

Deliberation and Learning in Monetary Policy Committees*

Henry W. Chappell, Jr.
Professor of Economics
University of South Carolina
Phone: 803-777-4940
Fax: 803-777-6876
chappell@moore.sc.edu

Rob Roy McGregor
Professor of Economics
University of North Carolina at Charlotte
Phone: 704-687-7639
Fax: 704-687-6442
rrmcgreg@uncc.edu

Todd A. Vermilyea
Vice President
Federal Reserve Bank of Philadelphia
Phone: 215-574-4125
Fax: 215-574-4146
Todd.Vermilyea@phil.frb.org

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Abstract

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We use records from Federal Open Market Committee (FOMC) meetings to investigate the importance of deliberation and learning in monetary policy decision-making in the period from 1970–1978 when Arthur Burns served as Chairman. We first propose a model of Bayesian learning in which FOMC members learn from each other as they sequentially reveal their policy preferences in a Committee meeting. Then, as an alternative, we investigate a model in which members defer to an emerging consensus. Neither model is supported by the data, suggesting that within-meeting deliberation might have had little effect on the quality of monetary policy decisions in the Burns era.

I. Introduction

Recent theoretical and experimental work on the monetary policy decision process supports the argument that committees may make better policy decisions than individuals (e.g., Blinder 2007, Blinder and Morgan 2005, Gerlach-Kristen 2006, and Lombardelli, Proudman, and Talbot 2005). Blinder (2004, pp. 38-39) offers four reasons why monetary policy committees might make better choices than individuals. First, when members have different preferences, diversification avoids extreme outcomes. Second, even if members have similar preferences, they might use different models to reach their conclusions. Third, members might use different forecasts or forecasting techniques. Finally, individuals might use different modes of reasoning—or “heuristics”—to approach problems. The last three reasons in Blinder’s list suggest that members bring distinct perspectives or information to a committee meeting. Deliberation in the committee meeting requires members to confront their differences and could result in both learning and better policy decisions.

Former Bank of England Monetary Policy Committee (MPC) member Richard Lambert (2005) and former Federal Reserve Bank of Boston President Cathy Minehan (2006) have pointed to the importance of deliberation in monetary policy committee meetings. Particularly revealing are Minehan’s (2006) comments about her experience on the Federal Open Market Committee (FOMC):

One highly important element in dealing with uncertainty is the strength of the committee itself. In that regard, it is perhaps fashionable to deride committee decision making in general as bureaucratic and cumbersome. My view is that in situations where

there are many possible philosophical approaches and a lot at stake, a committee helps its members to both see all aspects of the issue, and weigh the risks and costs of a particular decision. As with other vital institutions, like the Supreme Court, there is value to a committee decision on policy versus one taken by a single executive.

The importance of deliberation in various decision-making contexts has also been addressed in political science. Austen-Smith and Feddersen (2006) contribute to the literature on jury deliberation by offering a theoretical analysis of how different voting rules shape voters' incentives to share information prior to a vote being taken. Barabas (2004) finds evidence that deliberation is an effective way to disseminate information and shape opinions about public policy issues. U.S. Supreme Court Justice Stephen Breyer has explained how deliberation matters in Supreme Court conferences (cited in Brafman and Brafman 2009, Kindle Location 1764):

“If someone is going to write a dissent ... they have a point, they have some kind of point they're trying to make. Quite often the opinion [of the majority] is changed somewhat in response to comments and opinions [of the dissenters]. Occasionally—maybe once or twice a year—the whole Court shifts.”

Even when dissenters don't have enough votes to change the Court's opinion, they still affect the process. “It makes the other person take account of the point. They have to answer it or they have to take it into account,” Breyer said.

In the case of the FOMC, Bailey and Schonhardt-Bailey (2008) use a full-text content analysis of the 1979 and 1980 FOMC transcripts to study the importance of deliberation in the decision to shift to anti-inflationary policy under Chairman Paul Volcker. They conclude that “deliberation in the FOMC did indeed ‘matter’ both in 1979 and 1980” (p. 404) as Volcker led his colleagues to adopt a new operating procedure and maintain a more restrictive monetary policy stance. Bailey and Schonhardt-Bailey (2009) extend their analysis to the 1979-1999 period and find that the role of deliberation declined from the Volcker era to the Greenspan era; Woolley and Gardner (2009) concur with this result. Even in light of previous theoretical and empirical work on deliberation, though, Bailey and Schonhardt-Bailey (2009, p. 22) nevertheless argue that “too little attention has been given to understanding the process of deliberation in policymaking and how this yields outcomes (decisions) and the quality of those outcomes. Very few decisions on public policy are taken without some form of deliberation.”

This paper extends the literature by empirically investigating the importance of deliberation and learning in Federal Open Market Committee meetings during the 1970-1978 era in which Arthur Burns served as Chairman. Our analysis uses FOMC records that reveal the stated policy positions of individual Committee members and the order in which those members spoke in a series of meetings. The Burns era data are well-suited to our purposes for several reasons. First, Burns apparently respected a “no-lobbying” convention and did not explicitly attempt to influence others’ positions or

mobilize support for his own position prior to meetings.¹ Second, Burns also respected the independence of Federal Reserve staff in making recommendations to the Committee (Axilrod 2009, p. 62). Third, Burns (unlike Alan Greenspan) did not routinely speak first in the order—this feature of the data can permit us to better identify influence via learning that is distinct from deference to the Chairman. These circumstances resulted in meetings that tended not to be highly formal or scripted, and members' recorded policy prescriptions ranged widely. Deliberation and learning might be more easily detected under these conditions.

We initially propose a model of Bayesian learning in which FOMC members learn from each other as they sequentially reveal their desired interest rate targets in a Committee meeting. The model has implications for the structure of error covariances across members and meetings in a panel data regression explaining members' interest rate preferences. As an alternative, we investigate a model in which members might defer to an emerging consensus, even when that consensus choice might conflict with an individual's Bayesian logic. Neither model is supported by the data. Our inability to detect influences from one member to another provides a notable negative result. This result suggests that deliberation, at least within the confines of the FOMC's interest rate policy discussion, may have little effect on the quality of the Committee's decisions, possibly because all useful information is shared prior to the policy discussion. Moreover, deliberation might have other effects that we are not able to capture. For example,

¹ Our source for this claim is a February 21, 2002, telephone interview conducted by one of the authors with Jeffrey Bucher, a member of the Board of Governors during the Burns era.

deliberation might not affect the interest rate a member prefers at a given meeting but might affect the path that member expects the interest rate to follow in the future. The models and heuristics that members rely on over time might also be shaped by deliberation. Our analysis addresses the role of deliberation in the context of the FOMC interest rate policy discussion but does not address these possible longer-term effects.

II. Data from FOMC Deliberations

Our data set consists of desired interest rate targets for individual FOMC members over the complete series of Burns era meetings and also a record of the order of speaking in each of those meetings. For February 1970 through March 1976, the data were obtained from the Committee's *Memoranda of Discussion*. The *Memoranda* were discontinued in 1976, so the data for April 1976 through February 1978 were obtained from meeting transcripts (available from Arthur Burns's personal papers archived in the Gerald Ford Presidential Library). Both sources provide detailed descriptions of members' statements of preferred policy options in the course of the policy go-around.

Burns era FOMC meetings normally followed a standard protocol. The consideration of monetary policy began with a staff presentation discussing economic conditions, forecasts, and possible policy options. Following the staff presentation, individual members offered their own impressions of economic conditions, with district Reserve Bank presidents emphasizing conditions in their regions. The economics discussion was followed by the policy go-around, in which members offered and defended their own preferred policy options, normally expressed as target ranges for the federal funds rate. The order in which members spoke in the go-around varied across meetings.

Our data are derived from statements attributed to members in the policy go-around. Following procedures described in Chappell, McGregor, and Vermilyea (2004, 2005, 2007), we were able to identify members' desired federal funds rates directly from the information provided in the textual record in 1426 of 1782 (80.0%) member-meeting observations, including both voting and non-voting members of the Committee.² Our sample includes all member-meeting observations where a target rate could be coded.

III. A Model of Bayesian Learning

This section presents a model of Bayesian learning in which committee members speak sequentially in a meeting. In this model, each member has private information about the appropriate setting for the committee's interest rate target, and later speakers have an opportunity to learn from the statements made by earlier speakers.³ Our formal

² On some occasions, members spoke several times in a single meeting. In these cases, the portion of the text that revealed an interest rate preference was used to determine a member's position in the speaking order.

³ Sibert (2006), following Banerjee (1992) and Bikhchandani, Hirshleifer, and Welch (1998), has presented a scenario in which Bayesian learning might result in an information cascade. In an information cascade, committee members might rationally ignore their own private information and defer to preceding speakers, so that learning is short-circuited. As Bikhchandani, Hirshleifer, and Welch (1998) note, however, information cascades occur only when allowed communications include small numbers of discrete options. In our model, members can report continuous interest rate recommendations, so information cascades cannot occur. Our assumption that reported

model is framed narrowly in terms of Bayesian calculations based on sequential data revelation, but our intention is to represent learning more broadly. For example, a “signal” in our model might not literally refer to a discrete data increment but could instead be a novel inference based on an alternative decision-making heuristic.

Letting R_{it}^* refer to the stated interest rate target of the i^{th} committee member to speak in meeting t , we assume that

$$R_{it}^* = \bar{R}_i + u_{it}. \tag{1}$$

In this equation, \bar{R}_i indicates the “normal” interest rate that speaker i would favor in meeting t , given prevailing observed macroeconomic conditions, while u_{it} is a discretionary deviation from \bar{R}_i that reflects non-public information available to speaker i . Speaker i ’s normal rate preferences are assumed to be known to other committee members.⁴ We want to consider how u_{it} is determined for each speaker.

We further assume that each speaker in the meeting receives a private signal, denoted e_{it} , of the optimal deviation from the normal interest rate for period t . The optimal deviation, designated ε_t , is not observed, but is the same for all committee

rates are continuous is a reasonable approximation for the Burns era, when reported target ranges were much more flexible and varied than they have been in the last two decades.

⁴ Historically, there have been well-known differences in policy preferences across FOMC members. For example, in the Burns years, St. Louis Fed President Darryl Francis was known for a systematic tendency to favor monetary tightness, while Governor Sherman Maisel was more likely to favor ease.

members. The distribution of the signal e_{it} is normal with known variance σ^2 and a mean of ε_t ; the latter condition implies that e_{it} is an unbiased signal of ε_t . Further, ε_t is itself a time-varying random variable; in each period, ε_t is drawn from a normal distribution with mean zero and variance τ^2 . The problem facing each speaker i is to calculate an expected value for ε_t , given knowledge of the signal and the prior distribution of ε_t .

Consider the problem for the first speaker in the meeting. Speaker 1 observes e_{1t} and knows the prior distribution from which this signal is drawn. He will determine a desired interest rate, $R_{1t}^* = \bar{R}_{1t} + u_{1t}$, where $u_{1t} = E(\varepsilon_t | e_{1t})$ is given by the solution to a Bayesian updating problem, as shown below:

$$u_{1t} = E(\varepsilon_t | e_{1t}) = \frac{\tau^2}{\sigma^2 + \tau^2} e_{1t}. \quad (2)$$

More weight is attached to the signal, e_{1t} , when the prior distribution of ε_t is more diffuse (τ^2 is high) and when the signal has less noise (σ^2 is smaller). We assume that member 1 truthfully reports his preference, R_{1t}^* , to the committee.⁵

⁵ Tillmann (2010) has presented evidence that non-voting FOMC members tend to exaggerate their inflation forecasts in an attempt to influence policy deliberations. If a committee member systematically overstated (or understated) desired rates over a series of meetings, though, this should not influence others; instead, it would simply change the normal rate expected for member i . Unsystematic misstatements would normally not produce any advantage for i . In addition, if members' signals are verifiable, i.e., if they can be checked with an originating source, then incentives to misreport would be low.

Now consider the problem facing the second committee member to speak.

Speaker 2 knows that speaker 1 has advocated interest rate R_{1t}^* . Since speaker 2 also knows \bar{R}_{1t} (that is, she knows the normal preferences of speaker 1), then speaker 2 can infer $u_{1t} = R_{1t}^* - \bar{R}_{1t}$. Further, knowing u_{1t} , speaker 2 can use equation (2) to infer what signal, e_{1t} , must have been received by speaker 1. Speaker 2 also receives an independent signal, e_{2t} , so she has knowledge of two signals rather than one.

Speaker 2 will calculate her desired interest rate, $R_{2t}^* = \bar{R}_{2t} + u_{2t}$. Based on her knowledge of the two signals, she will set $u_{2t} = E(\varepsilon_t | e_{1t}, e_{2t})$. Again, this is a Bayesian updating problem with the solution

$$u_{2t} = E(\varepsilon_t | e_{1t}, e_{2t}) = \frac{\tau^2}{\sigma^2/2 + \tau^2} \left(\frac{e_{1t} + e_{2t}}{2} \right). \quad (3)$$

This solution is analogous to that in equation (2), differing only because speaker 2 updates on the basis of two signals rather than one. By similar reasoning, the i^{th} speaker in a meeting can infer the signals received by all preceding speakers and will determine a desired interest rate, $R_{it}^* = \bar{R}_{it} + u_{it}$, such that

$$u_{it} = E(\varepsilon_t | e_{1t}, e_{2t}, \dots, e_{it}) = \frac{\tau^2}{\sigma^2/i + \tau^2} \left(\frac{e_{1t} + e_{2t} + \dots + e_{it}}{i} \right). \quad (4)$$

Let \mathbf{U}_t be the covariance matrix for the u_{it} error terms appearing in equation (1).

Elements of \mathbf{U}_t are given by

$$c_{ij} = E(u_{it}u_{jt}) = \frac{1}{\max(i, j)} \left(\frac{\tau^2}{\sigma^2/i + \tau^2} \right) \left(\frac{\tau^2}{\sigma^2/j + \tau^2} \right) \sigma^2. \quad (5)$$

Elements of this matrix are necessarily positive. Variances (i.e., the c_{ii} elements of the matrix) can either increase or decrease with i . The error correlation for a pair of speakers is higher when the two speakers are closer to one another in the order and when both speak later in the order.⁶

Again consider equation (1), which describes the preferred interest rate of the i^{th} speaker in a meeting:

$$R_{it}^* = \bar{R}_{it} + u_{it}. \quad (1)$$

Over time, different individuals populate the committee and the speaking order varies, with the implication that the i^{th} speaker is a different person across meetings. Letting the index k refer to distinct individuals serving across meetings, we define a set of dummy variables, d_{kit} , for $k=1, \dots, K$, such that $d_{kit} = 1$ when the i^{th} speaker in meeting t is individual k ; otherwise $d_{kit} = 0$. We now specify that speaker i 's normal interest rate for meeting t can be represented by

$$\bar{R}_{it} = \sum_{k=1}^K \alpha_k d_{kit} + v_t, \quad (6)$$

where α_k is an individual-specific intercept and v_t is a meeting fixed effect. Substituting equation (6) into equation (1) yields

⁶ Elements of the error correlation matrix depend on neither σ^2 nor τ^2 ; those elements are given by $\rho_{ij} = \sqrt{ij}/\max(i, j)$. For a given j (indexing the second of two speakers), the correlation is higher when i is closer to j . For a given difference, $j-i$, the correlation is higher when j is higher.

$$R_{it}^* = \sum_{k=1}^K \alpha_k d_{kit} + v_t + u_{it}. \quad (7)$$

Given a sample of desired interest rates for individual monetary policy committee members in a sequence of meetings, we can estimate equation (7). This is a linear regression model specifying that the desired interest rate for speaker i in meeting t is a function of meeting and member fixed effects and the error, u_{it} .

As we have shown, the Bayesian learning hypothesis has implications for the structure of the covariance matrix of the u_{it} . Equation (5) describes error covariances for members within a meeting; covariances for error terms across meetings will equal zero. For a data set that pools over members and meetings, stacks meetings, and orders members by speaking position within meeting blocks, the error covariance matrix will be block diagonal, with meeting blocks consisting of entries described by equation (5). That is, the error covariance matrix for the complete sample, \mathbf{U} , will have blocks for meetings, $\mathbf{U}_1, \mathbf{U}_2, \dots, \mathbf{U}_T$, such that

$$\mathbf{U} = \begin{bmatrix} \mathbf{U}_1 & 0 & \cdots & 0 \\ 0 & \mathbf{U}_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \mathbf{U}_T \end{bmatrix}, \quad (8)$$

with each block taking the form

$$\mathbf{U}_t = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1N_t} \\ c_{21} & c_{22} & \cdots & c_{2N_t} \\ \vdots & \vdots & \ddots & \vdots \\ c_{N_t,1} & c_{N_t,2} & \cdots & c_{N_t,N_t} \end{bmatrix}. \quad (9)$$

In equation (9), N_t indicates the number of speakers in meeting t , and the elements c_{ij} are determined by equation (5).

Given this structure, the regression model (7) is an instance of the general linear model, with a covariance matrix whose elements depend on the parameters τ^2 and σ^2 . If τ^2 and σ^2 were known, equation (7) could be estimated by generalized least squares (GLS). In the current application, estimates of τ^2 and σ^2 are of central concern, so we will estimate all parameters by the maximum likelihood method.

To test the model, we embed it in a more general formulation and then determine if the special case can be rejected. For this purpose, we consider a simple extension in which an additional independent white noise error term, z_{it} , is appended to equation (7):

$$R_{it}^* = \sum_{k=1}^K \alpha_k d_{kit} + v_t + u_{it} + z_{it}. \quad (10)$$

In this equation, z_{it} is assumed to be normal with mean zero and variance γ^2 .

Expressions for composite error covariances for this equation are identical to those given in equation (5); variances are each higher by γ^2 .⁷ In the special case where $\tau^2 = 0$, equation (4) implies that u_{it} disappears from the model. Equation (10) then becomes the classical linear regression model with a constant error variance (γ^2) and zero error covariances. In contrast, if $\gamma^2 = 0$, z_{it} disappears from the model, and the original

⁷ The composite error term in the equation is $u_{it} + z_{it}$. Covariances of the composite error term are given by $E[(u_{it} + z_{it})(u_{jt} + z_{jt})] = E[u_{it}u_{jt}] = Cov(u_{it}, u_{jt})$ for $i \neq j$. The variance of the composite error term is given by $E[(u_{it} + z_{it})^2] = E(u_{it}^2) + E(z_{it}^2) = Var(u_{it}) + \gamma^2$.

Bayesian learning model holds. In intermediate cases, the existence of learning should lead to parameter estimates that result in positive within-meeting error correlations across members.

Equation (10) can be regarded as a convenient econometric generalization of equation (7); however, it can also be given a behavioral interpretation. Suppose that each committee member receives two verifiable signals in a meeting and that both signals are revealed to the full committee in the policy go-around. One signal, e_{it} , contains information that is relevant to all members of the committee, as in our original model. However, the second signal is idiosyncratic and irrelevant for members speaking after i . For example, speaker i might report that he has learned the terms of a wage contract negotiated by a large corporation—this might be relevant information for all and reflected in e_{it} . He might also report that sunspot activity has increased and that he associates sunspots with expansions. Sunspots would presumably influence his rate preference through the z_{it} error component without influencing the decisions of others.⁸

⁸ The FOMC transcripts provide evidence that members differed in the information they considered relevant. For example, Burns once derided St. Louis Fed President Lawrence Roos for relying on the monetarist-inspired St. Louis forecasting model. Burns said, “I would have liked your comments better if you had not based it on the model. The St. Louis model does not get high marks for its predictive power. In fact, it gets very low marks in the economics profession” (*FOMC Transcripts*, January 17, 1977, Tape 6, p. 20). In later years, Wayne Angell often reported on the price of gold, while other members showed little interest.

IV. Bayesian Learning: Econometric Results

In Table 1, we report maximum likelihood estimates of parameters of our general specification and also the special case corresponding to the Bayesian learning model. The table does not report member fixed effects ($K = 51$) or meeting fixed effects ($T = 99$), which are similar across specifications. The iterative procedure that we use in estimation does not directly provide coefficient standard errors, so we instead report the results of likelihood ratio tests for hypotheses of interest.

The first column of the table reports estimates of the generalized model, which are not favorable for Bayesian learning. In particular, the estimate of τ^2 is equal to zero (as a variance, it cannot be less than zero). This outcome corresponds to the special case of the classical regression model, in which error variances are constant and covariances equal zero. The requirement that covariances be positive was a key implication of the Bayesian learning hypothesis, and that prediction is not supported.

In the table's second column, we impose the Bayesian learning model restriction that $\gamma^2 = 0$. That restriction is overwhelmingly rejected ($\chi^2(1) = 929.14$, $p = 0.0000$), and estimates of the other parameters are not sensible in terms of the underlying model. The estimates imply that both the prior distribution for ε_i and signals of its level are essentially uninformative.

A cursory analysis of sample covariances from OLS residuals of equation (7) reinforces our conclusions about Bayesian learning and reveals why the model performs poorly. Of 171 non-diagonal elements of the sample covariance matrix, 111 entries are negative, with an average covariance of -0.0018 and an average correlation of -0.0735. There is no evidence to support the hypothesis that off-diagonal elements of the error

covariance matrix are positive, as required by the Bayesian learning theory.

Consequently, our rejection of models in which individuals behave as perfect Bayesians (and in accord with other restrictive modeling assumptions) is not surprising. However, less restrictive models in which individuals are “imperfect” Bayesians should also imply the existence of positive error covariances. Their absence suggests that models based on more general forms of learning do not adequately describe FOMC deliberations in the Burns years.

Our analysis has so far neglected any special role that might exist for the FOMC’s Chairman. In our sample, Chairman Burns most often spoke either first or last.⁹ When Burns spoke first, his position would be observable to all. In a model of Bayesian learning, the information provided would also be identical for all, and special influence from the Chairman should be captured by the meeting-specific fixed effects included in the model. When Burns spoke last, his position would affect no one, just as if he were a rank-and-file member. Consequently, our tests for the presence of Bayesian learning are likely to be robust to the omission of Chairman-specific effects in the model.¹⁰

The last column of Table 1 provides additional evidence that our conclusions are not dependent on our handling of the Chairman. There we report estimates of a

⁹ In 63 meetings where a preference was coded for Burns, he spoke either first or last 41 (65.1%) times.

¹⁰ We are not arguing that the Chairman has no influence on others. Rather, we suggest that evidence of Bayesian learning based on the sequence of statements by rank-and-file members is unlikely to be affected by the presence or absence of the Chairman’s power.

specification identical to that of column 1 (the generalized Bayesian learning model), but we estimate over a sample that excludes 37 meetings in which the Chairman spoke in the first half of the order. This leaves us with a sample of 862 individual rate observations in 62 meetings where the Chairman's remarks in the go-around would not have influenced most speakers. The results of the estimation reinforce our earlier findings. Again the estimate of τ^2 is equal to zero, implying that error covariances equal zero and contradicting the prediction of the Bayesian learning hypothesis.

Our results are also robust to other alterations of the model. We have generalized equation (7) to permit differences across individuals in responsiveness to prevailing macroeconomic conditions, including forecasts of inflation and economic growth. Our key results are unchanged by this modification—the Bayesian learning hypothesis is soundly rejected. We have also considered whether Governors and Reserve Bank presidents might differ in the influence they have on their colleagues. To do this, we examined sample error covariance matrices calculated using residuals from subsets of speaker pairs in which (i) a Governor spoke first or (ii) a Reserve Bank president spoke first.¹¹ The resulting covariance matrices differed little, and in each case average covariances were negative, so there is no added support for the Bayesian learning hypothesis.

¹¹ In principle, it would be better to reformulate our model to account for Bayesian learning when preceding speakers differ in their accuracy. This is a complex problem that would be difficult to implement empirically.

V. An Alternative Model: Consensus-Seeking

The character of individual interactions in FOMC meetings might be rather different from that modeled by the theory of section III. In that model, deliberation led to convergence of information over a sequence of speakers. However, deliberation might be thought of in terms of converging policy positions rather than converging information.

Consider a concrete example to distinguish these phenomena. Suppose that in the absence of information from others, I would like to see the federal funds rate set at 5.00% in this meeting. Now suppose that St. Louis Fed President Darryl Francis (a Burns era FOMC member) has spoken before me and advocated a rate of 5.25%. Because Francis is well-known for his aversion to inflation and a resulting tendency to favor high interest rates, I know that he would normally favor a rate of 5.50% under prevailing conditions. Since Francis actually favors a rate of 5.25%, I infer that his private information indicates that this is a time for easier policy than normal. Bayesian reasoning leads me to also favor an easier policy and a rate below 5.00%. If I instead behave in a more mechanically consensual fashion, I will adjust my reported preference in the direction of an emerging consensus. If Francis precedes me and favors 5.25%, I adjust my preference toward his and report a rate above 5.00%. In this example, Bayesian and consensual motivations lead me in opposite directions.

We now consider a model to systematically investigate consensual behavior. To that end, we modify equation (1) as follows:

$$R_{it}^* = \bar{R}_i + \omega_{it} + \beta[\tilde{R}_{it} - (\bar{R}_i + \omega_{it})], \quad 0 \leq \beta \leq 1. \quad (11)$$

In equation (11), \tilde{R}_{it} is the average policy position of all members who have spoken before speaker i in meeting t . The error term, ω_{it} , is assumed to be a white noise

disturbance; it is not derived from the Bayesian calculus of section III. The equation implies that speaker i adjusts his stated target rate to eliminate a part of the gap between the average rate advocated by preceding speakers and his own initially preferred rate, $\bar{R}_{it} + \omega_{it}$. Substituting (6) for \bar{R}_{it} and rearranging, we obtain

$$R_{it}^* = (1 - \beta) \left(\sum_{k=1}^K \alpha_k d_{kit} + v_t \right) + \beta \tilde{R}_{it} + (1 - \beta) \omega_{it}. \quad (12)$$

This equation describes a regression of members' target interest rates on member and meeting fixed effects and on \tilde{R}_{it} . Support for policy convergence would be indicated by a value of β that is greater than zero and less than one.

To estimate (12), we exclude the first speaker in each meeting from the sample, because \tilde{R}_{it} is not observed for the first speaker. Our concern is with the estimate of β , so complete results (with meeting and member fixed effects) for the estimation of (12) are not reported. The estimation produces a perversely negative and significant estimate of β ($\hat{\beta} = -0.5401$, $t = -6.5822$). We have also estimated generalizations of (12) in which β is a function of the number of individuals speaking before speaker i .¹²

Estimates of these models also imply negative or small values for β .¹³ We then altered

¹² When β is a function of the number speaking before i , the specification of (11) implies that the equation error term is heteroscedastic. We have accounted for heteroscedasticity in our estimation.

¹³ There is one partial exception. When β is assumed to be a logistic function of the number of speakers, and thereby constrained to the zero to one interval, the estimates imply large (0.25 and higher) values of β for speakers in positions 16 and higher in the

the model to permit differential impacts of Governors and Reserve Bank presidents by including separate averages for preceding speakers in each group; neither coefficient estimate was positive, and that for Reserve Bank presidents was perversely negative and significant. We earlier found no support for information convergence based on Bayesian learning; we now find no support for policy convergence based on consensus-seeking.

VI. Conclusions

Using data gleaned from FOMC deliberations, we assembled a data set that describes individual Committee members' stated monetary policy preferences and the order of speaking in a series of meetings. We then used that data to test a model of Bayesian learning, in which information is revealed as members speak sequentially in a meeting. Our test was based on implications of the model for the structure of error covariances in a panel data regression explaining members' stated interest rate targets over a series of meetings. That model was strongly rejected by the data. We then proposed an alternative model in which pressures for consensus characterized FOMC members' interactions, but that model was also rejected.

Our results fail to support the proposition that later speakers are influenced by earlier speakers in the FOMC's policy go-around. This does not necessarily imply that members act in a completely independent fashion, nor does it imply that deliberation cannot have longer-term effects that our analysis does not capture. A plausible interpretation of our results is that all useful information is revealed prior to the policy

order. However, in most meetings, the number of coded speakers was less than 16, and the overall fit of this model was poor.

go-around, rather than as the policy go-around proceeds (Swank, Swank, and Visser 2008).¹⁴ This interpretation would be consistent with the existence of efficient information dissemination across Committee members under existing institutions. However, the policy go-around provides the key forum in which members offer and defend their policy recommendations. Our inability to detect influences related to members' interactions provides a notable, if negative, result. (We again caution that our analysis does not address the potential influence of deliberation on the models, policy rate forecasts, or modes of reasoning used by FOMC members over time.)

Under Alan Greenspan's tenure as Fed Chairman, deliberation in the policy go-around became shorter and more scripted (Woolley and Gardner 2009, Bailey and Schonhardt-Bailey 2009). This may partly be attributed to increasing dominance by Greenspan himself, whose speech occupied an increasing portion of the proceedings (Chappell, McGregor, and Vermilyea 2005, pp. 131-132). It may also be related to the Fed's 1993 decision to publish near-verbatim transcripts of meeting discussions with a five-year lag and a resulting hesitancy of members to speak freely (Meade and Stasavage 2008). Our results do not directly address the issue of dominance by the Chairman, but

¹⁴ To be specific, Swank, Swank, and Visser (2008) argue that requiring monetary policy committees to become more transparent about their decisions will lead to the organization of pre-meetings in which the real deliberations occur, with the formal meetings serving only as scripted endorsements of the decisions reached in the pre-meetings. This argument implies that the official meeting records will not yield any evidence that MPC members learn from each other during the policy discussions. Our evidence for the Burns FOMC is entirely consistent with this implication.

they do inform us about the limitations of deliberation. For the Burns years, when deliberation in the policy go-around was relatively wide-ranging, we have been unable to find evidence that members' statements notably influenced their colleagues who spoke after them. This suggests that a reduction in deliberation might not have large direct effects within the narrow environment of the Committee's proceedings. Admittedly, reduced deliberation could change the way that members behave outside of the formal meetings in ways that our analysis cannot detect.

Table 1. Results for the Bayesian Learning Model

Parameter	Generalized Model	Bayesian Learning Model	Generalized Model, Burns Speaks Late ^c
τ^2	0.0000	4.0041	0.0000
σ^2	NA ^b	182.4117	NA ^b
γ^2	0.0334	0.0 ^a	0.04162
Number of Observations	1426	1426	862
Log-likelihood	400.92	-63.64	147.19

^a Parameter value is restricted to the value shown.

^b When $\tau^2 = 0$, σ^2 is not identified.

^c The sample excludes meetings in which Burns spoke in the first half of the order.

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