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Dispersion of FOMC Policymakers: Evidence from Individual Economic Projections with Identities*

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Abstract

This paper analyzes the Federal Open Market Committee (FOMC) policymakers' economic projections with identities published after 2007 and presents three sets of results. First, the dispersion of projections across policymakers is associated with the regional economic conditions they represent and their monetary policy preferences. Second, the policymakers' reaction function is consistent with the Taylor rule and satisfies the Taylor principle for stability. Their projections align with Okun's law and the Phillips curve. Finally, the efficiency evaluations to test the unpredictability of forecast errors and revisions indicate that the efficiency is rejected by many policymakers, with rejections concentrated in the years following the Great Recession.

Keywords: FOMC, Individual Projections, Regional Influence, Policy Preference, Forecast Efficiency

J.E.L. codes: C53, E43, E47, E58

1 Introduction

Economic projections released by Federal Open Market Committee (FOMC)'s policymakers play a key role in monetary policy communication, by providing a timely economic outlook and offering an indication of the future course of monetary policy. This has been more pronounced since 2007, when the FOMC substantially expanded the scope of its projections and extended its forecast horizons. The FOMC chair routinely refers to the summary of economic projections (SEP) in their remarks at the post-meeting press conferences, and the public is keenly aware of them. However, a formal analysis of individual policymakers' projections is limited due to the embargo policy—only the summary is available in real time, and individual projections with policymakers' identities are only made available to the public after five or ten years.

With a few years (2007–2014 and 2016–2019) of new projections that include policymakers' identities, researchers are now able to conduct a number of empirical exercises that were previously infeasible.[1] First, we now have the ability to analyze whether FOMC policymakers' individual characteristics influence their newly expanded projections. Previous studies have documented the effects of factors such as regional economic conditions, voting status, and personal backgrounds using projections made before 2007, which were released twice a year forecasting one year ahead.[2] In contrast, this paper examines more recent projections that provide significantly more data, as they are released four times a year forecasting three years ahead. Whether the previously observed patterns persist in these expanded projections is a highly policy-relevant question—one that this paper investigates for the first time. Second, the newly introduced projections for the federal funds rate from 2012 enable us to estimate the policymakers' reaction function controlling for individual characteristics. We are also able to examine whether the policymakers' individual projections are consistent with macroeconomic principles such as Okun's law and the Phillips curve. Third, we can examine the forecast revisions and errors of individual policymakers, as the new dataset enables us to track policymakers across different meetings. In particular, we can check whether FOMC policymakers' projections are consistent with the benchmark of the full-information rational expectations (FIRE) model.

[1] Arai (2023) analyzed the FOMC's anonymous individual economic projections without identity. For an assessment based on the aggregate summary of economic projections, see Arai (2016) and Kalfa and Marquez (2019).

[2] For an overall assessment of the projections before 2007, see Romer (2010). For the influence of regional economic conditions, see Bennani (2016), Bennani et al. (2018a), Chappell et al. (2005), Eichler et al. (2018), Meade and Sheets (2005), Schultefrankenfeld (2020), and Sheng (2015): For voting status, see Jung and Latsos (2015), Nakazono (2013), and Tillmann (2011): For policymakers' personal backgrounds, see Bordo and Istrefi (2023), Malmendier et al. (2021) and Smales and Apergis (2016).

To conduct these exercises, this paper employs regression analysis and efficiency evaluation. The regression analysis captures the comovement across different macroeconomic projections. For example, we can estimate the reaction function (Taylor rule) by regressing the projections of the federal funds rate on the inflation and unemployment gaps. Similarly, we can examine the relationship between unemployment and output growth projections (Okun's law) and unemployment and inflation projections (the Phillips curve). Measures of regional economic conditions and preferences for monetary policy are added as additional control variables. The efficiency evaluations test the implications that both forecast revisions and forecast errors are unpredictable under the FIRE model.

Three sets of results arise from this analysis. First, regional economic conditions and preferences for monetary policy significantly influence policymakers' economic projections. Specifically, regional bank presidents tend to forecast higher unemployment rates and lower inflation when their districts experience higher unemployment, anticipating a more severe economic downturn at the national level than what materializes. This finding aligns with Chappell et al. (2005) and Meade and Sheets (2005), who also demonstrated that regional factors influence voting patterns.[3] Furthermore, policymakers who exhibit a preference for higher federal funds rates tend to forecast inflation significantly higher than the realized values.

Second, policymakers' reaction functions are consistent with the Taylor rule, raising the federal funds rate in response to a positive inflation gap and a negative output gap, for which we use the unemployment gap as a proxy. The collective response to the inflation gap is estimated to be larger than 1, which is consistent with the Taylor principle for stability. FOMC policymakers' projections are also largely consistent with Okun's law and the Phillips curve—the association between unemployment and output growth projections is strongly negative, while the negative association between inflation and unemployment projections is weak and dispersed. These results are consistent with Arai (2023) using anonymous individual projections.

Finally, there is substantial heterogeneity across FOMC policymakers in their efficiency evaluations—the FIRE model is rejected for many FOMC policymakers, regardless of their status in the committee. The rejections are concentrated in the periods after the Great Recession, with the unemployment rate between 2009 and 2010 and output growth and inflation between 2012 and 2013. The accuracy of economic projections measured by relative root-mean-squared errors (RMSE) also varies substantially across policymakers. The test for information rigidity shows that individual

[3] Bobrov et al. (2024) confirmed this result using more disaggregated regional economic data.

policymakers overreact to incoming news to revise their forecasts.

This study has several macroeconomic implications. First, it enhances our understanding of the FOMC's communications by providing a quantitative analysis. As highlighted in Blinder et al. (2008), effective communication on monetary policy has become increasingly crucial, particularly in the post-financial crisis period when the Federal Reserve adopted unconventional monetary policy.[4] Bernanke (2016) discusses that the FOMC's economic projections are informative because they reveal not only "information about key long-run parameters" but also "indirect information about the FOMC's reaction function."[5] The quantitative analysis in this study follows this perspective and helps the public interpret the FOMC's policy responses.

Second, this study finds substantial heterogeneity among FOMC policymakers and highlights the importance of regional economic conditions and policy preferences in shaping their projections. Overlooking these individual variations could mislead policy interpretation. For example, Couture (2021) identified significant gaps between the FOMC's SEP and private forecasters' interest rate predictions, attributing these gaps to a lack of central bank credibility. However, private forecasters may account for variations across FOMC policymakers when forming their expectations. In that case, the observed gap between the SEP and private forecasts might instead reflect individual variations that private forecasters implicitly incorporate into their assessments. On the policymakers' side, savvy members may strategically present extreme views to amplify the influence of their projections, exploiting the anonymity of the process. In any case, the FOMC's projections should be interpreted with caution, particularly in real time when policymakers' identities are not disclosed.

Third, this study provides empirical evidence of the newly expanded projections by FOMC policymakers, highlighting their deviation from the FIRE model. Building on the influential works of Romer and Romer (2000) and Sims (2002), numerous studies have examined the accuracy of forecasts made by Federal Reserve staff and FOMC policymakers to identify such deviations.[6] More broadly, research on survey forecasts identifies deviations from the FIRE model and proposes various explanations.[7] This paper contributes additional empirical evidence to this body of literature.

[4] See Dell'Ariccia et al. (2018) and Kuttner (2018) for details.

[5] For an analysis of the Federal Reserve's long-term unemployment rate, see Binder (2021). For an analysis of the Federal Reserve's reaction function, see Arai (2023) and Gonzalez-Astudillo and Tanvir (2023). For the reaction function perceived by the public, see Bauer et al. (2022), Bundick (2015), Kim and Pruitt (2017), and Pierdzioch et al. (2016). For a more critical review of the FOMC's communications, see Faust (2016).

[6] For comparisons between forecasts by Federal Reserve staff and FOMC policymakers, see Bennani et al. (2018b), El-Shagi et al. (2016), Ellison and Sargent (2012), Gamber and Smith (2009), Hogan (2022), and Romer and Romer (2008). For comparisons with other survey forecasts, see Coibion and Gorodnichenko (2012) and Ellis and Liu (2013).

[7] Explanations include information rigidity by Coibion and Gorodnichenko (2012), diagnostic expectations by Bauer et al. (2022), asymmetric loss functions or conservatism by Elliott et al. (2005) and Ellison and Sargent

Finally, the analysis of the FOMC's numerical projections in this paper contributes to a growing body of literature that scrutinizes the FOMC's textual communications and public perception. As documented in Swanson and Jayawickrema (2023) and Granziera et al. (2024), FOMC policymakers' communications have a significant impact on asset prices and inflation expectations, and understanding the nature of their communications is critical to understand the conduct of US monetary policy.[8] The newly expanded projections include a variety of information that was not previously available, such as the path of appropriate monetary policy and projections in the longer run. The analysis of these projections complements the findings of the literature and facilitates our understanding.

The remainder of this paper is organized as follows: Section 2 describes the data and notation. Sections 3 and 4 outline the efficiency evaluation and regressions used in this analysis. Section 5 presents the main empirical results, and Section 6 offers concluding remarks.

2 Data and Notation

2.1 Data

The FOMC's economic projections are the numerical projections of several macroeconomic series over the next two to three years and over the longer run:[9] real GDP growth, the unemployment rate, personal consumption expenditures (PCE) inflation, and core PCE inflation. Since 2012, the FOMC has started publishing the projected path of the future federal funds rate (FFR) associated with these macroeconomic projections.

The FOMC's economic projections are the annual projections that target the level or growth rate in the fourth quarter of a given year. Although all the participants in the FOMC meetings submit their projections, only a set of summary statistics, such as the ranges, central tendency, and median, are released immediately after each meeting.[10] The FOMC releases these projections four times a year, typically in March, June, September, and December. Recently, individual FOMC

(2012), Bayesian learning by Lahiri and Sheng (2008) and Farmer et al. (2024), and structural breaks by Rossi and Sekhposyan (2015).

[8]For the analysis of the languages used in FOMC policymakers' speeches, see Aruoba and Drechsel (2024), Gáti and Handlan (2023), Sharpe et al. (2022), and Shapiro and Wilson (2021). For the analysis focusing on the high-frequency impact of policymakers' speeches, see Swanson (2023).

[9]Projections over the longer run were added in 2009. Federal Open Market Committee (2024) describes longer-run projections as "the rates of GDP growth, inflation, and unemployment to which a policymaker expects the economy to converge over time—maybe in five or six years—in the absence of further shocks and under appropriate monetary policy."

[10]The FOMC began to release median projections in September 2015.

policymakers' economic projections have been made available to the public, and, at the time of writing, those with policymakers' identities are available from 2007 to 2014 and from 2016 to 2019.[11]

We use the data of policymakers who released at least 10 projections over the sample period as a baseline. Table 1 lists the names of the policymakers, their affiliations, and the number of projections made by them. In summary, we have 39 FOMC policymakers during the sample period, with 16 belonging to the board of governors and 23 belonging to regional federal reserve banks.

2.2 Notation

In this paper, we denote the forecast of the macroeconomic variable y by forecaster i in the qth quarters of year t forecasting h years ahead ($h = 0, \dots, 3$) as $\hat{y}^i_{t+h|t,q}$. We also define the forecast revision for year $t+h$ made in the qth quarters of year $t+j$, for any j, such that $0 \leq j \leq h$, as follows:

$$r^i_{t+h|t+j,q} \equiv \begin{cases} \hat{y}^i_{t+h|t+j,1} - \hat{y}^i_{t+h|t+j-1,4} & \text{for } j = 1,2,3. \\ \hat{y}^i_{t+h|t+j,q} - \hat{y}_{t+h|t+j,q-1} & \text{for } q = 2,3,4 \text{ and } j = 0,\dots,3. \end{cases} \tag{1}$$

In other words, forecast revisions are the difference between the forecasts made in the current and previous quarters targeting the same year. The forecast revisions for the first quarter are defined as the difference from the forecast made in the last quarter of the previous year.

Similarly, the forecast errors for year $t+h$ made in the qth quarters of year $t+j$ is defined as follows:

$$e^i_{t+h|t+j,q} \equiv y_{t+h} - \hat{y}^i_{t+h|t+j,q}, \tag{2}$$

where y_{t+h} is the realized value of macroeconomic variable y at year $t+h$. The forecast errors are defined as the difference between the forecast and the realized value.[12]

[11] The data in 2015 are currently unavailable because the embargo period was shortened from 10 years to 5 years in 2016.

[12] Following Reifschneider and Tulip (2007) and Faust and Wright (2009), the data recorded two quarters later is used as the realized value. More recently, Reifschneider and Tulip (2019) proposed a method to use the data in current vintage with appropriate adjustments, but this has only modest implications for the results.

2.3 Calculation of Annual Changes

The FOMC's economic projections are in the form of growth rates for real GDP growth, PCE inflation, and core PCE inflation, whereas they are based on the levels for the unemployment rate. For use in later analysis, we compute the annual change in the unemployment rate as follows:

$$\Delta \hat{U}^i_{t+h|t,q} \equiv \begin{cases} \hat{U}^i_{t|t,q} - U_{t-1|t,q} & \text{for } h = 0 \\ \hat{U}^i_{t+h|t,q} - \hat{U}^i_{t+h-1|t,q} & \text{for } h = 1, 2, 3, \end{cases} \tag{3}$$

where $U_{t-1|t,q}$ is the real-time realized value of year $t-1$ observed in the qth quarters of year t. In other words, the annual changes are calculated by taking the difference between the real-time realized value and the projections for the nowcasts ($h = 0$) and computing the incremental changes in the projections for the subsequent forecasts ($h = 1, 2, 3$).

3 Regression Analysis

In this section, we conduct a regression analysis to investigate (1) the reaction function of FOMC policymakers, (2) consistency with Okun's law and the Phillis curve, and (3) the influence of regional economic conditions and policy preference.

3.1 Reaction Function

The reaction function of FOMC policymakers characterizes their monetary policy decisions in response to changing economic conditions by taking the trade-offs in policy objectives into account. Typically, the FOMC's reaction function is described by the Taylor rule, in which the optimal interest rate depends on the inflation and output gaps.[13] Following Arai (2023), we replace the output gap with the unemployment gap as follows:[14]

$$i_{t+h} = \rho + \phi^{\pi}(\pi_{t+h} - \pi^*) - \phi^U(U_{t+h} - U^n_{t+h}), \tag{4}$$

where i_t is the nominal interest rate, π^* is the target inflation rate, and U^n_{t+h} is the natural rate of unemployment. The constant, ρ, could be interpreted as the equilibrium real interest rate that prevails when both the inflation and unemployment gaps are closed. Although it is common to

[13] For example, see Chapter 3 of Galí (2015).

[14] This is due to a sudden and large revision in the FOMC's output growth projections in the longer run, which makes the estimation unreliable.

include the past interest rate to capture the inertia in policy rates, we do not do so following Rudebusch (2006).

Following Kim and Pruitt (2017), we employ the Tobit estimation proposed by Amemiya (1984) to account for the nonlinearity associated with the effective lower bound (ELB) of the nominal interest rate. We first characterize the forecasts of a hypothetical interest rate implied by the Taylor rule as $\tilde{i}^i_{t+h|t,q}$, which is made by policymaker i in the qth quarters of year t forecasting h years ahead and is not constrained by the ELB as follows:

$$\tilde{i}^i_{t+h|t,q} = \rho_i + \phi^\pi_i(\hat{\pi}^i_{t+h|t,q} - \hat{\pi}^i_{LR|t,q}) - \phi^U_i(\hat{U}^i_{t+h|t,q} - \hat{U}^i_{LR|t,q}) + \varepsilon^i_{t+h|t,q}, \tag{5}$$

where $\hat{\pi}^i_{t+h|t,q}$ and $\hat{U}^i_{t+h|t,q}$ are the corresponding forecasts of the inflation and unemployment rate, respectively. The subscript LR denotes projections over the longer run.

Then, we assume that the published forecasts of the federal funds rate by policymaker i, $\hat{i}^i_{t+h|t,q}$, are censored at zero as follows:

$$\hat{i}^i_{t+h|t,q} = \begin{cases} \tilde{i}^i_{t+h|t,q} & \text{if } \tilde{i}^i_{t+h|t,q} > 0, \\ 0 & \text{if } \tilde{i}^i_{t+h|t,q} \leq 0. \end{cases} \tag{6}$$

In other words, we only observe the forecasts of the Taylor-rule implied policy rate $\tilde{i}^i_{t+h|t,q}$ when it is positive. The likelihood for a given policymaker i is written as follows:

$$\begin{aligned} L_i = & \prod_{t\in T^0_i}\left(1-\Phi\left[\frac{\rho_i + \phi^\pi_i\left(\hat{\pi}^i_{t+h|t,q} - \hat{\pi}^i_{LR|t,q}\right) - \phi^U_i\left(\hat{U}^i_{t+h|t,q} - \hat{U}^i_{LR|t,q}\right)}{\sigma}\right]\right) \\ \times & \prod_{t\notin T^0_i}\left(\frac{1}{\sigma}\varphi\left[\frac{\hat{i}^i_{t+h|t,q} - \rho_i - \phi^\pi_i\left(\hat{\pi}^i_{t+h|t,q} - \hat{\pi}^i_{LR|t,q}\right) + \phi^U_i\left(\hat{U}^i_{t+h|t,q} - \hat{U}^i_{LR|t,q}\right)}{\sigma}\right]\right), \end{aligned} \tag{7}$$

where Φ and φ denote the cumulative distribution function and the probability density function of the normal distribution. T^0_i is defined as the set of samples where the ELB becomes binding, namely, $T^0_i \equiv \{t = 1, \ldots, T : \hat{i}^i_{t+h|t,q} = 0\}$.[15] The parameters are estimated by maximizing the likelihood.

To have a sufficiently large sample for estimation, this regression could be estimated by pooling

[15] As a matter of practice, the cutoff is set as 0.13 for the estimation, since FOMC policymakers choose the midpoint of the range of the federal funds rate—0.13 corresponds to the midpoint of the lowest range between 0 and 0.25.

across policymakers as follows:

$$\hat{i}^i_{t+h|t,q} = \rho + \phi^\pi(\hat{\pi}^i_{t+h|t,q} - \hat{\pi}^i_{LR|t,q}) - \phi^U(\hat{U}^i_{t+h|t,q} - \hat{U}^i_{LR|t,q}) + X^i_{t+h|t} + \varepsilon^i_{t+h|t,q}, \tag{8}$$

where $X^i_{t+h|t}$ is the control variables, including the dummy variables for meeting dates, policymakers' statuses (governors, regional bank presidents, or voting/non-voting members), or individuals.[16] The estimated coefficients ϕ^π and ϕ^U can be interpreted as the collective responses of the FOMC against the inflation and unemployment gaps.

3.2 Okun's Law

Okun's law shows a negative relationship between changes in the unemployment rate and output growth, which characterizes a short-run fluctuation in the economy, as follows:

$$\Delta U_t = \alpha - \beta \Delta Y_t, \tag{9}$$

where ΔU_t is the change in the level of the unemployment rate and ΔY_t is the growth rate of output. Typically, we assume the coefficient, α, to be 1.5% and the magnitude of the slope, β, to be 0.5 for the US economy.[17]

It is straightforward to test whether the individual FOMC policymaker's projections are consistent with Okun's law using the following regression:

$$\Delta \hat{U}^i_{t+h|t,q} = \alpha_i - \beta_i \Delta \hat{Y}^i_{t+h|t,q} + X^i_{t+h|t} + \varepsilon^i_{t+h|t,q}, \tag{10}$$

where $\Delta \hat{U}$ is the forecast of the annual changes in the unemployment rate, $\Delta \hat{Y}$ is the corresponding forecast for GDP growth, and X is the other control variables. The estimated constant α_i and slope coefficient β_i reflect the dispersion across policymakers. To have a sufficiently large sample for estimation, we pool projections across policymakers.

[16] For simplicity, a general notation is adopted for these variables, varying across time and individuals.

[17] For example, see Mankiw (2016).

3.3 The Phillips Curve

The regression for the Phillips curve, which describes a trade-off between inflation and unemployment, is constructed in a similar manner. A typical Phillips curve is defined in gap form as follows:

$$\pi_{t+h} = E_t[\pi_{t+h}] - \theta(U_{t+h} - U^n_{t+h}) + v_{t+h}, \tag{11}$$

where π is the rate of inflation, U^n is the natural rate of unemployment, and v is the supply shock.[18]

This specification of the Philips curve could be tested by taking the first-order differences of the projections as follows:

$$\Delta\hat{\pi}^i_{t+h|t,q} = \gamma_i - \theta_i \Delta\hat{U}^i_{t+h|t,q} + X^i_{t+h|t} + \nu^i_{t+h|t,q}. \tag{12}$$

where $\Delta\hat{\pi}^i_{t+h|t,q}$ is defined in the same way as in Equation (3). Conceptually, the constant term includes the annual changes in inflation expectations and the natural rate of unemployment at a given FOMC meeting. By setting it as a constant, we effectively assume that policymaker i has the same expectations for inflation and the natural rate of unemployment across horizons, which is consistent with the data. The estimated constants γ_i and slope coefficients δ_i reflect the dispersion across policymakers. Similar to the discussion in the previous sections, we can pool the projections across policymakers for estimation purposes.

3.4 Regional Economic Conditions

To evaluate the influence of regional economic conditions on policymakers' projections, we add it as a control variable to the regressions discussed above. Since earlier studies have found a significant influence of regional economic conditions on policymakers' projections and decisions, assessing whether it is the case for newly expanded projections is an empirically important question.[19]

We focus on the projections made by regional bank presidents and use the regional unemployment rate as a proxy for regional economic conditions. The regional unemployment rates are computed by aggregating state-level unemployment rates covered by each regional federal reserve bank, weighted by the share of a state's population. The data for state-level unemployment rate is obtained from the Bureau of Labor Statistics' website, and the population data is obtained from

[18] For example, see Mankiw (2016).

[19] For earlier studies, see Bobrov et al. (2024), Chappell et al. (2005), Meade and Sheets (2005), and Sheng (2015).

the Census Bureau's website.[20] To match the availability of data with the timing of an FOMC meeting, we use the regional unemployment rate of the month preceding the meeting or the change in the regional unemployment rate observed in the month preceding the meeting.

3.5 Policy Preference

To examine whether preference for monetary policy significantly influences projections, we regress forecast errors for each macroeconomic variable on a constant and the dummy variables for hawkish policymakers (D^i_{Hawk}), who prefer policy tightening as follows:

$$e^i_{t+h|t,q} = \alpha + \beta D^i_{Hawk} + \varepsilon^i_{t+h|t,q}. \tag{13}$$

The dummy variables for hawkish policymakers (D^i_{Hawk}) are constructed based on the average of the residuals of the estimated reaction function in Section 3.1. By construction, these residuals reflect factors that cannot be fully explained by systematic responses to inflation and unemployment gaps. Therefore, the positive residuals could be interpreted as a proxy of preference for monetary policy tightening. Based on the magnitude of the residuals, we designate five policymakers as hawkish policymakers: Charles Plosser (Philadelphia), Jeffrey Lacker (Richmond), Richard Fisher (Dallas), Esther George (Kansas City), and Randal Quarles (Board), sorted by the magnitude of their residuals.

4 Forecast Evaluation

This section provides an idea of forecast efficiency evaluation under the symmetric loss function. Then, we introduce the efficiency evaluation focusing on revisions and forecast errors. The discussion in this section follows Arai (2016), with modified notations.

4.1 Optimal Forecasts under the Symmetric Loss Function

This paper employs an efficiency evaluation based on a symmetric loss function. An optimal forecast for forecaster i, $\hat{y}^{i*}_{t+h|t+j,q}$, should minimize the expected loss of the forecasts, $L(\cdot)$, which is a function of the forecast errors in the available information set $\Omega^i_{t+j,q}$, as follows:

[20] Since the borders of the districts do not exactly match state borders, there are some overlaps. For a more thorough treatment based on county-level disaggregated data, see Bobrov et al. (2024).

$$\hat{y}^{i*}_{t+h|t+j,q} = \underset{\hat{y}^{i}_{t+h|t+j,q}}{\arg\min}\, E[L(e^{i}_{t+h|t+j,q})|\Omega^{i}_{t+j,q}], \tag{14}$$

By taking the first-order condition,[21] we derive the following optimality condition:

$$\hat{y}^{i*}_{t+h|t+j,q} = E[y_{t+h}|\Omega^{i}_{t+j,q}]. \tag{15}$$

This condition implies that the optimal forecasts should be the conditional mean of the series. Based on this implication, Mincer and Zarnowitz (1969) proposed a regression based on forecast errors and Nordhaus (1987) proposed a regression based on forecast revisions.

4.2 Evaluation Focusing on Forecast Revisions

We use five test statistics to test the forecast efficiency focusing on the forecast revisions. First, we use three test statistics focusing on the time-series properties of forecast revisions: (1) bias, (2) first-order autocorrelation, and (3) the Wald statistic of the revisions. To formally define these statistics, consider a first-order autoregression of forecast revisions as follows:

$$r^{i}_{t+H|t+j,q} = \alpha^{i}_{t+H} + \beta^{i}_{t+H} \cdot \Big(r^{i}_{t+H|t+j,q-1} + \mathbb{1}(q=1)(r^{i}_{t+H|t+j-1,4} - r^{i}_{t+H|t+j,q-1})\Big) + \varepsilon^{i}_{t+H}, \tag{16}$$

where H is the longest annual horizon to forecast (3) and $\mathbb{1}(\cdot)$ is the indicator function. For the projections made in the first quarter ($q = 1$), the projections made in the fourth quarter of the previous year ($r^{i}_{t+H|t+j-1,4}$) are treated as the lagged revisions.

The forecast efficiency suggests that forecast revisions are unpredictable for the fixed target year, $t + H$, which implies both the intercept, α^{i}_{t+H}, and the coefficient on lagged revisions, β^{i}_{t+H}, are zero. We use them as the first and second test statistics, respectively. The third test statistic, the Wald statistic, jointly tests if $\theta_{t+H} \equiv [\alpha^{i}_{t+H}, \beta^{i}_{t+H}]'$ is a zero vector. The sample Wald statistic is computed as follows:

$$\hat{W}^{i}_{t+H} = (H+1)Q\ \hat{\theta}^{i\prime}_{t+H}[Avar(\hat{\theta}^{i}_{t+H})]^{-1}\hat{\theta}^{i}_{t+H}, \tag{17}$$

where $Avar(\hat{\theta}^{i}_{t+H})$ is the asymptotic variance-covariance matrix of $\hat{\theta}^{i}_{t+H}$. The asymptotic variance is estimated without any autocorrelation correction because the forecast efficiency implies that

[21] For details, see Chapter 15 of Elliott and Timmermann (2016).

revisions are serially uncorrelated.

For the tests using signs of forecast revisions, we use two summary statistics: (1) the ratio of positive forecast revisions and (2) the ratio of the cases in which the consecutive forecast revisions have the same sign. The advantage of focusing on signs is that they give the exact distribution of test statistics, which enables us to do the exact test. The fourth test statistic summarizes how often the forecast revision is positive. Since the sign of revisions can be regarded as an outcome of the Bernoulli trial under forecast efficiency, the number of positive revisions should follow *Binomial* $((H+1)Q, 0.5)$, which is divided by $(H+1)Q$ to normalize it as the ratio.

To define the test statistic, we first define the indicator variable $i^{P}_{t+H|t+H}$ for a target period of $t+H$ as follows:

$$i^{P,i}_{t+H|t+j,q} = \begin{cases} 1 & \text{if} \quad r^{i}_{t+H|t+j,q} > 0, \\ 0 & \text{otherwise.} \end{cases} \tag{18}$$

Then, the test statistic is defined as the ratio of the sum of these indicator variables to the total number of forecast revisions:

$$b^{P,i}_{t+H} = \frac{1}{(H+1)Q} \sum_{j=0}^{H} \sum_{q=1}^{Q} i^{P,i}_{t+H|t+j,q} \tag{19}$$

Similarly, we can define the fifth test statistic, which summarizes how often the consecutive forecast revisions have the same sign, as being either positive or negative. Since such an event can also be regarded as an outcome of the Bernoulli trial under the forecast efficiency, the number of such cases should follow *Binomial* $((H+1)Q-1, 0.5)$, which is divided by $(H+1)Q-1$ to normalize it as the ratio.

Let $i^{C,i}_{t+H|t+j,q}$ be the indicator variable for a target period of $t+H$ as follows:

$$i^{C,i}_{t+H|t+j,q} = \begin{cases} 1 & \text{if} \quad r^{i}_{t+H|t+j,q} \cdot r^{i}_{t+H|t+j,q-1} > 0, \\ 0 & \text{otherwise.} \end{cases} \tag{20}$$

Then, the test statistic is defined as the ratio of the sum of these indicator variables to the total number of consecutive forecast revisions:[22]

$$b^{C,i}_{t+H} = \frac{1}{(H+1)Q-1}\sum_{h=1}^{H-1} i^{C,i}_{t+H|t+j,q}. \tag{21}$$

A concern about focusing on signs is that it may over-simplify the forecast revisions, and thus the tests may not have enough power. However, as presented in a Monte Carlo exercise and the empirical results in Arai (2016), the loss of power associated with this simplification is not detrimental. Given these test statistics, the joint test statistics across different years are computed by averaging individual test statistics.

4.3 Forecast Accuracy

To evaluate the accuracy of forecasts, we compute the RMSE for each policymaker against a benchmark forecasts $e^{*}_{t+h|t+j,q}$ as follows:

$$RMSE_i = \sqrt{\frac{\sum_{t=T_s}^{T_e}\sum_{h=0}^{H}\sum_{j=0}^{h}\sum_{q=1}^{Q}\left(e^{i}_{t+h|t+j,q}\right)^2}{\sum_{t=T_s}^{T_e}\sum_{h=0}^{H}\sum_{j=0}^{h}\sum_{q=1}^{Q}\left(e^{*}_{t+h|t+j,q}\right)^2}}. \tag{22}$$

This statistic summarizes the relative accuracy of a policymaker's forecasts against the benchmark, with the number less than unity implying a policymaker's forecasts are more accurate. We aggregate the forecasts across all horizons to use as many samples as possible, and the inference is based on Clark and West (2007) for nested forecasts.[23]

4.4 Information Rigidity Test

Coibion and Gorodnichenko (2015) proposed a novel forecast evaluation method that combines forecast errors and revisions and interpreted the rejections of efficiency as evidence of information rigidity. Their baseline efficiency evaluation was presented as follows:

$$e^{i}_{t+h|t+j,q} = \alpha + \beta r^{i}_{t+h|t+j,q} + \varepsilon^{i}_{t+h}. \tag{23}$$

The rationale behind this approach is that the coefficient β captures how forecasters respond

[22] When a value of the forecast revision is zero, we compute these test statistics in two steps. First, we randomly assign a sign with a probability of 0.5 to compute these statistics. Second, we repeat this random assignment many times (100 times in this paper) to treat the mean as the test statistic.

[23] Appendix A discusses a formal analysis of forecast accuracy applying the Mincer-Zarnowitz evaluations, with corresponding results presented in Appendix Table A1.

to incoming news, which is reflected in forecast revisions. Coibion and Gorodnichenko (2015) used the mean of forecast revisions across forecasters to capture the consensus on the news and found sluggish reactions, which they interpreted as evidence of sticky information. In contrast, Bordalo et al. (2020) analyzed forecast revisions at the individual level, and found the evidence of overreaction. They proposed the framework of diagnostic expectations to reconcile these two empirical observations.[24]

According to Bordalo et al. (2020), the signs of this response can be linked to forecasters' reactions to new information. For instance, suppose that the response is positive. This would indicate that positive revisions lead to an increase in forecast errors, implying that forecasts systematically underestimate realized values. In other words, forecasters do not fully incorporate positive news, thereby underestimating the values. Thus, a positive response suggests an underreaction to new information, whereas a negative response indicates an overreaction.

5 Results

5.1 Regression Analysis

Tables 2 and 3 show the estimates of the reaction function, Okun's law, and the Phillips curve, following the ideas in Equations (8), (10), and (12) with different specifications. There are two main takeaways from the results. First, FOMC policymakers' projections largely follow the Taylor rule, Okun's law, and the Phillips curve, even after controlling for individual fixed effects. For the reaction function, the responses to the unemployment and inflation gaps are estimated to be negative and positive, respectively, which are consistent with the standard Taylor rule. In addition, the responses to the inflation gap are estimated to be larger than 1, which is consistent with the Taylor principle for stability. For Okun's law, the negative association between GDP growth and the unemployment rate is statistically significant for any specification. The explanatory power of the regression is high with R^2 ranging between 0.70 and 0.76. For the Phillips curve, the negative association between the unemployment rate and inflation is also statistically significant for all specifications, although the explanatory power of the regression is much weaker than for Okun's law, with R^2 ranging between 0.08 and 0.29.

Second, the dispersion across policymakers is substantial and may be systematically related to the status of the policymakers in some cases. Figures 1, 2, and 3 present the results based

[24]For a recent review, see Bordalo et al. (2022). For an econometric discussion, see McElroy and Sheng (2021).

on individual fixed effect and slope coefficients.[25] As indicated in the figures, there is substantial dispersion across policymakers, some of which may be related to their status. The estimated fixed effect for the voting members is -0.08 in Okun's law regression, and for board members it is -0.04 in the Phillips curve regression (Core PCE), both of them are statistically significant. Similarly, the board members' estimated responses for the unemployment and inflation gaps are both smaller than those of the regional bank presidents, with estimated coefficients of -0.22 and -0.39 for interaction terms. These results suggest that board members tend to be more sensitive to the unemployment gap than to the inflation gap.[26]

5.2 Regional Conditions and Policy Preferences

Table 4 presents the results of controlling for regional economic influence. Panel A shows the association between macroeconomic projections (the unemployment rate, inflation, and the federal funds rate) and the level of regional unemployment. Panel B shows the association between macroeconomic projections and regional economic conditions after controlling for the macroeconomic relationships discussed in Section 5.1. There are three main findings. First, the association between macroeconomic projections and regional unemployment is statistically significant for all variables. As the regional unemployment rate becomes higher, FOMC policymakers tend to forecast a higher national unemployment rate, lower inflation rate, and lower federal funds rate. Second, this significant association remains even after controlling for the macroeconomic relationships. In panel B, we check whether the residual of the macroeconomic relationships (Okun's law, the Phillips curve, and the Taylor rule) are systematically associated with regional economic conditions. The coefficients of the changes in the regional unemployment rate are statistically significant for the unemployment rate and inflation. This result implies that FOMC policymakers tend to revise their unemployment projections upward and revise their inflation projections downward when they observe an increase in their region's unemployment rates, expecting a more serious economic downturn at the national level. Third, even though the federal funds rate and the regional unemployment rate are negatively correlated, this significant correlation disappears once we control for the reaction function. This is likely because the influence of regional economic conditions has already been incorporated into policymakers' national unemployment projections. Therefore, the regional unemployment rate has

[25] Due to the small sample, we present the estimates of the reaction function based on the linear model allowing the constant and the response against the unemployment gap to vary across policymakers.

[26] Bauer et al. (2022) used the linear model to estimate the reaction function at the ELB. Appendix Table A3 shows that estimates of the reaction function based on the linear model are generally similar to estimates based on the Tobit model.

no additional explanatory power on the federal funds rate.

Table 5 presents the results of checking the influence of a preference for policy tightening. Specifications (1) and (3) use a subset of three hawkish policymakers, while specifications (2) and (4) use the benchmark of five hawkish policymakers. The results indicate that hawkish policymakers' forecast errors for inflation—both headline and core PCE—are significantly negative, while forecast errors for other variables are not statistically significant. Since forecast errors are defined as the realized values minus the forecasts, negative forecast errors imply that policymakers tend to overestimate inflation on average.

These results show that hawkish policymakers' inflation and federal funds rate projections systematically deviate from the realized values, potentially providing evidence of the strategic usage of economic projections. For instance, hawkish policymakers may present higher inflation projections to justify advocating for an earlier liftoff or higher federal funds rates than would be realized. Alternatively, one could argue that hawkish policymakers are so concerned about inflation that they project higher federal funds rates as a precaution. In either case, hawkish policymakers make systematic errors in their inflation and federal funds rate projections jointly, which may reflect strategic considerations in their forecasts. This interpretation aligns with earlier studies, such as Nakazono (2013), which suggested that regional bank presidents often adopt extreme views to influence the consensus.

5.3 Evaluation Based on Revisions

Table 6 summarizes the results of individual policymakers' efficiency evaluation based on forecast revisions. The table lists the number of policymakers whose efficiency is significantly rejected with a 5% level for target years between 2009 and 2019.[27] The results of the joint test combining information across different target years are also listed. As indicated in the table, individual policymakers' efficiency is significantly rejected in many cases for all variables, although there is some dispersion across the target years and series. For example, the efficiency of real GDP growth projections is rejected for many policymakers for the target years of 2011 and 2012, while that for unemployment rate projections is strongly rejected for the target years of 2009 and 2010. The efficiency of PCE inflation projections is strongly rejected for 2012 and 2013, while that of core PCE inflation is accepted in most cases. Reflecting these rejections in individual target years, the joint efficiency for real GDP, the unemployment rate, and PCE inflation projections are rejected

[27] We focus on the years that give us at least eight projections for a given target year.

for several policymakers—for example, the joint efficiency for unemployment projections is rejected for 6 policymakers out of 28 based on the Wald statistics.

To illustrate the evolution of the forecasts when the efficiency is strongly rejected, Figure 4 shows the time series of individual policymakers' projections: the target years of 2012 for GDP growth and PCE inflation and 2010 for the unemployment rate. The figures reveal several common patterns in the forecasting behavior of FOMC policymakers. They initiate their projections somewhere close to their long-run projections when they forecast three years ahead. Then, they slowly adjust their projections over time by responding to incoming information as the forecast horizon becomes shorter. The inertia created by this gradual adjustment of forecasts introduces a systematic tendency in forecast revisions, which leads to the rejection of the FIRE model.

There are two key takeaways from these results. First, the results of efficiency evaluations are consistent with economic narratives during and after the Great Recession. FOMC policymakers underestimated the impact of the Great Recession on the labor market at the beginning, which resulted in the inefficiency of unemployment projections between 2009 and 2010. Furthermore, FOMC policymakers continued to be optimistic about the recovery from the Great Recession, which led to the inefficiency of output growth projections and PCE inflation projections between 2012 and 2013—output did not recover as quickly as FOMC policymakers expected and inflation was stagnant at a lower level. Of course, forecasting during the Great Recession was extremely challenging for economists, and FOMC policymakers were not the only ones who made systematic mistakes.[28] However, quantifying such systematic mistakes consistent with economic narratives is one contribution of this paper.

Second, these results differ slightly from the analysis by Arai (2016) based on aggregate projections—while Arai (2016) accepted the efficiency of inflation projections, this paper rejects their efficiency. This difference is due to the increased power of the efficiency evaluation by exploiting cross-sectional variations across individual policymakers. When we focus on the aggregated SEP, diverse views in inflation projections cancel out across policymakers so that we can no longer detect inefficiency. The difference in results highlights the tradeoff of focusing on aggregated projections—they filter out diverse views in the committee to focus on the consensus, with the cost of losing potentially meaningful variations.

[28] For the forecasts during the Great Recession, see Barnichon and Nekarda (2012), Dominguez and Shapiro (2013), Elsby et al. (2010), and Ng and Wright (2013).

5.4 Rejections in Efficiency Evaluations

Table 7 summarizes individual policymakers' efficiency evaluations by reporting the proportion of cases in which their efficiency is rejected by five test statistics across 26 policymakers.[29] The table presents individual test results for specific target years. We focus on the proportion of rejections because the number of projections varies among policymakers due to differences in their service periods.

This table highlights a strong association between the service during the Great Recession and the rejections of efficiency. The top seven policymakers in the table all served during or after the Great Recession. In particular, when a policymaker's tenure was concentrated around the Great Recession, their probability of rejection tends to be higher, regardless of their status within the committee. For example, Kevin Walsh (11.2%, Board), Thomas Hoenig (10.0%, Kansas City), and Donald Kohn (8.3%, Board) all left the FOMC shortly after the Great Recession. Even if a policymaker's tenure includes the Great Recession, its impact appears to be diluted over time if policymakers serve longer. Overall, this result suggests that economic conditions play a decisive role in determining inefficiency.

5.5 Forecast Accuracy and Information Rigidity

Table 8 summarizes individual policymaker's forecast accuracy, by computing the RMSE against the median projections.[30] As indicated in the table, there is no significant difference between governors and regional bank presidents, except for the projections of the federal funds rate. Regional bank presidents exhibit substantially less accurate projections for the federal funds rate, with an average RMSE of 1.18, while that for the governors is 0.94. Some regional bank presidents have fairly high RMSEs: 2.44 for Charles Plosser (Philadelphia), 1.89 for Jeffrey Lacker (Richmond), and 1.66 for Richard Fisher (Dallas). This is largely due to the projections made during the period of the ELB—these regional bank presidents projected a faster liftoff of interest rates or a faster pace of tightening, which did not materialize in the FOMC's decisions. In other words, this high RMSE for federal funds rate projections likely reflects the preference of some regional bank presidents for monetary policy tightening. This stark difference among FOMC participants is consistent with the results in Section 5.2 and may reflect the division of the committee described in Faust (2016).

[29] Since we focus on policymakers with at least eight revisions for a target year, the number of policymakers in this analysis is significantly smaller than in the benchmark sample.

[30] Appendix Table A2 shows the results using the Tealbook forecasts as a benchmark.

Table 9 presents the results of the information rigidity test described in Equation (23) for various macroeconomic variables. Although the results vary across variables and specifications, the coefficients of the revisions are significantly negative in most cases. These results are consistent with the results in the previous subsection indicating the departure from the FIRE model. Furthermore, the negative coefficients imply that FOMC policymakers tend to overreact to incoming news. This tendency is particularly pronounced for PCE inflation and core PCE inflation, where the responses are significantly negative across all specifications. These results align with Bordalo et al. (2020), who found negative associations between forecast errors and revisions and proposed diagnostic expectations as an explanation for short-term overreactions.

6 Conclusion

This study investigates the FOMC's individual economic projections with identities to evaluate the extent of divergence among policymakers. This paper finds that regional economic conditions and preferences for monetary policy significantly influence policymakers' economic projections. This paper also provides empirical evidence for standard macroeconomic concepts, such as Okun's law, the Phillips curve, and the Taylor rule to underscore their relevance in shaping FOMC policymakers' projections. By testing the unpredictability of forecast revisions and errors, the study finds that individual policymakers' efficiencies vary, with inefficiencies clustering around the years after the Great Recession.

The results discussed in this paper highlight the substantial dispersion among FOMC policymakers. While the FOMC's economic projections have become an increasingly important tool for policy communication, it is essential to recognize that they are shaped by policymakers with different backgrounds and views, influenced by various factors such as regional economic conditions and individual policy preferences. Although the SEP is a powerful communication tool for conveying policymakers' views on the economy and the future course of monetary policy, the public should exercise caution when interpreting the SEP—especially in real time, when policymakers' identities are not disclosed. Further investigation of individual projections with identities, once a longer sample becomes available, may reveal additional interesting patterns, which we leave as a topic for future research.

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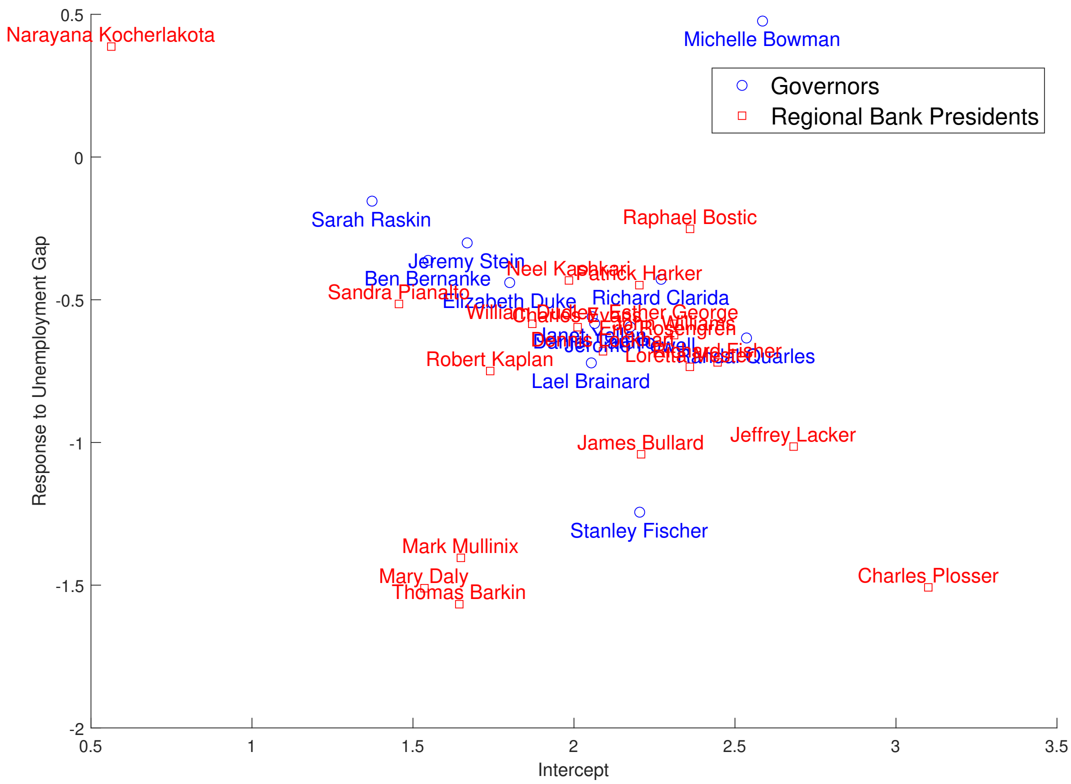


Figure 1: Estimated Intercept and Response to the Unemployment Gap for the Reaction Function

Note: The figure shows the estimated intercept and the reactions to the unemployment gap in Equation (8). Blue circles represent the governors while red squares represent regional bank presidents.

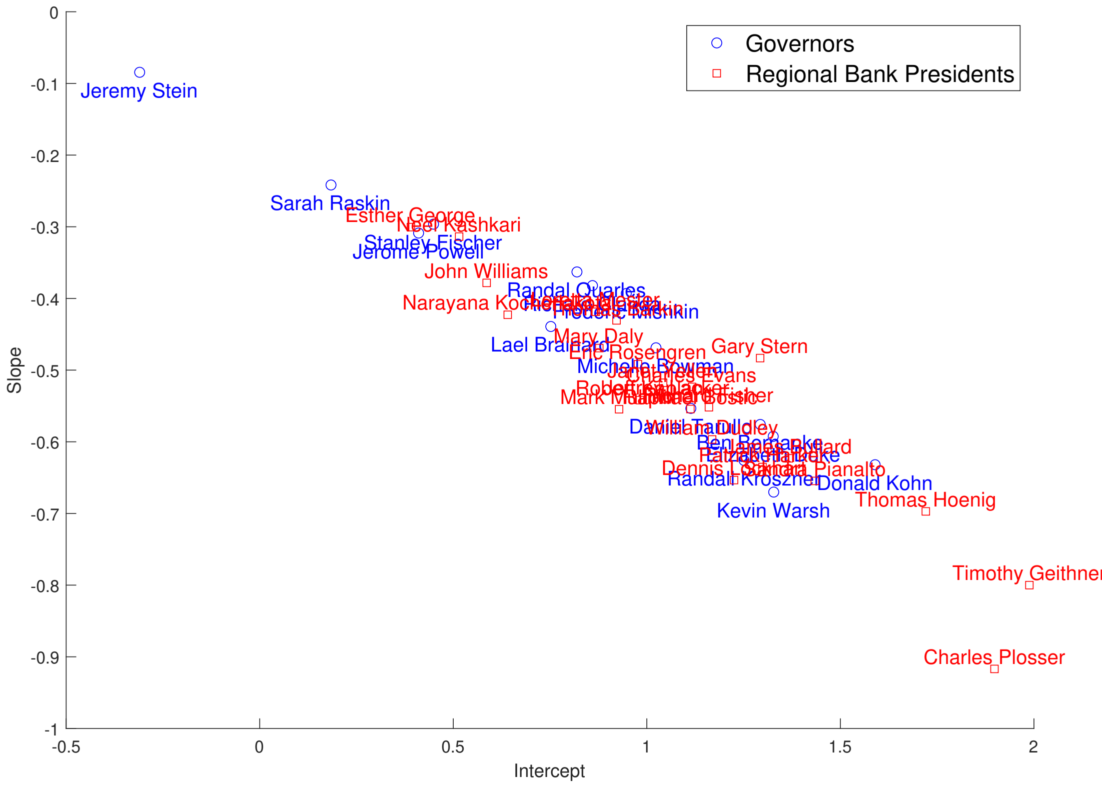


Figure 2: Estimates of Okun's Law for FOMC Policymakers

Note: The figure shows the estimated intercept and slope of Okun's law in Equation (10). Blue circles represent the governors while red squares represent regional bank presidents.

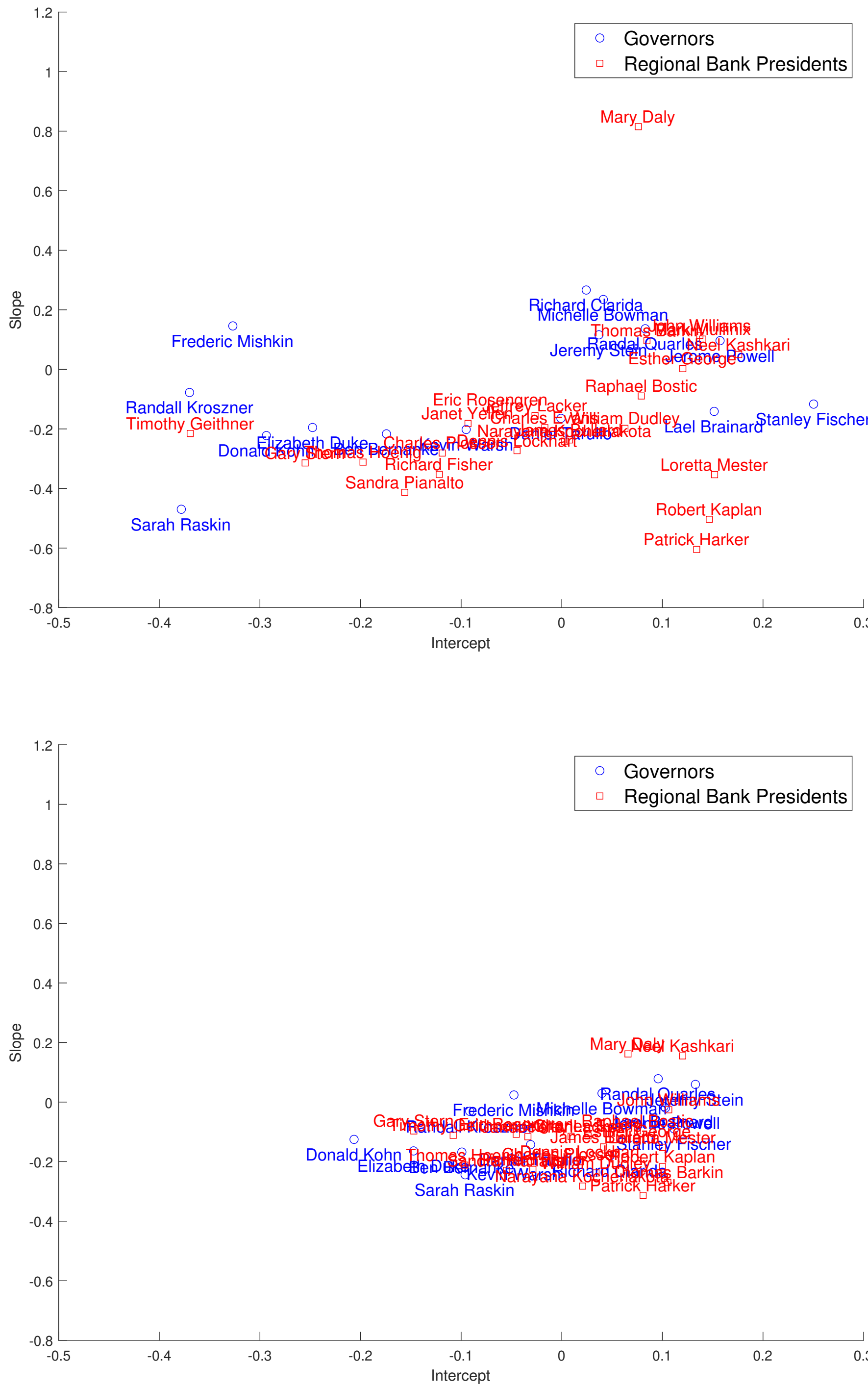
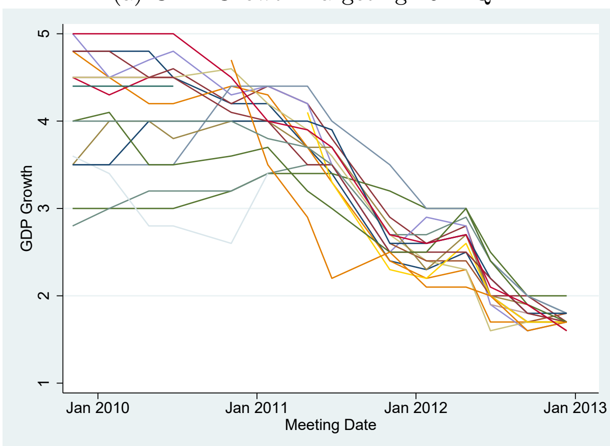


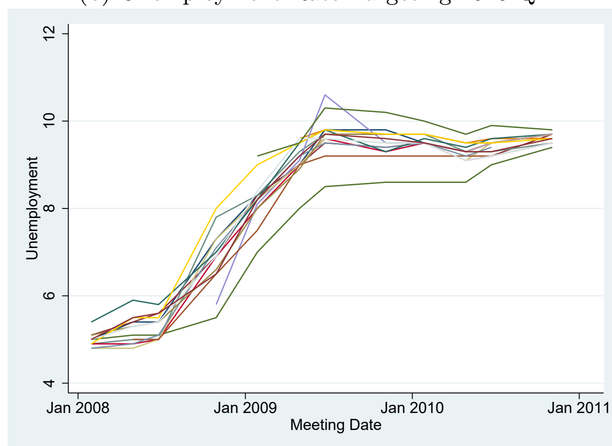
Figure 3: Estimates of the Phillips Curve (PCE and Core PCE)

Note: The figure shows the estimated intercept and slope of the Phillips Curve in Equation (12) using the measures of PCE inflation (top) and Core PCE inflation (bottom). Blue circles represent the governors while red squares represent regional bank presidents.

(a) GDP Growth Targeting 2012 Q4



(b) Unemployment Rate Targeting 2010 Q4



(c) PCE Inflation Targeting 2012 Q4

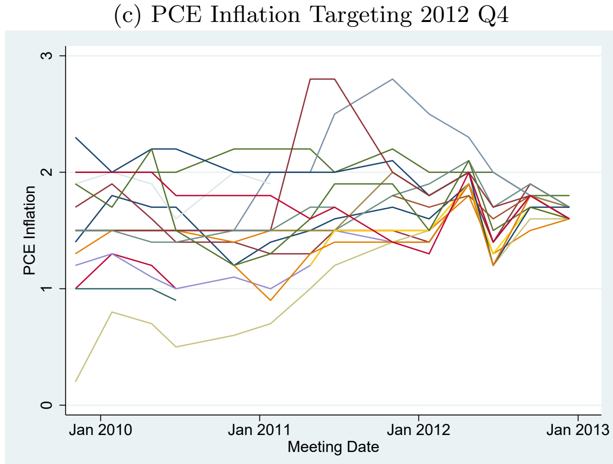


Figure 4: Time Series of FOMC's Individual Projections

Note: The figures show the individual policymakers' economic projections across time, with each line representing an individual policymaker. Figure (a) shows the GDP growth projections for the fourth quarter of 2012 starting November 2009, Figure (b) shows the unemployment rate projections for the fourth quarter of 2010 starting October 2007, and Figure (c) shows the PCE inflation for the fourth quarter of 2012 starting November 2009.

Name	Affiliation	Number of Obs.
Ben Bernanke	Board	107
Lael Brainard	Board	82
Michelle Bowman	Board	23
Richard Clarida	Board	28
Elizabeth Duke	Board	84
Stanley Fischer	Board	45
Donald Kohn	Board	45
Randall Kroszner	Board	17
Frederic Mishkin	Board	13
Jerome Powell	Board	122
Randal Quarles	Board	41
Sarah Raskin	Board	52
Jeremy Stein	Board	36
Daniel Tarullo	Board	127
Kevin Warsh	Board	54
Janet Yellen	Board	161
Raphael Bostic	Atlanta	50
Dennis Lockhart	Atlanta	143
Eric Rosengren	Boston	197
Charles Evans	Chicago	193
Loretta Mester	Cleveland	86
Sandra Pianalto	Cleveland	111
Richard Fisher	Dallas	125
Robert Kaplan	Dallas	72
Esther George	Kansas City	135
Thomas Hoenig	Kansas City	62
Neel Kashkari	Minneapolis	72
Narayana Kocherlakota	Minneapolis	97
Gary Stern	Minneapolis	28
William Dudley	New York	152
Timothy Geithner	New York	17
John Williams	New York	143
Patrick Harker	Philadelphia	67
Charles Plosser	Philadelphia	125
Thomas Barkin	Richmond	36
Jeffrey Lacker	Richmond	147
Mark Mullinix	Richmond	14
Mary Daly	San Francisco	23
James Bullard	St. Louis	190

Table 1: List of Policymakers and Their Affiliations

[a] This table shows the policymakers' names, affiliations, and number of projections.

[b] When the policymakers have multiple affiliations over the sample period, the latest affiliation is listed.

	Specifications				
	(1)	(2)	(3)	(4)	(5)
Constant	1.89^{**}	3.25^{**}	3.72^{**}	2.08^{**}	2.07^{**}
Unemp. Gap	-0.98^{**}	-1.34^{**}	-1.57^{**}	-0.94^{**}	-0.98^{**}
Inf. Gap	2.19^{**}	2.11^{**}	2.14^{**}	2.26^{**}	2.03^{**}
Board				-0.01	
Board × Unemp. Gap				-0.22^{**}	
Board × Inf. Gap				-0.39^{*}	
Voting					0.03
Voting × Unemp. Gap					0.00
Voting × Inf. Gap					0.19^{*}
Fixed Effect					
Individual	Yes		Yes		
Meeting		Yes	Yes		
Log Likelihood	−1405.66	−1457.5	−1256.35	−1548.67	−1553.39
Num.Obs.	1651	1651	1651	1651	1651

Table 2: Estimates for the Reaction Function Based on the Tobit Model

a. This table shows the estimates of the reaction function in Equation (8) with different specifications. PCE is used as a measure of inflation.

b. Inference is based on heteroscedasticity-robust standard errors. ** denote the significance level at 1%.

	Specifications				
	(1)	(2)	(3)	(4)	(5)
Panel A: Okun's Law					
Constant	1.27**	1.40**	1.52**	1.12**	1.18**
GDP Growth	−0.57**	−0.55**	−0.56**	−0.56**	−0.58**
Board				0.00	
Board × GDP				0.01	
Voting					−0.08**
Voting × GDP					0.03**
R^2	0.72	0.75	0.76	0.70	0.70
Panel B: Phillips Curve (PCE)					
Constant	−0.18**	−0.01	−0.02	−0.02	−0.03*
Unemployment	−0.22**	−0.23**	−0.24**	−0.23**	−0.25**
Board				−0.04	
Board × GDP				0.06	
Voting					0.01
Voting × GDP					0.05**
R^2	0.11	0.24	0.24	0.08	0.08
Panel C: Phillips Curve (Core PCE)					
Constant	−0.10**	−0.12**	−0.16**	−0.02**	0.01
Unemployment	−0.16**	−0.16**	−0.16**	−0.17**	−0.17**
Board				−0.04**	
Board × GDP				0.03**	
Voting					0.00
Voting × GDP					0.02
R^2	0.18	0.28	0.29	0.15	0.14
Fixed Effect					
Individual	Yes		Yes		
Meeting		Yes	Yes		
Num. Obs.	2646	2646	2646	2646	2646

Table 3: Regression Estimates for Okun's Law and the Phillips Curve

a. This table shows the estimates of Okun's law in Equation (10) (Panel A) and the Phillips curve in Equation (12) (Panel B and C, using PCE and Core PCE as a measure of inflation, respectively) with different specifications.

b. Inference is based on Inference is based on cluster-robust standard errors across individuals. ** denote the significance level at 1%.

Panel A: Correlation				
	Unemployment	PCE	Core PCE	FFR
Constant	1.18**	2.19**	2.25**	3.79**
Regional Unemployment	0.75**	−0.06**	−0.08**	−0.37**
R^2	0.76	0.07	0.20	0.28
Panel B: Correlation Controlling for Macroeconomic Relationships				
	Okun	Phillips	Phillips (Core)	Taylor
Constant	1.10**	−0.01	0.02	2.14**
Regional Unemployment				0.03
Changes in Regional Unemployment	0.79**	−0.46**	−0.45**	
GDP Growth	−0.55**			
Unemployment		−0.21**	−0.15**	
Unemployment Gap				−0.98**
Inflation Gap				2.31**
R^2	0.72	0.10	0.18	
Log Likelihood				−1202.46
Num. Obs.	1856	1856	1856	1145

Table 4: Influence of Regional Unemployment

a. This table shows the association between FOMC policymaker's macroeconomic projections and the regional unemployment rate. Panel A shows the correlation between macroeconomic projections made by regional bank president i ($\hat{X}^i_{t,q}$) and the regional unemployment rate of the month preceding a FOMC meeting ($R^i_{t,q}$): $\hat{X}^i_{t+h|t,q} = \alpha + \beta R^i_{t,q} + \varepsilon^i_{t+h|t,q}$.

b. Panel B shows the association controlling for macroeconomic relationship described in Section 3. The exact regression models are listed below:

Okun: $\Delta\hat{U}^i_{t+h|t,q} = \alpha - \beta\Delta\hat{Y}^i_{t+h|t,q} + \delta\Delta R^i_{t,q} + \varepsilon^i_{t+h|t,q}$,

Phillips: $\Delta\hat{\pi}^i_{t+h|t,q} = \gamma - \theta\Delta\hat{U}^i_{t+h|t,q} + \delta\Delta R^i_{t,q} + \nu^i_{t+h|t,q}$,

Taylor: $\hat{i}^i_{t+h|t,q} = \rho + \phi^\pi(\hat{\pi}^i_{t+h|t,q} - \hat{\pi}^i_{LR|t,q}) - \phi^U(\hat{U}^i_{t+h|t,q} - \hat{U}^i_{LR|t,q}) + \delta R^i_{t,q} + \varepsilon^i_{t+h|t,q}$,

where $\Delta R^i_{t,q}$ is the changes in regional unemployment rates observed in the month preceding the meeting.

c. Inference is based on cluster-robust standard errors across individuals. ** denote the significance level at 1%.

	Specifications			
	(1)	(2)	(3)	(4)
Panel A: GDP Growth Forecast Error				
Constant	-0.80^{**}	-0.82^{**}	-0.80^{**}	-0.81^{**}
Hawk Dummy	0.06	0.17^{**}	0.05	0.10
R^2	0.00	0.29	0.00	0.29
Panel B: Unemployment Forecast Error				
Constant	0.10	0.12^{**}	0.10	0.12^{**}
Hawk Dummy	0.18	0.06	0.17	0.05
R^2	0.01	0.62	0.00	0.62
Panel C: PCE Forecast Error				
Constant	-0.33^{**}	-0.32^{**}	-0.33^{**}	-0.33^{**}
Hawk Dummy	-0.13^{*}	-0.18^{**}	-0.11^{*}	-0.14^{**}
R^2	0.01	0.38	0.00	0.38
Panel D: Core PCE Forecast Error				
Constant	-0.23^{*}	-0.23^{**}	-0.23^{**}	-0.23^{**}
Hawk Dummy	-0.09	-0.15^{*}	-0.09	-0.12^{*}
R^2	0.01	0.29	0.01	0.28
Meeting Date FE		Yes		Yes
Num. Obs.	2222	2222	2222	2222

Table 5: Forecast Error and Policy Preference

[a.] This table shows the estimates of policy preference in Equation (13) with different specifications. Three policymakers (Charles Plosser, Richard Fisher, and Jeffrey Lacker) are identified as hawks in specifications (1) and (2), and two policymakers (Esther George and Randal Quarles) are added for specifications (3) and (4).

[b] Inference is based on cluster-robust standard errors across individuals. ** denote the significance level at 1%.

Projected Year	Bias	Autocorreation	Wald	Signs, Positive	Signs, Consecutive
Panel A: Real GDP Growth					
2009	10/12 (2/4)	3/12 (2/4)	0/12 (0/4)	0/12 (0/4)	1/12 (0/4)
2010	0/14 (0/5)	0/14 (0/5)	0/14 (0/5)	1/14 (0/5)	0/14 (0/5)
2011	3/16 (2/5)	3/16 (1/5)	4/16 (2/5)	0/16 (0/5)	1/16 (1/5)
2012	5/15 (3/5)	3/15 (0/5)	6/15 (2/5)	2/15 (0/5)	0/15 (0/5)
2013	3/17 (1/5)	2/17 (1/5)	6/17 (1/5)	3/17 (1/5)	1/17 (0/5)
2014	1/16 (0/4)	1/16 (0/4)	2/16 (0/4)	1/16 (0/4)	1/16 (0/4)
2015	0/14 (0/3)	4/14 (0/3)	0/14 (0/3)	0/14 (0/3)	0/14 (0/3)
2016	2/11 (1/3)	2/11 (0/3)	2/11 (0/3)	0/11 (0/3)	0/11 (0/3)
2017	0/10 (0/3)	2/10 (0/3)	1/10 (0/3)	1/10 (0/3)	0/10 (0/3)
2018	4/12 (0/2)	3/12 (0/2)	5/12 (0/2)	3/12 (0/2)	1/12 (0/2)
2019	0/13 (0/3)	1/13 (0/3)	0/13 (0/3)	0/13 (0/3)	0/13 (0/3)
Panel B: Unemployment Rate					
2009	12/12 (4/4)	0/12 (0/4)	9/12 (4/4)	12/12 (4/4)	8/12 (4/4)
2010	14/14 (5/5)	9/14 (3/5)	11/14 (4/5)	10/14 (4/5)	2/14 (1/5)
2011	5/16 (1/5)	5/16 (3/5)	3/16 (1/5)	2/16 (0/5)	1/16 (0/5)
2012	0/15 (0/5)	0/15 (0/5)	0/15 (0/5)	0/15 (0/5)	0/15 (0/5)
2013	0/17 (0/5)	0/17 (0/5)	1/17 (1/5)	0/17 (0/5)	0/17 (0/5)
2014	2/16 (1/4)	3/16 (1/4)	5/16 (2/4)	1/16 (0/4)	0/16 (0/4)
2015	3/14 (1/3)	3/14 (0/3)	5/14 (1/3)	1/14 (0/3)	1/14 (0/3)
2016	0/11 (0/3)	0/11 (0/3)	0/11 (0/3)	0/11 (0/3)	0/11 (0/3)
2017	0/10 (0/3)	1/10 (0/3)	2/10 (0/3)	0/10 (0/3)	0/10 (0/3)
2018	1/12 (0/2)	0/12 (0/2)	3/12 (0/2)	0/12 (0/2)	0/12 (0/2)
2019	4/13 (2/3)	3/13 (0/3)	2/13 (0/3)	0/13 (0/3)	1/13 (0/3)

Table 6: Number of Policymakers Whose Efficiency is Rejected

Projected Year	Bias	Autocorreation	Wald	Signs, Positive	Signs, Consecutive
Panel C: PCE Inflation					
2009	0/12 (0/4)	2/12 (1/4)	0/12 (0/4)	0/12 (0/4)	0/12 (0/4)
2010	0/14 (0/5)	0/14 (0/5)	0/14 (0/5)	0/14 (0/5)	0/14 (0/5)
2011	4/16 (1/5)	0/16 (0/5)	1/16 (0/5)	2/16 (0/5)	0/16 (0/5)
2012	0/15 (0/5)	12/15 (5/5)	9/15 (5/5)	1/15 (0/5)	0/15 (0/5)
2013	0/17 (0/5)	4/17 (1/5)	1/17 (1/5)	0/17 (0/5)	1/17 (1/5)
2014	0/16 (0/4)	2/16 (1/4)	1/16 (0/4)	0/16 (0/4)	0/16 (0/4)
2015	0/14 (0/3)	3/14 (1/3)	1/14 (1/3)	0/14 (0/3)	1/14 (0/3)
2016	0/11 (0/3)	4/11 (0/3)	1/11 (0/3)	0/11 (0/3)	0/11 (0/3)
2017	0/10 (0/3)	1/10 (0/3)	1/10 (0/3)	0/10 (0/3)	0/10 (0/3)
2018	0/12 (0/2)	1/12 (0/2)	2/12 (0/2)	0/12 (0/2)	0/12 (0/2)
2019	1/13 (1/3)	5/13 (0/3)	2/13 (0/3)	0/13 (0/3)	0/13 (0/3)
Panel D: Core PCE Inflation					
2009	0/12 (0/4)	2/12 (1/4)	0/12 (0/4)	0/12 (0/4)	0/12 (0/4)
2010	0/14 (0/5)	0/14 (0/5)	0/14 (0/5)	0/14 (0/5)	0/14 (0/5)
2011	1/16 (1/5)	3/16 (0/5)	1/16 (0/5)	1/16 (0/5)	1/16 (0/5)
2012	1/15 (0/5)	0/15 (0/5)	0/15 (0/5)	0/15 (0/5)	0/15 (0/5)
2013	0/17 (0/5)	0/17 (0/5)	0/17 (0/5)	0/17 (0/5)	0/17 (0/5)
2014	0/16 (0/4)	5/16 (2/4)	2/16 (0/4)	0/16 (0/4)	0/16 (0/4)
2015	0/14 (0/3)	3/14 (1/3)	2/14 (1/3)	0/14 (0/3)	0/14 (0/3)
2016	0/11 (0/3)	3/11 (0/3)	1/11 (0/3)	0/11 (0/3)	0/11 (0/3)
2017	2/10 (0/3)	2/10 (0/3)	2/10 (0/3)	0/10 (0/3)	0/10 (0/3)
2018	0/12 (0/2)	1/12 (0/2)	0/12 (0/2)	0/12 (0/2)	0/12 (0/2)
2019	1/13 (0/3)	1/13 (0/3)	0/13 (0/3)	0/13 (0/3)	0/13 (0/3)
Panel E: Joint Test across Years					
Real GDP	2/28 (1/10)	3/28 (1/10)	2/28 (0/10)	3/28 (2/10)	2/28 (1/10)
Unemployment	6/28 (3/10)	6/28 (3/10)	6/28 (3/10)	5/28 (2/10)	4/28 (1/10)
PCE	2/28 (1/10)	5/28 (1/10)	4/28 (2/10)	2/28 (1/10)	4/28 (1/10)
Core PCE	3/28 (1/10)	4/28 (1/10)	1/28 (0/10)	2/28 (1/10)	3/28 (1/10)

Table 6 (Continued): Number of Policymakers Whose Efficiency is Rejected

[a.] This table shows the number of individual FOMC policymakers, whose efficiency is rejected by the test statistics described in Section 4.2 with the significance level of 5%. The total number of policymakers is listed on the denominator. The inference is based on bootstrap.

[b.] The number of policymakers in the board of governors, whose efficiency is rejected, is listed in parenthesis, with the total number of governors in the denominator.

[c.] Some policymakers are excluded due to the small sample, which may make the number of policymakers smaller than those who participated in the meeting.

Rank	Policymaker	Affiliation	Service Years in Sample	Individual Tests (%)
1	Kevin Warsh	Board	2007-11	11.2
2	Thomas Hoenig	Kansas City	2007-11	10.0
3	William Dudley	New York	2009-14, 2016-18	10.0
4	Donald Kohn	Board	2007-10	8.3
5	Charles Plosser	Philadelphia	2007-14	8.1
6	Janet Yellen	Board	2007-14, 2016-18	8.0
7	Sandra Pianalto	Cleveland	2007-14	7.1
8	Patrick Harker	Philadelphia	2016-19	6.7
9	Loretta Mester	Cleveland	2014, 2016-19	6.3
10	Ben Bernanke	Board	2007-14	5.7
11	Esther George	Kansas City	2011-14, 2016-19	5.6
12	Richard Fisher	Dallas	2007-14	5.0
13	Sarah Raskin	Board	2010-14	5.0
14	Neel Kashkari	Minneapolis	2016-19	5.0
15	Charles Evans	Chicago	2007-14, 2016-19	4.6
16	James Bullard	St. Louis	2008-14, 2016-19	4.5
17	Daniel Tarullo	Board	2009-14, 2016-17	4.3
18	Jeffrey Lacker	Richmond	2007-14, 2016-17	3.9
19	Eric Rosengren	Boston	2007-14, 2016-18	3.8
20	Dennis Lockhart	Atlanta	2007-14, 2016-17	3.3
21	Narayana Kocherlakota	Minneapolis	2009-14	3.3
22	John Williams	New York	2011-14, 2016-18	2.5
23	Elizabeth Duke	Board	2008-13	2.0
24	Jerome Powell	Board	2012-14, 2016-19	0.7
25	Lael Brainard	Board	2014, 2016-19	0.0
26	Robert Kaplan	Dallas	2016-19	0.0

Table 7: Inefficiency of Individual Policymakers

[a.] This table shows the individual policymakers' efficiency evaluations by showing the proportion of cases where individual and joint efficiency is rejected. The policymakers are sorted with the results of individual tests.

[b.] We focus on policymakers with at least eight revisions for a target year. The number of target years varies across policymakers, depending on their service period.

Name	GDP	Un. Rate	PCE	Core PCE	FFR
Panel A: Governors					
Ben Bernanke	1.02	1.01	0.97**	1.03	0.65**
Michelle Bowman	1.03	0.96	1.02	0.99	1.00
Lael Brainard	0.97**	1.04	0.94**	0.96**	0.92**
Richard Clarida	0.98**	0.90**	1.02	0.97	0.91**
Elizabeth Duke	1.16	1.21	1.04	1.17	1.47
Stanley Fischer	0.97**	1.01	0.90**	0.92**	1.03
Donald Kohn	1.11	1.06	1.18	1.21	-
Randall Kroszner	0.90**	1.05	1.02	1.07	-
Frederic Mishkin	0.90**	0.99	1.02	1.14	-
Jerome Powell	1.01	1.03	0.90**	0.97**	0.98**
Randal Quarles	1.05	0.96**	1.01	1.09	1.12
Sarah Raskin	1.00	1.28	0.78**	0.82**	0.47**
Jeremy Stein	1.04	0.98	0.84**	0.92**	1.10
Daniel Tarullo	1.05	1.17	1.01	0.92**	0.76**
Kevin Warsh	0.80**	1.01	1.07	1.16	-
Janet Yellen	1.10	1.02	0.99**	1.10	0.83**
Average	1.00	1.04	0.98	1.02	0.94
Panel B: Regional Bank Presidents					
Thomas Barkin	0.98	0.93**	1.08	1.06	1.03
Raphael Bostic	0.97**	0.96**	1.07	1.09	0.90**
James Bullard	1.01	1.00*	1.20	1.28	1.38
Mary Daly	0.97**	1.01	0.97**	1.00	0.96**
William Dudley	1.14	0.95**	1.09	1.17	0.96**
Charles Evans	1.07	1.00	0.94**	1.01**	0.85**
Richard Fisher	1.02	0.96**	1.19	1.234	1.66
Timothy Geithner	1.18	1.02	0.80**	0.85**	-
Esther George	0.99**	1.04	1.08	1.11	1.38
Patrick Harker	1.00	0.94**	1.11	1.11	1.02
Thomas Hoenig	0.98*	1.00	1.07	1.08	-
Robert Kaplan	0.97**	0.98	1.15	1.14	0.92**
Neel Kashkari	1.02	1.07	0.97**	0.97**	0.81**
Narayana Kocherlakota	0.90**	0.88**	1.14	1.47	0.76**
Jeffrey Lacker	0.90**	0.97**	1.04	1.00**	1.89
Dennis Lockhart	0.77**	1.00	1.08	1.18	1.16
Loretta Mester	1.04	1.04	1.00	1.00	1.17
Mark Mullinix	0.98	1.05	1.00	1.00	1.26
Sandra Pianalto	0.91**	1.01	1.06	1.00**	0.88**
Charles Plosser	0.81**	1.10	1.06	1.37	2.44
Eric Rosengren	1.03	1.03	1.13	1.33	1.16
Gary Stern	0.95**	0.96**	1.08	1.02	-
John Williams	1.01	1.04	0.87**	0.91**	1.09
Average	0.98	1.00	1.05	1.11	1.18

Table 8: Relative RMSE of Individual Policymakers Against the Median

[a.] This table shows the RMSE of each policymaker's projections relative to the median projections for each series (GDP growth, unemployment rate, headline and core PCE inflation, and the federal funds rate). The MSE of projections at all horizons are combined to compute the relative RMSE.

[b.] Inference is based on Clark and West (2007) testing whether the accuracy of individual projection is equal to the median. * and ** denote the significance level at 5% and 1%, respectively.

	Specifications				
	(1)	(2)	(3)	(4)	(5)
Panel A: GDP Growth					
Constant	-0.59^{**}	-0.63^{**}	-0.61^{**}	-0.61^{**}	-0.60^{**}
Revisions	-0.13	-0.49^{**}	-0.33	-0.32^{**}	-0.34^{**}
R^2	0.00	0.58	0.47	0.80	0.82
Panel B: Unemployment Rate					
Constant	-0.01	0.08	0.09	0.11^{**}	-0.01
Revisions	0.94^{**}	-0.12	-0.18	-0.43^{**}	-0.45^{**}
R^2	0.11	0.53	0.80	0.96	0.97
Panel C: PCE Inflation					
Constant	-0.27	-0.27^{**}	-0.27^{**}	-0.21^{**}	-0.24^{**}
Revisions	-0.36^{**}	-0.50^{**}	-0.37^{**}	-0.43^{**}	-0.45^{**}
R^2	0.03	0.71	0.46	0.83	0.88
Panel D: Core PCE Inflation					
Constant	-0.21^{*}	-0.21^{**}	-0.21^{**}	-0.21^{**}	-0.11^{**}
Revisions	-0.34^{**}	-0.49^{**}	-0.29^{**}	-0.40^{**}	-0.45^{**}
R^2	0.03	0.53	0.35	0.70	0.82
Num.Obs.	1859	1859	1859	1859	1859
Panel E: Federal Funds Rate					
Constant	-0.48^{*}	-0.49^{**}	-0.48^{**}	-0.48^{**}	-0.17
Revisions	-0.10	-0.17	-0.04	-0.12	-0.30^{**}
R^2	0.00	0.33	0.04	0.43	0.64
Fixed Effect					
Target Year		Yes		Yes	Yes
Meeting Date			Yes	Yes	Yes
Individuals					Yes
Num. Obs.	1031	1031	1031	1031	1031

Table 9: Results of Information Rigidity Test

[a.] This table shows the results of information rigidity test described in Equation (23) for different variables (Panel A to E) with different specifications (Specifications (1) to (5)).

[b.] Inference is based on cluster-robust standard errors across individuals. * and ** denote the significance level at 5% and 1%, respectively.

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A Forecast Evaluation based on Errors

We also conduct the forecast evaluation based on the implication that forecast errors are unpredictable proposed by Mincer and Zarnowitz (1969). In this paper, we conduct the joint tests across annual forecast horizons. First, we stack all the forecast errors at the fixed horizons as $(H+1)Q \times 1$ vector, $e^i_{t+h} \equiv [e^{i\prime}_{t+h|t}, \ldots, e^{i\prime}_{t+h|t+h}]'$ where $e^i_{t+h|t+j} \equiv [e^i_{t+h|t+j,1}, \ldots, e^i_{t+h|t+j,Q}]'$. Then, we run the MZ evaluation based on vector as follows:

$$\begin{bmatrix} e^i_{t+h|t} \\ \vdots \\ e^i_{t+h|t+h} \end{bmatrix} = \begin{bmatrix} 1_{Q,1} & & 0 \\ & \ddots & \\ 0 & & 1_{Q,1} \end{bmatrix} \begin{bmatrix} \alpha^i_h \\ \vdots \\ \alpha^i_0 \end{bmatrix} + \begin{bmatrix} \varepsilon^i_{t+h|t} \\ \vdots \\ \varepsilon^i_{t+h|t+h} \end{bmatrix}, \tag{24}$$

where $1_{Q,1}$ is $Q \times 1$ vector of ones, and α^i_h summarizes the bias of the forecasts targeting h years ahead. The forecast efficiency implies that forecasts are unbiased at any horizon, which can be jointly tested with the Wald statistics of the regression coefficients, $\{\alpha^i_h\}$.[31]

Table A1 shows the Wald statistics of forecast efficiency evaluation presented in Equation (24). Consistent with the results of RMSE, there are no significant differences between the governors and regional bank presidents and we found inefficiency in nearly all policymaker's projections. The Wald statistics of FFR projections are extremely large for some policymakers who served during the period of ELB—Ben Bernanke (Board), Elizabeth Duke (Board), Sarah Raskin (Board), Jeremy Stein (Board), Sandra Pianalto (Cleveland), and Charles Plosser (Philadelphia). This is because the variance of the projections becomes extremely low for their service period low due to ELB, which magnifies the Wald statistics. This result reflects the limitation of forecast efficiency evaluation based on the stationarity of time series. Another thing to note is that the results are notably different from the efficiency evaluation focused on the revisions due to their different natures. While the former focuses on the internal consistency of the forecasters while the latter focuses on overall accuracy of the forecasts.

[31] The variance-covariance matrix of the coefficients are estimated with appropriate autocorrelation correction, since the error terms are likely to be correlated due to the overlapping structure of forecast errors.

B Tables

Name	GDP	Un. Rate	PCE	Core PCE	FFR
Panel A: Governors					
Ben Bernanke	78.84**	3.86	6.65	2.82	265.73**
Lael Brainard	22.63**	6.69	19.31**	16.89**	21.37**
Elizabeth Duke	137.25**	0.15	1.92	0.47	275.78**
Stanley Fischer	30.77**	152.05**	6.91	20.50**	34.69**
Donald Kohn	47.89**	42.61**	3.68	0.32	-
Randall Kroszner	27.05**	239.93**	56.41**	32.37**	-
Jerome Powell	9.52*	16.22**	83.06**	94.39**	42.90**
Randal Quarles	18.87**	140.15**	206.11**	131.64**	51.10**
Sarah Raskin	54.79**	193.03**	12.97**	7.04	274.58**
Jeremy Stein	250.55**	359.13**	120.69**	98.17**	195.18**
Daniel Tarullo	28.02**	88.58**	3.53	0.56	8.36
Kevin Warsh	13.65**	23.02**	3.94	9.13*	-
Janet Yellen	41.65**	3.21	1.61	3.15	17.46**
Panel B: Regional Bank Presidents					
Raphael Bostic	20.28**	8.76*	132.20**	95.17**	37.79**
James Bullard	51.36**	6.37	61.39**	187.78**	11.91**
William Dudley	29.79**	7.06	27.41**	76.25**	28.40**
Charles Evans	61.22**	7.06	20.15**	30.09**	18.13**
Richard Fisher	65.48**	5.07	16.32**	17.52**	74.06**
Timothy Geithner	48.33**	95.71**	285.03**	27.53**	-
Esther George	9.64*	54.10**	155.79**	210.44**	133.26**
Patrick Harker	16.37**	11.05*	45.93**	48.14**	49.15**
Thomas Hoenig	72.98**	25.75**	0.65	1.24	-
Robert Kaplan	47.61**	8.01*	59.82**	57.39**	37.14**
Neel Kashkari	7.35	12.93**	18.40**	13.62**	7.67
Narayana Kocherlakota	122.97**	23.13**	61.83**	353.41**	16.49**
Jeffrey Lacker	29.97**	1.42	13.90**	37.64**	144.34**
Dennis Lockhart	20.97**	4.26	13.58**	47.54**	17.79**
Loretta Mester	7.46	15.12**	69.58**	66.93**	80.14**
Sandra Pianalto	82.74**	5.14	21.03**	14.46**	296.24**
Charles Plosser	104.17**	36.45**	97.52**	299.09**	356.94**
Eric Rosengren	48.34**	5.08	0.85	0.43	46.69**
Gary Stern	24.65**	54.21**	3.72	5.66	-
John Williams	5.99	39.55**	111.76**	99.03**	59.37**

Table A1: Wald Statistics for the Efficiency Evaluation Focusing on Forecast Errors

[a.] This table shows the Wald statistics based on Equation (24) testing the rationality of each policymaker's projections.

[b.] Inference is based on bootstrapped standard errors. * and ** denote the significance level at 5% and 1%, respectively.

[c.] When the policymakers have multiple affiliations over the sample period, the latest affiliation is listed.

Name	GDP	Un. Rate	PCE	Core PCE	Average
Panel A: Governors					
Ben Bernanke	0.82^{**}	0.97^{**}	0.75^{*}	0.91^{**}	0.86
Lael Brainard	0.94^{**}	1.00	0.88^{*}	0.94^{**}	0.94
Elizabeth Duke	0.91^{**}	1.13	0.69^{*}	0.97^{**}	0.92
Stanley Fischer	0.65^{**}	1.34	0.61^{*}	0.92^{**}	0.88
Donald Kohn	0.91^{**}	1.05	0.81	0.89^{**}	0.91
Jerome Powell	0.95^{**}	0.97^{**}	1.00^{*}	1.04^{**}	0.99
Sarah Raskin	0.68^{**}	1.08	0.73^{**}	0.97^{**}	0.87
Jeremy Stein	0.76^{**}	0.84^{**}	1.30	1.34	1.06
Daniel Tarullo	0.80^{**}	1.02	0.84^{**}	0.82^{**}	0.87
Kevin Warsh	0.74^{**}	1.01	0.77^{*}	0.85^{**}	0.84
Janet Yellen	0.90^{**}	1.01	0.80^{*}	0.98^{**}	0.92
Average	0.82	1.04	0.83	0.97	0.92
Panel B: Regional Bank Presidents					
Raphael Bostic	0.98^{**}	0.90^{*}	1.00	1.06	0.98
James Bullard	0.97^{**}	0.99^{*}	0.98^{**}	1.27^{**}	1.05
William Dudley	0.87^{**}	0.82^{**}	0.91^{**}	0.97^{**}	0.89
Charles Evans	0.92^{**}	0.98^{**}	0.74^{*}	0.94^{**}	0.90
Richard Fisher	0.85^{**}	0.93^{**}	0.98^{*}	1.14^{**}	0.98
Esther George	0.95^{**}	0.96^{**}	1.24	1.35	1.12
Patrick Harker	0.99^{*}	0.90^{**}	1.09	1.18	1.04
Thomas Hoenig	0.84^{**}	1.01	0.74^{*}	0.84^{**}	0.85
Robert Kaplan	0.97^{**}	0.92^{*}	1.07	1.13^{*}	1.02
Neel Kashkari	0.99^{*}	1.00	0.88^{*}	0.86^{**}	0.93
Narayana Kocherlakota	0.69^{**}	0.74^{**}	0.85^{**}	1.20^{**}	0.87
Jeffrey Lacker	0.79^{**}	0.93^{**}	0.86^{*}	1.03^{**}	0.90
Dennis Lockhart	0.71^{**}	0.97^{**}	0.87^{*}	1.11^{**}	0.92
Loretta Mester	1.04	1.01	0.88^{**}	0.98^{**}	0.98
Sandra Pianalto	0.78^{**}	0.97	0.91^{*}	0.95^{**}	0.90
Charles Plosser	0.79^{**}	1.08^{*}	0.83^{**}	1.38^{**}	1.02
Eric Rosengren	0.90^{**}	0.99^{*}	0.88	1.13	0.98
Gary Stern	0.84^{**}	0.97^{*}	0.72	0.81^{**}	0.84
John Williams	0.93^{**}	0.98	0.83^{**}	0.99^{**}	0.93
Average	0.89	0.95	0.91	1.07	0.95

Table A2: Relative RMSE of Individual Policymakers (Compared with Tealbook)

[a.] This table shows the RMSE of each policymaker's projections relative to the median projections for each series during the corresponding sample period. The MSE of projections at all horizons are combined to compute the relative RMSE.

[b.] Inference is based on bootstrapped standard errors. * and ** denote the significance level at 5% and 1%, respectively.

[c.] The classification is based on the latest affiliation when the policymakers have multiple affiliations over the sample period.

	Specifications				
	(1)	(2)	(3)	(4)	(5)
Constant	2.14^{**}	2.42^{**}	1.91^{**}	2.13^{**}	2.14^{**}
Unemp. Gap	-0.62^{**}	-0.64^{**}	-0.65^{**}	-0.65^{**}	-0.66^{**}
Inf. Gap	1.59^{**}	1.56^{**}	1.58^{**}	1.62^{**}	1.59^{**}
Board				0.00	
Board × Unemp. Gap				0.01	
Board × Inf. Gap				−0.14	
Voting					0.03
Voting × Unemp. Gap					0.01
Voting × Inf. Gap					0.03
Fixed Effect					
Individual	Yes		Yes		
Meeting		Yes	Yes		
R^2	0.72	0.74	0.77	0.68	0.68
Num. Obs.	1651	1651	1651	1651	1651

Table A3: Regression Estimates for the Reaction Function (Linear Model)

[a.] This table shows the estimates of the reaction function in Equation (8) with different specifications. PCE is used as a measure of inflation.

[b.] Inference is based on heteroscedasticity-robust standard errors. ** denote the significance level at 1%.