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

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Abstract

Almost every public policy decision is preceded by a process of deliberation, where policymakers exchange information and advocate for a particular outcome. Yet, beyond scarce evidence on the relevance of communication coming from field and laboratory experiments, few studies have analyzed the role played by sequential deliberation in policy-relevant decision-making bodies. To fill this gap, I estimate a model of policymaking that incorporates social learning via deliberation. In the model, committee members with different ideologies and expertise speak in sequence, allowing them to weight their own information against recommendations made by others. The empirical application uses records from Federal Open Market Committee (FOMC) meetings. I find the process of deliberation changes members’ policy recommendations in significant ways. Most notably, the information learned during sequential deliberation oftentimes dominates private information. Incorporating sequential learning explains the pattern of observed policy recommendations extremely well and improves the fit over characterizations that focus on ideological divisions and differences in members’ expertise.

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1 Introduction

In almost all relevant decision-making bodies (such as courts, juries, legislative committees, governmental agencies, corporate board of directors, academic committees, 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 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 come 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]), have private values (Meirowitz [2006]; Meirowitz [2007]), and/or care about their reputation (Ottaviani and Sorensen [2001]). 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 protocols of conversation 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 (Barabas [2004]; Dickson, Hafer and Landa [2008]; Dickson, Hafer and Landa [2015]; Fujiwara and Wantchekon [2013]; Goeree and Yariv [2011]; Karpowitz and Mendelberg [2011]; Karpowitz and Mendelberg [2014]; Humphreys, Masters and Sandbu [2006]; Wantchekon [2012]) 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 a policy-relevant body such as U.S. 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. However, 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 paper, I overcome these limitations by introducing the effect of social learning into an empirical model of committee policy-making that accounts for members’ ideological biases and differences in the quality of private information (Iaryczower and Shum [2012]). In the model, members are privately informed about the true state of the world and speak openly in front of the rest of the committee about their desired policy. The deliberation protocol is sequential, a feature that captures the nature of debate associated with most deliberative committees (Van Weelden [2008]). In this way, by the time their turn to speak arises, members have already learned the content of the statements made by previous speakers and incorporate this information using Bayes’ rule. (Banerjee [1992]; Bikhchandani, Hirshleifer and Welch [1992]; Smith and Sørensen [2000]). Therefore, this process of sequential learning captures how members’ private information interacts with information obtained via deliberation to form a post deliberative belief about the true state of the world.

I structurally estimate the model with a novel Bayesian approach that directly recovers members’ preference and expertise parameters, while incorporating the informational value of deliberation contained in the statements of early speakers. This approach allows me to quantify the effects of learning from sequential deliberation on the behavior of committee members, which would not be possible with reduced-form methods, given the non-experimental nature of the data.

I estimate the model using data from deliberation records of the Federal Open Market Committee (FOMC), 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, by regulating the economy and affecting households’ and firms’ expectations, the decisions that the FOMC implements have important policy implications. Second, a significant part of FOMC meetings follows a sequential deliberation process, where members voice their opinions in a fixed order of speech. I exploit this feature to disentangle the contribution of individual members throughout the policy debate. Third, historical FOMC deliberation
transcripts are publicly available, allowing me to extract the actual communication protocols among members including their speaking position and policy recommendations. Fourth, real-time data, in the form of staff forecasts and economic indicators, which FOMC members observed while deliberating monetary policy is also publicly available.

A fundamental question to assess the relevance of deliberation is to what extent allowing participants to talk with one another results in decisions that pool the information and expertise of committee members. To answer this question, I develop a test to assess whether FOMC members reported their information truthfully. I exploit the information contained in individual economic forecasts that members submit for discussion at FOMC meetings before the sequential deliberation process takes place. The results from this test provide evidence of three related findings that account for the heterogeneity observed in members’ 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, I find that compared to common information, these biased forecasts are the most important predictor of members’ policy recommendations. Overall, I reject the notion that the FOMC is a homogenous body of experts where information is efficiently aggregated.

Having found that information in FOMC individual forecasts is not truthfully reported, I then show there is still a substantial amount of information transmitted through the sequential deliberation of policy recommendations. The results from the structural estimation suggest substantial effects of deliberation as an information-sharing mechanism that were omitted in previous empirical literature. First, with the structural 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. For instance, under the observed sequential deliberation process, policy outcomes are significantly different from those that would be obtained if policy recommendations were made simultaneously. Third, for any given committee composition, I quantify the effect of modifying the order of speech on the quality of decision-making via counterfactual simulations and provide the optimal speaking order that maximizes the quality of implemented policies.

I compare the predictions and performance of the 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
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.

The rest of the paper is organized as follows. Section 2 describes the data and relevant institutional characteristics of the FOMC for the empirical analysis. Section 3 shows evidence that FOMC members do not report information truthfully before the sequential deliberation process. Section 4 develops and estimates the sequential deliberation model and performs counterfactual exercises. Section 5 compares the performance of the sequential deliberation model against alternative behavioral models using a variety of goodness-of-fit measures. Section 6 discusses some implications of strategic behavior for FOMC recommendations. Finally, section 7 presents concluding remarks.

2 Data and FOMC’s Institutional Background

Monetary policy decisions in the U.S. are the sole responsibility of the FOMC, which meets around eight times a year to set the short-term rate for open market operations. The FOMC consists of seven members of the Board of Governors and the twelve presidents of district Reserve Banks. All board members along with five of the twelve
district presidents have voting rights at any given meeting. 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.

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. The latter are chosen to serve five-years renewable terms by their board of directors, which represent diverse interest groups.

FOMC meetings throughout the period under study followed a standard protocol with four main stages. First, the staff offered an outline of economic conditions and forecasts. After the staff’s presentations, individual members discussed their own impressions of the state of the economy, emphasizing first, regional conditions and then, the national and international economic situation. The discussion of economic conditions was usually followed by the policy go-around. At this stage, the staff presented possible policy alternatives and their consequences to inform the committee as it proceeded to select a policy directive. Then, individual members verbally expressed their preferred policy position sequentially, with an order that varied across meetings. Finally, the chairman crafted a directive that was brought to a formal vote by majority rule.

In principle, given the structure of FOMC meetings, we can analyze the information contained in economic forecasts, policy recommendations and voting records for each FOMC member. In practice, FOMC voting records are not very informative to explain members’ behavior, mainly because dissenting votes are extremely rare in the policymaking history of the FOMC, as can be observed in Figure 1. The light blue bars in this figure show the yearly evolution of the number of dissenting votes with respect

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1From 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.

2For 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.

3One of the seven governors is appointed chairman by the U.S. President for a four-year term subject to a Senate confirmation.

4The 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.

5The presentation on the current state of the economy prepared by the staff is contained in a report that members receive before each meeting labeled the “Green Book”, which contains data on the national economy, as well as the staff forecasts for the U.S. economy.

6The “Beige Book” contains a summary of the economic conditions pertaining each of the twelve districts as organized by district presidents.
Figure 1: History of Dissents at the FOMC. This figure presents the history of counts of yearly counts of dissent looking at both voting records (light blue), available for the period 1966-2008 and voiced preferences (dark blue), available for the period 1970-2008, with the exception of the Martin (1966-1970) and Volcker (1980-1986) chairmanships.

to the chairman’s policy proposal for the period 1966-2008, which covers five different chairmen. Under 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 coincides with the implemented policy rate at any given meeting.

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

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\[7\] In 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.
2000’s, focused precisely on these records, as this quote from Yohe [1966] summarizes:

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 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. Just by looking at the discrepancies in dissent between deliberation and voting stages, we 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. Thus, for the empirical analysis, I use two main variables extracted from FOMC records: the individual economic forecasts FOMC members submit for monetary policy meetings and individual policy recommendations, together with members’ speaking order.

2.1 Individual Policy Recommendations

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

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8These unedited textual records are publicly available at www.federalreserve.gov
extended this 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 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 and remained at this level throughout that year.9

I classified 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 by the board staff before the policy go-around takes place.10

I quantify a composite benchmark from these different alternatives by computing the median proposed policy offered by the staff. Then, based on the textual records of deliberations, I coded members as recommending a high policy rate \( (r_{it} = 1) \) whenever their desired Fed funds rate target was equal or higher than the staff median proposal and a low policy rate \( (r_{it} = 0) \), otherwise. In those instances in which desired rates were 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.

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 members of the FOMC for a total of 3,490 policy recommendations. Table 1 presents the distribution of policy recommendations, along with the average macroeconomic conditions during each of the regimes 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.

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9In 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.

10This data is contained in the Blue Book provided to members at any FOMC meeting.
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 1: Policy Recommendations by Chairmanship, 1970-2008

<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>3.62</td>
<td>6.32</td>
<td>5.79</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>4.58</td>
<td>5.93</td>
<td>5.87</td>
</tr>
<tr>
<td>Greensspan ('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>3.95</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>0.85</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>4.45</td>
</tr>
</tbody>
</table>

Note: Author’s calculations. Meet denotes the total number of meetings per period. Rec denotes the number of recommendations by period. Size refers to the median size of the committee for each period. Unan % is the percentage of unanimous recommendations by 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, respectively. M1 denotes average money growth around the date of FOMC meetings.

2.2 Individual Economic Projections

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 Philadelphia Fed. The data contains the forecasts of output growth, inflation, and unemployment provided by individual FOMC members for the period 1992-2003, that covers part of the Greenspan regime.

FOMC members submit these forecasts for the record before the meetings of January-February and July preceding the chairman’s semi-annual testimony to Congress. Members discussed and exchanged these expectations based on information available at the time these meetings took place, which includes staff projections reported in the Green Book, 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 32 committee members are available from the
Figure 2: Dispersion of Individual FOMC Inflation Forecasts. This figure presents for each January-February meeting the mean inflation forecasts for the current year (i.e., 10 months-ahead forecast) in black along with its cross-sectional distribution in grey. The figure shows in the actual value of inflation at the end of the year calculated from real-time data (source: Philadelphia Fed).

January meeting of 1992 to the July meeting of 2003.\textsuperscript{11}

Individual FOMC members provided their forecasts of inflation, output growth and unemployment for the end of the current and following years. Figure 2 presents, as an example, the distribution of current-year inflation forecasts made at the January-February meeting of each year over the period 1992-2003, when this data is available. The mean forecasts are indicated by the dashed black line, while each individual forecast is indicated in grey. The actual value of inflation is presented for each variable in the red solid line. This value is calculated using real-time data as observed by FOMC members roughly three months after its realization.

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 February meeting in 1994, when inflation at the end of the year was 2.6%. The mean forecast across members at that meeting was 2.98%. This mean forecast laid very close to the

\textsuperscript{11}As noted in Romer [2010], an important subtlety with this data, is that the FOMC chairman was not required to submit any projection, which prevents us from comparing members’ reports with those of the chairman (i.e., Alan Greenspan for this period).
actual outcome realized 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 ones submitted by district president Tom Melzer from the St. Louis Fed, who forecasted inflation as high as 4%, which was 34% larger that the committee consensus.

3 A Test of Truthful Reporting

Given the sizable dispersion in individual forecasts, a fundamental question to assess their quality is to what extent these forecasts reveal members’ private 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 [2000]; Goeree and Yariv [2011]). Hence, when committee members share the same objectives, accounting for variation in individual behavior is straightforward, as it can be rationalized by differences in the information observed by policy makers.

Yet, from an empirical standpoint, quantifying whether the observed dispersion in observed behavior comes from information dispersion, 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, I exploit the information contained in individual FOMC forecasts. These forecasts might be a function of, if not reflect, the expectations of FOMC members about the future state of the economy regarding inflation, output, and unemployment.

The quality of these individual forecasts to test for honest reporting of information comes from the fact that, during this 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 could 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]).

In the remainder of this section, I provide a test to assess whether FOMC members submitted economic forecasts that were consistent with truthful information-sharing.

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12 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.
The evidence from this exercise overwhelmingly suggests that FOMC members did not report publicly available information sincerely. Therefore, we are left in the need to delve more deeply into other potential explanations that reconcile the heterogeneity in members’ choices at the deliberation stage of the FOMC policy-making process.

3.1 Identification and Estimation

To identify whether members truthfully reported their available information or not, I test for departures from the benchmark case of honest forecasting, where 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 an informative private 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, or unemployment). Let \( q_{it} \sim N(y_t, \tau_i) \) denote this signal. Under MSE, the honest forecast, \( f_{it}^* \), solves

\[
    f_{it}^* \equiv \arg\min_{f_{it}} E[L(y_t - f_{it})|q_{it}],
\]

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.\(^{13}\)

An important implication of this benchmark case is that the dispersion we observe in FOMC forecasts in Figure 2 should be explained exclusively from differences in members’ information \( q_{it} \). This is because members, under this benchmark, share the same symmetric loss function.

Let us 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

\[
    E[E[e_{it}^*|q_{it}]|q_{it}] = E[e_{it}^*|q_{it}] = 0
\]

Using a sample counterpart of the above moment condition, I can empirically validate whether FOMC members adhered to truthful reporting of information in their

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\(^{13}\)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 \( f_{it}^* = E[y_t|q_{it}] = \frac{\tau_i}{\pi^2 + \nu} q_{it} + \frac{\nu}{\pi^2 + \nu} \mu \). Although this specification is 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 \( \mu \).
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 predictions. Thus, the empirical test should include variables that we can be certain, were part of FOMC members’ information set at the time they reported their economic projections. For this reason, I extracted relevant information from FOMC meetings that were available to FOMC members before each meeting took place. In particular, I included the board staff’s estimate of the output gap (\( \text{gap}_t \)), defined as the difference between actual output growth and the output growth that is consistent with full employment. This variable, reported in the *Greenbook*, 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.

In addition, I included members’ past forecast errors (\( e_{i,t-1} \)), defined as members’ most recent available error, given published information on the realized outcomes. This variable was surely known by FOMC members by the time they submitted new predictions, and I use it to assess whether FOMC members learned from their previous mistakes.

Finally, I included the cross-sectional average of a sample of private sector forecasts (\( f^*_{ct} \)) obtained from *Consensus Economics*, which is a private firm that polls professional forecasters regarding their expectations on relevant macroeconomic variables.\(^{14}\) This measure represents a proxy of market expectations regarding the same variables that FOMC members predict. These forecasts were collected at least two weeks in advance of FOMC meetings and as such, can be considered as available information by the time deliberations took place.

As suggested by Capistran [2008], I implement a single regression to evaluate FOMC members’ predictions that has the forecast error as its dependent variable:

\[
e_{it} = \alpha + \beta_0 \text{gap}_t + \beta_1 e_{i,t-1} + \beta_2 (f^*_c - f_{i,t}) + \epsilon_{it}.
\]  

\(^{14}\)The information of the survey can be found at www.consensus economics.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 (3). Thus, the null hypothesis can be expressed as \( H_0 : \alpha = \beta_0 = \beta_1 = 0 \). The parameter \( \beta_2 \) in this equation can be interpreted as the relative weight assigned to \( f_t^c \) under honest forecasting, that is, if one would want to forecast \( y_t \) as accurately as possible.\(^{15}\)

Point estimates for the coefficients of equation (3) can be computed consistently through pooled OLS. 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: i) different error variance across FOMC members (i.e., within homoskedasticity and between heteroskedasticity), ii) correlation of contemporaneous shocks across members, iii) contemporaneous shocks for consecutive years for each member and iv) across members. The procedure to provide uncertainty estimates with the characteristics just mentioned can be found in appendix A.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Inflation (1)</th>
<th>Output (2)</th>
<th>Unemployment (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bias(( \alpha ))</td>
<td>-0.254**</td>
<td>0.414*</td>
<td>-0.125</td>
</tr>
<tr>
<td></td>
<td>(0.119)</td>
<td>(0.250)</td>
<td>(0.093)</td>
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<tr>
<td>Output Gap (( \beta_0 ))</td>
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<tr>
<td></td>
<td>(0.050)</td>
<td>(0.055)</td>
<td>(0.055)</td>
</tr>
<tr>
<td>Lagged Error (( \beta_1 ))</td>
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<td>0.188</td>
<td>0.564**</td>
</tr>
<tr>
<td></td>
<td>(0.224)</td>
<td>(0.246)</td>
<td>(0.263)</td>
</tr>
<tr>
<td>Private Forecast (( \beta_2 ))</td>
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<td>0.098</td>
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</tr>
<tr>
<td></td>
<td>(0.199)</td>
<td>(0.293)</td>
<td>(0.287)</td>
</tr>
</tbody>
</table>

\( H_0 : \alpha = \beta_0 = \beta_1 = 0 \)  
(p-value) 2.934 2.32 2.50

\( H_0 : \beta_2 = 1 \)  
(p-value) 0.087 0.127 0.113

Observations 499 499 499
Members 32 32 32

Table 2: Honest Forecasting Test. The estimated equation is: \( e_{it} = \alpha + \beta_0 \text{gap}_t + \beta_1 e_{i,t-1} + \beta_2(f_t^c - f_{i,t}) + \epsilon_{it} \). Pooled OLS estimates with confidence intervals calculated using standard errors consistent with heteroskedasticity, serial, and spatial correlation.

---

\(^{15}\)To see this, ignore for the moment \( \beta_0 \) and \( \beta_1 \) and notice that \( e_{it} = y_t - f_{it} = \alpha + \beta_2(f_t^c - f_{i,t}) + \epsilon_{it} \) is equivalent to estimating \( y_t = \alpha + \beta_2 f_t^c + (1 - \beta_2)f_{i,t} + \epsilon_{it} \).
3.2 Results

The results of testing the null hypothesis of honest forecasting on FOMC individual forecasts of inflation, output growth, and unemployment are presented in Table 2. Looking at the pooled behavior of FOMC members, we can reject the null hypothesis of honest forecasting for inflation, and for individual components of this hypothesis for output growth, and unemployment. In the case of inflation, FOMC forecasts were systematically biased, significantly over-estimating the true value of inflation around 0.25%. In addition, FOMC forecasts failed to efficiently incorporate information contained in private sector predictions, $f^c_t$. In fact, 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. In the case of output growth, FOMC members were biased in their predictions, but in the opposite direction of inflation, with an under-estimation of 0.41% with respect to the actual outcome. For unemployment, FOMC members did not efficiently incorporate relevant and available public information that could have improved the accuracy of their forecasts. In particular, unemployment forecasts were inefficient in the use of information contained in their own past forecast errors ($e_{i,t-1}$). This evidence points to the fact that FOMC members, on average, were sluggish in revising their unemployment forecasts as new information arrived. Additionally, they did not incorporate useful information contained in the output gap ($gap_t$). For instance, as inflationary pressures escalated due to increases in the output gap, FOMC members kept over-predicting unemployment with respect to its realized value.\footnote{Beyond the results for the pooled sample presented above, I found considerable heterogeneity in the distribution of forecast biases across members. In the case of inflation, 58% of all FOMC members significantly biased their forecasts, over-estimating the actual outcome. For output growth, 48% of FOMC members under-estimated the realized outcome, whereas 29% of all FOMC members over-estimated unemployment.}

One important caveat regarding the interpretation of the results presented above is that honest forecasting involves a joint hypothesis of MSE loss and efficient use of available information. Thus, rejection of the null hypothesis could be driven by the violations of any of those 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 institutional appointment process at the FOMC to show that the biased nature of these forecasts cannot be explained from random mistakes across members, and indeed, it is systematically related to members’ individual characteristics, such as their appointment process.

In the case of district presidents, who come from regional Federal Reserve Banks, I test whether the local economic conditions they face are correlated with their forecast errors. For this purpose, I construct a measure of the gap between regional and national
Figure 3: Regional Unemployment and Forecast Biases of District Presidents. This 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 and black ticks represent the observed distribution in the gap between regional and national unemployment.
unemployment.\footnote{For the empirical specification, I include a separate dummy variable for Reagan-appointees, following Havrilesky and Gildea [1992] and Chappell, Havrilesky and McGregor [1993] who found that appointees during the Reagan presidency differed notably from the rest of Republican-appointees in that, in practice they were strong advocates of looser monetary policy during the 1980’s, closer to the behavior of Democrat-appointees in other periods.} For the predictions of board governors, who are appointed by the executive, I test whether their errors react differentially to inflationary pressures, as measured using fluctuations in the output gap ($gap_t$), according to the party label of the President who appointed them.\footnote{The regional unemployment rate is calculated as a population-weighted mean of unemployment data at the county level for each specific Bank geographic region. The regional unemployment figure at each meeting is a moving average of the unemployment in the last three months.}

The results of testing for regional bias in FOMC predictions are presented in Figure 3, 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 president under-predicts inflation and output growth in 0.2% and 0.4%, respectively, while over-predicting unemployment in approximately 0.4%.

Second, Figure 4 presents the effect of the output gap ($gap_t$) on forecast biases by partisanship. Overall, when inflationary pressures increase, as signaled by increments in the output gap, a typical Republican-appointee significantly reports a more pessimistic forecast of inflation and a more optimistic forecast for unemployment than her Democrat-appointee counterpart. For output growth forecasts the results are subtler, with Reagan-appointees significantly over-estimating growth, but with no systematic differences between the rest of Republican-appointees and their Democrat-appointed counterparts.

The evidence presented thus far allows us to confidently reject the hypothesis that FOMC members are truthfully sharing the information contained in the forecasts they submit at FOMC meetings, which are discussed in the deliberation process and serve as input for the policy recommendations FOMC members voice during the policy go-around. Appendix B shows evidence that, compared to available common information provided by the board staff in the form of economic indicators and forecasts, these biased forecasts are the most significant predictor of individual policy recommendations at the policy go-around. These differences in policy recommendations ultimately map
Figure 4: Executive Appointment and Forecast Biases of Board Governors. This figure shows the average forecast biases of Republican, Reagan, and Democrat-appointed Governors for inflation, output growth and unemployment with 90% confidence intervals.

into the actual policy directive that the chairman puts on the table, which historically has won a majority of votes at every FOMC meeting. This policy directive reflects
indeed a summary measure of these voiced opinions. In fact, as shown also in Appendix B, it is the case that the policy directive cannot be distinguished from either the median or the mean policy recommendations across FOMC members.

4 Explaining Policy Recommendations in the FOMC

In spite of members reporting biased information contained in their individual forecasts, in this section I show there is ample opportunity for information transmission through the sequential deliberation on policy. I propose the sequential deliberation model to explain the heterogeneity in individual policy recommendations and assess the extent of social learning. The model extends the framework of Iaryczower and Shum [2012], who 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]). On the one hand, the ideological biases can be interpreted as the different views of committee members regarding the tradeoff between inflation and unemployment. On the other hand, the quality of private information captures the expertise of committee members to gauge inflationary pressures. Moreover, the presence of private information captures privileged access to relevant data that oftentimes members have while deliberating monetary policy. This can be the result of their interaction with contacts from the private sector, regional interests groups, and early access to certain economic indicators. Additionally, the heterogeneity in the quality of information is consistent with differences in resources regarding each committee member’s staff and the forecasts they produce.

Conditional on differences in 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 arises because members, after listening to early speakers, weight the information contained in previous recommendations against their own according to Bayes rule. The sequential learning of Bayes-rational individuals was first introduced by Banerjee [1992], Bikhchandani, Hirshleifer and Welch [1992], 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 Bayesian-updating in a “reduced-form” framework. The main limitations of their study, which prevents them to find any evidence of learning from deliberation, is that they assume members have the same quality of information, so that the value of previous recommendations is assumed away in their exercise. 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, the FOMC meeting of March 1994 under Greenspan as chairman. At this meeting, Philadelphia district president Ed Boehne was the first FOMC to speak and stated a recommendation in favor of tightening the policy rate 50 basis points, which was 25 basis point 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 Broadus 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, the empirical model is able to assess whether Broaddus’ recommendation would have been different in 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 world, the sequential deliberation model is able to attribute this effect to learning and not to the quality of Broaddus’ private information, giving a more precise assessment of his ability as policymaker.

¹⁹For a literature review see Bikhchandani, Hirshleifer and Welch [1998].
4.1 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 implements a decision $d_t \in \{0, 1\}$, where 0 represents the lower of two possible rate changes and 1 the higher. In the context of the FOMC, $d_t$ can be think 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.\footnote{A model that takes into account the presence of dissents in the voting stage would be relevant to explain monetary policy in a dynamic setting, where dissents may have an effect on future actions of fellow members, as in Riboni and Ruge-Murcia [2014].}

Member $i$’s preferences over her own recommendation ($r_{it}$) depends on a binary state of the economy, $\omega_t \in \{0, 1\}$, that encompass unknown inflationary pressures, where $\omega_t = 1$ represents the high inflation state (consistent with a high interest rate) and $\omega = 0$ is the low inflation state (consistent with a low interest rate).

With full information, members want their recommendation to match the state, $r_{it} = \omega_t$. This behavioral assumption is sincere in the sense that FOMC members do not account for how their recommendation will influence subsequent speakers and the chairman’s policy directive. I address the potential for strategic behavior in section 6, where I show that strategic considerations do not seem to play a significant role in explaining the observed behavior of FOMC members.

The payoffs of $r_{it} = \omega_t = 0$ and $r_{it} = \omega_t = 1$ are normalized to zero. However, members disagree on the costs of implementing the incorrect decision (i.e., mismatching the state). Member $i$ suffers a cost $\pi_i \in (0, 1)$ when she recommends a low rate in a high inflation state ($r_{it} = 0$ when $\omega_t = 1$) and of $1 - \pi_i$ when she incorrectly recommends the high rate in a low inflation state ($r_{it} = 1$ 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 vote for the higher rate. Thus, $\pi_i > \frac{1}{2}$ reflects her bias towards the higher policy rate (i.e., member $i$ is “hawk”), while $\pi_i < \frac{1}{2}$ reflects a bias towards the lower policy rate (i.e., member $i$ is a “dove”).

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

1. The inflation state $\omega_t$ is realized but unobserved to committee members. In addition, the sequential order of speech is exogenously given. 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 $i$ form beliefs on $\omega_t$ by relying on three sources of information. First, there is public available information captured in members’ common prior beliefs, $\rho_t \equiv Pr[\omega_t = 1]$. Second, member $i$ observes an informative private signal $s_{it} | \omega_t \sim N(\omega_t, \sigma_i^2)$. 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 denote member $i$’s expertise (i.e., lower $\sigma_i$ denotes higher expertise). 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 $\omega_t$.

3. With this information at hand, the strategy for member $i$ is defined by a map $\gamma_{it} : \mathbb{R} \times \{0,1\}^{(n(i)-1)} \rightarrow (0,1)$, where $\gamma(s_{it}, x_{n(i),t}) \equiv Pr[r_{it} = 1 | s_{it}, x_{n(i),t}]$. I assume that each member speaks exactly once, and her recommendation is immediately heard by the chairman and all other members.

4. The 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 $x_{Ct} = (r_{1t}, \ldots, r_{Nt})$ and chooses the policy directive $d_t$. Therefore, his strategy is a map $\gamma_{Ct} : \mathbb{R} \times \{0,1\}^N \rightarrow (0,1)$.

Note that by the normality assumption on $s_{it}$, the likelihood ratio

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

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

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

$$= \frac{1}{1 + \left(\frac{1-\rho_t}{\rho_t}\right)L(s_{it})^{-1} \prod_{j=1}^{n(i)-1} \Psi(s^d_{jt})} \geq 1 - \pi_i;$$
Manipulating the normal density, \( r_{it} = 1 \) whenever

\[
s_{it} \geq \frac{1}{2} + \sigma_i^2 \left[ \log \left( \frac{1 - \pi_i}{\pi_i} \right) + \log \left( \frac{1 - \rho_t}{\rho_t} \right) + \sum_{j=1}^{n(i)_t - 1} \log \left( \Psi(x_{jt}) \right) \right] \equiv s^*(\pi_i, \sigma_i, x_{it}, \rho_t).
\]

(5)

where

\[
\Psi(x_{jt}) \equiv \left[ \frac{\gamma_{jt,0}(s_{jt}^*)}{\gamma_{jt,1}(s_{jt}^*)} \right]^{r_{jt}} \left[ \frac{1 - \gamma_{jt,0}(s_{jt}^*)}{1 - \gamma_{jt,1}(s_{jt}^*)} \right]^{1-r_{jt}},
\]

(6)

and \( s_{jt}^* \) denote the value of \( s_{jt} \) such that \( s_{jt} = s^*(\tilde{\pi}_j, \sigma_j, x_{jt}, \rho_t) \)

The equilibrium probability of \( r_{it} = 1 \) in state \( \omega_t \) can be written as

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

(7)

Notice how the signal cutoff, \( s_{it}^* \), varies across both members and meetings. First, movements over time in the cutoff are captured by changes in the common prior \( (\rho_t) \) and by changes in the history of policy recommendations. Also, differences in cutoffs across FOMC members can be explained by members’ heterogeneity in both preferences, \( \pi_i \), and expertise, \( \sigma_i \).

Since behavior in this model is completely characterized by the signal cutoff, \( s_{it}^* \), 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

\[
Pr[r_t] = \sum_\omega \rho_t^{\omega_t} (1 - \rho_t)^{1-\omega_t} \prod_{i=1}^{N+1} \gamma_{it,\omega_t}(s_{it}^*)^{r_{it}} [1 - \gamma_{it,\omega_t}(s_{it}^*)]^{1-r_{it}}.
\]

(8)

The likelihood in equation (8), as a function of equilibrium cutoffs, implicitly accounts for the history of previous recommendations in the sequential deliberation process given in equation (6). To better understand the role of this relevant parameter, consider the case where, for a given meeting \( t \), member \( i \) is the second to speak \( (n(i)_t = 2) \), right after member \( j \) \( (n(j)_t = 1) \). In this scenario, the influence of member \( j \) on the equilibrium cutoff \( s_{it}^* \) can be written as

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

For instance, suppose that member \( j \) recommends a high policy rate (i.e., \( r_{jt} = 2 \))
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., $\log(\gamma_{jt,0}) - \log(\gamma_{jt,1})$). In the case where member $j$’s probability of matching the state is as likely as incorrectly recommending a high rate when the true state of the economy is $\omega_t = 0$, 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 ($r_{jt} = 1$), his probability of correctly matching the high state is larger than the probability of incorrectly recommending $r_{jt} = 1$ when $\omega_t = 0$ (i.e., $\log(\gamma_{jt,0}) - \log(\gamma_{jt,1}) < 0$). This additional information embedded in the recommendation of member $j$, will reduce member $i$’s equilibrium cutoff in equation (5), making him more prone to follow member $j$’s recommendation (i.e., $r_{it} = 1$).

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 5, which shows the effect of varying the expertise of member $j$ on member $i$’s optimal cutoff, $s_{it}^*$ and probabilities, $\gamma_{it,0}$ and $\gamma_{it,1}$. Notice that, as $s_{jt}$ becomes more informative, the probability that members’incorrectly matching both inflation states diminishes, which makes his 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 5 shows that this effect is higher when the recommendation of $j$ 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.

### 4.2 Estimation and Identification

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

As I focus on expressive behavior, where FOMC members care about matching

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21Notice also, that the value of information of member $j$’s recommendation can also work in the other direction. That is, 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 $r_{it} = 0$. 

---
Effect of $\sigma_j$

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Effect of $\pi_j$

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<td>Dove</td>
<td>0.3</td>
</tr>
<tr>
<td>Hawk</td>
<td>0.8</td>
</tr>
<tr>
<td>0.2</td>
<td>0.5</td>
</tr>
<tr>
<td>0.6</td>
<td>0.2</td>
</tr>
<tr>
<td>0.7</td>
<td>0.7</td>
</tr>
</tbody>
</table>

Figure 5: Hypothetical Effect of Member $j$ Recommending $r_{jt} = 1$ on Member $i$’s Behavior. This figure presents the effect of varying the expertise and ideological bias of a committee member $j$ who speak right before member $i$, on her equilibrium cutoff and probability of following $j$’s recommendation. The changes in both expertise and bias come from the actual parameters’ distribution across members in the data.

their own recommendations to the state of the economy, I can directly recover both preferences and expertise parameters from the likelihood function in equation (8). 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 in both states of the world, controlling for individual and time-varying covariates. Then, they recover the structural parameters by solving for the equilibrium conditions of the voting game in both expressive and strategic cases.

One benefit from the “direct” approach 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 committee members and policy meetings. Finally, it allows me to estimate parameter uncertainty directly, 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) via the Hamiltonian Monte Carlo method (Homan and Gelman [2014]). This technique includes ancillary parameters that allow the algorithm to move farther 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, is the computation of the equilibrium condition, and the subsequent construction of the likelihood ("the inner loop"), and second is 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 the value of deliberation included in the term \(\sum_{j=1}^{n(i)_t-1} \log (\Psi(x_{jt}))\), and update the optimal cutoff accordingly.

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 (5).
2. Given \(s_{it}^{*}\), compute \(\gamma_{it,0}(s_{it}^{*})\) and \(\gamma_{it,1}(s_{it}^{*})\) using equation (7).
3. Compute \(\sum_{j=1}^{n(i)_t-1} \log (\Psi(x_{jt}))\) using equation (6).
4. Compute the increment of the likelihood at every time period \(t\) from equation (8).

Approximation of the Joint Posterior Distribution (Outer Loop): Given the likelihood function in equation (8), we can write the posterior distribution of the vector of parameters \((\theta)\) as a proportion of the product of the likelihood and its prior distribution

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

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

\[\text{Equation (8)}\]

\[\text{Approximation of the Joint Posterior Distribution is implemented in the software STAN developed (Team [2015]).}\]
where I have aggregated the increments to the likelihood over FOMC meetings and $\lambda$ denotes the vector of hyperparameters of the model.

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

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

where $\delta$ is a fixed coefficient that is normally distributed. The value imposed on the variance is consistent with an uninformative prior for $\rho_t \approx \frac{1}{2}$. $X_\kappa$ 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, $\mathbb{E}$(Inflation), unemployment, $\mathbb{E}$(Unemployment), and GDP growth, $\mathbb{E}$(RGDP Growth). In addition, to fully control for changes in the composition of the FOMC over time and for the different agenda-setting power across chairmen, I include as a covariate the identity of the FOMC chairman at the time of the meeting (Burns, Miller, Greenspan, or Bernanke). These chairman effects are important because one main difference in the deliberation protocol across FOMC regimes involves the intervention of the chairman in the policy go-around. Burns and Miller sometimes spoke early, stating a preference for a particular policy rate. Greenspan routinely spoke right after the staff, suggesting a specific proposal. Bernanke, on the other hand, usually did not state a preference in 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 structural parameters and their respective hyperparameters, I use the following distributional assumptions based on the natural scale of each parameter:

$$
\pi_i \sim Beta(\alpha, \beta), \text{ for } i = 1, \ldots, 57.
$$

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

$$
\alpha, \beta \sim U(0, 10),
$$

$$
\tau_\sigma \sim Cauchy(0, 2).
$$

3. I obtained posterior samples of the vector of parameters from its 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 iter-
Figure 6: Speaking Order over Time for Six Members. This figure shows, for each member, the speaking order in which they provided their policy recommendations.

I assessed convergence for each parameter based on the potential scale reduction factor, $\hat{R}$ (Gelman and Rubin [1992]).

Having laid out the estimation procedure, the intuition for identification of the model is as follows. In the case of the common prior, $\rho_t$, the identification comes from the presence of a common value in the empirical model. In particular, the prior is identified from the frequency in which the majority of FOMC members recommend the high rate. This comes from the fact that high values of the common prior 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.

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 again from the “common val-
Figure 7: Speaking Order Across FOMC Members. This figure shows the mean speaking order for each FOMC member across meetings, along with 90% confidence intervals. Points denote the distribution of speaking ranks for each FOMC member across meetings. Darker colors denote higher relative frequency of each speaking rank.

The identification for the effect of the sequence of recommendation histories given by equation (6) hinges on the variation across meetings in the speaking order. To see this issue, consider the equilibrium cutoff in equation (5) in the extreme case where the speaking order is constant across meetings. In this scenario, the entire variation in the history of recommendations $X_t$ would be driven by the variation in the common prior ($\rho_t$) which would make jointly identification of $\rho_t$ and $\Psi(x_{jt})$ infeasible. In addition, it would not allow me to disentangle the effect from the order of speech from that of the individual biases and expertise of committee members. Fortunately for the empirical
Figure 8: Observable Covariates on Order of Speech. The figure provides the change in speaking position when a covariate move from the minimum to maximum in the sample given the estimated coefficients from an OLS regression. Thick and thin solid lines denote 90% and 95% confidence intervals, respectively.

identification, FOMC speaking order varied substantially across members and meetings in a way that is not correlated with observable characteristics of FOMC member. In this way, we are able to observe FOMC members sharing her policy recommendation in different speaking orders along their tenure. According to anecdotal evidence, there was no prescribed order to speak in the policy go-around before each meeting. 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 or his ideal place on the list, but the secretary would accommodate all FOMC members at his discretion. Then, the chairman would call upon the FOMC in the order of that list (Meyer [1998]).

Figure 6 shows, as an example, the variation in speaking order of six FOMC members over time. The first column of this figure 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 this small variation comes from the fact that, historically, the New York district president has served as the FOMC vicechairman and as such, traditionally has been granted the right to speak first in the sequence. Still, even for these members, we can find meetings where they spoke late in the policy go-around, which serve to separately identify the effect of the speaking order from the effect of indi-
Figure 9: Determinants of the Prior ($\rho_t$) at each Meeting. The figure provides the effect of increasing each of the covariates on the prior $\rho_t \equiv Pr(\omega_t = 1)$. Solid circles give the posterior median, with horizontal lines corresponding to the interquartile range of the posterior distribution. The counterfactual increase in the covariate of interest is a change from its minimum to its maximum value in the sample. For each estimate, all other covariates are set at their mean sample values.

Individual characteristics on subsequent speakers, as given in equation (6). The other four plots in the figure show FOMC members speaking at different position across meetings with no systematic pattern, which is also the case for the rest of FOMC members. To see this, Figure 7 plots the mean speaking order of each FOMC member in the sample,
along with the distribution of speaking ranks along their tenure. 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 the meetings in any particular speaking order (with a 6% standard deviation). Most importantly is that the variation in the order of speech is not related to individual characteristics and observable choices of committee members and therefore, not manipulated by committee members. To assess the validity of this claim, Figure X plot the change in speaking position as a function of observable covariates that include member characteristics, meeting characteristics and choices of members that vary across meetings captured in the forecasts that members submitted for discussion in the available period of 1992-2003. Indeed, the results show no statistically significant coefficients at even the 10% level.

A more formal identification argument related to the estimation of the likelihood function from equation (8) is to notice that, conditional on the unobserved state $\omega_t$, the observed vector of recommendations, $r_t$, follows a finite mixture distribution with mixing distribution 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 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.

4.3 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 $\omega_t$. The left panel of Figure 9 displays the expected prior estimated from equation 9, under hypothetical values of the explanatory variables. In particular, these counterfactual scenarios are constructed by changing each covariate from its minimum to its maximum value in the sample, while keeping the rest of explanators at their mean values. The main point of interest from these results is to notice that the economic indicators

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23 We use an ordinary least squares regression (OLS). The dependent variable is the order of speech and the independent variables are Appointment that takes a value of one if a member is a board governor and zero, otherwise. Previous Policy, which is the prevailing policy rate at previous meeting. Money growth, which is a three-month moving average of M1 money growth. Staff Median Policy, which is the median policy alternative proposed by the staff before the policy go-around. Unemployment (Staff) and Inflation (Staff) are the staff forecasts of inflation and unemployment. Unemployment (Member), Inflation (Member), Real Growth (Member), and Nominal Growth (Member) are individual member forecasts.

24 Visual inspection of the traceplots for each parameter of interest shows no evidence of label-switching, which is a common in other Bayesian mixture models.
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 example, increments in expected output growth, $E(RGDP \text{ Growth})$, increases in the money supply, $M1$, as well as higher levels of the prevailing policy rate, $Previous Policy$, are all associated with larger inflationary pressures and with predicted increments of the common prior $\rho_t$. Also, increments in expected unemployment, $E(\text{Unemployment})$, are perceived by FOMC members as diminishing inflationary pressures, while increasing the negative risks for economic growth. Another important result is that, conditional on the level of other explanators, the positive effect of increments in staff inflation forecasts, $E(\text{Inflation})$, do not exert a statistical significant effect on the predicted common prior ($\rho_t$). However, this null effect is a consequence of including both the growth of money and the lagged policy in the same specification, both of which are highly correlated with the evolution of inflation expectations, particularly during the Burns and Miller regimes in the 1970’s.\footnote{Excluding money growth from the empirical model renders expected inflation statistically significant. The results are available upon request.}

The center panel of Figure 9 plots the chairman fixed effects on the common prior $\rho_t$. Consistent with historical accounts of the FOMC and its chairmen (Meltzer [2010]; Woodward [2001]), the significant coefficient of the Greenspan dummy is consistent with the large influence he exerted on the rest of the FOMC during his mandate, mainly through his informal agenda-setting powers. For instance, Greenspan was known for stating his policy preference and building a strong case in favor of it before the policy go-around took place. 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. The lower panel of Figure 9 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 follows the actual tradeoff between inflation and output remarkably close. For instance, the estimated $\rho_t$ decreases in periods with deteriorating output and unemployment, and increases following economic expansions and higher inflation risks. In fact, the gray shades in the lower panel of Figure 9 shows that sustained declines in the estimated common prior ($\rho_t$) are very closely associated with the presence and duration of all four economic recessions that hit the U.S. economy in the period 1970-2008, as measured by the National Bureau of Economic Research (NBER). In addition, the common prior closely follows fluctuations in output growth, as captured by monthly changes in industrial production.

The left panel of Figure 10 summarizes the findings related to the estimates of pref-
Figure 10: Ideological Biases, $\pi_{i}$. 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 right 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 sequential deliberation model and ideal points, $z_{i}$, as recovered by the spatial ideological model. The figure provides the ranking of preference biases across members. 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 0.17 for Dallas district president Robert McTeer to 0.73 for Darryl Francis, district president of the St. Louis Fed during the Burns period. The recovered ideological biases seem to show a high degree of polarization, with 65% of the committee showing ideological biases that are statistically different from 0.5, which captures ideologically neutral members. In fact, the right panel of Figure 10 shows that the ideological placement of FOMC members in the sequential deliberation model is extremely similar to the rank order and the ideological distribution that can be obtained from estimating a spatial ideological model to the pattern of policy recom-
Figure 11: Ideological Bias Estimates by Committee Characteristics. The figure provides posterior summaries of the ideological bias of FOMC committee members, $\pi_i$, aggregated by appointment (left panel) and party of the executive that appointed the board governors (right panel). 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 10% of the meetings are included.

Figure 12: Correlation between Forecast Biases and Estimated Ideal Points from Voiced Recommendations (Greenspan Era). The figure provides the results of a linear fit, along with 90% confidence intervals between ideological biases $\pi_i$ and individual and forecast biases for inflation, output growth and unemployment calculated as realized value minus forecasted value ($y_{it} - f_{it}$).
This ideological characterization fits well the profile of FOMC members on both extremes of the distribution. For instance, on the “hawkish” side, the spatial model places Tom Melzer, another president of the St. Louis Fed during the 1990’s, who has been recognized by the popular press as one of the “hawkish” members in the history of the FOMC. In fact, at almost every speech he gave as district president 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 placed 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 preference 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 left panel of Figure 11. The figure provides posterior summaries of the ideal points of FOMC members aggregated by appointment, that is between board governors and district presidents (left panel) and party of the executive that appointed the board governor, splitting the sample between Democrat and Republican-appointees (right panel).

I find that board governors, who are appointed by the U.S. President, are 18% more “dovish” than district presidents, who are appointed by regional board of directors comprised of different banking and industry interests. These results confirm previous studies on the FOMC that have explained this finding in terms of the political pressure through appointment that U.S. presidents exert 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. Although the differences through appointment between presidents and governors within the FOMC are robust, the right panel of Figure 11 shows that preference differences across members are not significant.

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I estimate a Bayesian version of a multilevel IRT model on policy recommendations. The details of the estimation can be found in appendix C.
when I split the sample of board governors by partisan appointment.

Having placed FOMC members according to their ideological biases, I assess whether these preference differences are able to explain the heterogeneity in the biases of FOMC members, as quantified in the previous section. For this purpose, I correlate the ideological biases of each FOMC member during the Greenspan period for which we have individual forecasts, with their mean forecast biases for inflation, output and unemployment. I present the results of this exercise in Figure 12. We can see that a purely ideological account of members’ differences is unable to explain the observed deviations from truthful behavior in FOMC forecasts. The fit between ideological biases and individual forecast biases is indistinguishable from zero at conventional levels.

The above evidence suggests that 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 one considers two important features of monetary policy deliberation. First, is the notion that...

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**Figure 13: Expertise Estimates by Committee Characteristics.** The figure provides posterior summaries of the measure of expertise of FOMC committee members, $\sigma_i$, at the individual level (left panel) and by appointment (right panel). 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.
Figure 14: Correlation between Ideological Bias, $\pi_i$ and Expertise, $\sigma_i$. 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 \textit{sequential deliberation model}.

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, is 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 variation in FOMC members’ expertise in gauging the state of the economy is depicted in Figure 13. Here, we can see a sizable amount of heterogeneity across FOMC members, with an interquartile range that goes from a signal quality ($\sigma_i$) of 0.68 for Chairman Burns to 1.73 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 FOMC. 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 do not correlate with their expertise, as can be seen in Figure 14. The evidence from this figure clearly points out the null relationship between ideology and expertise in the particular case of the FOMC. This is an empirical result coming from the observed behavior of FOMC members in the data, as the structural model does not impose any
covariance structure between members’ preferences and their information.

When we 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 the right panel of Figure 13. However, all of the chairmen in the sample, 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 FOMC chairman and as such, his expertise to track the evolution of economic conditions is crucial in determining the quality of the policy implemented. To quantify this last implication, consider estimating the probability that chairmen Greenspan and Burns give a correct policy directive when they follow their private information. In the notation of the model, this means computing $\gamma_{it,1}$, when $\omega_t = 1$ and $1 - \gamma_{it,0}$, when $\omega_t = 0$. For this exercise, assume that both chairmen observe a common prior $\rho_t = 0.5$. In the case of Alan Greenspan, given his individual level parameters, $\pi_i = 0.38$ and $\sigma_i = 0.99$, we have $s_{it}^* = 0.99$. Greenspan’s signal precision, along with his ideology leads to a probability of correctly predicting both high and low inflation states of $\gamma_{it,1} = 0.501$ and $1 - \gamma_{it,0} = 0.842$, with a total probability of correctly predicting the true state of the world of $(0.5 \times 0.501) + (0.5 \times 0.842) = 0.67$.

In the case of chairman Burns, who has a similar ideological bias ($\pi_i = 0.37$) than Greenspan’s but with a higher ability ($\sigma_i = 0.68$) imply a lower cutoff of $s_{it}^* = 0.75$, which leads him to predict better both low and high inflation states with $1 - \gamma_{it,0} = 0.86$ and $\gamma_{it,1} = 0.65$, and a higher probability of proposing the correct directive of $0.5 \times 0.86 + 0.5 \times 0.65 = 0.76$.

The above counterfactual exercises assume that chairmen Miller and Greenspan submit their policy directives in isolation, without taking into consideration the policy recommendations of FOMC members. To quantify the informational content of deliberation with respect to private information, Table 3 presents the effects of different recommendation histories on the FOMC chairman’s behavior. For ease of explanation, consider a small version of the FOMC that was in place in the early 2000’s with just three members: the chairman Alan Greenspan, the vicechairman William McDonough and a typical “hawk” member, such as Alfred Broaddus. Assume further that the common prior is $\rho_t = 0.5$. In the reference case, Greenspan proposes a directive $d_t$ based exclusively on the common prior and his private information as shown above. Given the estimates of his structural parameters, this translates into a total probability of incorrectly recommending the high rate of $Pr[r_{Ct} = 1] = 0.5 \times 0.158 + 0.5 \times 0.501 = 0.33$. Now, consider the case where there is a policy go-around with McDonough speaking first, followed by Broaddus, and finally Greenspan crafting the directive. The results

\[27\] The estimates employed for the counterfactual exercises correspond to the posterior median distribution of the parameters of interest.
from this exercise are summarized in Scenario 1 in Table 3, which shows the behaviors of Broaddus and Greenspan after incorporating their potential recommendation histories. Under this scenario, Broaddus and Greenspan can potentially listen to two and four different combinations of recommendations, respectively. For each of these different combinations, we can assess how Greenspan’s cutoff and recommendation probabilities would change given these recommendation histories.

For instance, faced with both McDonough and Broaddus recommending the low rate, Greenspan would update his information and act accordingly by increasing his cutoff to 2.3 and considerably reducing the probability of recommending a high rate from 0.33, in the baseline scenario, to 0.055. In contrast, faced with contradictory recommendations, Greenspan implicitly weights both biases and expertise of previous speakers. On the one hand, when a known expert like McDonough recommends the lower rate, and a biased member such as Broaddus the high rate, it does not significantly alter Greenspan’s behavior compared to the baseline scenario (i.e, \( Pr[r_{Ct} = 1] = 0.37 \)). This is because McDonough’s recommendation conforms to Greenspan’s own assessments and Broaddus’ “hawkish” bias is heavily discounted when recommending a high rate. On the other hand, when the contradictory advice comes from Broaddus recommending a low rate (i.e., a history \((0, 1)\)), this particular history carries a lot of information. This is because Greenspan infers that Broaddus must have been received a very low signal that overcame his “hawkish” bias and thus, adjusts accordingly by decreasing the probability of recommending a high rate to \( Pr[r_{Ct} = 1] = 0.12 \), which represents more than a twofold decrease from the case where Greenspan sets the policy directive in isolation.

In Scenario 2 of Table 3, we modify the composition of the committee by switching the expertise of vicechairman McDonough for that of Gerald Corrigan, who is a less able policy-maker, as estimated by the model \( (\sigma_i = 1.74) \), and had also served as vicechairman of the FOMC under Greenspan. The results of this exercise show that, Corrigan’s lower ability makes him less influential on changing Greenspan’s behavior compared to the advice given by McDonough, except where the recommendation history is \( X_t = (1, 0) \). This is because, in face of a lower expertise from Corrigan, Greenspan weights more heavily Broaddus’ recommendations, which go against his bias, reducing Greenspan’s probability of recommending the high rate to \( Pr[r_{Ct} = 1] = .11. \)

Finally in Scenario 3, we substitute McDonough’s ideological bias for that of a more “hawkish” member like president Tom Melzer \( (\pi_i = 0.57) \). In this case, faced with a “hawk” committee, Greenspan would heavily discount any histories with recommendations to increase the policy rate, and would weight more those histories where the “hawk” committee recommends a lower rate.

Overall, this counterfactual exercise shows there exists plausible scenarios where
members significantly change their behavior after incorporating previous recommendations compared to the scenario in which we assume they ignore other members and follow their own information. Moreover, assessing the expertise of committee members is drastically changed once we incorporate the value of sequential deliberation into members’ behavior. In particular, compared to a counterfactual scenario, where members give simultaneous recommendations ignoring the sequential deliberation process, there is a substantial decrease in the precision of members’ expertise estimates, from an average expertise around 0.46 to one around 1.3, which represents almost a threefold decrease in members’ private expertise.28 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 15, which compares the expertise estimates under learning from deliberation (i.e. sequential deliberation model and without learning (i.e., simultaneous model. The reason behind these discrepancies arises from the relevance of deliberation as an information-sharing mechanism. The simultaneous model assumes that FOMC members provide their policy statements and reveal their private information without observing the information submitted by others. Hence, it interprets any potential value of information contained in the history of recommendations of early speakers as a better quality of private information. By explicitly accounting for the presence of information complementarities through sequential deliberation, the role of private information in the quality of members’ recommendations is attenuated and more importantly, is disentangled from the social learning embedded in the deliberation process.

In any given policy go-around, the FOMC chairman, after listening to the policy recommendations of individual members, arrives at a policy directive that is officially voted by majority rule. As this directive obtained at least a majority of votes at every meeting in the period under study, I compute a measure of the quality of decision-making by focusing on the chairman’s policy directive. As a measure of quality, I compute the probability that the chairman proposes a policy directive that is consistent with the true state of the economy. Then, I can assess how this quality changes when the speaking order of FOMC members is modified via counterfactual simulations. In particular, I look at the quality of the chairman’s policy directive given any counterfactual order of speech he might face. As before, the total probability that the chairman proposes a correct policy directive can be expressed as $\rho_t \gamma_{Ct,1}(s^*_t) + (1 - \rho_t)(1 - \gamma_{Ct,0}(s^*_t))$. This measure can be computed under any committee composition and history of recommendations observed by the chairman, $x_{Ct} = (r_{1t}, \ldots, r_{Nt})$. As an example, consider the committee composition at the meeting of March 1970, where 9 FOMC members and the chairman participated in the policy go-around. For that committee composition

28 The details and estimation of the model without deliberation can be found in Appendix D.
and estimated common prior, I computed the probability of correct policy directives for any of the $9! = 362880$ possible speaking orders and ranked them according to the quality of the chairman’s policy directive. The results of this counterfactual exercise are presented in Figure 16. As can be seen, the speaking order has a significant impact on the quality of decision-making. In particular, the probability that the directive is consistent with the state of the economy goes from 0.57 to 0.77 from the least to the most favorable order of speech. This corresponds to an effect of 35% on the quality of the policy directive. In addition, we can compare the quality of the policy directive under the observed order in the data with respect to any potential counterfactual speaking ranking. For instance, the probability that the policy directive is consistent with the true state of the economy is 0.63 for the observed speaking order at the meeting held in March, 1970. This quality is significantly lower than the one that would have been obtained by ranking members according to their ideological biases ($\pi_i$) or their expertise ($\sigma_i$), which would have yielded a probability of correctly implementing the policy directive of around 0.73.

Figure 15: Expertise under the Sequential Deliberation and Simultaneous Models. The figure provides the distribution of the expertise ($\sigma_i$) estimates under the two different models.
Table 3: The Value of Deliberation for a Three-member FOMC. In Scenario 1, all the parameters are fixed at their median posterior distribution. In Scenario 2, $\sigma_1$ is increased to the value for president Corrigan ($\sigma_1 = 1.74$). In Scenario 3, $\pi_1$ is increased to the bias of president Melzer ($\pi_1 = 0.57$).

<table>
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<th>$X_t$</th>
<th>$s^*_{it}$</th>
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<th>$\gamma_{it,1}$</th>
<th>$s^o_{it}$</th>
<th>$\gamma_{it,0}$</th>
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<td>0.010</td>
<td>0.095</td>
<td>2.104</td>
<td>0.017</td>
<td>0.133</td>
<td>2.638</td>
<td>0.004</td>
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</tr>
<tr>
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<td>0.190</td>
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<td>0.833</td>
<td>0.107</td>
<td>0.457</td>
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</table>

Figure 16: Optimal Speaking Order. The figure shows, for any given order, the probability that the chairman proposes a policy directive consistent with the true state of the economy. The dashed black line denotes the median of the posterior distribution and the shaded region in blue denote the interquartile range. The highlighted orders in black dots are: Observed, which denotes the observed order at the meeting of March, 1970. Ideology, which ranks members according to their bias ($\pi_i$), from most to least biased. Expertise, which ranks members according to their expertise ($\sigma_i$), from most to least expert.
5 Model Fit Comparison

In the previous section I have shown that the sequential deliberation model provides a framework to disentangle the value of private information from social learning. In addition, I have found 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 \((\text{Error})\). The second indicator is the excess error rate \((\text{excess error})\) 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 \((\text{EPCP})\), which was proposed by Herron [1999] to alleviate the coarse classification rule in fitted probabilities of binary outcomes, which can over-estimate the true fit of the model.

The left panel of Figure 17 presents a summary of the posterior distribution of each of the three goodness-of-fit measures. The findings from this Figure show that 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 91% of the individual recommendations in the sample, compared to 75% for the simultaneous model and 85% for the spatial ideological model. Also, using the expected proportion of correctly

\[29\text{The estimation details of this model are given in Appendix C.}\]
\[30\text{Details and additional results of the estimation of this model can be found in Appendix D.}\]
predicted recommendations \((EPCP)\) as metric, we have that the \textit{sequential deliberation model} correctly predicts 81\% of recommendations, whereas the \textit{spatial ideological} and the \textit{simultaneous} models correctly predict 70\% and 63\% of recommendations, respectively.

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 11 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 is a graphical summary of the correctly classified recommendation rates against the incorrectly classified ones, for different cutoffs \(c\) for which \(r_{it} = 1\) if \(\hat{P}(r_{it} = 1) > c\). As can be seen in the right panel of Figure 17, 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

Figure 17: Fit Measures Across Models. The left panel of the figure present goodness-of-fit statistics for the \textit{sequential deliberation}, \textit{spatial ideological} and \textit{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. The right panel of the figure presents a model comparison based on ROC curves, where the 45-degree line corresponds to a random prediction model.
The comparison across models presented above focuses on in-sample fit, in which I have contrasted observed versus classified policy recommendations using the entire data to estimate models’ 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 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 simultaneous and sequential deliberation models. I implement this exercise 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 meeting \( t \) and member \( i \). To avoid computing an exact LOO, which would require re-fitting the model a total of 3,490 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 an out-of-sample predictive success rates of 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.

6 Discussion: Strategic Recommendations

The sequential deliberation model I proposed in the previous section abstracted from potential strategic behavior, in which FOMC members act as if their recommendations were pivotal for the policy directive. Empirically, strategic considerations have been analyzed using voting records and simultaneous voting under the simultaneous model (Hansen, McMahon and Velasco-Rivera [2014]; Iaryczower and Shum [2012]; Iaryczower and Katz [2015]). In these settings where there is a given voting rule, members can calculate their pivotality in a straightforward fashion by computing those instances in which their vote breaks a tie. In the case of FOMC deliberations, the information provided by strategic considerations is harder for members to incorporate into their behavior. The reason is that to compute their pivotality, members would need to assess how their recommendations would change the chairman’s optimal cutoff directly, as well
as indirectly through their influence on subsequent recommendations. For instance, given that the FOMC could have up to 19 members at any given meeting, a member in the first speaking position would need to compute her influence on the subsequent $2^{18} = 262144$ potential recommendations.

To consider the possibility of strategic behavior in FOMC recommendations, first I take an empirical perspective on the issue by testing an observable implication of pivotality, which is that the speaking order should matter in members’ optimal behavior beyond the informational value contained in previous recommendations. Thus, I compute a strategic version of the sequential deliberation model that accounts for a time-varying probability cutpoint, $\zeta_{it}$, where members propose a high rate, $r_{it} = 1$, whenever $Pr[\omega_t = 1|s_{it}, x_{n(i)_{it}}] \geq \zeta_{it}$. I estimate a flexible form for this cutpoint that depends on members’ individual biases ($\delta_i$), which capture preference differences, as well as on speaking order effects, which are meant to capture strategic behavior. I classify the 18 potential speaking positions that I observe in the data into three categories: Early Speaker, which is a dummy variable that takes the value of one if member $i$ speaks in position $n(i)_t = 1, \ldots, 6$ and zero, otherwise. Middle Speaker, which is a dummy variable that takes the value of one if member $i$ speaks in position $n(i)_t = 7, \ldots, 12$ and zero, otherwise. Late Speaker, which is a dummy variable that takes the value of one if member $i$ speaks in position $n(i)_t = 13, \ldots, 18$ and zero, otherwise. I choose the following functional form to constrain $\zeta_{it} \in [0,1]$:

$$
\zeta_{it}(\delta_i, p_t) \equiv \frac{\exp(\delta_i + \beta_{order} I_t)}{1 + \exp(\delta_i + \beta_{order} I_t)}; \quad \delta_i \sim N(0, \tau_\delta); \quad \tau_\delta \sim Cauchy(0, 2); \quad \beta_{order} \sim N(0, I)
$$

I estimate the model with the Bayesian “direct” approach introduced in the previous section. The results from this exercise are presented in Figure 18. This figure shows a summary of the posterior distribution of speaking order effects on the probability cutpoint, $\zeta_{it}$. The null effect of the speaking order on the optimal behavior of committee members is indicative that, at least in the case of the FOMC, order of speech considerations does not seem to affect members’ behavior beyond learning from previous recommendations.

To assure that these results are not driven by the specific functional form used to account for strategic considerations, I compute the exact value of the information contained in the pivotal event of FOMC members. For this exercise I focus on the last two members in the speaking order across FOMC meetings. First, looking at the behavior of last speakers is relevant because it is for them that the pivotal event is straightforward to compute, as they can only affect the chairman behavior directly. Thus, a member who is last in the speaking order can easily calculate and incorporate this event into her recommendations. Second, next-to-last speakers are relevant, as they allow
me to show how the pivotal event becomes more complicated to incorporate in members’ behavior, as they need to consider, not only how their recommendations might affect the chairman directly, but also indirectly through subsequent recommendations. Empirically, I compute the pivotal event across all last and next-to-last speakers in the sample and assess whether the informational value of this event in the data can be statistically differentiated from zero or not.

The pivotal event, $PIV_t^i$ for the last member at meeting $t$ (i.e., $n(i)_t = N$) is depicted in Figure 19. The solid line denotes the chairman’s signal space, $\mathbb{R}$. The pivotal event is depicted in the red region where $s_{it} \in [s_{Ct}^*(r_{it} = 1), s_{Ct}^*(r_{it} = 0)]$. In this region member $i$’s recommendation determines the chairman’s optimal cutoff.

The pivotal event can be incorporated into the information structure of the sequential deliberation model using Bayes’ rule as follows:

$$Pr[\omega_t = 1|s_{it}, x_{n(i),t}, PIV_t^i]$$
This information structure implies a cutoff rule, where member \( i \) recommends \( r_{it} = 1 \) whenever

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

(10)
where

$$\Pr[PIV_i^j|\omega_t] = \Phi\left(\frac{s_{Ct}^*(r_{it} = 0) - \omega_t}{\sigma_C}\right) - \Phi\left(\frac{s_{Ct}^*(r_{it} = 1) - \omega_t}{\sigma_C}\right).$$  \hspace{1cm} (11)$$

The effect of pivotality on the behavior of member $j$, who is the next-to-last member in the speaking order (i.e., $n(j)_t = N - 1$ and $n(i)_t = N$) is illustrated in Figure 20. In the lower panel we can see that member $j$ can influence the last speaker (member $i$) in the red region whenever $s_{it} \in [s_{it}^*(r_{jt} = 1), s_{it}^*(r_{jt} = 0)]$. In the top panel we can see that the effect of member $j$’s recommendation on the chairman’s behavior is subtler. First, in the red region where $s_{Ct} \in [s_{Ct}^*(r_{jt} = 1, r_{it} = 1), s_{Ct}^*(r_{jt} = 0, r_{it} = 0)]$, we have the pivotal event in which member $j$ influences the chairman through the behavior of the last speaker. However, even in the case in which member $j$ does not change the last speaker’s behavior, he could directly affect the chairman’s policy directive in the blue and green intervals of the chairman’s signal space. In particular, when the last speaker recommends the high rate, this is given by the blue interval where $s_{Ct} \in [s_{Ct}^*(r_{jt} = 1, r_{it} = 1), s_{Ct}^*(r_{jt} = 0, r_{it} = 1)]$, and when the last speaker recommends the low rate this is given in the green interval where $s_{Ct} \in [s_{Ct}^*(r_{jt} = 1, r_{it} = 0), s_{Ct}^*(r_{jt} = 0, r_{it} = 0)]$. Thus, the effect of the pivotal event for the next-to-last speaker in state $\omega_t$ is given by

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

$$+ \Phi\left(\frac{s_{it}^*(r_{jt} = 0) - \omega_t}{\sigma_i}\right) \left[\Phi\left(\frac{s_{Ct}^*(0, 1) - \omega_t}{\sigma_C}\right) - \Phi\left(\frac{s_{Ct}^*(0, 0) - \omega_t}{\sigma_C}\right)\right]$$

$$+ \Phi\left(\frac{s_{Ct}^*(0, 1) - \omega_t}{\sigma_C}\right) - \Phi\left(\frac{s_{Ct}^*(1, 1) - \omega_t}{\sigma_C}\right).$$

I compute the posterior distribution of the information contained in the last and next-to-last speakers’ pivotal event and compute $(1 - \alpha)$ credible intervals using the $\alpha/2$ and $(1 - \alpha)/2$ percentiles of the distribution, for any $\alpha \in (0, 1)$. The results from this exercise are given in Figure 21. The blue and red densities in this figure show the posterior distribution of the last and next-to-last speakers’ pivotal events, respectively. Overall, the information of the pivotal events for these late speakers is negligible and not statistically different from zero at even the 90% level, with median values of 0.11 and 0.05 for the last and next-to-last speakers, respectively. These results are supportive evidence that the recommendations of last speakers are consistent with expressive behavior, in which members care about matching their recommendations to the true state of the economy. Second, besides the null statistical effect of pivotality, the estimated magnitude of these effects are also substantively small to meaningfully affect members’ behavior. To put these estimates in perspective, consider that a very small
change in members’ preferences from say 0.5 to 0.45 would have an absolute effect on the equilibrium cutoff of around $|\log(\frac{45}{55})| = 0.20$, which is almost twice the estimated effect of the last speaker’s pivotal event and four times the estimate of the next-to-last speaker’s pivotal event.

Figure 21: Posterior Distribution of the Pivotal Event for the Last Two Members to Speak in the Policy Go-around. This figure shows the posterior distribution of the pivotal event in equation 11 with 90% credibility interval and the median of the distribution in dotted lines.

The evidence presented so far, although suggestive that strategic behavior does not seem to be driving members’ heterogeneity, should be taken with caution. First, this argument applies exclusively to a decision-making committee with the characteristics of the FOMC, in terms of size and deliberation structure. We cannot extrapolate this finding to other deliberative settings. Nonetheless, in small committees, where pivotal events are easy to compute, the direct estimation of the strategic model is straightforward.

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 delibera-
tion 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 advo-
cating 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 im-
portant 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 pol-
cy policy recommendations that members provide at the deliberation stage. The results of
the empirical model using deliberation records of FOMC meetings change the com-
mon characterization of this committee in terms of ideological differences and, instead,
emphasize the role of information acquisition as a key determinant of members’ het-
erogeneity. 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 paper, by quantifying social learning effects
from sequential deliberation, should inform future research on the relevance of learn-
ing 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 organi-
zations, 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 sequen-
tial 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 delib-
eration 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.
References


URL: [http://mc-stan.org/](http://mc-stan.org/)


A Estimation of the Robust Variance-Covariance Matrix

The elements of $\Omega$ are estimated using the OLS residuals of equation 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

$$\sigma_i^2 = \frac{1}{TH} \sum_{h \in \{5,10,17\}} \sum_{t=1992}^{2003} \hat{\epsilon}_{t,h,i}^2.$$  

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

$$\gamma_{ij} = \frac{1}{TH} \sum_{h \in \{5,10,17\}} \sum_{t=1992}^{2003} \hat{\epsilon}_{t,h,i}\hat{\epsilon}_{t,h,j}, \forall \ i \neq j.$$  

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

$$\omega_i = \frac{1}{11} \sum_{t=1992}^{2000} \hat{\epsilon}_{t,5,i}\hat{\epsilon}_{t,17,i}.$$  

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

$$s_{ij} = \frac{1}{11} \sum_{t=1992}^{2002} \hat{\epsilon}_{t,5,i}\hat{\epsilon}_{t,17,j} + \hat{\epsilon}_{t,5,j}\hat{\epsilon}_{t,17,i}, \forall \ i \neq j.$$  

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

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

where $X = (1, \text{gap}_{t,h}, \epsilon_{t,j,h}, (f_{t,h} - f_{t,h}))$ 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.

I estimate the weight of individual FOMC forecasts, relative to those submitted by the Board staff, in explaining the actual pattern of individual recommendations.

The left panel of Figure 22 summarizes the results from this exercise, where I plot counterfactual scenarios in which I vary each covariate from its minimum to its maximum value in the sample and compute its effect on the change in the probability from going for an easier to a tighter policy relative to the chairman’s policy directive. To compute this counterfactual scenario, I use an ordered probit model with member-specific effects to explain the discrete voiced preferences over policy (i.e., disagreement toward easier policy, agreement with the chairman’s proposal, disagreement toward tighter policy) as a function of both members’ individual and staff forecasts on inflation, output growth, and unemployment, while controlling for member-specific effects, output gap, and the status quo policy.

The results from the estimation show that the information given by the staff to FOMC members does not significantly predict their voiced policy recommendations. In fact, none of the staff forecasts is significantly correlated to the observed pattern of recommendations. Instead, changes in voiced policy recommendations are explained exclusively from their own individual assessments of the future state of inflation. This is indeed the case, even when staff forecasts pass the test of honest forecasting and, at least in the case of inflation, are more accurate than the ones submitted by FOMC members. (Romer and Romer [2008]).

These differences in policy recommendations ultimately map into the actual policy directive that the chairman puts on the table, which historically has always won a majority of votes. Here, I present the relevance of the opinions voiced by FOMC members at the deliberation stage by showing that the policy rate adopted throughout FOMC’s history reflects, at least, some summary measure of these voiced opinions. In fact, it is the case that empirically we cannot distinguish the policy directive from either the median or the mean policy recommendations across FOMC members. To show this, I correlate the chairman’s policy directive, $d_t$, at every FOMC meeting against the median and mean policy recommendations, $\text{median}(r_{it})$ and $\text{mean}(r_{it})$, respectively:

\begin{align*}
    d_t &= \alpha + \beta \text{median}(r_{it}) + \epsilon_t, \\
    d_t &= \alpha' + \beta' \text{mean}(r_{it}) + \epsilon'_t.
\end{align*}

The adopted policy ($d_t$) would be, on average, the same as the summary recommenda-
Figure 22: Weight of Individual Forecasts on Policy Recommendations and Weight of Policy Recommendations on Policy Adopted. The left panel of the figure shows the estimated probability difference between voicing a preference towards tighter monetary policy and voicing a preference towards easier monetary policy. The changes in probability are computed when we move each covariate from its minimum to its maximum value in the sample. The right panel of the figure shows the relationship between the policy adopted and the median and mean policy recommendation by showing the estimated coefficients of the regressions $d_t = \alpha + \beta \text{median}(r_{it}) + \epsilon_t$ and $d_t = \alpha' + \beta' \text{mean}(r_{it}) + \epsilon'_t$. Points in black (red) denote the median (mean) model. Vertical lines denote 90% Confidence Intervals.

As can be seen in the right panel of Figure 22, we cannot reject the null hypothesis of equality for the period under study, with the exception of the policies adopted during the year in which Miller served as the FOMC chairman, where the policy adopted was around 30 basis points lower than the median and mean policy recommendations.

Note that the previous exercise does not distinguish the influence that individual members exert on the chairman or on others, it just shows, in reduced-form, the alignment between policy recommendations and policies adopted.

C 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, \( U(d) = -(z_i - r)^2 + \eta_i \) (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 \( \eta_{i1} - \eta_{i0} \sim N(0, \tau^2_t) \), 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 \( z_i \sim N(0,1) \), \( \kappa_t \sim N(0,\sigma^2_\kappa) \), \( \lambda_t \sim LN(0,\sigma^2_\lambda) \), \( \sigma^2_\kappa \), \( \sigma^2_\lambda \sim \text{Cauchy}(0,2) \) for \( i = 1 \ldots, 57 \), and \( t = 1 \ldots, 265 \).

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 rates.

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]).
Figure 23: Ideal Point Estimates. The figure provides posterior summaries of the ideal point 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.
Figure 24: Ideal Point Estimates by Committee Characteristics. The figure provides posterior summaries of the ideal point of FOMC committee members, $z_i$, aggregated by appointment (left panel) and party of the executive that appointed the Board Governor (right panel). 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.
D 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:

$$s^*(\pi_t, \sigma_t, \rho_t) = \frac{1}{2} + \sigma_t^2 \left[ \log \left( \frac{1 - \pi_t}{\pi_t} \right) + \log \left( \frac{1 - \rho_t}{\rho_t} \right) \right] . \quad (13)$$

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

![Figure 25: Determinants of the Prior ($\rho_t$) at each Meeting for the Simultaneous Model.](image)
The figure provides the effect of increasing each of the covariates on the prior $\rho_t \equiv Pr(\omega_t = 1)$. Solid circles give the posterior median, with horizontal lines corresponding to the interquartile range of the posterior distribution. The counterfactual increase in the covariate of interest is a change from its minimum to its maximum value in the sample. For each estimate, all other covariates are set at their mean sample values.

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 $t$
Figure 26: Ideological Estimates, $\pi_i$ for the *Simultaneous Model*. The left panel of the figure provides posterior summaries of 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 right 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.

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 30.

In terms of the variation across members, the left panel of Figure 30 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 30, 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 became 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 28: Expertise Estimates by Committee Characteristics for the *Simultaneous Model*. The figure provides posterior summaries of the measure of expertise of FOMC committee members, $\sigma_i$, at the individual level (left panel) and by appointment (right panel). 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.
Figure 29: Correlation between Ideological Bias, $\pi_i$, and Expertise, $\sigma_i$. 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 30: 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.