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Evaluating the economic forecasts of FOMC members

Xuguang (Simon) Sheng *

Department of Economics, American University, USA

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ABSTRACT

This paper provides a detailed analysis of the forecasts of real GDP, inflation and unemployment made by individual members of the Federal Open Market Committee (FOMC) for the period 1992–2003. Despite a general tendency for the committee members to underpredict real GDP over the sample period, we find evidence suggesting that the FOMC has a considerable amount of information about output growth, beyond what is known by commercial forecasters. We also document a substantial level of variation in the members' forecasts, which can be explained in part by the differences in economic conditions between Federal Reserve districts. The members' heterogeneous forecasts for output growth and inflation contain useful information for explaining their preferred policy settings, beyond that in the Greenbook forecasts.

1. Introduction

Since May 2009, the Federal Reserve has been releasing individual forecasts for each *Monetary Policy Report* with a ten-year lag. The FOMC individual forecasts are important because they contain information about the individual FOMC policy preferences. For the public, these short-term forecasts provide a benchmark to allow them to gauge how policy makers respond to news about inflation. The forecasts also provide information about the FOMC's assessment of the trend in real GDP growth and the associated business cycle stage. Romer (2010) briefly introduces this potentially valuable new dataset on monetary policy, and Banternghansa and McCracken (2009), Bhattacharjee and Gelain (2011), Nunes (2012), and Tillmann (2010) have examined other aspects of the dataset. We contribute to this growing body of literature by further evaluating individual members' forecasts for 1992–2003, and analyzing how these forecasts contextualize their preferred policy setting.

Using the econometric framework for analyzing three-dimensional panel data of forecasts, we document a general tendency of FOMC participants to underpredict real GDP and overpredict inflation and unemployment during the sample period. Our panel data analysis indicates a degree of individual bias and inefficiency in the use of public information among the committee members. Despite these flaws, however, the committee members exhibit a superior performance in predicting the slowdown of output growth in 1995 and the recovery in 2002. This outperformance provides further evidence that the FOMC participants have a considerable amount of information about output growth beyond what is known by commercial forecasters.

Besides the performance of the whole, the individual data allow us to find genuine diversity in the participants' views regarding probable outcomes for output growth and inflation. Our empirical estimates show that the deviation of each member's forecast from the mean can be explained partly by the economic conditions of the member's Federal Reserve district. Furthermore, regional economic conditions and other factors documented in the recent literature can account in part for the difference between the FOMC and Greenbook forecasts. For a discussion

* Correspondence to: 4400 Massachusetts Ave., N.W., American University, Washington, DC, 20016-8029, USA. Tel.: +1 202 885 3782.

E-mail address: sheng@american.edu.

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of these factors, see Bhattacharjee and Gelain (2011), Ellison and Sargent (2012), and Nunes (2012). This close association between regional economic conditions and member output growth forecasts provides a plausible explanation for why the FOMC output growth forecasts add value to the Greenbook forecasts.

To explore the influence of the member's projections on their preferred policy settings, we estimate the monetary policy reaction functions. First, we construct a dataset of preferences drawn from the transcripts of FOMC meeting during the Greenspan years. Based on these preferences, we find that members' projections for output growth and inflation contain useful information beyond that contained in the Greenbook forecasts for explaining their preferred federal funds rates. We also document a substantial degree of policy inertia. These findings are consistent with those of Fendel and Rülke (2012) and Orphanides and Wieland (2008), who find that FOMC decisions can be explained predominately in terms of the FOMC's projections. The connection between projections and policy preference provides further evidence of the importance of economic forecasts in making monetary policy. Since we find that these forecasts are closely related to regional economic conditions, our research supports another strand of the literature that has confirmed the influence of these regional factors on FOMC members' policy preferences, see for example Chappell, McGregor, and Vermilyea (2008) and Meade and Sheets (2005).

The paper is organized as follows. Section 2 describes the data used in our analysis. In Section 3, we explore the rationality and heterogeneity of FOMC members' forecasts. In Section 4, we investigate the potential influence of the members' forecasts on their policy preferences, and Section 5 concludes.

2. Data

We study a panel of forecasts of real GDP, inflation and unemployment from both the staff and members of the FOMC. The particular inflation forecasts we analyze are those of the consumer price index for 1992–1999 and the chain-type price index for personal consumption expenditures (PCE) for 2000–2003. This section describes the source of these forecasts, as well as the actual data used for the purpose of forecast evaluation.

In compliance with the Full Employment and Balanced Growth Act of 1978 (often referred to as the "Humphrey–Hawkins Act"), the Chairman of the Federal Reserve Board reports the economic projections of the FOMC members to the Congress biannually. Since 1979, the Federal Reserve has been releasing the range of these forecasts. Starting in 1983, the range was supplemented with a central tendency, constructed by discarding the extreme forecasts. Many papers have evaluated the FOMC "consensus" forecast, defined as the midpoint of the reported range (or central tendency); see Gavin and Mandal (2003), McNees (1995), and Reifschneider and Tulip (2007), among others. In an act of greater transparency, the Federal Reserve has since released the available individual forecasts for each Monetary Policy Report from January 1992 to July 2002. This starting date reflects gaps in the Federal Reserve's documentation, while the ending date reflects a decision by the FOMC to release the individual data with a ten-year lag, rather than the standard five-year lag. Currently, this dataset includes the forecasts of all participants other than the Chairman at FOMC deliberations; that is, both voting and non-voting FOMC members.[1] We examine the forecasts of real GDP, inflation and unemployment. Real GDP and inflation forecasts are for the fourth-quarter-over-fourth-quarter growth rate, while the unemployment rate forecasts are for the fourth quarter of the target year. The February forecasts are for the current year, and the July forecasts are for the current year and the next year. We simply denote these forecasts as approximately 6-, 12- and 18-month-ahead forecasts. More specifically, we label the forecasts made in July for the next year as 18-month-ahead, those made at the beginning of February as 12-month-ahead, and those made in July for the current year as 6-month-ahead forecasts.[2] The individual forecasts released by the Federal Reserve are the final forecasts after the associated FOMC meeting and after the members have seen one another's forecasts. These final forecasts may differ from the forecasts that members had originally submitted before each FOMC meeting; however, it is not clear whether the Federal Reserve has information about the initial forecasts.

Named the "Greenbook" forecast, the staff of the Board of Governors prepare forecasts before each meeting of the FOMC. They typically forecast inflation, growth and unemployment for five or six quarters into the future. However, the forecast horizon varies over time depending on the date of the FOMC meeting. For a benchmark comparison, we use the Greenbook forecasts for the same variables made at the ends of January and June, which are roughly a week before the FOMC meetings.

For the purpose of forecast evaluation, we use appropriate actual values. As is well known, the NIPA data, such as real GDP, often go through substantial revisions. Obviously, the most recent revision is not appropriate because of contemporaneous adjustments for definitions and classifications. The first release is also unsatisfactory, due to the incompleteness of the initial estimates. For the NIPA variables, including real GDP and the PCE chain-type price index, we choose the so-called "final" estimates, which are released roughly three months after the end of the quarter.[3] This revision is the appropriate series for our assessment, because it is based on relatively complete data, but is of approximately the same period as the forecasts we are analyzing. The timing of the actual values is not so sensitive for the CPI and the unemployment rate, and consequently, we assess the forecasts based on the first released data, which are taken from the Greenbook.

[1] The FOMC individual members' forecasts are available from the Philadelphia Fed website.

[2] Note that since November 2007, the FOMC individual forecasts have been being made four times a year rather than twice a year, and the forecast horizon has been extended by an additional year.

[3] The "final" estimates are the real-time data available from the Federal Reserve Bank of Philadelphia.

Table 1
Root mean squared error in consensus forecasts.

Variable	Horizon	Greenbook	FOMC				
			All members	Governor	Regional bank	Voter	Non-voter
Real GDP	6 months	0.91	0.80	0.82	0.80	0.83	0.77
	12 months	1.35	1.27	1.33	1.25	1.29	1.25
	18 months	1.60	1.51	1.57	1.49	1.52	1.50
Inflation	6 months	0.40	0.44	0.40	0.46	0.44	0.45
	12 months	0.42	0.50	0.44	0.53	0.48	0.54
	18 months	0.65	0.71	0.68	0.73	0.73	0.71
Unemployment	6 months	0.31	0.30	0.29	0.30	0.30	0.29
	12 months	0.46	0.55	0.55	0.55	0.55	0.55
	18 months	0.78	0.74	0.75	0.74	0.75	0.73

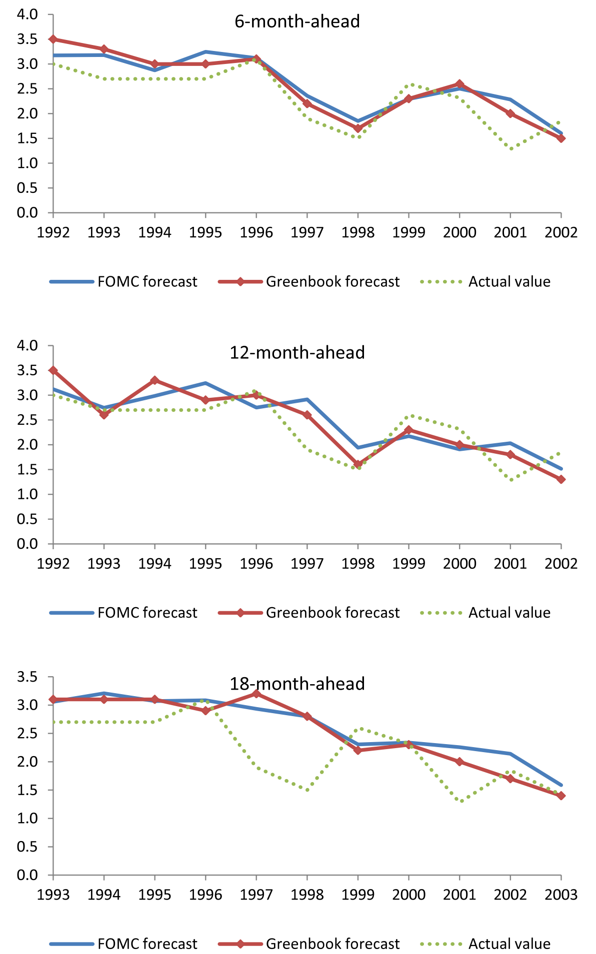


Fig. 1. Inflation forecasts: FOMC vs. Greenbook.

3. Rationality and heterogeneity of FOMC members' forecasts

Given the forward-looking nature of monetary policy, decision-making depends heavily on predictions of inflation, output growth and unemployment. Good predictions may make a positive contribution to meeting monetary policy objectives. As a consequence, evaluating the committee members' forecasts is crucial. This section starts with a detailed analysis of the rationality of members' forecasts for 1992–2003. We then investigate the performances of policy-makers' forecasts during two interesting episodes: the 1995 growth slowdown and the 2002 recovery. Finally, we explore a potential explanation for the differences in forecasts among members.

3.1. Forecast evaluation

We begin by comparing the accuracy of the FOMC consensus forecasts to those of the staff forecasts. Table 1 reports the summary statistic of interest, the root mean squared error (RMSE). Two findings are worth noting. First, for almost all horizons, the FOMC mean forecasts improve on the Greenbook forecasts for both output growth and the unemployment rate. However, for predicting inflation, the staff outperforms the FOMC members. A simple plot of inflation forecasts in Fig. 1 shows that the staff performs best for short-term forecasts. The staff inflation forecasts track the actual inflation closely, with the correlations between the two series being 0.87 for 6 months ahead (vs. 0.80, the correlation between the FOMC forecasts and actual inflation) and 0.81 for 12 months ahead (vs. 0.65). This outperformance is consistent with the results of Gavin and Mandal (2003), who find that the FOMC inflation forecasts do not contribute useful information beyond those of the staff. Second, and somewhat surprisingly, there are systematic differences in forecast accuracy between the governors and the regional bank presidents. Compared to governors, the regional bank presidents are better at predicting output growth, but worse at predicting inflation. Similar, though less clear-cut, differences also exist between voting and non-voting committee members.[4] One possible explanation could be that the forecasts of the regional bank presidents for the economy as a whole are influenced by the conditions in their Federal Reserve districts. We explore this possibility later in the paper.

In the above analysis, we began simply by using the mean as the "consensus", and assessing its accuracy. However, it is possible that no consensus exists. Following

[4] All members of the Board of Governors and the president of New York Fed have voting rights at each FOMC meeting. The remaining eleven district Reserve Banks are divided into four rotation groups: (1) Boston, Philadelphia, and Richmond, (2) Cleveland and Chicago, (3) Atlanta, St. Louis, and Dallas, and (4) Minneapolis, Kansas City, and San Francisco. Within each group, voting rights rotate among the Banks annually.

Table 2
Analysis of individual FOMC members' forecast biases.

Members	Real GDP			Inflation			Unemployment		
	$\hat{\phi}_i$	SE	$\hat{\sigma}^2_{\epsilon(i)}$	$\hat{\phi}_i$	SE	$\hat{\sigma}^2_{\epsilon(i)}$	$\hat{\phi}_i$	SE	$\hat{\sigma}^2_{\epsilon(i)}$
Atlanta	0.31	(0.39)	0.10	−0.35*	(0.17)	0.05	−0.06	(0.19)	0.01
Boston	0.55	(0.39)	0.06	−0.35*	(0.17)	0.04	−0.18	(0.19)	0.02
Chicago	0.36	(0.39)	0.05	−0.25	(0.17)	0.02	−0.12	(0.19)	0.02
Cleveland	0.28	(0.39)	0.13	−0.05	(0.18)	0.14	−0.08	(0.19)	0.03
Dallas	0.25	(0.39)	0.10	−0.11	(0.18)	0.08	−0.09	(0.19)	0.02
Kansas City	0.44	(0.39)	0.07	−0.26	(0.17)	0.04	−0.11	(0.19)	0.02
Minneapolis	0.32	(0.39)	0.08	−0.46*	(0.17)	0.05	−0.15	(0.19)	0.02
New York	0.43	(0.39)	0.06	−0.34*	(0.17)	0.03	−0.17	(0.19)	0.02
Philadelphia	0.24	(0.39)	0.04	−0.14	(0.17)	0.03	−0.12	(0.19)	0.01
Richmond	0.34	(0.39)	0.04	−0.35*	(0.17)	0.05	−0.10	(0.19)	0.02
San Francisco	0.39	(0.39)	0.05	−0.15	(0.17)	0.03	−0.19	(0.19)	0.02
St. Louis	0.19	(0.39)	0.08	−0.50*	(0.19)	0.19	−0.04	(0.19)	0.03
Governor	0.42	(0.39)	0.02	−0.18	(0.17)	0.01	−0.18	(0.18)	0.01

Note: Standard errors are in parentheses.
* Denotes significance at the 5% level.

Schnader and Stekler (1991), we construct the histograms of individual forecasts to see whether there is consensus.[5] Sometimes the distributions of output growth, inflation and unemployment forecasts are bimodal. In such cases, there are at least two distinct collective opinions, and no consensus. Similarly, the distribution of forecasts is relatively flat in some cases, indicating no consensus. Since consensus may not exist, it is necessary to evaluate forecasts at the individual level. To avoid complications caused by long gaps in the data, we treat each regional bank, not the bank president, as the basic unit in our analysis. Following Banternghansa and McCracken (2009), we aggregate governors through an average rather than by individuals. As a result, between January 1992 and July 2002, we have 13 "regular members" who contributed a total of 1287 individual forecasts, forming the basis of our analysis in this section.

Our study follows from the classical framework proposed by Davies and Lahiri (1995) for analyzing three-dimensional panel data of forecasts. See Clements, Joutz, and Stekler (2007) and Davies, Lahiri, and Sheng (2011) for recent applications of the Davies–Lahiri framework. For N individuals, T target years, and H forecast horizons, let F_{ith} be the forecast of the variable of interest made by agent i for the target year t and h periods ahead to the end of the target year, and let A_t be the actual value of the variable. The individual forecast error, e_{ith}, is defined as

$$e_{ith} = A_t - F_{ith}. \tag{1}$$

Following Davies and Lahiri (1995), we decompose e_{ith} as:

$$e_{ith} = \phi_i + \lambda_{th} + \varepsilon_{ith}, \tag{2}$$

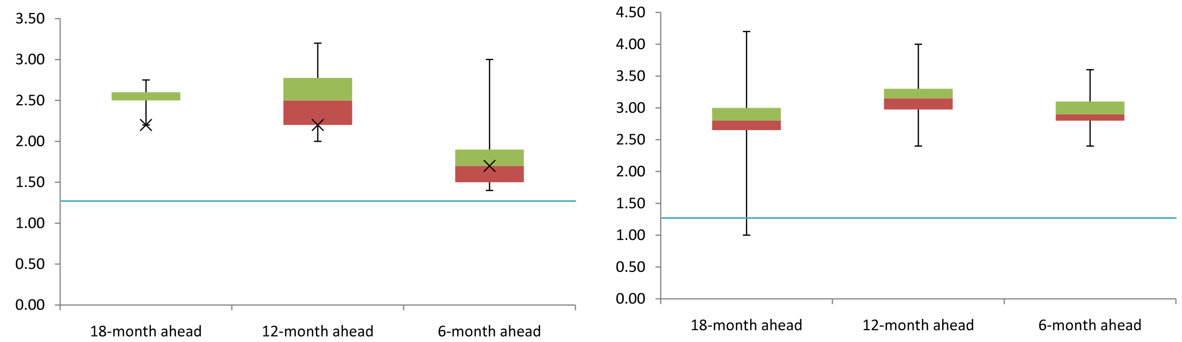
$$\lambda_{th} = \sum_{j=1}^{h} u_{tj}. \tag{3}$$

Eq. (3) specifies the common component λ_{th} as the accumulation of all shocks, u_{tj}, that occurred from h periods ahead to the end of target year t. The first and third components of the forecast error are specific to individual forecasters, and distinguish a possible individual bias ϕ_i from an idiosyncratic error ε_{ith}, which might reflect individual sentiment or measurement errors.

To test for individual bias, we construct the forecast error covariance matrix, denoted by $\hat{\Omega}$, and perform GMM on Eq. (2) using individual-specific dummy variables to estimate the ϕ_i. The Appendix provides further details on the construction of the forecast error covariance matrix. Table 2 shows the estimated results. For real GDP, the mean forecast error is positive for all regular members, indicating a general tendency to underpredict the actual output growth over the period 1992–2003, as most of them were surprised by the productivity acceleration that began in the mid-1990s. In contrast, regular members tend to overpredict inflation and unemployment, as is shown by the negative sign of the mean forecast errors. Moreover, the mean forecast errors differ significantly from zero at the 5% level in almost half of the cases for predicting inflation. For output growth, the estimated standard errors are twice those of inflation. These larger standard errors indicate the possibility of the estimation for output growth over this small sample being imprecise. As such, our results should be interpreted with the small sample size in mind. Despite this caveat, the results reported in Table 2 indicate that a certain degree of bias does exist in predicting all three variables over the sample period. Part of these biases can be explained by the asymmetric loss functions among the committee members (Pierdzioch, Rülke, & Tillmann, 2013), or by the worst-case scenario forecasts (Ellison & Sargent, 2012).

Table 2 also reports the estimated idiosyncratic error variance, $\hat{\sigma}^2_{\varepsilon(i)}$. While the values are very similar across the individual members for the unemployment forecasts, the idiosyncratic error variances display a considerable degree of heterogeneity with respect to the output growth and inflation forecasts. More specifically, in predicting output growth, the Cleveland Fed exhibits the highest level of forecast error variance, followed by the Atlanta and Dallas Feds. In predicting inflation, St. Louis Fed has the highest forecast error variance, followed by Cleveland Fed. This fairly high level of individual heterogeneity in the FOMC is also found among professional forecasters, as has been shown by the US Survey of Professional Forecasters (Davies

[5] To save space, the histograms of these forecasts are not reported.



(a) FOMC members' and Greenbook forecasts. (b) Blue Chip forecasts.

Fig. 2. Box-and-whisker plots of forecasts for the 1995 growth slowdown. Note: The bottom and top of the boxes are the first and third quartiles, the bands inside the boxes are the median, and the ends of the whiskers are the minimum and maximum of individual forecasts. The solid horizontal line represents the actual output growth of 1.27% for the year 1995. The marks × in chart (a) show the Greenbook forecasts.

Table 3
Analysis of FOMC members' forecast efficiency.

Variable	Real GDP	Inflation	Unemployment
Intercept	0.24*	0.05	−0.14*
	(0.06)	(0.04)	(0.03)
Lagged forecast revision	0.23*	−0.19*	−0.13*
	(0.10)	(0.08)	(0.07)

Note: Dependent variable: forecast revision. Standard errors are in parentheses.
* Denotes significance at the 5% level.

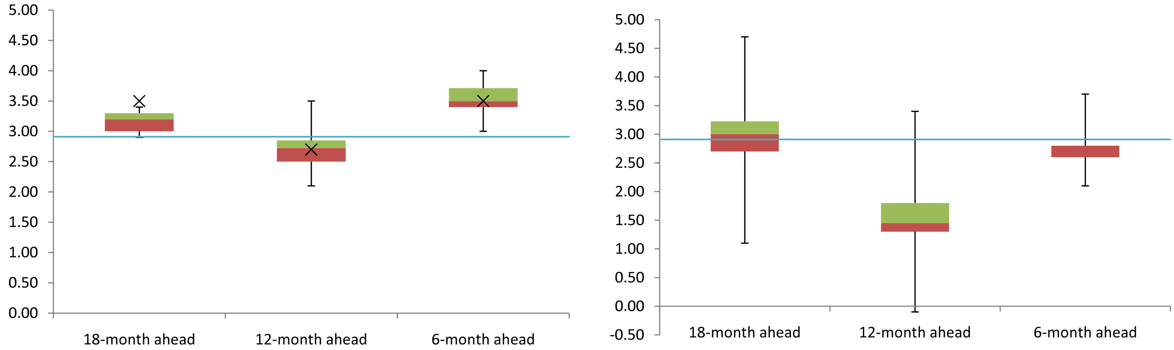
& Lahiri, 1995) and the UK Survey of External Forecasters (Boero, Smith, & Wallis, 2008).

Next, we explore whether the committee members use information efficiently in making their forecasts. The standard efficiency test looks for a correlation between the forecast error and information known to the forecaster in real time. Given the relatively short time span of the dataset, we adopt the weak efficiency test proposed by Nordhaus (1987). Nordhaus' test requires that forecast revisions be uncorrelated with lagged forecast revisions. One advantage of this test is that it is completely independent of the measured actuals. See Isikler, Lahiri, and Loungani (2006) and Loungani, Stekler, and Tamirisa (2013) for recent applications of Nordhaus' test in evaluating GDP forecasts. Table 3 reports the test results. We find that, for all three variables, the lagged forecast revision significantly explains the current forecast revision at the 5% level of significance.[6] The estimated slope coefficient is positive for real GDP, implying that if members revise their output forecast upwards in the February meeting, they tend to revise the forecast upwards again at the following July meeting. In contrast, the estimated slope coefficients are negative for inflation and unemployment, which is largely consistent with the findings of Tillmann (2011).

In summary, our panel data estimates indicate a certain degree of individual bias and inefficiency in the committee members' use of public information over the period 1992–2003. Although such a broad analysis is informative, some specific episodes are of particular interest. To compare the forecasting performances of policy makers with those of commercial forecasters, we focus on the 1995 output slowdown, the one blemish on an otherwise impressive period in the US, and the recovery for the year 2002. The new individual-level dataset gives us an opportunity to examine what was happening among policy-makers during these time periods. Did some members catch the slowdown or recovery? How about other professional forecasters? To answer these questions, we construct box-and-whisker plots of individual forecasts for output growth.

In general, the 1995 slowdown took everyone by surprise. Real GDP growth fell from 4.14% in 1994 to 1.27% in 1995. However, the output growth picked up again in 1996 just as quickly as it had fallen, reaching a level of 3.14%. Panel (a) in Fig. 2 presents the results for FOMC members. The 18-month-ahead forecasts clustered around the long-run average growth rate for real GDP at about 2.5%. The individual forecasters started to "break apart" from the cluster at 12 months ahead, with the majority of the forecasts ranging from 2.2% to 2.8%. It is interesting to note that some members, such as the Chicago and Boston Feds, were able to foresee the 1995 slowdown at the 12-month horizon. At the 6-month horizon, almost all members revised their forecasts downward significantly. One notable exception is the Cleveland Fed, which actually increased the forecast from 2.75% at 18 months ahead to 3% at 6 months ahead. For the Greenbook forecast, while it remained at 2.2% for the 18- and 12-month-ahead forecasts, the 6-month-ahead forecast was revised down to 1.7%. More striking is the fact that the disagreement among policy makers increased as the forecast horizon shortened, indicating an unusually high level of uncertainty during this episode. The picture for commercial forecasters is quite different. As panel (b) in Fig. 2 shows, the majority of forecasts in the Blue Chip ranged from 2.7% to 3.3% for all three horizons. The forecast disagreement declined as the fixed-event date neared. Ironically, the Inforum-University of Maryland had a forecast which was very close to the actual at 18 months ahead, but it increased its forecast to 3% at 12 months ahead, and revised it further to 2.9% at 6 months ahead. Compared to other professional forecasters, the committee members exhibit superior performances in

[6] It is worth noting that, based on a shorter sample period, 1992–2000, Tillmann (2011) could not find a statistically significant coefficient on the lagged GDP forecast revisions. Again, this introduces the issue of the impact of the short sample period on the interpretation of the forecast evaluation results.



(a) FOMC members' and Greenbook forecasts. (b) Blue Chip forecasts.

Fig. 3. Box-and-whisker plots of forecasts for the 2002 growth recovery. Note: The bottom and top of the box are the first and third quartiles, the bands inside the boxes are the median, and the ends of the whiskers are the minimum and maximum of individual forecasts. The solid horizontal line represents the actual output growth of 2.91% for the year 2002. The marks × in chart (a) show the Greenbook forecasts.

predicting the slowdown of output growth for the year 1995.

Another interesting episode is the quick recovery of output growth in 2002 from the shallow recession in the preceding year: real GDP increased from 0.48% in 2001 to 2.91% in 2002. Fig. 3 presents the box-and-whisker plots of output growth forecasts for the year 2002 among FOMC members (panel (a)) and commercial forecasters (panel (b)). At 18 months ahead, the majority of forecasts ranged from 2.7% to 3.2%, though there was a substantial level of disagreement among commercial forecasters. At 12 months ahead, while the policy makers were able to predict the 2002 recovery, almost all commercial forecasters failed to do so. Indeed, many Blue Chip forecasts were well below 1.8%, and the most pessimistic prediction was −0.1%, given by Daiwa Institute of Research. At the 6-month-ahead horizon, however, most commercial forecasters had predictions which were very close to the actual value.

To conclude, these two case studies provide further evidence that the FOMC participants have a considerable amount of information about output growth beyond what is known to commercial forecasters. This result corroborates the findings of El-Shagi, Giesen, and Jung (2012) and Romer and Romer (2000) that the staff forecasts of the Fed and ECB have an information advantage over private forecasters for output.

3.2. Forecast disagreement

As we have already seen in Figs. 2 and 3, the committee members disagreed greatly regarding forecasts of output growth. Furthermore, Table 2 shows that there is a considerable degree of heterogeneity in the GDP and inflation forecasts over the sample period. In this subsection, we explore one possible explanation for these differing forecasts among committee members.[7]

Although FOMC members have access to the same information and a common Greenbook, the members are not given any specific assumptions about the conduct of monetary policy. Instead, members condition their forecasts on their judgments of "appropriate" policy, which may differ from what they perceive to be the most likely path of monetary policy. However, as was argued by Coibion and Gorodnichenko (2012), since monetary policy actions have only gradual effects on prices and output, differences in assumptions about the future path of monetary policy are unlikely to have significant effects on the members' forecasts of inflation and output growth in the medium run. In order to understand the differences across members, we explore the possibility that their forecasts for the economy as a whole may be correlated with the economic conditions in their Federal Reserve districts. The Beige Book prepared before each FOMC meeting summarizes the anecdotal information collected by regional bank presidents from meetings with their business contacts. As was shown by Balke and Petersen (2002), the Beige Book has information about current quarter real GDP growth which is not present in other indicators such as the Blue Chip forecasts. The regional bank presidents have also emphasized that such contacts affect their views about economic conditions. For example, as Cleveland Fed President Pianalto stated in her speech on October 1, 2009,

> "*To try to clarify my perspective on the economy, I also spend a lot of time talking with businesspeople—the heads of Fortune 500 companies, owners of small and medium-sized enterprises, and CEOs from large regional banks and small community banks*".

In addition, individual policy makers might be pressured by their constituents to advocate policies that are appropriate for their regions. For instance, as was stated by Cleveland Fed President Jordan on November 16, 1999, in FOMC Transcripts,

[7] There is a large body of literature that examines the sources of such disagreement among professional forecasters, including the imperfect information models of Coibion and Gorodnichenko (2012) and Mankiw, Reis, and Wolfers (2004); the differential interpretation of information from Lahiri and Sheng (2008); the asymmetric loss function of Capistrán and Timmermann (2009); the heterogeneity in prior beliefs from Lahiri and Sheng (2010) and Patton and Timmermann (2010); and the role of central bank transparency from Dovern, Fritsche, and Slacalek (2012), Ehrmann, Eijffinger, and Fratzscher (2012) and Hubert (in press).

"*And if we see some weakness in our area, that will make it difficult for those of us in the middle part of the country to have a proper perspective on the appropriate national, let alone international, monetary policy.*"

To explore the effects of regional influences on the members' forecasts, we follow Meade and Sheets (2005) in calculating the deviation of the regional from the national unemployment rate (UNDIFF). These series are available from the St. Louis Fed. An important point in our analysis is the need to ensure that the variable UNDIFF reflects only information which was available to the FOMC members in real time. To that end, we limit our data to what would have been available to the FOMC by early February or early July. More specifically, to match the timing of the February forecasts, we use the actual unemployment rate in December of the previous year. To match the timing of the July forecasts, we use the actual unemployment rate in May of the current year.

We regress the deviation of each member's forecast from the mean forecast (Dev) on its lagged value, UNDIFF and a dummy variable for voting status (VS):

$$\mathrm{Dev}_{it} = \beta_0 + \beta_1 \mathrm{Dev}_{i,t-1} + \beta_2 \mathrm{UNDIFF}_{it} + \beta_3 \mathrm{VS}_{it} + \varepsilon_{it}. \quad (4)$$

The estimated results are presented in Panel A of Table 4. Coefficient estimates on the lagged dependent variable show a considerable degree of persistence in the deviation of each member's forecast from the mean in predicting output growth and inflation. The coefficient for UNDIFF in the GDP forecast is negative and significant (p-value of 0.07), indicating that a rise in the regional unemployment rate (for a given national rate) lowers the forecasts for national output growth compared to the average. This fairly strong influence of the regional unemployment rate on their forecasts for output growth may, in part, explain why the regional bank presidents are better at predicting output growth than the governors. Often the regional bank presidents know what is happening in their region of the country well before the hard data are collected by national statistical agencies. This sheds additional light on the recent findings of Romer and Romer (2008) that the FOMC output growth forecasts add some value to the Greenbook forecasts. This is also consistent with Berger, Ehrmann, and Fratzscher (2011), who find that the heterogeneity among professional forecasters in predicting FOMC decisions depends on both the skills of analysts (such as their educational and employment background) and geography (such as regional economic conditions). However, the regional unemployment rate does not seem to play an important role in predicting national inflation and unemployment. Furthermore, we cannot find significant differences in the deviation of regional bank presidents' forecasts from the average between voting and non-voting members.

One potential problem with the above analysis is that the committee members did not observe the mean forecast at the time when the forecast was made. To address this issue, we study the deviation of each member's forecast from the Greenbook forecast, which all of the FOMC members had access to. Panel B of Table 4 shows that a rise in the regional unemployment rate (for a given national rate) tends to lower forecasts for national GDP and

Table 4
Regional influence on FOMC members' forecasts.

Variable	Real GDP	Inflation	Unemployment
Panel A: Dependent variable: the deviation of each member's forecast from the mean forecast			
Intercept	0.10	0.07	−0.04
	(0.07)	(0.06)	(0.05)
Lagged dependent variable	0.13*	0.36**	0.05
	(0.07)	(0.06)	(0.06)
UNDIFF	−0.12*	0.04	−0.02
	(0.07)	(0.05)	(0.05)
Voting status	0.00	0.04	0.00
	(0.03)	(0.03)	(0.02)
Panel B: Dependent variable: the deviation of each member's forecast from the Greenbook forecast			
Intercept	−0.04	−0.04*	0.01
	(0.03)	(0.02)	(0.01)
Lagged dependent variable	0.06*	0.20**	0.01
	(0.04)	(0.04)	(0.02)
UNDIFF	−0.07*	−0.02	0.02
	(0.04)	(0.04)	(0.02)
Voting status	0.00	0.04	−0.01
	(0.03)	(0.03)	(0.02)

Note: UNDIFF is the deviation of the regional from the national unemployment rate. For January/February forecasts for the current year, we use the unemployment rate in the December of the previous year, and for June/July forecasts for the current year, we use the unemployment rate in May of the current year. Voting status is a dummy variable, equal to 1 if voting and 0 otherwise. All regressions include fixed effects by members. Panel cross-section robust standard errors are in parentheses.
* Denotes significance at the 10% level.
** Denotes significance at the 5% level.

inflation and raise forecasts for national unemployment compared to the corresponding Greenbook forecasts. Thus, the difference between the FOMC and Greenbook forecasts can be explained in part by regional economic conditions. The recent literature documents other potential factors. For example, Ellison and Sargent (2012) assume that the FOMC's forecasts depict a worst-case scenario which is used to design decisions that are robust to the misspecification of the staff's model. In a similar vein, Bhattacharjee and Gelain (2011) hypothesize that the FOMC forecasts take possible model specifications into account by averaging over a collection of plausible alternative models in a Bayesian world. Nunes (2012), on the other hand, finds that the difference between the FOMC and Greenbook forecasts can be explained by the influence of the White House and private sector forecasts.

4. FOMC members' forecasts and their monetary policy preferences

Given that the FOMC members are not only professional forecasters, but also policy-makers, the forecasts made by the members may have a direct impact on the setting of interest rates. Typically, the studies in the literature have used FOMC voting records to make inferences about the

Table 5
Monetary policy reaction function estimates.

Variable	Model 1		Model 2		Model 3		Model 4	
Intercept	−0.09	(0.13)	0.24*	(0.14)	0.23	(0.14)	0.30**	(0.14)
Pre-meeting funds rate	0.92**	(0.01)	0.90**	(0.01)	0.90**	(0.01)	0.89**	(0.01)
Member's real GDP forecast	0.15**	(0.02)	0.08**	(0.03)	0.08**	(0.03)	0.06*	(0.03)
Member's inflation forecast	0.22**	(0.03)	0.16**	(0.04)	0.15**	(0.04)	0.16**	(0.04)
Member's unemployment forecast	−0.09**	(0.02)	0.10*	(0.06)	0.10*	(0.06)		
Greenbook real GDP forecast			0.04	(0.03)	0.04	(0.03)	0.06**	(0.03)
Greenbook inflation forecast			0.10**	(0.04)	0.11**	(0.04)	0.12**	(0.04)
Greenbook unemployment forecast			−0.23**	(0.05)	−0.23**	(0.05)	−0.14**	(0.02)
Dummy for voting					0.00	(0.03)	0.00	(0.03)
Dummy for regional bank president					0.01	(0.03)	0.01	(0.03)

Note: The dependent variable is the FOMC member's desired federal funds rate. White heteroskedasticity-consistent standard errors are in parentheses.
* Denotes significance at the 10% level.
** Denotes significance at the 5% level.

committee members' policy preferences, see Meade and Sheets (2005) and the references therein. While voting records provide important indicators of policy preferences, they are limited in their scope of dissenting. The Fed traditions dictate that a member should "dissent" only if the chairman's proposal is unacceptable. Indeed, over the sample period we examined, there is only a 2.4% dissent rate in official votes.

To investigate the claim that the official votes cast by Fed policy makers do not reflect their "true" preferences, we construct a dataset of preferences drawn from the transcripts of FOMC meetings during the Greenspan years.[8] In the course of a Greenspan-era FOMC meeting, there were typically two rounds of discussion. During the first round, the members offered their views on the economic situation and the regional bank presidents provided specific economic developments in their regions. During the second round, all participants (both voting and nonvoting) voiced explicit policy preferences. They typically stated their positions as 25 or 50 basis point movements relative to Greenspan's proposal. We collect these preferences as indicating the participants' desired funds rates. This gives us a dataset consisting of 369 member-meeting observations obtained from 22 committee meetings.[9] The participants disagreed with the committee's adopted funds rate in 11.4% of these cases. Strikingly, this disagreement rate based on voiced preferences is more than four times the dissent rate in official votes.

Given the members' desired federal funds rates, we estimate the following monetary policy reaction functions to explain their preferred policy settings:

$$R_{it} = \boldsymbol{X_{it}}\beta + \varepsilon_{it}, \tag{5}$$

where R_{it} is member i's desired federal funds rate for meeting t. The vector $\boldsymbol{X_{it}}$ includes members' forecasts, Greenbook forecasts, and characteristic binary variables for detecting differences between voters and non-voters. In our regression, we also allow for the possibility that the FOMC members may have a preference for policy inertia by including the pre-meeting federal funds rate in $\boldsymbol{X_{it}}$. The coefficient β is a vector of parameters of interest and ε_{it} represents independent and identically distributed random errors.

Our initial specification assumes that the member's desired interest rates depend on their own projections and the funds rate before the meeting. Estimation results are displayed in the first column of Table 5. All coefficient estimates on the members' forecasts for national macroeconomic variables differ significantly from zero, and the signs suggest a strong countercyclical stabilization response. Furthermore, the coefficient on the pre-meeting funds rate is 0.92, indicating a substantial degree of inertia in setting policy. These results are similar to those of Fendel and Rülke (2012), who find that the often-used aggregate Taylor rule for the FOMC as a whole presents a good summary of the behaviors of individual members.

We next consider the added value of FOMC members' forecasts beyond the Greenbook forecasts. The second column of Table 5 reports the coefficient estimates with both the FOMC and the Greenbook forecasts in the regression. The coefficient estimates on the Greenbook forecasts are consistent with the hypothesis that the Fed "leans against the wind". The members' own projections for three macro variables continue to be significant factors in explaining their desired funds rates.[10] Because of the almost perfect correlation between the members' and Greenbook unemployment forecasts, we exclude the members' own unemployment projections from the regression, and our final model specification appears in the last column of Table 5.

Our general findings from estimating the monetary policy reaction function can be summarized as follows. First, the member's own projections for output growth

8 Another channel for voicing dissatisfaction with the Fed's monetary policy is via communication. Hayo and Neuenkirch (2013) find that speeches by Fed officials are influenced by regional variables, and that the regional bias tends to increase during recessions and financial crises.

9 See Meade (2005) for a detailed description of the coding procedures for the 1989–1997 period. We extend her dataset through to the end of 2002 for the analysis in this paper.

10 However, one puzzle appears. That is, the coefficient on the members' unemployment forecast turns out to be positive, which is hard to explain. Adding the dummy variables for voters or regional bank presidents does not solve the problem, as is shown in the third column of Table 5. Further investigation shows that this puzzle is caused by the multicollinearity, as the correlation between the members' and Greenbook unemployment forecasts is 0.98.

and inflation contain useful information beyond that contained in the Greenbook forecasts in explaining their preferred policy settings. These results corroborate the findings of Orphanides and Wieland (2008) that FOMC decisions can be explained predominately in terms of FOMC's own projections rather than observed outcomes. However, we go deeper, by basing our analysis on individual members' forecasts rather than on the potentially nonexistent consensus forecast. Second, our empirical estimates suggest that there is a systematic response to inflation and unemployment. According to Clarida, Galí, and Gertler (2000), the response to inflation can be calculated as $1.45(=\frac{0.16}{1-0.89})$, which is positive and noticeably greater than 1, suggesting that the Taylor principle holds. The response to unemployment, calculated as $-1.27(=\frac{-0.14}{1-0.89})$, is negative and also quite large, suggesting a strong countercyclical stabilization response. Third, we find a substantial degree of interest rate smoothing, in other words, a partial adjustment of the funds rate depending on the last period's realization.

The contribution of members' own forecasts in making monetary policy, together with the connection between member forecasts and regional economic development, relates to another strand of the literature that has confirmed the influence of regional economic conditions on FOMC members' policy preferences.[11] For example, Meade and Sheets (2005) find that FOMC members are responsive to regional conditions when voting on monetary policy. Chappell et al. (2008) conclude that regional economic conditions influence FOMC members' preferred funds rate.

5. Conclusion

We have conducted a detailed analysis of FOMC members' forecasts from January 1992 to July 2002 for output growth, inflation and unemployment. Our main empirical findings can be summarized as follows. First, we document a general tendency for FOMC participants as a whole to underpredict real GDP and overpredict inflation and unemployment during the sample period. Despite these flaws, the committee members exhibit superior performances in predicting the 1995 slowdown and the 2002 recovery in output growth. These two cases provide further evidence that the FOMC participants have a considerable amount of information about output growth beyond what is known to commercial forecasters. Second, we find a substantial degree of variation in the individual forecasts. The difference between the FOMC and Greenbook output growth forecasts can be explained in part by regional economic development. The influence of regional economic conditions on the members' forecasts, in turn, provides one possible explanation for the value added to the Greenbook forecasts by the FOMC output growth forecasts. Third, we find that the projections of individual members for output growth and inflation explain their preferred federal funds rates beyond that of the Greenbook forecasts. Furthermore, these preferred rates are strongly countercyclical and exhibit a strong degree of policy inertia. These findings add to the recent literature on the contribution of economic projections in making monetary policy.

Admittedly, our results may reflect our particular ten-year sample period, and as such, they should be interpreted with caution. However, our findings on the information advantage of FOMC members in predicting output growth, the influence of regional economic conditions on the members' forecasts, and the role of these forecasts in making monetary policy may still hold for a longer sample period.

Many questions remain to be explored in this valuable new dataset on monetary policy, particularly as the time period covered by the data is extended. Several of our findings prompt questions about participants' interpretations and efficient use of public information, the exploration of which would be worthwhile. Furthermore, our finding that the members' own economic projections can predominately explain their preferred policy setting may have implications for European monetary policy, since the national loyalties of the ECB's Governing Council members are presumably stronger than the regional loyalties of FOMC members.

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Appendix. Constructing the forecast error covariance matrix

For N individuals, T target years, and H forecast horizons, let F_{ith} be the forecast of the variable of interest made by agent i, for the target year t and h periods ahead to the end of the target year. The data are sorted first by individual, then by target year, and lastly by forecast horizon, so that the $1 \times NTH$ vector of forecasts F' takes the following form: $F' = (F_{11H}, \ldots, F_{111}, F_{12H}, \ldots, F_{121}, \ldots, F_{1TH}, \ldots, F_{1T1}, \ldots, F_{NTH}, \ldots, F_{NT1})$.

Let A_t be the actual value of the variable. The individual forecast error (e_{ith}) is defined as

$$e_{ith} = A_t - F_{ith}. \tag{A.1}$$

We decompose e_{ith} as:

$$e_{ith} = \phi_i + \lambda_{th} + \varepsilon_{ith}, \tag{A.2}$$

$$\lambda_{th} = \sum_{j=1}^{h} u_{tj}, \tag{A.3}$$

where $E(\varepsilon_{ith}) = 0$ and $E(u_{th}) = 0$ over all i, t and h, as implied by the rational expectation hypothesis. We assume

[11] The policy makers have also emphasized the potential use of forecasts in their decision making. For instance, as St. Louis Fed President Poole stated in his speech on August 31, 2006, "*For example, policy is forward looking, which means that from time to time the economic outlook changes sufficiently that it makes sense for the FOMC to set a funds rate target either above or below the level called for in the Taylor rule…*".

that $E(\varepsilon_{ith}^2) = \sigma_{\varepsilon(i)}^2$ and $E(u_{th}^2) = \sigma_u^2$ over all t and h. Following Davies and Lahiri (1995), the $NTH \times NTH$ forecast error covariance Ω takes the following form:

$$\Omega = \begin{bmatrix} A_1 & 0 & \cdots & 0 \\ 0 & A_2 & \cdots & 0 \\ \vdots & & & \\ 0 & 0 & \cdots & A_N \end{bmatrix}_{NTH\times NTH} + \begin{bmatrix} B & B & \cdots & B \\ B & B & \cdots & B \\ \vdots & & & \\ B & B & \cdots & B \end{bmatrix}_{NTH\times NTH}. \tag{A.4}$$

In our dataset with $N = 13, T = 12, H = 3$, the components in Eq. (A.4) are expressed as

$$A_i = \sigma_{\varepsilon(i)}^2 I_{TH\times TH}, \tag{A.5}$$

$$B = \begin{bmatrix} b & c & 0 & \cdots & & & 0 \\ c' & b & c & \cdots & & & 0 \\ \vdots & & & & & & \\ 0 & 0 & 0 & \cdots & c' & b & c \\ 0 & 0 & 0 & \cdots & 0 & c' & b \end{bmatrix}_{TH\times TH} \tag{A.6}$$

$$b = \sigma_u^2 \begin{bmatrix} 3 & 2 & 1 \\ 2 & 2 & 1 \\ 1 & 1 & 1 \end{bmatrix}_{H\times H} \tag{A.7}$$

$$c = \sigma_u^2 \begin{bmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix}_{H\times H}. \tag{A.8}$$

General expressions for estimates of the forecast error components in Eq. (A.2) are

$$\hat{\phi}_i = \frac{1}{TH}\sum_t \sum_h e_{ith}, \tag{A.9}$$

$$\hat{\lambda}_{th} = \frac{1}{N}\sum_i (e_{ith} - \hat{\phi}_i), \tag{A.10}$$

$$\hat{\varepsilon}_{ith} = e_{ith} - \hat{\phi}_i - \hat{\lambda}_{th}. \tag{A.11}$$

Since $E\left(\varepsilon_{ith}^2\right) = \sigma_{\varepsilon(i)}^2$, $\hat{\sigma}_{\varepsilon(i)}^2$ is obtained by regressing $\hat{\varepsilon}_{ith}^2$ on N individual-specific dummy variables. Similarly, since $E\left(\lambda_{th}^2\right) = h\sigma_u^2$, $\hat{\sigma}_u^2$ is obtained by regressing $\hat{\lambda}_{th}^2$ on a vector of horizon indices, h ($h = 1, 2, 3$ in our case). Substituting $\hat{\sigma}_{\varepsilon(i)}^2$ and $\hat{\sigma}_u^2$ into Eqs. (A.4)–(A.8), we get the estimated forecast error covariance matrix, $\hat{\Omega}$.

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Xuguang (Simon) Sheng is an Assistant Professor of Economics at American University. His research interests include time series econometrics, economic and financial forecasting. He has published in Journal of Econometrics, Journal of Applied Econometrics, Journal of Accounting and Economics, and Oxford Handbook on Economic Forecasting.