Finance and Economics Discussion Series

Federal Reserve Board, Washington, D.C.
ISSN 1936-2854 (Print)
ISSN 2767-3898 (Online)

Anchored to the Dot Plot: Central Bank Projections and Interest Rate Expectations

Eric Engstrom

2026-026

Please cite this paper as:
Engstrom, Eric (2026). "Anchored to the Dot Plot: Central Bank Projections and Interest Rate Expectations," Finance and Economics Discussion Series 2026-026. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2026.026.

Anchored to the Dot Plot: Central Bank Projections and Interest Rate Expectations

Eric Engstrom*

April 29, 2026

Abstract

In January 2012, the Federal Reserve began publishing the Summary of Economic Projections (SEP) "dot plot," revealing FOMC participants' projections for the federal funds rate. This paper documents a dual role for SEP projections in the formation of private interest-rate expectations. On one hand, SEP projections contain valuable information, achieving lower forecast errors than consensus surveys, VAR models, and several market-based measures at many horizons. Because the SEP is informative, some reliance on it by private forecasters is natural. On the other hand, because the SEP is updated only quarterly, SEP projections that are useful when released can become stale between updates. If private forecasts continue to place excessive weight on those earlier projections, they may respond too slowly to newly arriving information. Consistent with this prediction, survey forecast errors—and, to a weaker extent, market-based forecast errors—are systematically related to the gap between current expectations and lagged SEP projections, even after controlling for macroeconomic conditions, risk premia, and other predictors of forecast errors. The findings imply that official guidance can simultaneously improve average forecast accuracy while reducing the speed with which new information is incorporated into expectations.

JEL Codes: E43, E47, E52, E58, G12, G14
Keywords: anchoring bias, monetary policy expectations, Federal Reserve communications, forecast efficiency, dot plot, term structure

*Author affiliation: Board of Governors of the Federal Reserve System. The views in this manuscript are those of the author and do not represent those of the Board of Governors of the Federal Reserve System, or its staff.

1 Introduction

In January 2012, the Federal Open Market Committee (FOMC) began publishing the policy-rate "dot plot" as part of its Summary of Economic Projections (SEP), revealing participants' assessments of the appropriate future path of the federal funds rate. Introduced during the zero lower bound period to enhance transparency, the dot plot has since become one of the most closely watched elements of U.S. monetary policy communication, moving asset prices immediately upon release and receiving sustained attention from investors, policymakers, and the financial press.

An important question is how such highly salient official forecasts affect the formation of private-sector expectations. This paper documents two countervailing roles for the SEP. On one hand, I find that upon release the SEP contains valuable incremental information about future policy, and private expectations and asset prices respond measurably to SEP releases. On the other hand, the same signal appears to remain embedded in expectations after it has become stale, potentially consistent with private forecasts inefficiently anchoring to the SEP. As new information arrives between quarterly releases, survey forecasts and market-implied expectations under-adjust away from prior SEP projections.

The empirical analysis exploits both the introduction of the dot plot in 2012 and time-series variation in subsequent SEP projections. I first compare the forecast performance of SEP projections with alternative forecasts to assess their informational content, finding that the SEP is sufficiently informative that private forecasters are justified in placing some weight on it. To test for information rigidities associated with the SEP, I examine whether private ex-post forecast errors are systematically related to the distance between current private forecasts and the previous quarter's SEP projection. Under efficient updating, this gap should not predict subsequent errors. Instead, it does. For survey forecasts, SEP-based predictability complements a pre-existing tendency for errors to covary with lagged consensus revisions. For market-based expectations, related but weaker predictability patterns remain after controlling for macroeconomic conditions and standard proxies for term premia and risk compensation.

The macroeconomic relevance of this sluggish adjustment is illustrated by the 2022 tightening cycle. In December 2021, the median SEP projected a relatively gradual path for policy rates. By early 2022, however, incoming inflation data and policy communications pointed toward a faster pace of tightening. Yet both survey forecasts and forward rates adjusted only gradually away from the December benchmark, contributing to systematic underestimation of the speed and extent of subsequent rate increases. My estimates imply that reliance on stale SEP guidance materially slowed the upward adjustment of forward interest rates during this period. Information that had been useful in December had become a drag on updating by March.

More broadly, the findings suggest that official forecasts can improve average forecast accuracy while simultaneously slowing the incorporation of new information. The findings relate to a large literature documenting systematic errors in interest-rate forecasts and their asset-pricing implications. Piazzesi and Swanson (2008) show that federal funds futures forecast errors are predicted by employment growth and corporate bond spreads, especially during recessions. Cieslak (2018) finds that survey-based short-rate forecasts overextrapolate the current level of rates and underutilize business-cycle information, generating persistent errors. Schmeling et al. (2022) attribute predictable errors in Blue Chip forecasts to incomplete information about the Federal Reserve's reaction function during periods of financial stress and show that these errors help explain excess returns on interest-rate futures. Together, this literature highlights the importance of expectation-formation frictions for both forecasts and asset prices.

Closely related, Ichiue and Yuyama (2009) document partial adjustment in survey-based federal funds rate forecasts over 1982–2008, showing that forecast errors are predictable from forecast revisions. They interpret this sluggish updating as evidence that forecasters do not fully incorporate new information, potentially reflecting strategic considerations such as reputational concerns (Ehrbeck and Waldmann, 1996; Lamont, 2002). Campbell and

Sharpe (2009) develop an empirical framework for testing anchoring in consensus forecasts, showing that forecast errors for macroeconomic data releases are systematically related to forecast revisions. I build on this approach and adapt it to interest-rate expectations by allowing lagged SEP projections to serve as an additional salient reference point.

My contribution is to show that official projections can affect expectations through two distinct channels: by conveying useful information when released, and by serving as persistent reference points thereafter. This complements existing work on forecast inefficiency by identifying a concrete and economically important source of sluggish updating tied to central-bank communication. The paper also contributes to the literature on monetary-policy transmission by showing that related, though weaker, patterns appear in market-implied expectations, suggesting that official projections can generate these dual effects not only in survey beliefs but also in asset prices.

The remainder of the paper proceeds as follows. Section 2 describes the SEP and the conceptual framework. Section 3 describes the data and empirical methods. Section 4 presents the main results. Section 5 presents additional robustness exercises. Section 6 concludes.

2 Background and Conceptual Framework

2.1 The Summary of Economic Projections and the Dot Plot

The publication of policy-rate projections in January 2012 marked an important change in Federal Reserve communications. While the Federal Reserve had released summaries of policymakers' economic projections in various forms since the late 1970s, the modern quarterly Summary of Economic Projections (SEP), introduced in 2007, expanded both the frequency and scope of those releases by reporting projections for output growth, unemployment, and inflation over multiple horizons. Initially, however, the SEP did not include projections for the federal funds rate.

On January 25, 2012, the Federal Open Market Committee (FOMC) began publishing participants' assessments of the appropriate future level of the federal funds rate.[1] These projections are presented as individual observations for the current year, the following two calendar years, and the longer run. Their introduction coincided with the effective lower bound period, when forward guidance had become a central instrument of monetary policy and communication about the future path of rates had taken on unusual importance.

Publishing policy-rate projections served several related objectives. First, it increased transparency regarding how policymakers viewed the likely future course of monetary policy. Second, it reinforced forward guidance by providing more explicit information about the expected path of rates. Third, the distribution of projections conveyed uncertainty and heterogeneity across participants rather than presenting a single point forecast.

Federal Reserve officials have consistently emphasized that these projections are conditional individual assessments, not a committee consensus and not a commitment to any predetermined policy path. In practice, however, market participants often treat the distribution of dots—and especially the median projection—as a convenient summary signal of the expected trajectory of policy rates. Contemporary market commentary and immediate asset-price reactions to SEP releases suggest that the information content of the dots is taken seriously by investors.

This distinction between official intent and market interpretation is central to the analysis that follows. Because the SEP is updated only quarterly while macroeconomic and policy information arrives continuously, projections that are informative when released may become stale between publication dates. If market participants continue to place substantial weight on earlier SEP projections after newer information has arrived, those projections may remain embedded in private expectations and market prices longer than is warranted by efficient updating.

Such concerns have occasionally been noted by policymakers themselves. For example,

[1] The figure displaying these projections became informally known as the "dot plot."

FOMC minutes from January 2019 record that some participants were concerned that SEP projections were being interpreted as a consensus view or as indicating a predetermined policy path. The quarterly release schedule of the SEP, combined with its prominence in financial markets, makes this possibility empirically testable.

2.2 Anchoring Bias Theory and Empirical Framework

2.2.1 Theoretical Framework

This paper studies whether official central-bank projections influence private expectations in a manner consistent with efficient information use or with persistent reliance on salient prior guidance. The distinction is important because a public forecast such as the SEP may be highly informative when released, yet continue to affect expectations after newer information has arrived.

A large literature documents frictions in expectation formation. Sticky-information models (Mankiw and Reis, 2002) and rational-inattention frameworks (Sims, 2003; Woodford, 2003) imply that agents update gradually because acquiring and processing information is costly. Empirical work finds substantial evidence of such sluggish adjustment in professional forecasts (Coibion and Gorodnichenko, 2012, 2015). These frameworks, however, primarily predict slow responses to information in general. They do not by themselves imply disproportionate reliance on any particular signal.

The mechanism considered here is more specific. Private forecasters may place excess weight on a salient and widely observed public reference point when forming expectations. In the present context, the SEP is a natural candidate. It is highly visible, released by the central bank, provides explicit projections for the future policy path, and receives extensive financial-market attention. Such reliance could reflect several underlying forces, including behavioral anchoring (Tversky and Kahneman, 1974), information-processing costs, reputational concerns, or strategic incentives to remain close to a prominent public benchmark. I remain agnostic about these microfoundations and focus instead on a common reduced-form implication.

That implication is straightforward. Under rational expectations, forecast errors should be unpredictable conditional on information available when the forecast is formed. If private expectations place excessive weight on a salient prior signal, then the distance between current forecasts and that signal should help predict subsequent forecast errors. Forecasts that remain too close to an outdated anchor should systematically underreact when conditions have changed.

The SEP is particularly useful for studying this mechanism. It is released only quarterly, while macroeconomic news, policy communications, and financial-market information arrive continuously. As a result, projections that are informative when published may become stale between release dates. If private forecasters continue to rely on earlier SEP projections after subsequent information warrants revision, lagged SEP measures should retain explanatory power for future forecast errors even after controlling for other determinants of expectations.

The empirical analysis therefore tests whether deviations between private expectations and previously released SEP projections predict subsequent errors in survey forecasts and market-based expectations. Evidence of such predictability would be consistent with persistent overweighting of stale official guidance rather than fully efficient updating to newly available information.

2.2.2 The Baseline Anchoring Model

I begin with a simple reduced-form framework, following Campbell and Sharpe (2009), in which observed forecasts combine an efficient forecast with a salient reference point. This setup nests unbiased forecasting as a special case and yields a direct empirical test for anchoring.

Let

$$forc_t^{h*} = E_t[r_{t+h}] \tag{1}$$

denote the efficient forecast of the interest rate h quarters ahead. The associated forecast error is

$$u^h_{t+h} = r_{t+h} - forc^{h*}_t, \tag{2}$$

which has conditional mean zero and is orthogonal to information available at time t.

Suppose instead that the observed forecast is a weighted average of the efficient forecast and a salient anchor:

$$forc^h_t = \lambda_h forc^{h*}_t + (1 - \lambda_h) anch^h_t, \tag{3}$$

where $anch^h_t$ denotes the anchor and $\lambda_h \in (0, 1]$ is the weight placed on the efficient component of the forecast. Lower values of λ_h imply greater reliance on the anchor.

Subtracting the observed forecast from the realized rate yields the ex-post forecast error:

$$ferr^h_{t+h} = r_{t+h} - forc^h_t = b_h(forc^h_t - anch^h_t) + u^h_{t+h}, \tag{4}$$

where

$$b_h = \frac{1 - \lambda_h}{\lambda_h}. \tag{5}$$

The key empirical implication is that the distance between the current forecast and the anchor should help predict subsequent forecast errors if expectations place excessive weight on that anchor.

Following Campbell and Sharpe (2009), I first use the prior consensus forecast as the baseline reference point:

$$anch^h_t = forc^{h+1}_{t-1}. \tag{6}$$

This yields the baseline estimating equation:

$$ferr_{t+h}^{h} = a_h + b_h \left(forc_t^{h} - forc_{t-1}^{h+1} \right) + u_{t+h}^{h}. \tag{7}$$

Under unbiased and fully efficient forecasting, the null hypothesis is $a_h = b_h = 0$. A positive estimate of b_h indicates that revisions away from the prior consensus are systematically too small. When forecasts are revised upward relative to the previous consensus, realized rates still tend to exceed the forecast; when forecasts are revised downward, realized rates tend to fall short of the forecast. This pattern is consistent with anchoring to the prior consensus benchmark.

2.3 Testing the Effect of the SEP on Anchoring

The key empirical challenge is distinguishing efficient use of SEP information from persistent reliance on stale official guidance. Both mechanisms can generate correlation between private forecasts and SEP projections. I therefore employ three complementary tests: a structural-break comparison around the 2012 introduction of the dot plot, an orthogonality test based on the incremental predictive content of lagged SEP projections, and a composite-anchor specification that estimates the relative weight placed on prior consensus forecasts versus the SEP.

Structural Break Evidence

The first test asks whether the predictability of forecast errors changed after the introduction of the SEP dot plot. I estimate the baseline anchoring regression in Equation (7) separately over the pre-2012 and post-2012 periods. If the dot plot introduced an additional salient reference point, forecast errors may become more predictable in the post-SEP period.

This evidence is suggestive rather than dispositive. A break around 2012 could also reflect broader changes in the monetary-policy environment, including the effective lower bound, large-scale asset purchases, or heightened policy uncertainty. The remaining tests therefore exploit time-series variation in the specific content of SEP projections.

Orthogonality Test

The second test examines whether lagged SEP projections retain incremental explanatory power for forecast errors after baseline anchoring dynamics have been partialled out. Let sep_{t-1}^{h+1} denote the most recently available SEP projection for the federal funds rate at horizon h, typically from the previous quarter. I estimate

$$u_{t+h}^{h} = \alpha_h + \beta_h \left(forc_t^h - sep_{t-1}^{h+1}\right) + \varepsilon_{t+h}^{h}, \tag{8}$$

where u_{t+h}^{h} is the estimated residual from the baseline regression in Equation (7), obtained in a first stage.

If private forecasters have already incorporated the information contained in the SEP efficiently, then the gap between the current forecast and the most recent SEP projection should not predict subsequent residual forecast errors, implying $\beta_h = 0$. A positive estimate of β_h indicates that private expectations remain too close to the earlier SEP projection after newer information has arrived. When the private forecast lies above the lagged SEP, realized rates tend to exceed the forecast; when the private forecast lies below the lagged SEP, realized rates tend to fall short of the forecast.

Because this test exploits variation in the content of SEP projections rather than only a post-2012 indicator, it helps distinguish SEP-specific anchoring from generic changes in the post-2012 environment. I estimate this specification both with and without controls for alternative predictors emphasized in the literature, including the current level of rates, business-cycle conditions, forecast disagreement, and financial-market variables.

Composite Anchoring Model

The third test allows private expectations to be anchored simultaneously to the prior consensus forecast and to the SEP. I retain the anchoring structure in Equation (3) but specify the anchor as a weighted average of the two reference points:

$$anch_t^h = \omega_h forc_{t-1}^{h+1} + (1-\omega_h) sep_{t-1}^{h+1}, \tag{9}$$

where ω_h is the weight placed on the prior consensus forecast and $(1-\omega_h)$ is the weight placed on the SEP.

Substituting this composite anchor into Equation (3) implies the estimating equation

$$ferr_{t+h}^h = a_h + b_h \left(forc_t^h - forc_{t-1}^{h+1}\right) + c_h \left(forc_t^h - sep_{t-1}^{h+1}\right) + u_{t+h}^h. \tag{10}$$

Under the maintained linear specification, the coefficients b_h and c_h recover both the overall degree of anchoring and the relative importance of each reference point. Specifically,

$$b_h = \left(\frac{1-\lambda_h}{\lambda_h}\right)\omega_h, \qquad c_h = \left(\frac{1-\lambda_h}{\lambda_h}\right)(1-\omega_h). \tag{11}$$

This specification therefore provides estimates of both total anchoring intensity and the share attributable to prior consensus forecasts versus official SEP guidance. As in the orthogonality tests, I report specifications with and without additional controls.

3 Data and Empirical Methods

3.1 Data

The empirical analysis combines three measures of expectations: professional survey forecasts, market-implied expectations, and official SEP projections. This structure allows a comparison of how private forecasters, financial markets, and policymakers respond to the same evolving information set. All series are aligned to common forecast horizons and are constructed using only information available at the time expectations are formed. I also assemble a set of control variables motivated by the literature on the predictability of survey-and market-based interest-rate forecasts.

Blue Chip Economic Indicators

The primary measure of private-sector expectations is drawn from *Blue Chip Financial Forecasts* and *Blue Chip Economic Indicators*, long-running surveys of professional forecasters from major financial institutions and consulting firms. I focus on the quarterly consensus forecast for the federal funds rate, the Federal Reserve's primary policy instrument.

Blue Chip reports forecasts for the quarterly average federal funds rate at horizons of one through four quarters ahead. To align survey timing with the quarterly SEP release schedule, I use the final monthly survey published in each calendar quarter (March, June, September, and December). The resulting sample runs from 1983Q1 through 2026Q1, yielding 173 quarterly observations.

The realized target variable is the quarterly average effective federal funds rate, obtained from the Federal Reserve Bank of St. Louis FRED database.

Summary of Economic Projections

The Summary of Economic Projections (SEP) provides FOMC participants' individual assessments of the appropriate future level of the federal funds rate under their respective economic outlooks. The SEP has generally been released quarterly since January 2012 following the March, June, September, and December FOMC meetings.[2]

Each release reports participants' projections for the federal funds rate at the end of the current calendar year, the following two calendar years, and in the longer run. Because these projections are reported at calendar year-end dates rather than fixed forecast horizons, they must be mapped into horizon-based forecasts to be comparable with Blue Chip expectations.

For each release date t, I construct implied forecasts at horizons of one through five quarters ahead using linear interpolation across adjacent published year-end projections. I

[2] The second SEP in 2012 was released in April rather than March, and no SEP was published in June 2020 because of the COVID pandemic.

also use the target range for the federal funds rate announced in the post-meeting FOMC statement as an implicit zero-horizon observation. This approach provides a transparent benchmark mapping from year-end projections to quarterly horizons.[3]

I denote the resulting interpolated SEP forecast at horizon h by sep_t^h, which is directly comparable to the Blue Chip forecast $forc_t^h$. In all empirical specifications, I use only the most recently available SEP at the time private expectations are formed.

The SEP sample runs from 2012Q1 through 2026Q1, yielding 56 quarterly observations. Figure 1 plots the interpolated SEP path at one- through four-quarter horizons and illustrates the evolution of policy guidance from the effective lower bound period through the 2022–2023 tightening cycle and subsequent easing.

Market-Based Forecasts

In addition to survey forecasts, I construct market-implied expectations using Eurodollar futures and federal funds futures. Eurodollar futures settle on three-month LIBOR, while federal funds futures settle on the monthly average effective federal funds rate.

To obtain a longer historical series, I splice Eurodollar futures from 1986Q1 through 2004Q4 with federal funds futures from 2005Q1 through 2026Q1. A constant 25 basis-point adjustment is added to federal funds futures to account for the historical average spread between LIBOR and the federal funds rate. This splice is intended to provide a broadly comparable long-horizon market expectations series rather than a structural measure of risk-neutral expectations.[4]

These contracts are converted into implied forecasts at horizons of one through four quarters ahead, yielding 160 quarterly observations.

[3] Any conversion from year-end projections to fixed-horizon forecasts requires an interpolation assumption. Linear interpolation provides a simple benchmark.

[4] Analysis of SEP effects on futures-based forecasts naturally use only the post-2012 sample and are thus unaffected by the splicing of the two series.

Control Variables

To distinguish anchoring effects from alternative explanations for predictable forecast errors, I include control variables emphasized in prior work. These controls capture four broad influences: the level and slope of interest rates, macroeconomic conditions, financial risk conditions, and disagreement among forecasters.

Specifically, the baseline set includes the three-month Treasury bill rate, the slope of the yield curve (the ten-year Treasury yield minus the three-month Treasury bill rate), nonfarm payroll growth, the BBB corporate bond spread, and S&P 500 returns. For survey-based forecasts, I also include forecast disagreement. For market-based forecasts, I additionally include realized stock–bond covariance as a proxy for time-varying risk premia.

Appendix B provides detailed variable definitions and data sources.

Together, these data permit direct comparison of official guidance, professional forecasts, and market pricing under a common real-time information structure.

3.2 Empirical Methods and Inference

The empirical analysis relies primarily on predictive regressions of forecast errors on variables observable when forecasts are formed. Several features of the data complicate conventional inference. First, multi-quarter forecast errors overlap, inducing serial correlation that increases with the forecast horizon. Second, many regressors—including forecast revisions, deviations from anchors, and financial variables—are highly persistent. Third, innovations to these regressors may be contemporaneously correlated with forecast-error innovations because newly arriving information can affect expectations, revisions, and forecast errors simultaneously.

These issues are well known to distort standard predictive-regression inference, particularly in finite samples(Stambaugh, 1999; Bauer and Hamilton, 2018). I therefore report Newey–West t-statistics with a four-quarter lag length for reference, but base statistical significance primarily on bootstrap procedures.

The bootstrap is constructed to impose the null hypothesis that forecast errors are not predictable using lagged information while preserving the joint dynamics of the regressors and one-period forecast errors. Specifically, I estimate a first-order vector autoregression for the regressors. One-period forecast errors are then modeled as unpredictable conditional on lagged information, but allowed to depend contemporaneously on innovations to the VAR variables. This setup preserves the observed contemporaneous covariance between shocks to regressors and shocks to forecast errors while ruling out predictive relationships under the null.

I then jointly resample the estimated VAR and forecast-error innovations with replacement to generate artificial datasets. For each simulated sample, I reconstruct overlapping multi-quarter forecast errors by summing simulated one-period forecast errors over the relevant horizon and re-estimate the regression specifications used in the baseline analysis. In specifications that use generated regressors, such as orthogonality tests based on first-stage residuals, each bootstrap replication repeats the full estimation procedure.

This procedure yields empirical distributions of coefficient estimates and t-statistics that account for small-sample distortions arising from persistence, overlapping observations, and contemporaneous correlation. Reported p-values are calculated from the bootstrap distribution of t-statistics rather than from asymptotic critical values. In practice, the bootstrap critical values are generally more demanding than conventional asymptotic benchmarks. Unless otherwise noted, results are based on 1,000 bootstrap replications. Appendix A provides additional implementation details.

4 Results

4.1 Realized Policy Rates and Survey Expectations

Figure 2 plots the realized federal funds rate together with successive Blue Chip forecast paths for the subsequent four quarters. Two broad patterns are visible. First, forecast errors often display persistence: misses frequently continue in the same direction for several quarters rather than reversing quickly. Second, the character of forecast errors changes over time. Prior to 2012, forecasts commonly overpredicted subsequent policy rates, consistent with forecasters only gradually recognizing the long-run decline in nominal interest rates. After 2012, forecast errors appear smaller on average and less systematically one-sided, although sizable misses remain around major policy turning points.

4.2 Forecast Accuracy Comparison and the SEP

The persistence of forecast errors in Figure 2 does not imply that survey forecasts lack useful information. The relevant question is whether professional forecasts outperform standard alternatives. Table 1 addresses this question by comparing Blue Chip forecasts with three broad classes of benchmarks: a random walk forecast, a real-time macro-finance VAR, and market-implied expectations derived from Eurodollar and federal funds futures.[5] Forecast errors are measured relative to the realized quarterly average federal funds rate.

Table 1 shows that Blue Chip forecasts are competitive with, and generally superior to, these alternatives over the full sample. Across all horizons, Blue Chip produces lower root mean squared errors than both the random walk and the real-time VAR. Diebold–Mariano tests reject equal predictive accuracy relative to the random walk at horizons of one through three quarters. These results suggest that professional survey forecasts incorporate information beyond simple persistence in short-term interest rates or the information captured by a parsimonious macro-finance model.

By contrast, futures-based forecasts perform only modestly better than the random walk at short horizons and no better at longer horizons. They also exhibit sizable negative mean forecast errors. This likely reflects a combination of time-varying risk premia and measurement differences between futures settlement values and the realized target variable used

[5] The real-time macro-finance VAR(1) includes real GDP growth, CPI inflation, the federal funds rate, and the ten-year Treasury yield. The model is estimated recursively using samples that begin in 1980Q1 and end sequentially from 1983Q1 through 2026Q1. Out-of-sample forecasts are then constructed at horizons of one through four quarters.

here.[6]

Table 2 repeats the exercise for the post-2012 period and adds the median SEP projection. Two broad patterns emerge. First, forecast accuracy improves noticeably across all methods in the later subsample. Root mean squared errors are smaller for every forecasting approach considered. This likely reflects several factors, including the end of the long secular decline in nominal interest rates, repeated periods at the effective lower bound, and possibly the informational contribution of the SEP itself. Because these influences occur simultaneously, the overall improvement cannot be attributed solely to the SEP.

Second, and most important for this paper, the SEP performs strongly in the post-2012 sample. At the one-quarter horizon, the median SEP projection achieves the lowest RMSE among all methods considered. At longer horizons, it continues to outperform Blue Chip forecasts and the real-time VAR, while futures-based forecasts are roughly comparable at two quarters ahead and more accurate at three- and four-quarter horizons. The strong short-horizon performance of the SEP is consistent with policymakers possessing useful information about both the economic outlook and their likely reaction function. Diebold–Mariano tests indicate that SEP forecasts significantly outperform the random walk at the one-quarter horizon and marginally so at two quarters ahead.[7]

These results establish that the SEP contains economically meaningful information about the future path of policy rates. At the same time, strong average forecast performance does not imply efficient use over time: a signal can be informative when released yet receive excessive weight after new information arrives. The next section examines whether private forecasts continue to rely on earlier SEP projections after those projections have become stale.

[6] Eurodollar futures settle on end-of-quarter three-month LIBOR, while federal funds futures settle on the monthly average federal funds rate. Neither contract settles directly on the realized quarterly average effective federal funds rate used as the evaluation target in Tables 1 and 2. In addition, market-based forecasts are available only beginning in 1986Q1, implying a shorter effective sample for these comparisons.

[7] The SEP is released several weeks after Blue Chip survey responses are collected each quarter, giving it a modest timing advantage relative to Blue Chip. However, the SEP also outperforms the real-time VAR and remains highly competitive with contemporaneous market-based forecasts, indicating that its strong performance reflects genuine information content rather than timing alone.

4.3 Anchoring Results for Blue Chip Forecasts

Having established that Blue Chip forecasts are informative and competitive with alternative approaches, I now examine whether these forecasts exhibit systematic anchoring bias. I begin by documenting anchoring to prior consensus over the full sample, then assess whether this pattern varies over time.

4.3.1 Visual Evidence of Anchoring

If forecasters anchor to prior consensus, forecast revisions should be positively correlated with subsequent forecast errors. When forecasters revise their expectations upward, insufficient adjustment implies that realized rates will tend to exceed those forecasts, generating positive errors.

Figure 3 provides a visual assessment of this prediction by plotting ex-post forecast errors against ex-ante forecast revisions for each horizon. A positive relationship is evident across all panels: upward revisions tend to coincide with positive forecast errors, and downward revisions with negative errors. While this evidence is informal, it is consistent with anchoring behavior and motivates the regression analysis that follows.

4.3.2 Baseline Regression

Table 3 reports estimates of the baseline anchoring regression across three sample periods. Following Campbell and Sharpe (2009), I regress forecast errors on revisions relative to the prior consensus forecast:

$$ferr_{t+h}^{h} = a_h + b_h \left(forc_t^h - forc_{t-1}^{h+1}\right) + u_{t+h}^{h}. \tag{12}$$

Under efficient forecasting, forecast errors should be orthogonal to information available when the forecast is formed, implying $b_h = 0$. A positive coefficient indicates under-adjustment: when forecasters revise expectations upward, realized rates still tend to exceed their forecasts, consistent with continued reliance on the prior consensus benchmark.

Panel A shows clear evidence consistent with anchoring over the full sample. The coefficient on forecast revisions is positive at all horizons and statistically significant under bootstrap inference. Its magnitude rises monotonically with the forecast horizon, increasing from 0.23 at the one-quarter horizon to 0.90 at the four-quarter horizon. The regression explains a meaningful share of forecast-error variation, with in-sample R^2 values between 8 and 13 percent and out-of-sample R^2 reaching roughly 17 to 21 percent at horizons of two through four quarters.

Within the maintained anchoring model, these coefficients admit a convenient interpretation. Since $b_h = (1 - \lambda_h)/\lambda_h$, the implied weight on the efficient component of the forecast is $\lambda_h = 1/(1 + b_h)$. At the one-quarter horizon, the estimates imply $\lambda_h \approx 0.82$, suggesting limited reliance on the anchor. At the four-quarter horizon, λ_h falls to roughly 0.53, implying substantially greater weight on the prior consensus forecast.[8] This horizon pattern is economically intuitive: as uncertainty rises with forecast distance, salient reference points may become more influential. These findings are consistent with Ichiue and Yuyama (2009), who document similar partial-adjustment behavior in short-rate forecasts.

Panels B and C examine whether this baseline anchoring pattern changes over time. Panel B indicates positive coefficients throughout the pre-2012 period, although estimates become less precise at longer horizons. Panel C shows a more nuanced pattern in the post-2012 sample: the coefficient is smaller at the one-quarter horizon but larger at horizons of two through four quarters, rising to 1.28 at the four-quarter horizon. Regression fit also increases materially at medium and longer horizons.

This comparison should be interpreted cautiously. The post-2012 subsample is relatively short and coincides with substantial changes in the macroeconomic and policy environment, including the effective lower bound, unconventional monetary policy, and expanded use of forward guidance. As a result, the increase in medium- and long-horizon coefficient magni-

[8] Coefficients in excess of unity should be interpreted as reduced-form predictive effects rather than literal structural weights.

tudes may reflect several forces rather than a single structural change.

Taken together, these results provide consistent evidence of under-adjustment to prior consensus forecasts. Across specifications, anchoring effects become stronger with the forecast horizon, with the largest and most precisely estimated coefficients at horizons of three and four quarters. The stronger medium- and long-horizon predictability in the post-2012 sample is suggestive, but not conclusive, evidence that additional forces may have amplified anchoring after the introduction of the SEP. The next section examines this possibility directly.

4.3.3 Robustness of Baseline Regression to Alternative Theories

A substantial literature documents systematic errors in interest-rate forecasts and proposes mechanisms other than anchoring. Table 4 provides a demanding robustness exercise by estimating a multivariate "horse race" regression that includes the forecast revision variable together with several alternative predictors emphasized in prior work. The objective is to test whether the baseline anchoring relationship survives after controlling jointly for competing explanations.

The additional predictors are motivated by earlier studies. The short-rate level captures extrapolation from current policy settings (Cieslak, 2018). Employment growth and the BBB corporate bond spread proxy for business-cycle conditions and risk premia (Piazzesi and Swanson, 2008). Stock returns and forecaster disagreement capture financial-market conditions and uncertainty about policy (Schmeling et al., 2022). The term spread is a standard forward-looking indicator of macroeconomic conditions. Together, these controls represent several leading determinants of predictable forecast errors discussed in the literature.

Table 4 shows that the baseline anchoring result is highly robust. The coefficient on forecast revisions remains positive and statistically significant at every horizon, with magnitudes very close to those reported in the univariate baseline regressions. This stability indicates that the predictive relationship between revisions and subsequent forecast errors is not subsumed by standard macroeconomic or financial predictors.

The remaining controls display limited and inconsistent explanatory power. Some variables, such as the short rate or term spread at longer horizons, show occasional associations with forecast errors, but these effects are not statistically robust across horizons. Their inclusion does not materially alter the estimated anchoring relationship. Overall regression fit remains moderate and increases with the forecast horizon, reaching roughly 21 percent at the four-quarter horizon.

Taken together, the results indicate that under-adjustment relative to prior consensus forecasts is an important and robust feature of forecast-error predictability in Blue Chip data. The baseline anchoring relationship is also robust to alternative estimation methods that are less sensitive to outliers, including median (quantile) regression and modal regression; Appendix C reports these results.

4.3.4 SEP Orthogonality Test

The subsample evidence suggests that forecast errors became more predictable after 2012, but it does not establish whether this reflects SEP-specific effects or broader changes in the forecasting environment. To isolate the role of the SEP, I conduct orthogonality tests that ask whether lagged SEP-based measures retain incremental predictive power after controlling for baseline anchoring to the prior consensus forecast. This serves as the paper's core identification test of whether the SEP operated as an additional reference point in expectation formation.

Table 5 reports results from two versions of this exercise. Panels A and B examine whether the SEP gap—the difference between the current consensus forecast and the lagged SEP projection, $\left(forc_t^h - sep_{t-1}^{h+1}\right)$—predicts residual forecast errors from the baseline regressions. Panel A uses residuals from the simple baseline specification in Table 3, while Panel B uses residuals from the multivariate baseline in Table 4. Panels C and D provide a complementary test by examining whether the intensity of baseline consensus anchoring changed after 2012.

Panel A provides suggestive evidence. The SEP gap enters positively at all horizons, and the coefficients increase with the forecast horizon, but coefficient estimates are imprecise. Even so, the residual R^2 statistics are statistically significant at the three-quarter horizon and marginally significant at the four-quarter horizon.

Panel B presents the main results. After controlling for alternative predictors in the first-stage regression, the SEP gap retains substantial predictive power. Coefficients are positive at all horizons, marginally significant at two quarters ahead, and statistically significant at horizons of three and four quarters. The associated residual R^2 values indicate that the SEP gap explains a meaningful portion of variation left unexplained by the baseline model.

These findings indicate that lagged SEP projections capture something distinct from generic sluggishness or prior-consensus anchoring. If private forecasters had already incorporated SEP information efficiently, the gap between current forecasts and the earlier SEP should not systematically predict residual forecast errors. The fact that it does so at medium and longer horizons is consistent with private expectations adjusting too slowly away from prior SEP guidance.

Panels C and D consider an alternative explanation: that forecast errors became more predictable after 2012 simply because anchoring to the prior consensus intensified. The interaction between forecast revisions and a post-2012 indicator is generally small and statistically insignificant. This weak evidence for a structural increase in baseline anchoring strengthens the interpretation that the incremental predictability in Panels A and B is SEP-specific rather than a generic post-2012 shift.

Taken together, the results indicate that lagged SEP projections played an independent role in expectation formation. The SEP gap provides statistically and economically meaningful incremental explanatory power at medium-term horizons, consistent with forecasters treating earlier SEP projections as a distinct reference point rather than merely increasing reliance on prior consensus forecasts.

4.3.5 Composite Anchoring Model

The orthogonality tests show that lagged SEP projections contain incremental predictive power, but they do not quantify the relative importance of SEP-based anchoring versus prior-consensus anchoring. To address this question, I estimate a composite anchoring model over the post-SEP period that allows private forecasts to depend on both reference points simultaneously.

Table 6 reports results for SEP-only specifications (Panels A and B) and for the composite model (Panels C and D). Panels A and B estimate regressions using only the SEP gap as the anchoring variable, without and with controls, respectively. The SEP gap predicts forecast errors strongly at medium-term horizons. Without controls, coefficients are statistically significant at all horizons. With controls, significance is concentrated at horizons of two through four quarters. These results reinforce the earlier orthogonality tests and suggest that SEP-related anchoring is most relevant beyond the very short run.[9]

Panels C and D contain the main results. The composite anchoring coefficient is economically large and statistically significant at horizons of two through four quarters, indicating that a combination of prior-consensus and SEP-based reference points explains an important share of forecast-error variation. Depending on specification and horizon, the model attains R^2 values in the range of roughly 25 to 40 percent.

The implied weights indicate that both anchors matter, but their relative importance varies across horizons. In the preferred specifications with controls, the medium-horizon estimates assign greater weight to the lagged SEP projection than to prior consensus forecasts. At the one-quarter horizon, by contrast, weight estimates are imprecise and provide little evidence of a stable decomposition. These patterns are consistent with SEP guidance becoming most influential at horizons where policy expectations are less tightly pinned down by near-term conditions.

[9] Specifications that include only the control variables from Table 4 yield consistently inferior AIC values relative to specifications that also include anchoring variables, indicating that anchoring terms capture variation not explained by standard predictors.

The magnitude of the composite coefficient also implies substantial overall anchoring. Under the maintained model, $\beta_h = (1 - \lambda_h)/\lambda_h$, so that $\lambda_h = 1/(1 + \beta_h)$. Coefficients near two therefore imply that only about one-third of the fitted forecast reflects the independent component, with the remainder associated with the composite anchor. In this sense, private expectations appear to adjust only gradually away from salient reference points.

Figure 4 provides a visual illustration of these mechanisms. Panel A plots the realized federal funds rate together with raw Blue Chip forecast paths in the post-SEP sample. Forecasts often adjust only gradually during episodes of rapid policy change, most notably during the 2022–2023 tightening cycle.

Panel B plots forecasts corrected using the estimated bias adjustments from Table 6, Panel C. The corrected paths track the realized policy-rate path more closely, indicating that an important portion of forecast errors reflects systematic under-adjustment rather than purely unpredictable shocks.

Panel C decomposes the fitted bias correction into contributions from prior-consensus anchoring and SEP-based anchoring. At the four-quarter horizon, SEP-related effects are often sizable during periods of changing policy expectations. During the 2022–2023 tightening cycle, for example, anchoring to earlier SEP projections appears to have contributed materially to the tendency of private forecasts to underpredict the speed and extent of policy tightening. Correcting for both sources of anchoring brings forecast paths substantially closer to the ex-post trajectory of rates.

More broadly, the figure illustrates that forecast errors in the post-SEP period are consistent with a combination of anchoring to prior private consensus and to lagged official guidance. The composite model captures this behavior parsimoniously and helps explain why forecasts adjusted only gradually during major policy transitions.

4.4 Market-Based Expectations

While survey forecasts provide direct evidence on professional expectations, market-implied forecasts embedded in asset prices are central to monetary-policy transmission. Policy actions and communications affect the real economy largely through their effects on bond yields, equity prices, exchange rates, and broader financial conditions. Market prices also reflect the views of investors with capital at risk, creating stronger incentives for accuracy than survey responses alone.

A substantial literature therefore studies predictability in fixed-income markets rather than survey forecast errors. Piazzesi and Swanson (2008) show that federal funds futures excess returns are related to employment growth and corporate bond spreads. Cieslak (2018) documents predictability linked to the level of short-term interest rates, while Schmeling et al. (2022) show that stock returns and forecaster disagreement help explain excess returns on interest-rate futures. These patterns are typically interpreted as reflecting a combination of time-varying risk premia and expectation-formation frictions.

I examine market-implied expectations using Eurodollar futures through 2004Q4 and federal funds futures thereafter. The empirical analysis parallels the survey-based results, proceeding from baseline anchoring regressions to multivariate robustness tests, orthogonality tests, and composite-anchor models. Because futures prices reflect both expectations of future short rates and risk premia, the market-based evidence is naturally noisier than the survey evidence. Any remaining evidence of anchoring in these prices is therefore of particular interest.

The top panel of Figure 5 provides a visual illustration of these market-based forecasts. As with the survey forecasts in Figure 2, forecast errors often appear one-sided for extended periods and expectations sometimes adjust only gradually during episodes of rapid policy-rate change.

4.4.1 Baseline Anchoring

Table 7 reports baseline regressions for Eurodollar and federal funds futures, relating market-based forecast errors to revisions in Blue Chip consensus forecasts. The dependent variable is

$$ferr_{t+h}^{h} = r_{t+h} - fut_t^h,$$

where fut_t^h denotes the futures-implied rate. The regressor is the Blue Chip revision, $\left(forc_t^h - forc_{t-1}^{h+1}\right)$, which tests whether private-sector forecast revisions are associated with subsequent errors in market-implied expectations.

The full-sample results provide suggestive evidence of sluggish adjustment in futures markets. The coefficient on Blue Chip revisions is positive at all horizons and statistically significant through three quarters ahead, with marginal significance at the four-quarter horizon. Upward revisions in survey expectations therefore tend to be followed by positive forecast errors in futures-implied rates. At the same time, explanatory power is modest, with R^2 values generally below 6 percent, and substantially smaller than in the survey regressions.

The subsample results reveal a clearer pattern. In the pre-2012 period, the relationship between Blue Chip revisions and futures forecast errors is weak and not statistically robust. In contrast, in the post-2012 period, coefficients are positive at all horizons, marginally significant at two quarters ahead, and statistically significant at horizons of three and four quarters. The one-quarter coefficient remains small and insignificant, consistent with near-term information being incorporated more rapidly into market prices.

Taken together, these findings suggest that market-based expectations display some tendency toward gradual adjustment associated with prior-consensus forecast revisions, particularly at medium horizons in the post-2012 period. However, the evidence is weaker and less uniform than in survey data, where anchoring effects are pervasive across horizons and sample periods. This difference is not surprising, since futures prices reflect both expectations of future short rates and time-varying risk premia. Moreover, these baseline regressions do not yet control for other sources of predictability in futures markets.

4.4.2 Robustness to Alternative Predictors

Table 8 examines whether the baseline relationship between Blue Chip revisions and futures forecast errors survives once standard predictors from the literature are included. The specification augments the baseline regression with controls for macroeconomic conditions, financial variables, and proxies for time-varying risk premia and expectation-formation frictions. Following Diercks and Carl (2019), I also include the covariance between stock returns and forward-rate changes as an additional risk-premium measure.

The results indicate that the predictive content of Blue Chip revisions is not robust in this multivariate setting. Once controls are included, the coefficient on forecast revisions is no longer statistically significant at conventional levels, with only marginal evidence at the three-quarter horizon. This contrasts with the survey-based results, where prior-consensus anchoring remains strong even after controlling for similar predictors.

Several control variables instead display substantial predictive power. Most notably, the level of short-term interest rates is a strong predictor of forecast errors across horizons, consistent with the extrapolation mechanism emphasized by Cieslak (2018). Forecaster disagreement, the term spread, and stock–bond covariance also help explain futures forecast errors, particularly at medium and longer horizons. These findings suggest that predictability in market-based forecast errors reflects a combination of macroeconomic state variables and risk-premium channels documented in the literature.

Taken together, the evidence suggests that the variation attributed to Blue Chip revisions in the baseline specification overlaps importantly with other sources of predictability in futures markets. In this setting, prior-consensus anchoring is not cleanly identified once these controls are included. This highlights an important distinction between survey and market-based forecasts: while anchoring to prior consensus is a robust feature of survey expectations, market prices are more heavily influenced by broader macro-financial forces.

It also underscores the importance of including these controls in subsequent tests for SEP-based anchoring.

4.4.3 SEP Orthogonality Tests

Table 9 examines whether SEP-based measures retain incremental predictive power for market-implied forecast errors. The specification parallels the survey analysis by testing whether the SEP gap predicts residual forecast errors from baseline regressions. Panels A and B report the primary orthogonality tests using simple and multivariate first-stage baselines, respectively, while Panels C and D examine whether the intensity of baseline Blue Chip anchoring changed after 2012.

The key result emerges from comparing Panels A and B. In Panel A, which uses the simple baseline, the SEP gap is not statistically significant at any horizon, although coefficients are positive and increase with forecast distance. This suggests that SEP-related variation is not cleanly isolated in parsimonious specifications.

In contrast, Panel B shows that the SEP effect becomes materially clearer once standard controls are included. Coefficients on the SEP gap are positive at all horizons and marginally significant at horizons of three and four quarters. More importantly, the associated residual R^2 statistics are statistically significant at horizons of two through four quarters, indicating that the SEP gap explains a meaningful share of variation left unexplained by the multivariate baseline model. The coefficient magnitudes at longer horizons are also economically sizable, on the order of unity.

These findings suggest that lagged SEP projections influenced market-based expectations, but that the effect is partially obscured by other sources of predictability in futures markets. Once macro-financial controls are taken into account, SEP-related anchoring becomes more visible in the residual variation.

Panels C and D consider the alternative hypothesis that any increase in predictability after 2012 simply reflects a change in baseline anchoring to prior consensus forecasts. The results provide little support for this view. Interaction terms are generally small and statistically insignificant across horizons, with only limited evidence of changes at the one-quarter horizon. Overall, there is no consistent indication that baseline anchoring intensified in the post-2012 period.

Taken together, the results indicate that SEP projections contributed independently to the formation of market-based expectations. The evidence is somewhat more attenuated than in the survey data: statistical significance is weaker, and results are more sensitive to specification choices. Even so, the fact that lagged SEP projections retain predictive power in market prices after controlling for standard macro-financial variables is economically notable.

4.4.4 Composite Anchoring Model

Table 10 reports estimates of the composite anchoring model for market-implied forecasts over the post-SEP period. The specification parallels the survey analysis by allowing forecast errors to depend jointly on prior-consensus revisions and SEP-based measures. Panels A and B report SEP-only specifications without and with controls, respectively, while Panels C and D estimate the composite model without and with controls.[10]

Panels A and B provide additional evidence that SEP-based measures are relevant for futures forecast errors, particularly at medium and longer horizons. Coefficients on the SEP gap are positive throughout and become economically meaningful once controls are included, with marginal statistical significance at horizons of two through four quarters. This pattern is consistent with the orthogonality results in Table 9.

Panels C and D contain the composite specifications. At horizons of one and two quarters, the composite anchoring coefficient is small and imprecisely estimated. At horizons of three and four quarters, however, point estimates are materially larger and marginally significant, suggesting that a combined anchoring mechanism is more relevant at longer horizons. In

[10]Specifications that include only control variables yield consistently higher AIC values than those that incorporate anchoring terms, indicating that anchoring variables capture variation not explained by standard predictors.

the specification with controls (Panel D), the implied weights generally place greater relative importance on SEP-based anchoring than on prior-consensus anchoring, although these decompositions are estimated with considerable uncertainty.

Under the maintained model, the magnitude of the composite coefficients is also economically meaningful. Values near unity or above imply substantial reliance on the composite anchor relative to the independent component of expectations. While these estimates should not be interpreted too literally, they are consistent with gradual adjustment away from salient reference points in market prices.

Figure 6 provides a visual counterpart. Panel A plots the realized underlying short rate—LIBOR prior to 2005 and the federal funds rate thereafter—together with raw futures-implied forecast paths. As in the survey data, expectations often adjust only gradually during episodes of rapid policy-rate change. Panel B applies the bias corrections implied by Table 10, Panel D. The corrected forecast paths generally track the realized path more closely, suggesting that part of the observed forecast error reflects systematic under-adjustment rather than purely unpredictable shocks.

Panel C decomposes the fitted bias correction into contributions from prior-consensus and SEP-related anchoring. The SEP-related component is often economically meaningful at medium and longer horizons, reaching on the order of several tens of basis points during some episodes. During the 2022–2023 tightening cycle, for example, market-implied forward rates underestimated the speed and extent of policy tightening, and the model attributes part of that gap to continued reliance on earlier SEP projections. To the extent that forward rates adjusted more slowly than otherwise, this would have tended to delay some tightening in financial conditions.

Taken together, the composite model reinforces the broader pattern in the market-based evidence. SEP-related anchoring appears most relevant at longer horizons, while short-horizon expectations remain comparatively less affected. More generally, across both survey forecasts and market-implied paths, anchoring effects tend to be weakest at near-term horizons and stronger at medium and longer horizons, consistent with greater reliance on salient reference points when uncertainty is higher.

5 Conclusion

This paper documents a dual role for the Federal Reserve's Summary of Economic Projections (SEP) in the formation of interest-rate expectations. On one hand, SEP projections contain information that improves average forecast accuracy. In the post-2012 period, the median SEP projection generally outperforms consensus survey forecasts, simple time-series benchmarks, and several market-based measures at many horizons. On the other hand, the same signal can become a source of predictable error when private expectations continue to place substantial weight on earlier SEP releases after new information has arrived.

Three main findings support this conclusion. First, forecast errors are systematically related to the gap between current expectations and lagged SEP projections. This evidence is strongest in survey forecasts and is also present, in attenuated form, in market-based expectations. Second, the predictive content of lagged SEP measures remains after controlling for other determinants of forecast errors emphasized in prior work, including macroeconomic conditions, risk premia, and baseline forecast-revision dynamics. Third, the magnitudes are economically meaningful during periods of rapid policy change, most notably during the 2022–2023 tightening cycle.

The mechanism is straightforward. Because the SEP is updated only quarterly while macroeconomic and policy information arrives continuously, projections that are informative when released may become stale between publication dates. Forecasters then face a choice between continuing to rely on the most recent official guidance or revising expectations in response to incoming data. The evidence in this paper is consistent with expectations adjusting too slowly away from prior SEP projections. Related, though weaker, patterns in futures-implied expectations indicate that this predictable component is not confined to surveys, but can also be reflected in market prices and the term structure of interest rates.

These findings have broader implications for the economics of public communication. A public signal may improve the accuracy of private-sector expectations on average while simultaneously slowing the incorporation of subsequent information if it remains especially salient. The results therefore do not imply that the SEP is harmful overall; rather, they suggest that communication tools can generate both static informational benefits and dynamic inefficiencies.

For researchers, this paper provides a concrete channel through which official forecasts can shape both expectations and asset prices. For market participants, the results suggest that lagged official guidance may contain incremental information about subsequent forecast errors even after accounting for standard predictors. For policymakers, the findings imply that communication tools such as the SEP can influence not only expectations but also financial conditions during policy transitions.

More broadly, the choice of the frequency publication of the SEP appears to involve a communications tradeoff. More frequent updates could reduce reliance on stale guidance, but they might also amplify noise, create unwarranted confidence about the future path of policy, or complicate communication by reducing the constructive ambiguity that policymakers may sometimes value. Designing communication frameworks that preserve the informational benefits of official guidance while limiting dependence on outdated signals remains an important challenge for central banks.

References

Bauer, Michael D. and James D. Hamilton, "Robust Bond Risk Premia," *Review of Financial Studies*, 2018, *31* (2), 399–448.

Campbell, Sean D. and Steven A. Sharpe, "Anchoring Bias in Consensus Forecasts and Its Effect on Market Prices," *Journal of Financial and Quantitative Analysis*, 2009, *44* (2), 369–390.

Cieslak, Anna, "Short-Rate Expectations and Unexpected Returns in Treasury Bonds," *Review of Financial Studies*, 2018, *31* (9), 3265–3306.

Coibion, Olivier and Yuriy Gorodnichenko, "What Can Survey Forecasts Tell Us about Information Rigidities?," *Journal of Political Economy*, 2012, *120* (1), 116–159.

_ and _ , "Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts," *American Economic Review*, 2015, *105* (8), 2644–2678.

Diercks, Anthony M. and Justin Carl, "The Yield Curve and Bond Risk Premia: A U.S. Treasury Decomposition," *FEDS Notes*, 2019.

_ , Hiroatsu Tanaka, and Paul Cordova, "Asymmetric Monetary Policy Expectations," Finance and Economics Discussion Series, Board of Governors of the Federal Reserve System September 2022. Available at https://ssrn.com/abstract=3930267.

Ehrbeck, Tilman and Robert Waldmann, "Why Are Professional Forecasters Biased? Agency versus Behavioral Explanations," *Quarterly Journal of Economics*, 1996, *111* (1), 21–40.

Ichiue, Hibiki and Takashi Yuyama, "Using Survey Data to Correct the Bias in Policy Expectations Extracted from Fed Funds Futures Rates," *Journal of Money, Credit and Banking*, 2009, *41* (8), 1631–1647.

Lamont, Owen A., "Macroeconomic Forecasts and Microeconomic Forecasters," *Journal of Economic Behavior & Organization*, 2002, *48* (3), 265–280.

Mankiw, N. Gregory and Ricardo Reis, "Sticky Information versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve," *Quarterly Journal of Economics*, 2002, *117* (4), 1295–1328.

Morris, Stephen and Hyun Song Shin, "Social Value of Public Information," *American Economic Review*, 2002, *92* (5), 1521–1534.

Piazzesi, Monika and Eric T. Swanson, "Futures Prices as Risk-Adjusted Forecasts of Monetary Policy," *Journal of Monetary Economics*, 2008, *55* (4), 677–691.

Scharfstein, David S. and Jeremy C. Stein, "Herd Behavior and Investment," *American Economic Review*, 1990, *80* (3), 465–479.

Schmeling, Maik, Andreas Schrimpf, and Sigurd A. Steffensen, "Monetary Policy Expectation Errors," *Journal of Finance*, 2022, *77* (3), 1339–1391.

Sims, Christopher A., "Implications of Rational Inattention," *Journal of Monetary Economics*, 2003, *50* (3), 665–690.

Stambaugh, Robert F., "Predictive Regressions," *Journal of Financial Economics*, 1999, *54* (3), 375–421.

Trueman, Brett, "Analyst Forecasts and Herding Behavior," *Review of Financial Studies*, 1994, *7* (1), 97–124.

Tversky, Amos and Daniel Kahneman, "Judgment under Uncertainty: Heuristics and Biases," *Science*, 1974, *185* (4157), 1124–1131.

Woodford, Michael, "Imperfect Common Knowledge and the Effects of Monetary Policy," *Knowledge, Information, and Expectations in Modern Macroeconomics: In Honor of Edmund S. Phelps*, 2003, pp. 25–58.

Yao, Wenying and Lin Li, "A New Look at the Predictability of the Fed Funds Rate," *Journal of Applied Econometrics*, 2014, *29* (7), 1025–1039.

A Standard Errors and Inference

The overlapping structure of multi-period forecasts, combined with persistent regressors and limited sample size, renders standard asymptotic inference methods unreliable. I therefore employ bootstrap procedures based on resampling VAR residuals to address these challenges and provide valid small-sample inference. To compute standard errors and t-statistics for the coefficient estimates, I use Newey–West standard errors with $L = 4$ lags, exceeding the maximum degree of overlap ($H = 3$) in the regressions. This procedure addresses autocorrelation in the residuals but does not, by itself, account for potential small-sample bias or provide a null distribution for hypothesis testing. For those purposes, I employ a bootstrap procedure imposing the null of no predictability, following Bauer and Hamilton (2018).

The simulation proceeds in four steps. First, I estimate a restricted VAR(1) for the quarterly vector $Z_t = [ferr_t, X_t]$, where $ferr_t$ is the one-quarter-ahead forecast error and X_t contains the quarterly values of the regressors. The VAR is estimated with the restriction that lagged values of X_t do not predict $ferr_t$, imposing the null hypothesis of no predictability:

$$\begin{bmatrix} ferr_t \\ X_t \end{bmatrix} = A \begin{bmatrix} ferr_{t-1} \\ X_{t-1} \end{bmatrix} + \begin{bmatrix} u_t^{ferr} \\ u_t^X \end{bmatrix}. \tag{13}$$

The coefficient matrix A is restricted so that lagged X_{t-1} does not enter the equation for $ferr_t$. Importantly, the residuals u_t^{ferr} and u_t^X are allowed to be contemporaneously correlated.

Second, I resample the VAR residuals with replacement to preserve potential non-Gaussian features of the data. Third, I simulate the VAR forward using the estimated coefficients and bootstrapped shocks, generating artificial series $[ferr_t, X_t]$ with the same persistence and dependence structure as the observed data, but no predictability by construction. Fourth, I construct overlapping multi-period forecast errors from the simulated data and re-estimate the forecasting regressions using the same procedures applied to the actual data.

This process is repeated 1,000 times to obtain empirical distributions of coefficients, t-statistics, and R^2 measures under the null. Statistical significance is assessed by comparing observed statistics to these bootstrap distributions.

Inference for Alternative Estimators For the LAD and modal regressions reported in Tables A1 and A2, I employ a complementary bootstrap procedure. Specifically, I use a block bootstrap that resamples the joint vector $[ferr_t, X_t]$ using fixed-length blocks of 12 quarters. Coefficient standard errors are computed as the standard deviation across bootstrap replications. The block length of 12 quarters is chosen to capture the persistence and overlap structure of the data.

This approach is used because the LAD and modal estimators do not map directly into the VAR-based bootstrap framework used for the OLS specifications. To maintain consistency, the same block bootstrap procedure is applied to data generated under the null in the outer bootstrap simulations.

B Variable Definitions and Data Sources

B.1 Primary Variables: Survey Forecasts

Blue Chip Consensus Forecast ($forc_t^h$): Consensus forecast for the federal funds rate, h quarters ahead, from Blue Chip Financial Forecasts. Forecasts are taken from the final month of each quarter. Occasional missing values at the one- and three-quarter horizons are filled via linear interpolation between adjacent horizons. This interpolation affects only a small number of observations and does not materially affect the results. Missing five-quarter-ahead forecasts in early years are imputed using a regression on related Blue Chip forecasts, yielding an R^2 above 0.995. *Sample:* 1983Q1–2026Q1. *Source:* Blue Chip Financial Forecasts.

Realized Federal Funds Rate (r_t): Quarterly average of the effective federal funds rate. *Source:* FRED (FEDFUNDS).

B.2 Primary Variables: Summary of Economic Projections

SEP Median Projection (sep_t^h): Median FOMC projection for the federal funds rate. Year-end projections are interpolated to fixed horizons and adjusted by 1.5 months to align SEP projections with the quarterly-average timing convention used in survey forecasts. The June 2020 SEP is imputed at a value consistent with the effective lower bound. *Sample:* 2012Q2–2026Q1. *Source:* Federal Reserve Board, available at federalreserve.gov.

B.3 Primary Variables: Market-Based Forecasts

Futures-Based Forecast (fut_t^h): Market-implied forecast constructed from Eurodollar futures (1986Q1–2004Q4) and federal funds futures (2005Q1–2026Q1). Federal funds futures are adjusted by 25 basis points to approximate LIBOR. Forecast errors are constructed using the corresponding realized rate. *Sample:* 1986Q1–2026Q1. *Sources:* CME Datamine, Bloomberg, and FRED.

B.4 Control Variables

Short-Term Interest Rate Level (Short): The realized quarterly average federal funds rate at time t (equivalent to r_t). Following Cieslak (2018), this variable tests whether forecast errors are related to the current level of rates, potentially reflecting extrapolative bias. I use the 3-month Treasury bill rate from FRED: series DGS3MO.

Yield Curve Slope (Slope): Difference between the 10-year Treasury yield and the 3-month Treasury bill rate, in percentage points. The 10-year yield is extracted from the Federal Reserve Board's smoothed yield curve estimates using end-of-quarter values. This variable captures term structure information that may predict future rate changes. *Sources:* Federal Reserve Board Yield Curve Data and FRED series DGS3MO.

Nonfarm Payroll Employment Growth (Emp): Year-over-year log change in nonfarm payroll employment, in percent. Following Piazzesi and Swanson (2008) and Cieslak

(2018), this variable captures business cycle conditions that may affect monetary policy expectations and forecast errors. To handle the COVID-19 shock, I cap growth at ±10%; this constraint binds only in 2020Q2 (COVID crash) and 2021Q2 (one-year anniversary with 2020Q2 as base). *Source:* FRED series PAYEMS (final revised).

BBB Corporate Bond Spread (BBB Spread): Spread between the yield on 10-year BBB-rated corporate bonds and the 10-year Treasury yield, in percentage points. Following Piazzesi and Swanson (2008), this variable captures credit risk and financial stress that may affect interest rate expectations. I splice two data sources: the Lehman Brothers/Warga Fixed Income Database (1981–1996) and ICE BofA indices (1997–2026), both for 10-year BBB corporate bond yields. I convert to quarterly averages and compute the spread relative to the 10-year Treasury yield. *Sources:* Lehman Brothers Fixed Income Database (Warga, 1981–1996) and ICE BofA corporate bond indices (1997–2026); Federal Reserve Board Yield Curve Data for 10-year Treasuries.

Stock Market Returns (Stock Ret): Quarterly log change in the S&P 500 index, $100\times\log(SP500_t/SP500_{t-1})$. Following Schmeling et al. (2022), this variable captures wealth effects and financial market sentiment that may correlate with forecast errors. *Source:* FRED series SP500.

Forecaster Disagreement (Disagreement): Difference between the average forecasts of the top 10 and bottom 10 Blue Chip respondents for the 3-month Treasury bill rate at each horizon. Blue Chip Financial Forecasts reports the high and low forecast ranges, which I use to construct this dispersion measure. Following Schmeling et al. (2022), disagreement may signal periods of high uncertainty when forecast errors are larger. *Source:* Blue Chip Financial Forecasts (Wolters Kluwer).

Stock-Bond Covariance (Covar): Realized covariance between daily equity returns and daily changes in Treasury forward rates, summed over each quarter and scaled by 10,000. Formally, $Covar_t = 10{,}000 \times \sum_{d\in\text{quarter } t} \Delta\log(SP500_d) \times \Delta\log(100 - fwd_d(1yr))$, where $fwd_d(1yr) = 5y_d(1.25) - 4y_d(1.00)$ is the 1-year instantaneous forward rate from a smoothed

Treasury yield curve. The transformation $100 - fwd$ converts the forward rate to a "price" so that positive covariance indicates Treasuries hedge equity risk (both rise together). Following Diercks and Carl (2019), this variable captures time-varying risk premiums in Treasury securities. *Sources:* Daily S&P 500 from FRED series SP500; daily zero-coupon yields from Federal Reserve Board Yield Curve Data.

C Robustness to Alternative Estimators

A potential concern with the baseline OLS specification is sensitivity to outliers and non-normal error distributions. This is particularly relevant for interest rate forecasts during periods of extreme monetary policy accommodation or tightening. A related theoretical issue is that OLS-based predictability regressions implicitly assume that forecasts represent conditional means, whereas forecasters may instead report median or modal expectations.

To address these concerns, I consider two alternative estimation approaches. First, I estimate the baseline regression using median (quantile) regression, also known as Least Absolute Deviations (LAD). This approach minimizes absolute deviations rather than squared errors, making it more robust to extreme observations. The estimating equation remains:

$$ferr_{t+h}^{h} = a_h + b_h(forc_t^h - forc_{t-1}^{h+1}) + u_{t+h}^{h}, \tag{14}$$

but is estimated using the LAD objective function. In this setting, tests of $b_h = 0$ correspond to tests of unbiasedness for median forecasts.

Second, I employ modal regression, following Yao and Li (2014), which estimates the mode of the conditional distribution of forecast errors. Modal regression is well suited to settings where the error distribution is skewed or multimodal, as may occur across different monetary policy regimes. Moreover, Diercks et al. (2022) show that Blue Chip forecasts may align more closely with modal rather than mean expectations, providing additional motivation for this approach.

Tables A1 and A2 report the results. Across both alternative estimators, the qualitative patterns are similar to those obtained under OLS, with comparable signs, magnitudes, and statistical significance of the key coefficients. These findings indicate that the baseline results are not driven by outliers or by the choice of moment of the conditional distribution being estimated.

Table 1: Forecasting Federal Funds Rates, Model Performance

	1-*qtr*	2-*qtr*	3-*qtr*	4-*qtr*		1-*qtr*	2-*qtr*	3-*qtr*	4-*qtr*
Panel A: Random Walk					*Panel C: Real-Time VAR*				
Mean error	−0.0343	−0.0673	−0.0941	−0.1197	*Mean error*	−0.1246	−0.2383	−0.3335	−0.4228
	(0.0602)	(0.1180)	(0.1721)	(0.2230)		(0.0762)	(0.1393)	(0.1946)	(0.2441)
RMSE	0.4903	0.8736	1.2036	1.4962	*RMSE*	0.5684	0.9546	1.2803	1.5574
	(0.0551)	(0.0946)	(0.1289)	(0.1613)		(0.0671)	(0.1127)	(0.1520)	(0.1904)
					DM test	−1.14	−0.18	0.19	0.45
						(0.256)	(0.860)	(0.852)	(0.651)
Panel B: Blue Chip					*Panel D: ED/FF Futures*				
Mean error	−0.0641	−0.1580	−0.2640	−0.3825	*Mean error*	−0.3375	−0.4846	−0.6397	−0.8142
	(0.0373)	(0.0876)	(0.1466)	(0.2074)		(0.0308)	(0.0838)	(0.1490)	(0.2174)
RMSE	0.3866	0.7272	1.0446	1.3574	*RMSE*	0.4896	0.8472	1.1952	1.5433
	(0.0641)	(0.1025)	(0.1227)	(0.1486)		(0.0686)	(0.1422)	(0.1866)	(0.2210)
DM test	−4.06	−2.95	−2.29	−1.57	*DM test*	−2.30	−1.14	−0.39	0.27
	(0.000)	(0.003)	(0.022)	(0.116)		(0.021)	(0.255)	(0.693)	(0.790)

Notes: Sample period is 1983Q1-2026Q1 (N=173). Forecast errors computed against quarterly average federal funds rates. Standard errors in parentheses computed via block bootstrap with block length 12; p-values in parentheses for Diebold-Mariano (DM) test. Panel A reports statistics for a random walk forecast. Panels B–D report statistics for alternative forecasts with DM test against the random walk (negative values indicate better performance). Panel B: Blue Chip Financial Forecasts consensus forecasts for federal funds rate. Panel C: real-time VAR model estimated on GDP growth, CPI inflation, federal funds rate, and 10-year Treasury yield. Panel D: Eurodollar futures (1986Q1–2004Q4) spliced with federal funds futures (2005Q1–2026Q1); Eurodollar futures settle on end-of-quarter 3-month LIBOR, federal funds futures settle on monthly average federal funds rate.

Table 2: Forecast Error Statistics, Post-SEP Period (2012Q2-2026Q1)

	1-*qtr*	2-*qtr*	3-*qtr*	4-*qtr*		1-*qtr*	2-*qtr*	3-*qtr*	4-*qtr*
Panel A: Random Walk					*Panel C: Real-Time VAR*				
Mean error	0.0672	0.1391	0.2189	0.2992	*Mean error*	−0.0024	0.0441	0.0967	0.1460
	(0.0952)	(0.1857)	(0.2682)	(0.3444)		(0.0687)	(0.1266)	(0.1757)	(0.2228)
RMSE	0.4105	0.7624	1.0721	1.3430	*RMSE*	0.3478	0.5761	0.7502	0.8852
	(0.1136)	(0.2227)	(0.3203)	(0.3986)		(0.0885)	(0.1344)	(0.1685)	(0.1891)
					DM test	−2.78	−1.98	−1.65	−1.49
						(0.006)	(0.048)	(0.099)	(0.137)
Panel B: Blue Chip					*Panel D: ED/FF Futures*				
Mean error	−0.0569	−0.0344	0.0006	0.0315	*Mean error*	−0.2607	−0.2130	−0.1446	−0.0831
	(0.0361)	(0.1105)	(0.2055)	(0.3049)		(0.0222)	(0.0565)	(0.1335)	(0.2208)
RMSE	0.2409	0.4483	0.7172	1.0045	*RMSE*	0.2840	0.3616	0.5436	0.7826
	(0.0845)	(0.1075)	(0.1785)	(0.2570)		(0.0233)	(0.0664)	(0.0973)	(0.1693)
DM test	−2.40	−1.90	−1.65	−1.41	*DM test*	−2.41	−1.90	−1.69	−1.56
	(0.016)	(0.058)	(0.099)	(0.158)		(0.016)	(0.058)	(0.091)	(0.120)
Panel E: SEP									
Mean error	−0.1105	−0.1249	−0.1219	−0.1135					
	(0.0473)	(0.0885)	(0.1666)	(0.2548)					
RMSE	0.2192	0.3635	0.6039	0.8819					
	(0.0261)	(0.0646)	(0.1127)	(0.1888)					
DM test	−2.54	−1.90	−1.63	−1.40					
	(0.011)	(0.057)	(0.103)	(0.161)					

Notes: Sample period is 2012Q2-2026Q1 (N=56 observations, post-SEP period). Forecast errors computed against quarterly average federal funds rates. Standard errors in parentheses computed via block bootstrap with block length 12; p-values in parentheses for DM test. Panel A reports statistics for a naive random walk forecast (no-change from current quarter). Panels B–E report statistics for alternative forecasts with Diebold-Mariano (DM) test against the random walk (negative values indicate better performance than random walk). Panel B: Blue Chip Financial Forecasts consensus forecasts for federal funds rate. Panel C: real-time VAR model estimated on GDP growth, CPI inflation, federal funds rate, and 10-year Treasury yield using expanding estimation windows. Panel D: Eurodollar futures (through 2004Q4) spliced with federal funds futures (2005Q1 onwards); futures settle on end-of-quarter LIBOR or monthly average federal funds rate. Panel E: Federal Reserve Summary of Economic Projections (SEP) median federal funds rate projections.

Table 3: Blue Chip Forecast Errors, Baseline Anchoring Regressions

	1-*qtr*	2-*qtr*	3-*qtr*	4-*qtr*
Panel A: Full Sample (1983Q1-2026Q1)				
Intercept	−0.0428	−0.1135	−0.1789	−0.3134
	(1.45)[0.147]	(1.60)[0.149]	(1.53)[0.213]	(1.91)[0.128]
BC Rev	0.2261	0.4205	0.7178	0.9026
	(5.43)[0.000]	(3.52)[0.005]	(3.39)[0.002]	(2.86)[0.036]
$\overline{R}^2$	0.076[0.000]	0.088[0.002]	0.129[0.000]	0.114[0.002]
Out-of-sample R^2	0.077[0.000]	0.182[0.000]	0.213[0.000]	0.174[0.001]
Panel B: Pre-SEP Period (1983Q1-2012Q1)				
Intercept	−0.0314	−0.1547	−0.2816	−0.4926
	(0.76)[0.463]	(1.48)[0.185]	(1.64)[0.185]	(2.16)[0.103]
BC Rev	0.2556	0.3808	0.6138	0.7622
	(6.21)[0.000]	(2.76)[0.025]	(2.46)[0.064]	(2.07)[0.112]
$\overline{R}^2$	0.087[0.001]	0.058[0.014]	0.081[0.016]	0.070[0.033]
Panel C: Post-SEP Period (2012Q2-2026Q1)				
Intercept	−0.0590	−0.0523	−0.0292	−0.0037
	(1.71)[0.101]	(0.79)[0.490]	(0.26)[0.836]	(0.02)[0.987]
BC Rev	0.0903	0.5086	0.9663	1.2770
	(1.17)[0.344]	(2.29)[0.097]	(2.82)[0.049]	(2.98)[0.047]
$\overline{R}^2$	−0.022[0.295]	0.169[0.005]	0.277[0.000]	0.251[0.002]

Notes: The dependent variable is the ex-post forecast error, $ferr^h_{t+h} = r_{t+h} - forc^h_t$, where r_{t+h} is the realized quarterly average federal funds rate and $forc^h_t$ is the Blue Chip consensus forecast made at time t for horizon $t+h$. The regressor is the forecast revision, $forc^h_t - forc^{h+1}_{t-1}$, which measures the change in the consensus forecast relative to the prior quarter. Panel A reports results for the full sample (1983Q1-2026Q1), Panel B for the pre-SEP period (1983Q1-2012Q1), and Panel C for the post-SEP period (2012Q2-2026Q1). t-statistics in parentheses computed using Newey West standard errors (L=4); p-values in square brackets. Out-of-sample R^2 is computed using an expanding window recursive estimation scheme (Panel A only). Bootstrap p-values for t-stats, in-sample and out-of-sample R^2 are based on 1,000 replications under the null of no predictability.

Table 4: Blue Chip Forecast Errors, Robustness to Alternative Predictors

		BC Rev	*Stock*	*Disagr*	*Short*	*Term*	*Emp*	*Corp*
1-*qtr*	*Coef*	0.2208	0.0091	−0.0565	0.0069	0.0398	0.0068	−0.0006
		(4.35)[0.000]	(1.51)[0.167]	(−0.37)[0.713]	(0.32)[0.758]	(1.68)[0.137]	(0.57)[0.623]	(−0.01)[0.987]
	$\overline{R}^2$	0.085[0.007]						
2-*qtr*	*Coef*	0.3901	0.0105	−0.0530	−0.0368	0.0303	0.0312	−0.0343
		(2.64)[0.042]	(1.11)[0.307]	(−0.15)[0.878]	(−0.55)[0.659]	(0.50)[0.672]	(1.28)[0.297]	(−0.39)[0.755]
	$\overline{R}^2$	0.097[0.056]						
3-*qtr*	*Coef*	0.7033	0.0137	0.2620	−0.1510	−0.0281	0.0448	−0.0913
		(3.18)[0.016]	(1.16)[0.266]	(0.77)[0.554]	(−1.58)[0.272]	(−0.28)[0.830]	(1.16)[0.402]	(−0.60)[0.638]
	$\overline{R}^2$	0.167[0.040]						
4-*qtr*	*Coef*	0.9563	0.0218	0.4583	−0.2735	−0.1146	0.0790	−0.1482
		(3.33)[0.012]	(1.48)[0.173]	(1.33)[0.293]	(−2.41)[0.112]	(−0.83)[0.545]	(1.34)[0.368]	(−0.70)[0.589]
	$\overline{R}^2$	0.208[0.037]						

Notes: Multivariate regressions including all seven predictors jointly (1983Q1-2026Q1, N=173). The dependent variable is the ex-post forecast error, $ferr^h_{t+h} = r_{t+h} - forc^h_t$, where r_{t+h} is the realized quarterly average federal funds rate and $forc^h_t$ is the Blue Chip consensus forecast made at time t for horizon $t + h$. BC Rev = revisions to consensus Blue Chip forecast ($forc^h_t - forc^{h+1}_{t-1}$). Control variables: Stock (quarterly S&P 500 log return ×100), Disagr (top-10 minus bottom-10 Blue Chip forecasts of 3-month Treasury Bill at each horizon), Short (3-month T-bill rate level), Term (10yr-3m yield), Emp (12-month employment growth), Corp (BBB-10yr spread). All regressions include an intercept (not reported). t-statistics in parentheses; p-values in square brackets; computed using Newey West (L=4). Bootstrap p-values based on 1,000 replications under the null of no predictability.

Table 5: Blue Chip Forecast Errors, SEP Orthogonality Test

	1-*qtr*	2-*qtr*	3-*qtr*	4-*qtr*
Panel A: SEP Gap Orthogonality, Simple Baseline				
$SEP\ Gap$	0.0366	0.4231	0.8763	1.0996
	(0.47)[0.668]	(1.64)[0.174]	(1.86)[0.143]	(1.79)[0.148]
Residual R^2	0.0011[0.790]	0.0620[0.110]	0.1257[0.041]	0.1052[0.076]
Panel B: SEP Gap Orthogonality, Multivariate Baseline				
$SEP\ Gap$	0.0795	0.5802	1.1194	1.3263
	(1.09)[0.320]	(2.47)[0.059]	(2.89)[0.030]	(2.56)[0.042]
Residual R^2	0.0062[0.512]	0.1134[0.042]	0.2022[0.018]	0.1607[0.031]
Panel C: BC Rev Stability Test, Simple Baseline				
$BC\ Rev \times Post2012$	-0.1361	0.0877	0.2485	0.3744
	(-1.97)[0.081]	(0.43)[0.672]	(0.79)[0.462]	(0.95)[0.398]
Residual R^2	0.0405[0.110]	0.0075[0.528]	0.0283[0.268]	0.0323[0.272]
Panel D: BC Rev Stability Test, Multivariate Baseline				
$BC\ Rev \times Post2012$	-0.0752	0.1579	0.3228	0.3692
	(-0.88)[0.415]	(0.69)[0.513]	(1.04)[0.358]	(0.94)[0.398]
Residual R^2	0.0153[0.291]	0.0235[0.272]	0.0471[0.180]	0.0330[0.274]

Notes: This table reports orthogonality tests for the BC anchoring model. For each panel, the residuals from a first-stage regression are regressed on an appropriately lagged instrument to test for additional predictive power (an orthogonality test). Panels A and B test whether the SEP gap ($forc_t^h - SEP_{t-1}^{h+1}$) has incremental predictive power for residuals recovered from simple baseline (Panel A of Table 3) and multivariate baseline (Table 4). Panels C and D test whether BC Revision anchoring intensity changed post-SEP by including a BC Rev × Post2012 interaction term. t-statistics in parentheses; p-values in square brackets; computed via Newey West (L=4). Residual R^2 is the proportion of variance of the first-stage residuals explained by the additional regressor. Bootstrap p-values based on 1,000 replications under the null that the first stage model is correctly specified and there is no additional predictability in the second stage.

Table 6: Blue Chip Forecast Errors, Composite Anchor Model, Post-SEP Period

	1-*qtr*	2-*qtr*	3-*qtr*	4-*qtr*
Panel A: SEP Gap Anchor, No Controls				
SEP Gap	0.2005	0.8573	1.5942	1.8682
	(2.55)[0.013]	(2.49)[0.023]	(2.75)[0.018]	(2.57)[0.029]
$\overline{R}^2$	−0.007[0.182]	0.171[0.008]	0.267[0.002]	0.194[0.009]
Panel B: SEP Gap Anchor, With Controls				
SEP Gap	0.1374	1.0940	2.0954	2.6169
	(1.01)[0.395]	(3.03)[0.023]	(4.00)[0.010]	(3.92)[0.009]
$\overline{R}^2$	0.336[0.000]	0.249[0.065]	0.365[0.052]	0.327[0.158]
Panel C: Composite Anchor, No Controls				
Composite β	0.2117	0.8468	1.5984	2.0066
	(2.49)[0.026]	(2.92)[0.024]	(3.34)[0.018]	(3.31)[0.018]
$Weight: BC\ Rev$	0.2146	0.3697	0.3889	0.4645
	[−0.33, 0.75]	[−0.07, 0.81]	[0.09, 0.69]	[0.16, 0.77]
$Weight: SEP\ Gap$	0.7854	0.6303	0.6111	0.5355
	[0.25, 1.33]	[0.19, 1.07]	[0.31, 0.91]	[0.23, 0.84]
$\overline{R}^2$	−0.024[0.353]	0.204[0.003]	0.339[0.000]	0.293[0.001]
Panel D: Composite Anchor, With Controls				
Composite β	0.1852	1.0956	2.0799	2.6290
	(1.27)[0.263]	(3.01)[0.033]	(3.90)[0.007]	(3.86)[0.017]
$Weight: BC\ Rev$	0.8643	0.2579	0.2706	0.3974
	[−0.24, 1.97]	[−0.07, 0.58]	[0.00, 0.54]	[0.05, 0.75]
$Weight: SEP\ Gap$	0.1357	0.7421	0.7294	0.6026
	[−0.97, 1.24]	[0.42, 1.07]	[0.46, 1.00]	[0.25, 0.95]
$\overline{R}^2$	0.350[0.002]	0.256[0.057]	0.391[0.040]	0.387[0.129]

Notes: Sample period is 2012Q2-2026Q1, N=56. All regressions include an intercept (not reported). Panels A and B test SEP gap anchoring without and with controls (Stock, Disagr, Short, Term, Emp, Corp). Panels C and D test the composite anchor model combining BC Revision and SEP Gap without and with controls. The composite model is $ferr^h_{t+h} = a_h + \beta_h \left[w_h \left(forc^h_t - forc^{h+1}_{t-1}\right) + (1 - w_h)\left(forc^h_t - SEP^{h+1}_{t-1}\right)\right] + controls_t + u^h_{t+h}$, where β_h is the composite anchoring coefficient and w_h is the weight on BC Revision vs. SEP Gap anchoring. Panels B and D include controls but do not report their coefficients; $\overline{R}^2$ in these panels reflects predictive power from both anchoring variables and controls. t-statistics in parentheses with p-values in brackets computed using Newey West standard errors (L=4). Square brackets after weights show 90% confidence intervals (5th and 95th percentiles) computed using Newey West standard errors (L=4). Significance tests for $\overline{R}^2$ are conducted using a bootstrapping procedure under the null of no predictability (all coefficients= 0).

Table 7: Eurodollar/Fed Funds Futures Forecast Errors, Baseline Anchoring Regressions

	1-*qtr*	2-*qtr*	3-*qtr*	4-*qtr*
Panel A: Full Sample (1986Q1-2026Q1)				
Intercept	−0.0472	−0.1301	−0.2204	−0.3712
	(−1.45)[0.134]	(−1.80)[0.098]	(−1.85)[0.100]	(−2.13)[0.085]
BC Rev	0.1818	0.3530	0.5381	0.6107
	(2.24)[0.038]	(2.33)[0.044]	(2.50)[0.033]	(2.12)[0.077]
$\overline{R}^2$	0.026[0.009]	0.045[0.014]	0.059[0.009]	0.039[0.038]
Out-of-sample R^2	0.055[0.004]	0.095[0.004]	0.082[0.013]	0.022[0.064]
Panel B: Pre-SEP Period (1986Q1-2012Q1)				
Intercept	−0.0727	−0.2339	−0.4304	−0.7051
	(−1.43)[0.160]	(−2.13)[0.043]	(−2.54)[0.044]	(−2.99)[0.027]
BC Rev	0.2019	0.2942	0.3799	0.3589
	(1.93)[0.096]	(1.59)[0.157]	(1.58)[0.188]	(1.17)[0.355]
$\overline{R}^2$	0.019[0.054]	0.015[0.117]	0.012[0.191]	−0.003[0.401]
Panel C: Post-SEP Period (2012Q2-2026Q1)				
Intercept	0.0054	0.0428	0.1022	0.1590
	(0.26)[0.828]	(0.77)[0.528]	(0.99)[0.491]	(0.96)[0.510]
BC Rev	0.0524	0.3263	0.6611	0.9109
	(1.28)[0.265]	(2.13)[0.056]	(2.57)[0.029]	(2.73)[0.022]
$\overline{R}^2$	−0.025[0.327]	0.089[0.023]	0.169[0.012]	0.160[0.017]

Notes: The dependent variable is the ex-post forecast error, $ferr^h_{t+h} = r_{t+h} - fut^h_t$, where r_{t+h} is the realized rate and fut^h_t is the futures-implied rate. The forecast uses Eurodollar futures through 2004Q4 and fed funds futures from 2005Q1 onward, with a 25 basis point adjustment to the fed funds rate to account for the LIBOR-federal funds spread. BC Rev = revisions to consensus Blue Chip forecast ($forc^h_t - forc^{h+1}_{t-1}$). Panel A reports results for the full sample (1986Q1-2026Q1, N=160), Panel B for the pre-SEP period (1986Q1-2012Q1, N=104), and Panel C for the post-SEP period (2012Q2-2026Q1, N=56). t-statistics in parentheses with p-values in brackets computed using Newey West standard errors (L=4). $\overline{R}^2$ denotes adjusted R^2. Out-of-sample R^2 is computed using an expanding window recursive estimation scheme (Panel A only). Significance tests are conducted using a bootstrap procedure under the null hypothesis of no predictability.

Table 8: Eurodollar Futures and Federal Funds Futures Forecast Errors, Robustness to Alternative Predictors

	BC Rev	*Stock*	*Disagr*	*Short*	*Term*	*Emp*	*Corp*	*Covar*
1-*qtr Coef*	0.1265	0.0057	0.3799	−0.0739	−0.0370	0.0116	−0.0565	1.3992
	(1.26)[0.246]	(1.27)[0.237]	(1.51)[0.157]	(−2.32)[0.041]	(−1.19)[0.272]	(1.04)[0.360]	(−1.00)[0.330]	(1.56)[0.203]
$\overline{R}^2$	0.094[0.003]							
2-*qtr Coef*	0.2629	0.0034	0.7195	−0.2228	−0.1372	0.0339	−0.1652	1.6870
	(1.62)[0.166]	(0.46)[0.667]	(2.15)[0.066]	(−3.20)[0.013]	(−1.79)[0.141]	(1.43)[0.259]	(−1.47)[0.213]	(1.83)[0.135]
$\overline{R}^2$	0.155[0.016]							
3-*qtr Coef*	0.3721	0.0025	1.0161	−0.4083	−0.2724	0.0747	−0.2689	2.6267
	(1.98)[0.077]	(0.29)[0.803]	(2.97)[0.026]	(−4.40)[0.006]	(−2.53)[0.057]	(1.86)[0.164]	(−1.58)[0.239]	(2.59)[0.044]
$\overline{R}^2$	0.272[0.001]							
4-*qtr Coef*	0.4232	−0.0012	1.1095	−0.5536	−0.3949	0.1373	−0.3825	3.6988
	(1.84)[0.125]	(−0.12)[0.915]	(3.15)[0.025]	(−4.83)[0.005]	(−2.84)[0.050]	(2.21)[0.118]	(−1.67)[0.216]	(3.25)[0.016]
$\overline{R}^2$	0.326[0.003]							

Notes: Results cover 1986Q1-2026Q1. The dependent variable is the ex-post Eurodollar futures and federal funds futures forecast error. The dependent variable uses Eurodollar futures rates from the sample start through 2004Q4 and federal funds futures rates from 2005Q1 onwards. A 25 basis point adjustment is added to federal funds futures rates to account for the difference in credit risk between LIBOR and federal funds rates. BC Rev = revisions to consensus Blue Chip forecast ($forc_t^h - forc_{t-1}^{h+1}$). Control variables: Stock (quarterly S&P 500 log return ×100), Disagr (top 10 avg. minus bottom 10 avg. Blue Chip forecasts for federal funds rates), Short (3-month T-bill rate level), Term (10yr-3m yield spread), Emp (12-month nonfarm payroll growth), Corp (BBB-10yr spread), Covar (quarterly realized covariance between daily stock returns and daily changes in forward rates ×100). All regressions include an intercept (not reported). t-statistics in parentheses; p-values in square brackets; computed using Newey West standard errors (L=4). $\overline{R}^2$ denotes adjusted R^2. Significance tests are conducted using a bootstrap procedure under the null hypothesis of no predictability.

Table 9: Eurodollar Futures and Federal Funds Futures Forecast Errors, Orthogonality Tests

	1-*qtr*	2-*qtr*	3-*qtr*	4-*qtr*
Panel A: SEP Gap Orthogonality, Simple Baseline				
SEP Gap	0.0502	0.1739	0.4183	0.7574
	(0.40)[0.718]	(0.49)[0.674]	(0.82)[0.458]	(1.18)[0.286]
Residual R^2	0.0048[0.605]	0.0144[0.423]	0.0358[0.236]	0.0606[0.163]
Panel B: SEP Gap Orthogonality, Full Multivariate Baseline				
SEP Gap	0.1926	0.5645	0.9805	1.3014
	(1.38)[0.183]	(1.73)[0.124]	(2.09)[0.073]	(2.25)[0.070]
Residual R^2	0.0414[0.107]	0.1117[0.027]	0.1502[0.027]	0.1555[0.030]
Panel C: BC Revision Stability Test, Simple Baseline				
$BC\ Rev \times Post2012$	−0.1295	−0.0265	0.1233	0.3002
	(−3.57)[0.006]	(−0.19)[0.846]	(0.52)[0.644]	(0.95)[0.372]
Residual R^2	0.0876[0.028]	0.0009[0.813]	0.0087[0.546]	0.0253[0.311]
Panel D: BC Revision Stability Test, Full Multivariate Baseline				
$BC\ Rev \times Post2012$	−0.1170	0.0327	0.1700	0.1922
	(−1.83)[0.062]	(0.26)[0.779]	(0.74)[0.466]	(0.58)[0.566]
Residual R^2	0.0422[0.081]	0.0011[0.806]	0.0126[0.427]	0.0090[0.527]

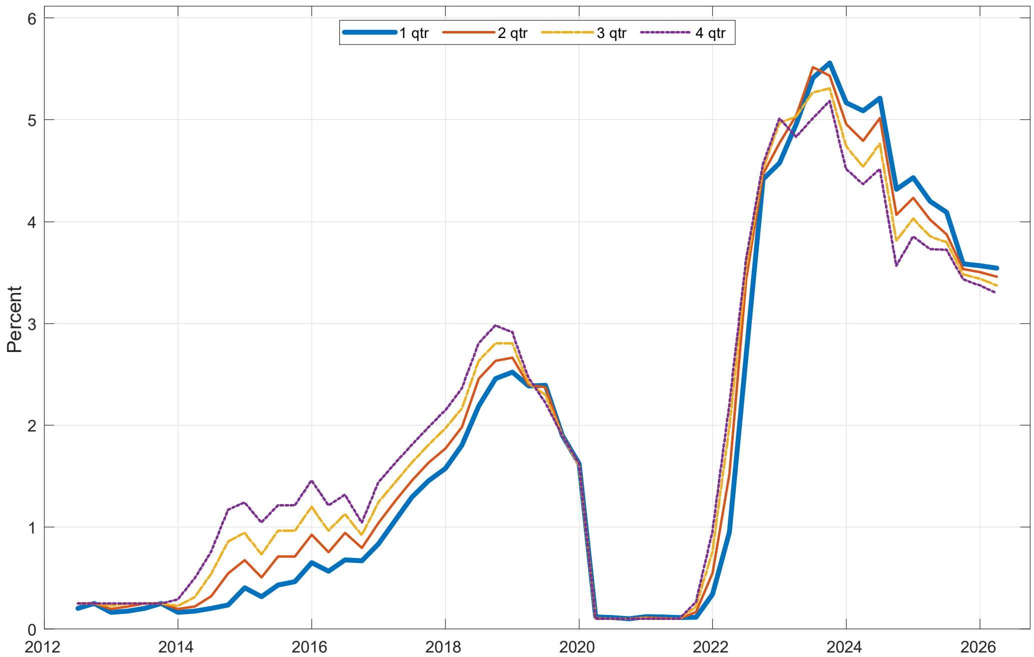
Notes: Sample period is 1986Q1-2026Q1 (N=160 for Panels C and D; N=56 for Panels A and B due to SEP availability). Dependent variable: Eurodollar futures and federal funds futures rate minus realized rate for the underlying money market instrument (percentage points). The dependent variable uses Eurodollar futures rates from the sample start through 2004Q4 and federal funds futures rates from 2005Q1 onwards. A 25 basis point adjustment is added to federal funds futures rates to account for the difference in credit risk between LIBOR and federal funds rates. For each panel, the residuals from a first-stage regression are regressed on an appropriately lagged instrument to test for additional predictive power (an orthogonality test). Panels A and B test whether the SEP gap ($forc_t^h - SEP_{t-1}^{h+1}$) has incremental predictive power for residuals recovered from the regressions in Panel C of Table 7 and Table 8. Panels C and D test whether BC Revision anchoring intensity changed post-SEP by regressing the same first-stage residuals onto $BC\ Rev$ in the post-SEP period. t-statistics in parentheses with p-values in brackets computed via Newey West (L=4). Residual R^2 is the proportion of variance of the first-stage residuals explained by the additional regressor. Significance tests are conducted using a bootstrapping procedure imposing the null that the first stage model is correctly specified and there is no additional predictability in the second stage.

Table 10: Eurodollar Futures and Federal Funds Futures Forecast Errors, Composite Anchor Model, Post-SEP Period

	1-*qtr*	2-*qtr*	3-*qtr*	4-*qtr*
Panel A: SEP Gap Anchor, No Controls				
SEP Gap	0.1875	0.5427	0.9616	1.2775
	(1.44)[0.213]	(1.41)[0.235]	(1.73)[0.145]	(1.83)[0.139]
$\overline{R}^2$	0.033[0.067]	0.086[0.042]	0.117[0.029]	0.108[0.060]
Panel B: SEP Gap Anchor, With Controls				
SEP Gap	0.1764	0.7290	1.3899	1.8128
	(1.36)[0.248]	(2.05)[0.095]	(2.37)[0.080]	(2.57)[0.060]
$\overline{R}^2$	−0.041[0.543]	0.125[0.265]	0.164[0.364]	0.229[0.311]
Panel C: Composite Anchor, No Controls				
Composite β	0.1880	0.5358	0.9651	1.3798
	(1.45)[0.167]	(1.47)[0.218]	(1.93)[0.102]	(2.25)[0.068]
$Weight: BC\ Rev$	0.0117	0.3828	0.5134	0.4995
	$[-0.28, 0.31]$	$[-0.26, 1.03]$	$[-0.03, 1.05]$	$[0.09, 0.91]$
$Weight: SEP\ Gap$	0.9883	0.6172	0.4866	0.5005
	$[0.69, 1.28]$	$[-0.03, 1.26]$	$[-0.05, 1.03]$	$[0.09, 0.91]$
$\overline{R}^2$	0.013[0.149]	0.100[0.068]	0.177[0.021]	0.174[0.042]
Panel D: Composite Anchor, With Controls				
Composite β	0.1462	0.7287	1.4058	1.8582
	(1.20)[0.271]	(2.03)[0.129]	(2.34)[0.082]	(2.56)[0.079]
$Weight: BC\ Rev$	−0.6157	−0.0039	0.2215	0.3298
	$[-1.50, 0.27]$	$[-0.39, 0.38]$	$[-0.14, 0.58]$	$[-0.11, 0.77]$
$Weight: SEP\ Gap$	1.6157	1.0039	0.7785	0.6702
	$[0.73, 2.50]$	$[0.62, 1.39]$	$[0.42, 1.14]$	$[0.23, 1.11]$
$\overline{R}^2$	−0.046[0.540]	0.103[0.310]	0.162[0.371]	0.246[0.335]

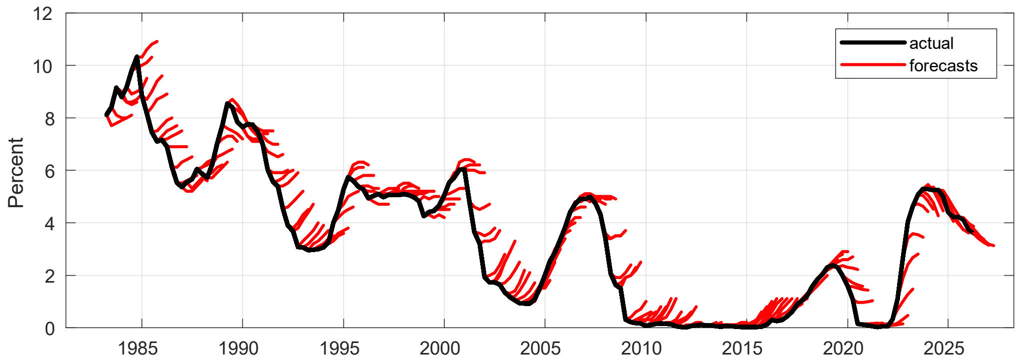
Notes: Sample period is 2012Q2-2026Q1 (N=56). The dependent variable is the forecast error using the realized rate for the underlying money market instrument. The dependent variable uses Eurodollar futures rates from the sample start through 2004Q4 and federal funds futures rates from 2005Q1 onwards. A 25 basis point adjustment is added to federal funds futures rates to account for the difference in credit risk between LIBOR and federal funds rates. Panels A and B test SEP gap anchoring without and with controls (Stock, Disagr, Short, Term, Emp, Corp, Covar). Panels C and D test the composite anchor model combining BC Revision and SEP Gap without and with controls. The composite model is $ferr^h_{t+h} = a_h + \beta_h \left[w_h \left(forc^h_t - forc^{h+1}_{t-1}\right) + (1-w_h)\left(forc^h_t - SEP^{h+1}_{t-1}\right)\right] + controls_t + u^h_{t+h}$, where β_h is the composite anchoring coefficient and w_h is the weight on BC Revision vs. SEP Gap anchoring. t-statistics in parentheses with p-values in brackets computed using Newey West standard errors (L=4). Square brackets after weights show 90% confidence intervals (5th and 95th percentiles) computed using Newey West standard errors (L=4). Significance tests for $\overline{R}^2$ are conducted using a bootstrapping procedure under the null of no predictability (all coefficients= 0).

Figure 1: Estimated SEP Projections at Constant Horizons



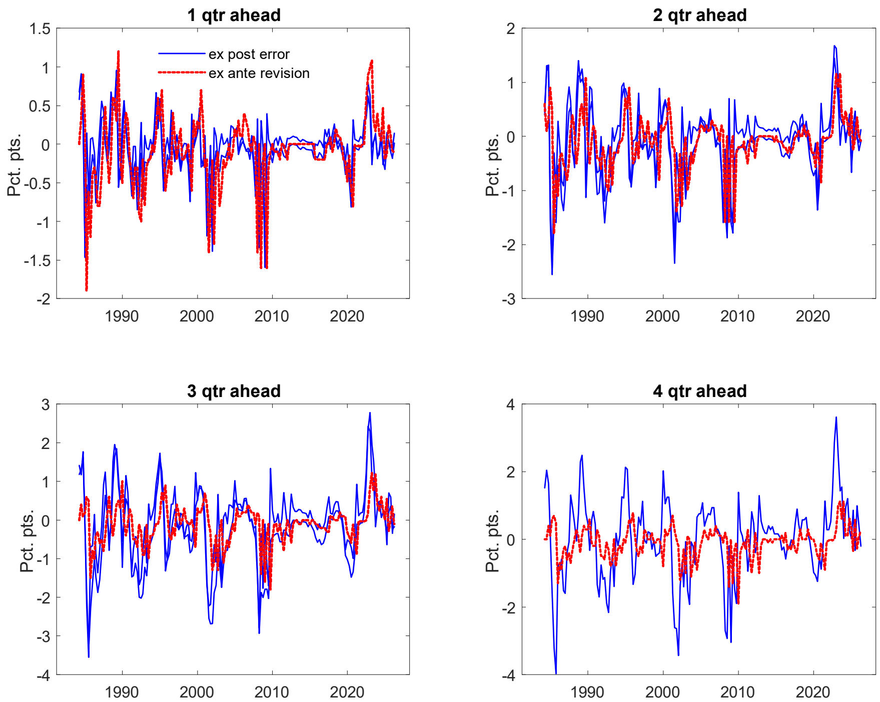
Notes: Sample period is 2012Q1-2026Q1. The heavy blue line is the 1-qtr ahead interpolated SEP projection. The thin red solid line is the 2-qtr ahead projection, the orange dash-dot line is the 3-qtr ahead projection and the purple dotted line is the 4-qtr ahead projection.

Figure 2: Ex-Post Actual and Ex-Ante Blue Chip Forecasts for 3-month Federal Funds Rates



Notes: Sample period is 1983Q1-2026Q1. In Panel A, the heavy black line is actual federal funds rates (quarterly average). The thin red lines are the real-time Blue Chip forecasts of the path of the rate, with each forecast plotted starting in the quarter in which the forecast was made.

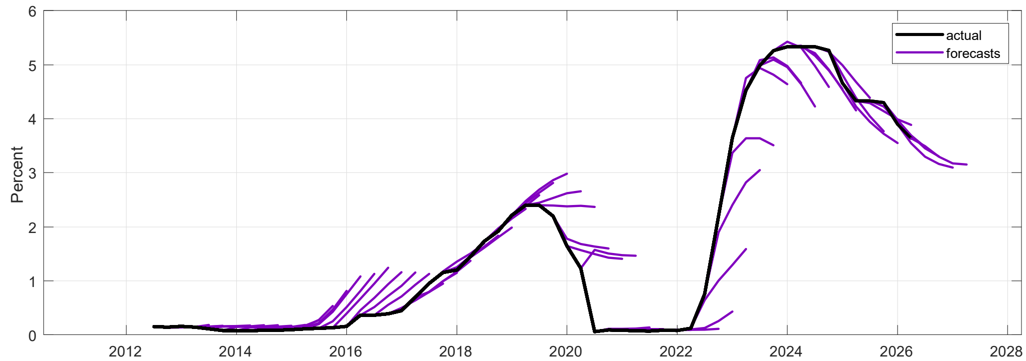
Figure 3: Ex-Post Blue Chip Forecast Errors and Ex-Ante Revisions for Federal Funds Rates



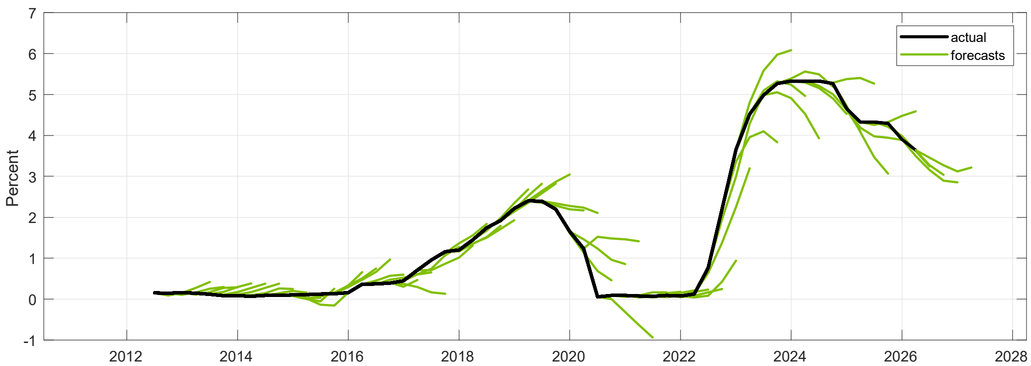
Notes: Sample period is 1983Q1-2026Q1 (N=173 observations). Each panel plots the ex-post forecast error (solid blue) of the Blue Chip forecast of the federal funds rate against the ex-ante revision to the Blue Chip forecast (dotted red). For example, at the 1-qtr horizon, the forecast error realized at period t (the realization at time t minus the forecast from period $t-1$) is plotted against (and lined up with) the revision that was made to the Blue Chip forecast at period $t-1$. Each panel plots the forecasts errors and ex ante revisions at a different horizon.

Figure 4: Ex-post Rate Path and Raw and Bias-Corrected Blue Chip Forecasts, post-SEP Sample

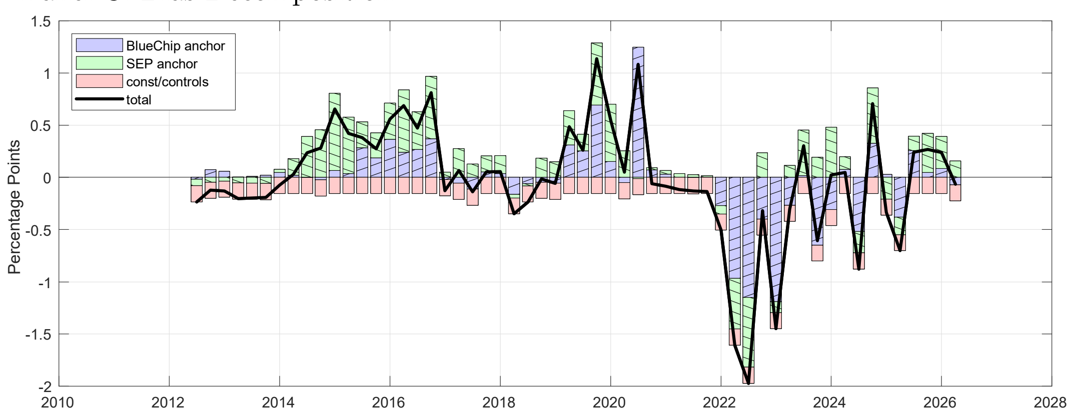
Panel A: Raw Blue Chip Forecasts



Panel B: Bias Corrected Blue Chip Forecasts

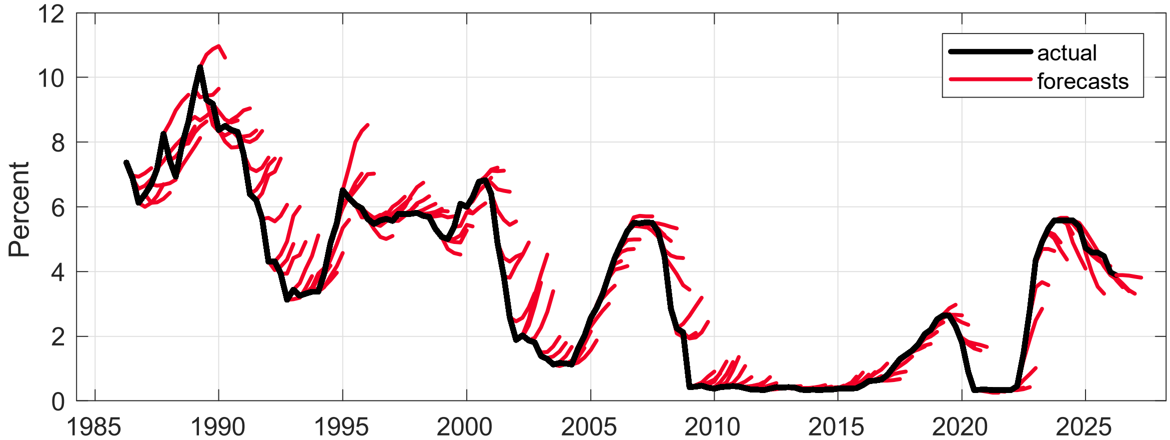


Panel C: Bias Decomposition



Notes: Sample period is 2012Q2-2026Q1. In Panel A, the heavy black line is actual federal funds rates (quarterly average). The thin colored lines are the real-time Blue Chip forecasts of the path of the rate, with each forecast plotted starting in the quarter in which the forecast was made. In Panel B, the bias-corrected forecasts from the regression of Table 6 Panel C are plotted. In Panel C, the bias from the regression of Table 6 Panel C is decomposed into sources of bias.

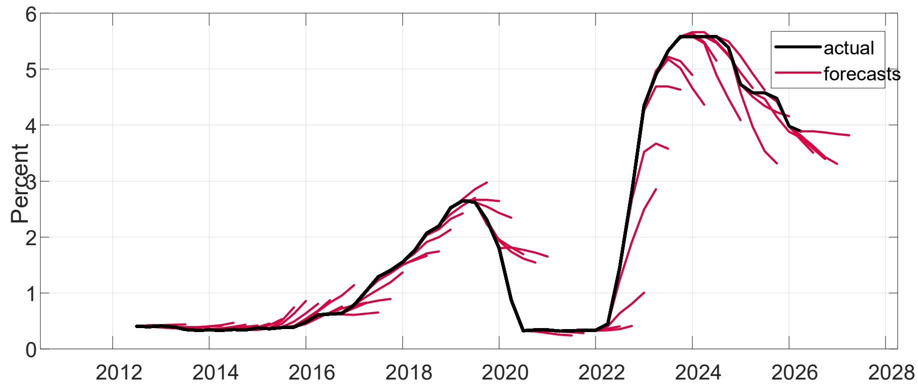
Figure 5: Ex-Post Actual and Ex-Ante Eurodollar/OIS Inplied Paths, Full Sample



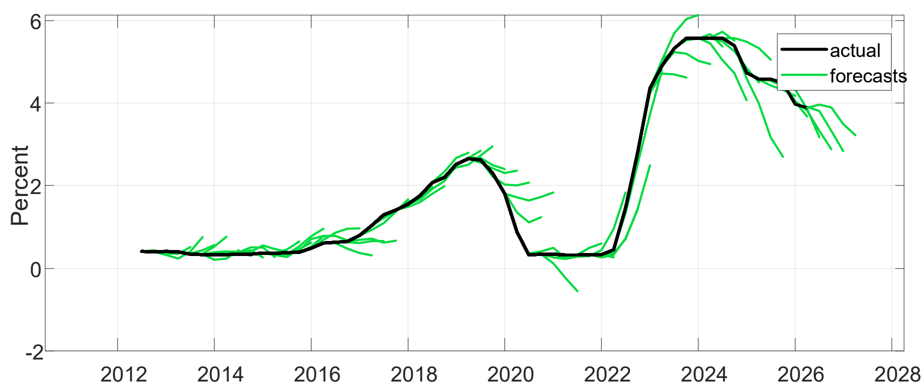
Notes: Sample period is 1986Q1-2026Q1. The heavy black line is actual LIBOR (pre-2005) or federal funds (post-2005) rate. The thin red lines are the real-time Eurodollar/federal funds futures paths, with each path plotted starting in the quarter in which it was observed.

Figure 6: Ex-post Rate Path and Raw and Bias-Corrected Eurodollar/Federal Funds Futures, post-SEP Sample

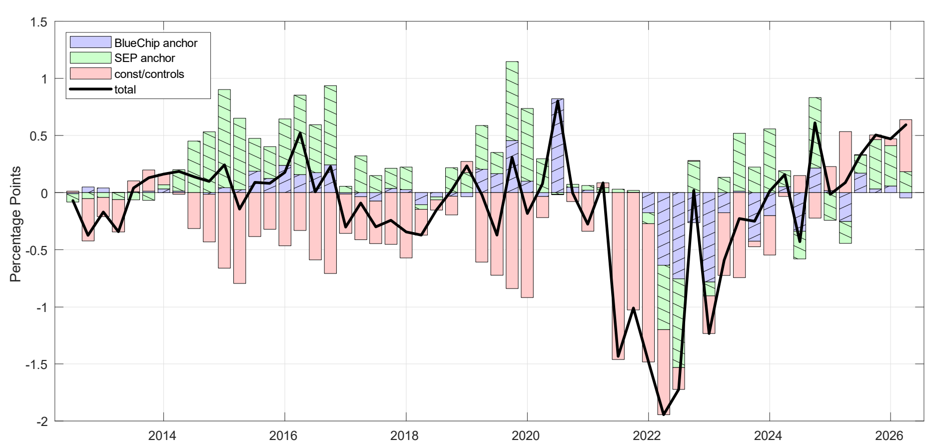
Panel A: Raw Futures Paths



Panel B: Bias Corrected Futures Paths



Panel C: Bias Decomposition



Notes: Sample period is 1986Q1-2026Q1. In Panel A, the heavy black line is actual LIBOR (pre-2005) or federal funds (post-2005) rate. The thin colored lines are the real-time future-implied forecasts of the path of the rate, with each forecast plotted starting in the quarter in which the forecast was made. In Panel B, the bias-corrected forecasts from the regression of Table 10 Panel D are plotted. In Panel C, the bias from the regression of Table 10 Panel D is decomposed into sources of bias.

1 Appendix

Table A1: Median Regression Across Subsamples

	1-*qtr*	2-*qtr*	3-*qtr*	4-*qtr*
Panel A: Full Sample (1983Q1-2026Q1)				
BC Rev	0.2167	0.3562	0.7862	1.1905
	(6.57)[0.000]	(2.78)[0.018]	(3.75)[0.004]	(4.28)[0.001]
Pseudo R^2	0.076[0.000]	0.057[0.001]	0.112[0.000]	0.107[0.000]
Panel B: Pre-SEP (1983Q1-2012Q1)				
BC Rev	0.2208	0.6260	0.8308	1.1343
	(3.51)[0.005]	(2.84)[0.018]	(4.05)[0.002]	(3.50)[0.008]
Pseudo R^2	0.058[0.001]	0.070[0.002]	0.096[0.000]	0.091[0.003]
Panel C: Post-SEP (2012Q2-2026Q1)				
BC Rev	0.3776	0.9633	1.3815	1.1771
	(2.23)[0.040]	(3.05)[0.024]	(2.98)[0.034]	(1.85)[0.139]
Pseudo R^2	0.122[0.003]	0.196[0.000]	0.200[0.000]	0.122[0.039]

Notes: The dependent variable is the ex-post forecast error, $ferr_{t+h}^{h} = r_{t+h} - forc_t^h$ for the Blue Chip consensus forecast of the federal funds rate. The regressor is the forecast revision, $forc_t^h - forc_{t-1}^{h+1}$. This table reports median (quantile, $\tau = 0.5$) regression results. Pseudo-R^2 measures proportional reduction in the quantile check function relative to a constant-only model. Panel A reports results for the full sample (1983Q1-2026Q1), Panel B for the pre-SEP period (1983Q1-2012Q1), and Panel C for the post-SEP period (2012Q2-2026Q1). t-statistics in parentheses computed via block bootstrap with block length 12. Significance is determined using a bootstrapping procedure that imposes the null of no predictability. p-values under the simulated null are reported in square brackets.

Table A2: Mode Regression Across Subsamples

	1-*qtr*	2-*qtr*	3-*qtr*	4-*qtr*
Panel A: Full Sample (1983Q1-2026Q1)				
BC Rev	0.1954	0.1687	0.4495	1.4911
	(4.01)[0.000]	(0.69)[0.446]	(0.93)[0.347]	(2.83)[0.004]
Pseudo R^2	0.067[0.000]	0.052[0.038]	0.090[0.016]	0.123[0.005]
Panel B: Pre-SEP (1983Q1-2012Q1)				
BC Rev	0.1807	0.2334	1.1268	1.5073
	(3.93)[0.002]	(1.21)[0.234]	(2.59)[0.012]	(2.72)[0.014]
Pseudo R^2	0.083[0.000]	0.055[0.119]	0.137[0.006]	0.179[0.002]
Panel C: Post-SEP (2012Q2-2026Q1)				
BC Rev	0.3008	0.6046	1.4601	1.5221
	(2.43)[0.015]	(1.34)[0.160]	(1.93)[0.078]	(2.08)[0.054]
Pseudo R^2	0.052[0.055]	0.075[0.103]	0.124[0.050]	0.102[0.111]

Notes: The dependent variable is the ex-post forecast error, $ferr^h_{t+h} = r_{t+h} - forc^h_t$ for the Blue Chip consensus forecast of the federal funds rate. The regressor is the forecast revision, $forc^h_t - forc^{h+1}_{t-1}$. This table reports mode regression results. Pseudo-R^2 measures proportional reduction in the objective function for the modal regression procedure relative to a constant-only model. Panel A reports results for the full sample (1983Q1-2026Q1), Panel B for the pre-SEP period (1983Q1-2012Q1), and Panel C for the post-SEP period (2012Q2-2026Q1). t-statistics in parentheses computed via block bootstrap with block length 12. Significance is determined using a bootstrapping procedure that imposes the null of no predictability. p-values under the simulated null are reported in square brackets.