Learning and Bandwagons in Monetary Policy Committees*

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Abstract

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We use records from Federal Open Market Committee (FOMC) meetings to investigate the existence of bandwagons 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 bandwagons can arise. Then, as an alternative, we investigate bandwagons in which members defer to an emerging consensus. Neither model is supported by the data, suggesting that bandwagons were not an important feature of monetary policy deliberations in the Burns era.

I. Introduction

It has been argued that committees may make better monetary policy decisions than individuals.[1] Blinder (2007, p. 121) makes the case succinctly when he states that "picking an individual central bank head is a bit like investing your entire portfolio in a single stock … It pays to diversify your central bank portfolio." Deliberation by a committee should result in broad dissemination of information, learning, and better-informed policy choices.[2]

This paper investigates learning and bandwagons in meetings of the Federal Open Market Committee (FOMC), the policymaking committee of the Federal Reserve. 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. Our data set is from the 1970 – 1978 era in which Arthur Burns served as Chairman. The Burns era data are well-suited to our purposes because Burns (unlike Alan Greenspan) did not routinely speak first in the order—this feature of the data can permit us to better distinguish a bandwagon phenomenon that is distinct from deference to the Chairman.

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[1] Blinder and Morgan (2005), Gerlach-Kristen (2006), and Lombardelli, Proudman and Talbot (2005) have presented evidence supporting this proposition.

[2] Sibert (2006), following Banerjee (1992) and Bikhchandani, Hirshleifer, and Welch (1998), provides a counterexample in which an information cascade can limit the revelation of information in a monetary policy committee. We discuss this possibility further in Section IV.

Members' recorded policy preferences ranged widely in Burns era meetings and discussions were not highly formal or scripted, so FOMC records offer appealing opportunities for the investigation of intra-meeting dynamics.

We initially propose a model of Bayesian learning in which bandwagons can arise as members sequentially reveal their desired interest rate targets in a 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 bandwagons in which members might defer to an emerging consensus, even when that consensus choice might conflict with an individual's Bayesian logic. We find no evidence of bandwagons of either variety.

II. Data

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*. For April 1976 through February 1978, the data 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 a target range 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. We recorded numerical targets from the original sources for members who (1) explicitly stated a desired range for the federal funds rate, (2) stated a preference for one of the Board staff's policy scenarios that had an explicit funds rate target range, or (3) stated agreement with a member who had previously been identified with a funds rate target range through (1) or (2). We then calculated a single-valued target for each member's desired federal funds rate as the midpoint of his stated target range. Using this classification scheme, 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. Our sample includes all member-meeting observations where a target rate could be coded. 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]

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[3] When Burns spoke late in a meeting, he often summarized the discussion and proposed a rate for the directive without clearly indicating his own preference. In such cases (when Burns spoke in the second half of the order), we coded a rate preference for him only if he explicitly indicated that his proposed rate was his own preference. Additional details

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.

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

$$R_{it}^* = \overline{R}_{it} + u_{it}\,. \tag{1}$$

In this equation, $\overline{R}_{it}$ 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 $\overline{R}_{it}$ that reflects non-public information available to speaker *i*. 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 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

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on our data and our process for coding individual members' desired federal funds rates can be found in Chappell, McGregor, and Vermilyea (2004, 2005, 2007).

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, $R_{1t}^* = \overline{R}_{1t} + u_{1t}$, where $u_{1t} = E(\varepsilon_t \mid e_{1t})$ is given by the solution to a Bayesian updating problem, as shown below:

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

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).

Now consider the problem facing the second committee member to speak. Speaker 2 knows that speaker 1 has advocated interest rate R_{1t}^*. Assuming that speaker 2 also knows $\overline{R}_{1t}$ (that is, she knows the normal preferences of speaker 1), then speaker 2 can infer $u_{1t} = R_{1t}^* - \overline{R}_{1t}$.[4] Further, knowing u_{1t}, speaker 2 can use equation (2) to infer

[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.

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

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

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

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

We can also calculate a covariance matrix, $\mathbf{U}_t$, for the u_{it} error terms appearing in equation (1). Elements of $\mathbf{U}_t$ are given by

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

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.[5]

Turning to econometric estimation, again consider equation (1), which describes the preferred interest rate of the i^{th} speaker in a meeting:

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

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 $k = 1, \ldots, K$, 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

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

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

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

[5] 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.

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 time and member fixed effects and the error, u_{it}.

We want to test the Bayesian bandwagon hypothesis, which we have shown 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, $\mathbf{U}_1$, $\mathbf{U}_2$, …, $\mathbf{U}_T$, such that

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

with each block taking the form

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

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 white noise error term, z_{it}, is appended to equation (7):

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

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.[6] In the special case where $\tau^2 = 0$, equation (4) implies that u_{it} terms disappear from the model. Equation (10) then becomes the classical linear regression model with a constant error variance (γ^2) and

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

zero error covariances. In contrast, if $\gamma^2 = 0$, z_{it} disappears from the model, and the original Bayesian bandwagon model holds.

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 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.[7]

[7] 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).

IV. Notes on Strategic Behavior and Information Cascades

Our model of Bayesian learning has implicitly assumed that speakers truthfully report interest rate preferences and that subsequent speakers correctly infer signals. For several reasons, we believe that the assumption of truthful reporting is a reasonable one. First, if a committee member systematically overstated (or understated) desired rates over a series of meetings, this would not influence others. This would simply change the normal rate expected for member *i*, $\overline{R}_{it}$. Second, in our model, all members receive signals of similar quality. If each member wants the committee as a whole to reach the best collective decision, no member would attach greater importance to his signal than to the signals of others, and there would be no reason to misreport. Finally, in many cases, it would be reasonable to assume that members' signals are verifiable. If a signal is reported in published data or can be checked with an originating source, any incentive to misreport would be reduced.

A second issue involves the possible existence of information cascades, in which herding eliminates learning.[8] In an information cascade, an individual rationally ignores his own signal in choosing an action; as a consequence, subsequent actors cannot learn from his choice. However, information cascades occur only when the actions of individuals do not fully reveal signals that they have received. In the model we have

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[8] See Banerjee (1992) for a seminal contribution and Bikhchandani, Hirshleifer, and Welch (1998) for a discussion of the information cascade phenomenon. Anderson and Holt (1997), Hung and Plott (2001), Noth and Weber (2003), and Alevy, Haigh, and List (2007) provide experimental evidence on information cascades.

presented, later speakers perfectly infer the signals received by their predecessors. This is a consequence of the assumption that speakers announce continuous, rather than discrete, interest rate preferences.[9]

This discussion of information cascades implies that the extent of "discreteness" in policy options may be an important matter. In the Burns era, the funds rate floated within ranges between meetings, and the range of rates advocated by members within meetings was often wide. For example, in February 1970 (the first meeting in our sample), the 14 members whose preferences were coded advocated five different funds rate target values in an interval spanning 100 basis points. Given these characteristics of the data, we believe that it is appropriate to treat members' target rates as continuous variables.

V. 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 bandwagon model. The table does not report member fixed effects ($K = 51$) or time fixed effects ($T = 99$), which are similar across specifications. The iterative procedure that we use in estimation

[9] As Bikhchandani, Hirshleifer, and Welch (1998, p. 159) conclude, "if the set of action alternatives is continuous … private signals can be perfectly inferred from actions, information aggregates efficiently, and cascades do not form." However, even if information aggregates efficiently as successive speakers state desired targets, positions taken by earlier speakers incorporate less information than those taken by later ones.

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 bandwagons. 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 bandwagon hypothesis, and that prediction is not supported.

In the table's second column, we impose the bandwagon model restriction that $\gamma^2 = 0$. That restriction is overwhelmingly rejected ($\chi^2(1) = 929.14$, $p = 0.0000$), and estimates of the other model parameters are not sensible in terms of the underlying model. The estimates imply that both the prior distribution for ε_t 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 bandwagons. 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 bandwagon theory. Because the model developed in section III is restrictive, the rejection of that specific strong formulation of Bayesian bandwagons 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 bandwagons based on more general forms of Bayesian learning were not an important feature of 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.[10] 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 its effects 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 bandwagons are likely to be robust to the omission of Chairman-specific effects in the model.[11]

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 specification identical to that of column 1 (the generalized bandwagon 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

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

[11] We are not arguing that the Chairman has no influence on others. Rather, we suggest that evidence of bandwagons 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.

estimate of τ^2 is equal to zero, implying that error covariances equal zero and contradicting the prediction of the Bayesian bandwagons hypothesis.

VI. An Alternative Model

The character of bandwagons might be rather different from those modeled by the theory of section III. In that model, bandwagons reflected convergence of information over a sequence of speakers. However, bandwagons might be thought of in terms of converging policy positions rather than converging information.

Consider a concrete example to distinguish these two bandwagon types. Assume that in the absence of information from others, my best guess would be that the federal funds rate should be 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%. A bandwagon reflecting consensual tendencies would suggest that, after hearing Francis, I should favor a policy that moves above 5.00% and toward 5.25%.

However, Francis was well known for his aversion to inflation and a resulting tendency to favor high interest rates. Under prevailing conditions, suppose that Francis would normally have favored a rate of 5.50%. Since Francis actually favored a rate of 5.25%, I infer that his private information indicates that this is a time for easier policy than normal, and I should favor easier policy as well. Therefore, I should favor a rate below 5.00%, not above it. This is the logic of the Bayesian bandwagons model of section III.

Results were not favorable to the Bayesian bandwagons hypothesis, but we have not ruled out the existence of bandwagons based on consensual policy convergence. To that end, we now modify equation (1) as follows:

$$R_{it}^{*}=\bar{R}_{it}+u_{it}+\beta\left[\tilde{R}_{it}-\left(\bar{R}_{it}+u_{it}\right)\right],\ \ 0\le\beta\le 1. \tag{11}$$

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, u_{it}, is now 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, $\bar{R}_{it}+u_{it}$. Substituting (6) for $\bar{R}_{it}$ and rearranging, we obtain

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

This equation describes a regression of members' target interest rates on member and meeting fixed effects and on $\tilde{R}_{it}$. Support for bandwagons based on 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 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

[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.

small values for β.[13] We earlier found no support for the existence of bandwagons based on Bayesian learning; we now find no support for bandwagons based on consensus-seeking. We should emphasize that this does not imply that consensual pressures are absent from FOMC deliberations. Consensus may be produced prior to the policy go-around, or consensus may be achieved at the voting stage that follows the go-around. Our result indicates that we do not see consensual pressure related to the speaking order as the policy go-around proceeds.

VII. Conclusions

Using data gleaned from FOMC deliberations, we assembled a data set that describes individual Committee members' stated monetary policy preferences and the order in which members spoke in a series of meetings. We then used that data to test a model of Bayesian learning, in which private information is revealed as members speak sequentially in a meeting. Our test is 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, rather than learning, could produce bandwagons, but that model was also rejected.

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

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. A plausible interpretation of our results is that all useful information is fully revealed prior to the policy go-around, rather than as the policy go-around proceeds. This interpretation would be consistent with the existence of efficient information dissemination across Committee members under existing institutions.

Table 1. Results for the Bayesian Bandwagon Model

Parameter	Generalized Model	Bandwagon 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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