies that the probability of giving a different recommendation than the one he would have given in the absence of private information is about 58%.

In the right panel of Figure C.6, I track the evolution of the median “FLEX” score over time for the period under study. From this plot, we can see one of the main substantive findings that come out of the quality of information model regarding behavior within the
FOMC, namely, that at least since the Volcker Revolution from 1979, the FOMC has become increasingly more responsive to their information and at the same time, has placed less emphasis on their ideological leanings.

The evolution of the decision-making towards a more informative process has been substantial, as it can be assessed from a comparison of “FLEX” scores during the Burns and Miller years with respect to last available information under Bernanke as chairman. On average, the value of information more than doubled in almost 30 years of monetary policy making from a “FLEX” score from around 0.2 to around 0.45.
Figure C.4: Ideological Estimates, $\pi_i$ for the Simultaneous Model. The left panel of the figure provides posterior summaries of the ideological bias, $\pi_i$, for each FOMC committee during the periods 1970-1979 and 1987-2008. Solid circles give the posterior median, with horizontal lines corresponding to the interquartile range of the posterior distribution. Committee members who participated in more than 30 meetings are included. The middle panel of the figure provides the result of a linear fit along with 90% confidence intervals between ideological biases $\pi_i$, as recovered by the Simultaneous Model and ideal points, $z_i$, as recovered by the Spatial model. The right panel of the figure provides posterior summaries of the ideal points of FOMC committee members, $z_i$, aggregated by appointment, where a member is either a president of a regional Federal Reserve Bank or a member of the Board of Governors.
Figure C.5: Expertise Estimates (Simultaneous Model). The left panel of the figure provides posterior summaries of the measure of expertise of FOMC committee members, $\sigma_i$. Solid circles give the posterior median, with horizontal lines corresponding to the interquartile range of the posterior distribution. Committee members who participated in more than 30 meetings are included. The right panel of the figure provides the results of a linear fit, along with 90% confidence intervals between ideological biases $\pi_i$ and individual expertise, $\sigma_i$, as recovered by the simultaneous model.

Figure C.6: FOMC’s FLEX Scores for the Simultaneous Model. The left panel of the figure provides posterior summaries of the median FLEX Score by FOMC Member. The dashed line represents the mean value across FOMC members. The right panel of the figure plots the smoothed (by 2nd degree local polynomial) time trend of the median FOMC by year. The shaded area corresponds to the posterior interquartile range.
C.3 Implied vs Exact Pivotality Effects

The exact pivotality effect for the last speaker is given in equation 4.4 in the main text, whereas the exact pivotality effect for the next-to-the-last speaker the pivotality effect is given by equation C.2 and depicted in Figure C.7.

\[
P_{t}[PIV_{j}^{i} | \omega_{t}] = \Phi \left( \frac{s_{it}^{*} (r_{jt} = 1) - \omega_{t}}{\sigma_{i}} \right) \left[ \Phi \left( \frac{s_{Ct}^{*} (1, 1) - \omega_{t}}{\sigma_{C}} \right) - \Phi \left( \frac{s_{Ct}^{*} (1, 0) - \omega_{t}}{\sigma_{C}} \right) \right] \\
+ \Phi \left( \frac{s_{it}^{*} (r_{jt} = 0) - \omega_{t}}{\sigma_{i}} \right) \left[ \Phi \left( \frac{s_{Ct}^{*} (0, 0) - \omega_{t}}{\sigma_{C}} \right) - \Phi \left( \frac{s_{Ct}^{*} (0, 1) - \omega_{t}}{\sigma_{C}} \right) \right] \\
+ \Phi \left( \frac{s_{Ct}^{*} (0, 1) - \omega_{t}}{\sigma_{C}} \right) - \Phi \left( \frac{s_{Ct}^{*} (1, 1) - \omega_{t}}{\sigma_{C}} \right). \tag{C.2} \]

Figure C.7: Pivotal Event for the Next-to-the-Last Member in the Speaking Order.
Figure C.8: **Determinants of Pivotality Effects**. This figure provides the effect of increasing each of the displayed covariates on the Pivotality Effect. Solid circles give the posterior median, with horizontal solid lines corresponding to the interquartile range of the posterior distribution and dashed lines corresponding to 95% posterior credible intervals. The counterfactual increase in the covariate of interest is a change from the 10th to the 90th percentile in the sample. For each estimate, all other covariates are set at their median sample values. The pivotality effect is estimated in the model as

$$\log\left(\frac{\Pr[\text{PIV}_i | \omega_t = 0]}{\Pr[\text{PIV}_i | \omega_t = 1]}\right) = \alpha_0 + \alpha_1 \text{Early}_it + \alpha_2 \text{Late}_it + \mathbf{X}_{it}'\mathbf{\beta}.$$ 

The matrix $\mathbf{X}_{it}$ of member-meeting level predictors includes member $i$’s experience in the form of an indicator variable ($\text{Experience}$), that takes the value of one if member $i$ has served in less than 34 meetings and zero otherwise. Here 34 meeting represents the 25th percentile of term length in the sample and allows me to classify members as experienced ($\text{Rookie} = 0$) and inexperienced ($\text{Rookie} = 1$). I include the fraction of remaining speakers after member $i$ who are inexperienced ($\% \text{ Rookie}$), the fraction of remaining speakers who are Federal Reserve presidents ($\% \text{ Presidents}$), the fraction of remaining speakers who are Democrat-appointed governors ($\% \text{ Democrat Appointment}$). For the remaining speakers after member $i$ at meeting $t$ I also include the average fraction of their past career (i.e., before the FOMC) in private financial institutions ($\% \text{ Financial Experience}$), as economists ($\% \text{ Economics Experience}$), within the ranks of the Federal Reserve ($\% \text{ Central Bank Experience}$). Finally, this specification include random effects for the order of speech of member $i$ ($\alpha_0$ and $\alpha_1$) where $\text{Early}$ ($\text{Late}$) takes the value of one (zero) if member $i$ speaks in the first (second) half of the policy go-around and zero otherwise.
Next-to-Last Speaker

Last Speaker

Figure C.9: Implied vs Exact Pivotality Effects for Last and Next-to-Last Speakers. The left panel of the figure provides the distributions across committee members of the relative weight of pivotality for the next-to-last speaker calculated both as a function of covariates (blue line) and computed exactly from the posterior update of the Chairman (red line). The right panel shows the results of the same exercise for the last speaker.
C.4 Goodness-of-Fit with Leave-One-Out Cross Validation

Figure C.10: **Fit Measures Across Models with LOO Cross Validation.** The Figure presents goodness-of-fit statistics for the *sequential deliberation* and *simultaneous* models. We estimate Bayesian versions of the percentage of Error (Error), the Excess Error Rate (Excess Error) and the expected proportion of correctly predicted recommendations (EPC), averaged by both committee member and meeting.

C.5 MCMC Statistics

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Figure C.11: **Trace Plots of Determinants of ρ_t.** The figure shows the post-burn traceplots for three chains of 10,000 iterations each with a burn-in of 5,000 iterations and a thinning of 100 iterations.

Figure C.12: **Trace Plots of Determinants of log \( \frac{Pr[PIV_t^2|\omega_t=0]}{Pr[PIV_t^2|\omega_t=1]} \).** The figure shows the post-burn traceplots for three chains of 10,000 iterations each with a burn-in of 5,000 iterations and a thinning of 100 iterations.

Figure C.13: **Trace Plots of Hyperparameters.** The figure shows the post-burn traceplots for three chains of 10,000 iterations each with a burn-in of 5,000 iterations and a thinning of 100 iterations.
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URL: http://mc-stan.org/


