# Overreaction Through Anchoring<sup>\*</sup>

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#### Abstract

Macroeconomic expectations among professional forecasters exhibit a puzzling pattern. Whereas individual forecasts robustly exhibit overreactions at the quarterly frequency, this is not the case at the annual frequency. Consistent with this finding, we provide evidence that forecasters partially offset their revisions within the calendar year. We explain these facts with a model of annual anchoring in which quarterly predictions must be consistent with annual predictions. We estimate our model to fit survey expectations and show that it provides a unified explanation for our empirical facts. Furthermore, our model yields frequency-specific estimates of information frictions which imply a larger role for inattention at the annual frequency.

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# 1 Introduction

In many situations, forecasts are made for two frequencies at the same time. For example, households might simultaneously budget both monthly and annual expenditures, managers at firms sometimes provide fiscal quarter and fiscal year guidance, and professional forecasters often accompany their annual predictions with a quarter-by-quarter path. Whenever forecasts are simultaneously made for multiple frequencies, a question of aggregation arises since, in principle, these forecasts must be consistent with one another. In this paper, we examine quarterly and annual predictions issued by professional forecasters and study the role that quarterly-to-annual consistency plays in explaining error predictability and other puzzling features of survey expectations.

Our focus on the link between quarterly and annual survey expectations is motivated by patterns that we uncover in the data. While there is robust evidence that individual forecasts exhibit overreaction at the quarterly frequency (Bordalo et al., 2020; Nordhaus, 1987; Kohlhas and Walther, 2021), this is not the case at the annual frequency. We document evidence for this fact using data from the U.S. Survey of Professional Forecasters (SPF) as well as other surveys and argue that, in a setting in which quarterly-to-annual consistency holds, these empirical patterns can only arise if forecasters reshuffle their predictions within the calendar year. For instance, a forecaster may offset an upward revision to her currentquarter prediction with a downgrade in her three-quarter ahead prediction. Traditional theories of expectation formation do not account for such reshuffling.

We provide further evidence consistent with our hypothesis by showing that forecasters partially offset their quarterly forecast revisions within the calendar year. In addition, we show that current-year forecasts *underreact* to past quarterly forecast errors. This implies that, as the calendar year progresses and quarterly realizations of the macroeconomic variable of interest are realized, forecasters update their corresponding annual forecasts only partially. Less than full pass through of quarterly realizations to the current-year forecast can be explained by quarterly revision offsetting. Finally, we provide evidence linking quarterly offsetting to quarterly overreactions by showing that quarterly overreactions appear to be concentrated among forecasters who engage in quarterly revision offsetting.

We offer two intuitive explanations for the patterns observed in the data which motivate our subsequent model. First, agents may have separate frequency-specific models that need to be reconciled. One way of doing this is to use the lower frequency prediction as an anchor and adjust the higher frequency forecasts to achieve consistency. Assuming that agents are more informed about the short run, they would optimally revise the near term based on new information and offset these updates further out along their projected path.

Second, forecasters may publicly commit to their lower frequency forecasts. Examples of such commitment can be observed when professional forecasters attach narratives to their lower frequency forecasts, when managers issue longer-run guidance, and when individuals plan major life events. In such cases, revising the lower frequency forecast may be costly. As a result, agents might engage in few revisions of lower frequency predictions, and instead reshuffle their higher frequency forecasts as they bring in new information.<sup>1</sup> Though we are unable to discern between these two explanations in the data, both can account for the observed quarterly overreactions documented in the literature.

To explain these facts, we build and estimate a model of multi-frequency forecasting. Our model is a hybrid sticky-noisy information model as in Andrade and Le Bihan (2013) with heterogeneous updating rates by frequency. Forecasters issue high and low frequency forecasts based on information gleaned from a contemporaneous high frequency private signal and the realization of the high frequency macroeconomic variable (i.e., a lagged public signal). High and low frequency updating are separate activities governed by distinct Calvo-like probabilities. Furthermore, forecasters are subject to a consistency constraint which requires a forecaster's sequence of high frequency predictions to aggregate up to her low frequency prediction.<sup>2</sup> Two key assumptions are responsible for generating offsetting and overreactions: consistency (i.e., high frequency forecasts aggregate up to the low frequency forecast) and low frequency inattention. Under these two assumptions, an upward revision in the near term must be offset by a downward revision later along the forecaster's projected path, as observed in the data.

<sup>&</sup>lt;sup>1</sup>We talked to a number of professional forecasters contributing to the surveys used here and these two explanations are consistent with how they devise their forecasts. There is thus anecdotal evidence of this updating behavior in the professional forecasting context.

<sup>&</sup>lt;sup>2</sup>The SPF requires forecasters to issue consistent predictions, a feature of the data which we verify in Appendix A.1. For real GDP growth, our primary variable of interest, quarterly (high frequency) forecasts in the data correspond to the quarter over quarter annualized growth rate, and annual (low frequency) forecasts correspond to the percentage change of the average quarterly level this year relative to the average quarterly level last year. Appendix A.3 and A.4 provide further details of the variable definitions.

Individual-level high frequency overreactions arise in our model because agents introduce past high frequency errors into their predictions through the consistency constraint.<sup>3</sup> For instance, when a forecaster updates her quarterly prediction but not her annual prediction, then any upward revision in the near term must be offset by downward revisions further out to remain consistent with the unchanged annual forecast. This in turn generates error and revision predictability.<sup>4</sup> Low frequency inattention is therefore a key ingredient which allows our model to generate quarterly overreactions.

We specify our model to fit quarterly (high frequency) and annual (low frequency) forecasts and estimate its parameters via the simulated method of moments (SMM) by targeting micro moments in the SPF. Our estimated model successfully fits both targeted and non-targeted moments. Overall, our estimates imply that annual anchoring can explain a meaningful share of observed overreactions across a range of measures. The estimated model can also generate empirically relevant degrees of underreaction in consensus forecasts.

Finally, we use the model to study information frictions. Our estimates reveal that information rigidities vary across frequencies and are more pervasive at the annual level. When averaging across the two frequencies, we obtain information frictions that are quantitatively similar to estimates previously documented in the literature (Coibion and Gorodnichenko, 2015; Ryngaert, 2017). Through a decomposition exercise, we find that noisy information is the dominant source of information frictions at the quarterly frequency while sticky information is the main driver of information frictions at the annual frequency.

Overall, our empirical and quantitative results imply that the multi-frequency nature of forecasting can explain some of the puzzling features of survey expectations. We develop a rational theory linking high and low frequency forecasts which can provide a unified explanation for overreaction, underreaction, and offsetting. While high and low frequency forecasts are connected through a consistency constraint, we acknowledge consistency itself can be achieved in rational or non-rational ways.

<sup>&</sup>lt;sup>3</sup>Similar to the apparent biases in Bürgi (2017), overreactions in our model arise among rational forecasters.

<sup>&</sup>lt;sup>4</sup>Our model assumes that forecasters are subject to a sticky information friction which implies that forecast updates are time dependent. One could alternatively model inattention as state dependent by characterizing a trade-off between the accuracy of the forecast and the cost of updating or processing information. We focus on time dependent updating for tractability and show that our estimated model can successfully match important targeted and non-targeted moments in the survey data.

A longstanding literature on expectation formation has studied forecast error predictability (Nordhaus, 1987; Clements, 1997; Pesaran and Weale, 2006; Patton and Timmermann, 2012; Coibion and Gorodnichenko, 2015). Recent evidence suggests that, at the individual level, forecasters overreact to news (Bordalo et al., 2020; Broer and Kohlhas, 2022; Bürgi, 2016). In this paper, we study three measures of overreaction (Bordalo et al., 2020; Nordhaus and Durlauf, 1984; Kohlhas and Walther, 2021). While we uncover robust evidence of quarterly overreactions, we do not find such evidence at the annual frequency. Furthermore, we document novel evidence that forecasters partially offset their revisions, and we show that this pattern can generate high frequency overreactions.

A separate literature on the real effects of monetary policy pioneered modern theories of imperfect information in macroeconomics (Lucas, 1972, 1973; Mankiw and Reis, 2002; Woodford, 2001; Sims, 2003). Relative to full information rational expectations, these theories are better able to speak to inertia in aggregate responses to shocks (i.e., underreaction). Andrade and Le Bihan (2013) show that sticky information and noisy information theories can match micro moments in survey expectations such as inattention or disagreement, but not both at the same time. We build on Andrade and Le Bihan (2013) by devising a multifrequency hybrid sticky-noisy information model. We find that by modeling heterogeneity in inattention across frequencies, we are able to jointly match realistic degrees of inattention and disagreement.

Following on these seminal sticky and noisy information models, which can only generate aggregate underreaction, a strand of the literature has proposed novel theories to explain the aforementioned evidence of overreactions (Afrouzi et al., 2021; Bordalo et al., 2020; Broer and Kohlhas, 2022; Kohlhas and Walther, 2021; Farmer et al., 2022). We offer a new explanation by building a model in which overreactions emanate from consistency constraints that arise under multi-frequency forecasting. Our model can jointly explain offsetting, overreactions, and underreactions.

The rest of the paper is organized as follows. Section 2 documents empirical evidence relating to overreactions and offsetting. Section 3 presents the offsetting revisions model. Section 4 discusses the estimation strategy and results. Section 5 quantifies the extent to which low-frequency anchoring can explain higher-frequency overreactions. Section 6 discusses the implications for estimates of information frictions. Section 7 concludes.

# 2 Overreaction at Quarterly and Annual Frequencies

### 2.1 Data

The data that we use for our main empirical results come from the SPF, a quarterly survey managed by the Federal Reserve Bank of Philadelphia. The survey began in 1968Q4 and collects quarterly and annual predictions across a range of macroeconomic variables over many horizons. We begin our sample in 1981Q3 when the SPF started to collect current-year forecasts and required them to be consistent with the associated quarterly forecasts.<sup>5</sup> In this sense, the consistency constraint that we impose in our model is directly motivated by the data.

While our main results focus on real GDP growth predictions, we examine SPF forecasts for other macroeconomic variables as well as real GDP growth forecasts from the Bloomberg (BBG) and Wall Street Journal (WSJ) surveys of forecasters in Appendix A.5. We estimate our model for these other variables and surveys, and include them in Table 7.

### 2.2 Quarterly Overreaction

Professional forecasts are known to exhibit overreactions (Bordalo et al., 2020; Kohlhas and Walther, 2021; Broer and Kohlhas, 2022; Angeletos et al., 2020; Kucinskas and Peters, 2022). Here, we review the robust evidence of overreaction in quarterly macroeconomic expectations through error and revision predictability regressions and then show that there is no such evidence of overreaction at the annual frequency.

Let  $F_t^i(x_{t+h})$  denote forecaster *i*'s forecast devised at time *t* for macroeconomic variable x at time t + h. Using this notation, we define three regression equations. We begin by estimating an errors-on-revisions regression:

$$x_{t+h} - F_t^i(x_{t+h}) = \beta_{0,h} + \beta_{1,h} \left[ F_t^i(x_{t+h}) - F_{t-1}^i(x_{t+h}) \right] + \epsilon_{t+h}^i, \tag{1}$$

a revision autocorrelation regression:

$$F_t^i(x_{t+h}) - F_{t-1}^i(x_{t+h}) = \gamma_{0,h} + \gamma_{1,h} \left[ F_{t-1}^i(x_{t+h}) - F_{t-2}^i(x_{t+h}) \right] + \varepsilon_{t+h}^i, \tag{2}$$

<sup>5</sup>To abstract away from the COVID-19 pandemic, our sample ends in 2019Q4.

	Current	quarter	One qua	rter ahead	Two quar	ters ahead	Year-ov	ver-year
	(1) Error	(2) Revision	(3) Error	(4) Revision	(5) Error	(6) Revision	(7) Error	(8) Error
Revision	$-0.266^{***}$ (0.059)		$-0.145^{**}$ (0.073)		$-0.334^{***}$ (0.066)		$-0.236^{*}$ (0.137)	
Previous revision		$-0.131^{**}$ (0.057)		$-0.302^{***}$ (0.055)		$-0.424^{***}$ (0.050)		
Realization								$-0.134^{*}$ (0.070)
Forecasters	162	153	153	153	152	152	148	150
Observations	4203	3555	3576	3542	3480	3446	3107	3118

Table 1: Overreaction among Individual Forecasters

Note: The table reports panel regression results from SPF forecasts of real GDP growth based on regressions (1), (2), and (3). Standard errors clustered by forecaster and time are reported in parentheses. \*\*\* denotes 1% significance, \*\* denotes 5% significance, and \* denotes 10% significance.

and an errors-on-outcome regression:

$$x_{t+h} - F_t^i(x_{t+h}) = \alpha_{0,h} + \alpha_{1,h}x_t + \eta_{t+h}^i.$$
(3)

Regressions (1) and (2) were first introduced as tests of weak efficiency in Nordhaus and Durlauf (1984) and Nordhaus (1987). The errors-on-revisions regression (1), which is widely employed in the survey expectations literature (Bordalo et al., 2020; Bürgi, 2016), relates ex-post errors to ex-ante revisions. If  $\beta_{1,h} < 0$ , then an upward revision predicts a more negative subsequent forecast error, implying that forecasters overreact to new information when updating their predictions.

Equation (2) does not rely on realized macroeconomic data and instead relates fixed event revisions across time. Here, we are interested in the coefficient in front of the lagged revision,  $\gamma_h$ . Rational expectations implies that forecasters use their information efficiently so that  $\gamma_h = 0$ . In other words, revisions are not serially correlated since yesterday's information set is a subset of today's information set. A negative value of  $\gamma_h$  indicates that an upward forecast revision today predicts a downward forecast revision tomorrow.

Finally, the errors-on-outcomes regression (3), studied in Kohlhas and Walther (2021), examines another form of error predictability. This regression differs from (2) in a subtle but important way. Here, if  $\alpha_{1,h} < 0$ , then forecasters overreact to public news relating to the macroeconomic aggregate of interest. The results from the errors-on-revisions regression, on the other hand, do not make a distinction between different types of news.

Table 1 reports all of the regression results. Across horizons, we find that a one percentage point upward forecast revision predicts a roughly -0.15 to -0.33 percentage point more negative subsequent forecast error. These estimates, reported in columns (1), (3), and (5), are in line with those in Bordalo et al. (2020) and Bürgi (2016). Furthermore, in columns (2), (4), and (6), we find that forecasters overrevise their predictions. Forecasters tend to overrevise more strongly at the one- and two-quarter ahead horizons, with point estimates hovering around -0.30 to -0.42.

The final two columns reproduce existing evidence of overreaction previously documented in the literature. Column (7) reports the errors-on-revisions regression specified in Bordalo et al. (2020) while the final column reports the errors-on-outcomes regression estimated in Kohlhas and Walther (2021).

### 2.3 No Annual Overreaction

To further examine whether there is evidence of annual anchoring in the data, we next estimate these regressions at the annual frequency. If forecasters reshuffle their quarterly predictions due to annual anchoring, then overreactions should be relatively stronger at the quarterly frequency than the annual frequency. Hence, the data would be consistent with annual anchoring if the annual analogs to (1), (2), and (3) yield weaker evidence of overreaction.

There are some limitations to estimating the overreaction regressions using annual forecasts. First, the mapping between quarterly and annual coefficients is non-linear, rendering quantitative comparisons challenging. We therefore focus on comparing the signs and statistical significance of the quarterly and annual coefficients. Second, we lose the rich term structure of forecasts when looking at reported annual predictions since respondents were not asked to issue longer-run annual forecasts for real GDP until 2009Q2. For this reason, we are unable to estimate regression (2). With these caveats in mind, we estimate only regressions (1) and (3).<sup>6</sup> The results are reported in Table 2.

<sup>&</sup>lt;sup>6</sup>For Q2, Q3, and Q4, we define the revision of the annual forecast as the change in the forecast of current-year growth relative to the forecast of current-year growth recorded in the previous quarter. For Q1,

	(1) Annual error	(2) Annual error
Annual revision	-0.023 (0.059)	
Annual realization		-0.026 (0.023)
Forecasters Observations	$137 \\ 3835$	$137 \\ 4682$

Table 2: No Annual Overreaction among Individual Forecasters

Note: The table reports panel regression results from SPF forecasts of real GDP growth based on regressions (1) and (3). Standard errors clustered by forecaster and time are reported in parentheses. \*\*\* denotes 1% significance, \*\* denotes 5% significance, and \* denotes 10% significance.

Column 1 of Table 2 reports the annual version of regressions (1) for real GDP growth and column 2 the annual version of regression (3). The point estimates in both cases are statistically insignificant, leading to a failure to reject the null hypothesis of full information rational expectations, consistent with annual anchoring.

### 2.4 Additional Evidence of Quarterly but not Annual Overreaction

We next document additional facts consistent with the notion that overreaction is present at the quarterly frequency but not at the annual frequency.

#### Underreaction of Annual Forecast to Quarterly News

Our focus on annual forecasts allows for previous quarterly realizations of the macroeconomic variable to play an important role in updating behavior. As quarterly realizations are observed with a lag throughout the year, these quarterly outcomes enter into the annual outcome arithmetically. The optimal forecast should fully incorporate past quarterly realizations such that the annual forecast error is unrelated to these past mistakes.

Empirically, we find that forecasters underreact to past mistakes since the annual forecast

we define the revision of the annual forecast as the change in the current-year forecast of growth relative to the next-year forecast of growth reported in the fourth quarter of the previous calendar year. See Appendix A.4 for details.

	(1) Annual error	(2) Annual error
Realized quarterly error	$\begin{array}{c} 0.053^{***} \\ (0.019) \end{array}$	$0.039^{**}$ (0.019)
Fixed effects	None	Forecaster
Observations	3832	3832

Table 3: Underreaction to Realized Quarterly Error

Note: The table reports panel regression results from SPF forecasts of real GDP growth based on regression (4). Standard errors clustered by forecaster and time are reported in parentheses. \*\*\* denotes 1% significance, \*\* denotes 5% significance, and \* denotes 10% significance.

error is positively correlated with past quarterly mistakes. To show this, we project the annual forecast error on the lagged quarterly forecast error:

$$x_Y - F_{Y,Q}^i(x_Y) = \beta_0 + \beta_1 \left[ x_{Y,Q-1} - F_{Y,Q-1}^i(x_{Y,Q-1}) \right] + \varepsilon_{Y,Q}^i, \tag{4}$$

where  $F_{Y,Q}^i(x_Y)$  denotes forecaster *i*'s forecast of the annual variable  $x_Y$  devised in year *Y* and quarter *Q*. Similarly,  $F_{Y,Q-1}^i(x_{Y,Q-1})$  denotes forecaster *i*'s prediction of *x* in the previous quarter. If forecasters optimally bring the lagged realization of the macroeconomic variable into their annual forecast, then the annual forecast error should be uncorrelated with the past quarterly error.

Column 1 of Table 3 reports the estimate of  $\beta_1$  which is positive. This means that when a forecaster issues a prediction for calendar year growth in Q2 after observing realized GDP in Q1, the forecaster's prediction responds less than one-for-one with the prediction error of Q1 GDP despite the fact that Q1 GDP should be fully incorporated in the annual forecast. Because the pass through of past quarterly GDP to the annual forecast tends to be less than one-for-one, this implies either that (i) forecasters do not "bring in" past realizations of the variable or (ii) forecasters "bring in" past realizations of the variable but offset this later in their projected annual path.

#### Quarterly Offsetting Revisions

Our empirical results thus far suggest that forecasters overreact substantially at the quarterly frequency but do not at the annual frequency. In addition, forecasters underreact to past prediction errors. We next show that forecasters partially offset their revisions within the calendar year.

Exploiting the term structure of forecasts in the SPF, we regress the fourth-quarter revision on the first-, second-, and third-quarter revisions. We run the following regression:

$$F_{Y,Q4}^{i}(x_{Y,Q4}) - F_{Y,Q3}^{i}(x_{Y,Q4}) = \alpha_{Q3} \left[ F_{Y,Q3}^{i}(x_{Y,Q3}) - F_{Y,Q2}^{i}(x_{Y,Q3}) \right] + \alpha_{Q2} \left[ F_{Y,Q2}^{i}(x_{Y,Q2}) - F_{Y,Q1}^{i}(x_{Y,Q2}) \right] + \alpha_{Q1} \left[ F_{Y,Q1}^{i}(x_{Y,Q1}) - F_{Y-1,Q4}^{i}(x_{Y,Q1}) \right] + \nu_{Q4}^{i},$$
(5)

where  $F_{YQ}^i(x_{YQ})$  denotes forecaster *i*'s forecast for real GDP growth in year Y and quarter Q.

We construct these calendar year variables as follows. In the first quarter of the year, the Q4 revision (i.e., the dependent variable) is the three-quarter ahead revision. In the second quarter of the year, the Q4 revision is the two-quarter ahead revision since the fourth quarter is now two periods ahead, and so on. Importantly, as the calendar year progresses, values of real GDP are realized and forecast revisions become past forecast errors. For instance, the Q1 revision in the first quarter of the year is the current-quarter revision, but when we enter into the second quarter of the year, Q1 real GDP is known and the forecaster "brings in" this news so that the Q1 revision becomes the lagged current quarter error.

Columns (1) through (3) of Table 4 report least squares estimates of (5) for real GDP growth forecasts under different fixed effect specifications. The estimates imply that forecasters offset their revisions within the calendar year. In particular, a one percentage point increase in the first quarter revision implies a 10 to 16 basis point downward revision to the fourth quarter forecast.

Offsetting calendar year revisions could naturally arise if the aggregate variable of interest exhibits certain dynamics. To examine this, we estimate a time series version of equation (5) using real-time real GDP growth and report the results in column (4) of Table 4. Based on our estimates, we find no evidence of a negative and significant coefficient, leading us to conclude that offsetting revisions are unlikely to be driven by the dynamics of real GDP

	(1)	(2)	(3)	(4)
	Fourth quarter	Fourth quarter	Fourth quarter	Fourth quarter
	revision	revision	revision	growth
Third quarter revision	0.266***	0.267***	0.229***	
	(0.068)	(0.064)	(0.065)	
Second quarter revision	0.060	0.061	0.034	
	(0.051)	(0.057)	(0.082)	
First quarter revision	-0.101**	-0.108**	-0.161**	
	(0.050)	(0.050)	(0.078)	
Third quarter growth				$0.716^{**}$
				(0.276)
Second quarter growth				0.109
				(0.263)
First quarter growth				0.009
				(0.133)
Fixed Effects	None	Forecaster	Forecaster, Time	None
Forecasters	162	151	151	
Observations	3932	3921	3921	39

Table 4: Offsetting Real GDP Revisions Within Calendar Year

Note: The table reports panel regression results from SPF forecasts based on regression (5). Standard errors for regression results in columns (1) through (3) are clustered by forecaster and time and are reported in parentheses. Newey-West standard errors are specified for time series regression in column (4). \*\*\* denotes 1% significance, \*\* denotes 5% significance, and \* denotes 10% significance.

growth.

### Linking Quarterly Offsetting to Quarterly Overreaction

A natural way to determine whether offsetting contributes to overreactions would be to determine whether forecasters who offset their revisions exhibit stronger overreactions in the data. We explore this next by running the following regression:

$$FE_{t+h}^{i} = \beta_0 + \beta_1 FR_{t+h}^{i} + \beta_2 \text{offset}_t^{i} + \beta_3 \left[ FR_{t+h}^{i} \times \text{offset}_t^{i} \right] + \varepsilon_t^{i}.$$
(6)

Note that regression (6) is a generalization of the error-on-revision regression (1), where FE denotes the forecast error and FR denotes the forecast revision, for notational convenience. If offsetting is not important, then we would expect  $\beta_2 = \beta_3 = 0$  and  $\beta_1 < 0$ , consistent with the results in Table 1. The coefficient  $\beta_3$  captures the extent to which offsetting matters for overreactions since the effect of a marginal increase in the forecast revision on the forecast error is now  $\beta_1 + \beta_3 \times \text{offset}_t^i$ .

We measure offsetting in the data by constructing a forecaster-quarter specific dummy variable that equals one whenever a forecaster's sequence of revisions exhibits a sign switch. We plot the results of the regression for quarterly horizons h = 0, 1, 2, 3 in Figure 1. The top panel of Figure 1 displays the estimates of the coefficient  $\beta_1$ , the middle panel displays estimates of  $\beta_2$ , and the bottom panel displays estimates of  $\beta_3$ .

At the current-quarter (CQ) and one-quarter ahead (1Q) horizons, we find that offsetting does not drive overreactions since  $\beta_3$  is statistically indistinguishable from zero while  $\beta_1$  is negative. At the two- and three-quarter ahead horizons, however, we find that offsetting appears to matter for overreactions. Here, we see that overreactions, which are quantified as  $\beta_1 + \beta_3$ , are driven by  $\beta_3$ . In other words, overreactions at these horizons are concentrated among forecasters who offset their revisions.

In general, finding a statistically significant estimate of  $\beta_3$  at any horizon suggests a role for offsetting in explaining overreactions. In this case,  $\beta_3$  is negative and significant at the two- and three-quarter ahead horizons, but insignificant at the current-quarter and one-quarter ahead horizons. Our results are consistent with the notion that forecasters who reshuffle their predictions based on quarterly-to-annual consistency constraints do so over longer horizons rather than shorter horizons since they are presumably more informed about the near term and they would like to remain accurate. We build this intuition into our model, which we detail in the next section.

# 3 A Model of Offsetting Revisions

We next present a general model of offsetting revisions. Our model is in the spirit of Andrade and Le Bihan (2013) with high and low frequency forecasts, each subject to a distinct updating probability. While we ultimately focus on quarterly and annual forecasts, the model presented here can be flexibly applied to other multi-frequency settings. Derivations of our results can be found in Appendix B.

After outlining the model, we discuss how high frequency overreactions arise through low frequency anchoring under a consistency constraint. Finally, we analyze a series of comparative statics in order to examine the ways in which the overreaction coefficients estimated in

Figure 1: Offsetting Drives Overreactions Over Longer Horizons



The figure plots the point estimate and 90% confidence interval of regression (6). Standard errors are clustered by forecaster and time. 'CQ' denotes current quarter, '1Q' denotes one-quarter ahead, '2Q' denotes two-quarters ahead, and '3Q' denotes three-quarters ahead.

the previous section depend on the model parameters.

### 3.1 Model Setup

The model is populated by forecasters that issue predictions about an exogenous variable which in part reflects a latent state  $s_t$ , subject to the realizations of noisy signals.<sup>7</sup> Forecasters issue high and low frequency forecasts which they may update at different points in time, subject to an aggregation constraint that requires the high frequency forecast to aggregate up to the low frequency forecast in every period.

More formally, forecasters predict the variable  $x_t$ , which is defined as a function of two components:

$$x_t = s_t + e_t, \quad e_t \sim N(0, \sigma_e^2)$$

The underlying state,  $s_t$ , follows an AR(1) process:<sup>8</sup>

$$s_t = (1 - \rho)\mu + \rho s_{t-1} + w_t, \quad w_t \sim N(0, \sigma_w^2),$$

with unconditional mean  $\mu$ , persistence  $\rho$ , and variance  $\frac{\sigma_w^2}{1-\rho^2}$ . The transitory component,  $e_t$ , is normally distributed and centered at zero with variance  $\sigma_e^2$ . The state is neither observed by forecasters nor by the econometrician. However, we assume that the parameters governing the data generating process are known to forecasters.

In the empirical section, we found that forecasters underreact to past high frequency prediction errors. Since we wish to capture this in our model, we assume that when updating their predictions, forecasters observe the previous realization of the variable,  $x_{t-1}$ . In addition, we assume that forecasters observe a contemporaneous private signal:

$$y_t^i = s_t + v_t^i, \quad v_t^i \stackrel{\text{i.i.d.}}{\sim} N(0, \sigma_v^2).$$

In this linear Gaussian set up, an optimal forecast would be obtained by employing the Kalman filter. However, forecasters cannot flexibly update their forecasts every period.

<sup>&</sup>lt;sup>7</sup>While our focus is on professional forecasters, this model can be applied to other decision makers such as households or firms by suitably modifying the objective function and by adding additional constraints.

<sup>&</sup>lt;sup>8</sup>In Appendix D.6 we explore a richer driving process which delivers qualitatively similar results to those reported in the subsequent sections.

Instead, in a given period, a forecaster is only able to revise her prediction for the higher frequency with probability q, and her prediction for the lower frequency with probability p.<sup>9</sup>

The Calvo-like probabilities, q and p, give rise to four distinct cases:

**Case 1:** With probability (1-q)(1-p), the forecaster does not update at all.

**Case 2:** With probability q(1-p), the forecaster updates the higher frequency forecast, but not the lower frequency forecast. In this case, she updates her higher frequency prediction based on the signals received and subject to the consistency constraint.

**Case 3:** With probability (1 - q)p, the forecaster updates her lower frequency forecast, but not the higher frequency forecast. We interpret this case as a scenario in which the forecaster simply "brings in" the latest release,  $x_{t-1}$ , and updates her prediction at the lower frequency accordingly. Importantly, the agent does not update the rest of the sequence of higher frequency forecasts.<sup>10</sup>

Case 4: With probability pq, the forecaster can optimally update predictions for both frequencies based on the signals received.

### **3.2** High Frequency Overreactions

From the perspective of the model, high frequency overreactions are due to Case 2 updating. As a result, the probability q(1-p) governs the signs and magnitudes of the coefficients reported in Table 1. Since any point in time can be defined by its low and high frequency pair (e.g., year-quarter), we will denote time t by its low  $\ell$  and high h frequency correspondence (i.e.,  $t = \ell h$ ). We can express the Case 2 prediction, in general, as:

$$\widehat{x}_{\ell h'|\ell h}^{i} = \mathbb{E}_{\ell h}^{i}(x_{\ell h'}) + \frac{1}{H} \sum_{h'=1}^{H} \left[ \mathbb{E}_{\ell h-j}^{i}(x_{\ell h'}) - \mathbb{E}_{\ell h}^{i}(x_{\ell h'}) \right], \quad \ell \in [0,\infty), \ h', h \in [1,H],$$
(7)

where H is the number of high frequency periods in one low frequency period (e.g., the number of quarters in a year). Furthermore,  $\hat{x}^i_{\ell h'|\ell h}$  denotes agent *i*'s reported prediction in period  $\ell h$  for some future high frequency period,  $\ell h'$ . The subscript  $\ell h - j$  refers to period

<sup>&</sup>lt;sup>9</sup>In principle, it is possible for forecasters to anchor over different frequencies. We abstract away from this for parsimony and due to lack of sufficiently rich survey data to inform the extent such heterogeneity.

 $<sup>^{10}</sup>$ This scenario does not play an important role in our findings. The estimated model, discussed in the next section, implies that Case 3 updating occurs only 0.001% of the time.

in which the low frequency prediction was last updated. The reported forecast is the sum of the optimal conditional expectation and a term capturing the gap between the path of the outdated low frequency forecast and what it should be based on the latest information.

We can rearrange (7) in order to more transparently characterize the source of overreactions:

$$\widehat{x}_{\ell h'|\ell h}^{i} = \underbrace{\frac{H-1}{H} \mathbb{E}_{\ell h}^{i}(x_{\ell h'}) + \frac{1}{H} \mathbb{E}_{\ell h-j}^{i}(x_{\ell h'})}_{\text{Traditional smoothing motive}} + \underbrace{\frac{1}{H} \sum_{h'' \neq h'}^{H} \left[ \mathbb{E}_{\ell h-j}^{i}(x_{\ell h''}) - \mathbb{E}_{\ell h}^{i}(x_{\ell h''}) \right]}_{\text{Source of overreactions}}$$

The first two terms on the right hand side of the above expression reflect averaging between current and past forecasts that arises in standard revision smoothing models (Scotese, 1994). The last term is responsible for generating overreactions in our model. This sum reflects the differences in the conditional expectations between  $\ell h$  and  $\ell h - j$  for the other periods over which the forecaster smooths her forecast. As high frequency data are realized within a low frequency period, this sum incorporates past forecast errors. To see this, note that (7) can be re-written as:

$$\widehat{x}_{\ell h'|\ell h}^{i} = \mathbb{E}_{\ell h}^{i}(x_{\ell h'}) - \frac{1}{H} \sum_{j=k}^{h-1} \left[ x_{\ell j} - \mathbb{E}_{\ell j}^{i}(x_{\ell j}) \right] - \frac{1}{H} \sum_{j'=h}^{H} \left[ \mathbb{E}_{\ell h}^{i}(x_{\ell j'}) - \mathbb{E}_{\ell h-k}^{i}(x_{\ell j'}) \right], \tag{8}$$

where the second term on the right hand side reflects past forecast errors.

Overreactions arise because low-frequency inattention and high-to-low frequency consistency, together, introduce past rational mistakes into the reported prediction. Based on the second term in (8), if  $x_{\ell h-1}$  comes in above expectations, then the forecaster will mark down her current forecast in order to preserve consistency.<sup>11</sup> As a result, a positive rational expectations error today predicts a positive ex-post forecast error tomorrow. These erroneous revisions are later corrected as new and relevant information arrives in the next period, generating observed overreactions.

 $<sup>^{11}</sup>$ Note that while inattention will result in aggregate underreaction at both frequencies, there is no individual-level underreaction at the annual frequency.



Figure 2: Overreaction and Model Parameters

Note: The figure plots the simulated BGMS coefficient as a function of the fundamental and informational model parameters. The bold line reflects the estimated parameters reported in Table 5. The gray lines reflect these same point estimates for all but one parameter, where that parameter is instead set to its lower (upper) bound based on a 95% confidence interval.

### 3.3 Analyzing the Model

We concentrate on the Bordalo et al. (2020) (BGMS) coefficient, which regresses year-overyear errors on year-over-year revisions. We note, however, that similar findings arise with the other measures of prediction efficiency reported in Table 1. Figure 2 plots simulated BGMS coefficients across a range of different parameter values collectively governing the state and signals.

The model features rich dynamics across horizons and frequencies. As a result, the coefficients studied in Section 2 are nonlinear functions of the underlying model parameters.<sup>12</sup>

 $<sup>^{12}\</sup>mathrm{We}$  derive the errors-on-revisions coefficient implied by the model in Appendix B.2.

To provide intuition for the model's ability to generate overreactions, we therefore rely on simulated comparative statics.

Panels 1 and 2 display the relationship between the BGMS coefficient and the parameters governing the latent state. Based on Panel 1, as the underlying process approaches a unit root, the scope for overreactions declines. This is consistent with Bordalo et al. (2020) and Afrouzi et al. (2021) who find that overreactions are decreasing in  $\rho$ . From the lens of our model, a more persistent variable reduces the scope for forecast reshuffling through the consistency constraint since the variability of the system is increasingly driven by persistent shocks. Panel 2 reports the results for the state volatility,  $\sigma_w$ . Similar to Panel 1, here we find that the scope for overreactions is decreasing in  $\sigma_w$ . As  $\sigma_w$  rises, forecast errors are increasingly driven by the persistent shock which, again, reduces the volatility of offsetting.

On the other hand, Panels 3 and 4 show that the BGMS coefficient is decreasing in public and private noise. All else equal, higher noise variances mean that forecast errors are increasingly driven by transitory shocks. Since these shocks are short lived, agents find themselves often changing the manner in which they offset their revisions, raising the volatility of forecast reshuffling and generating stronger observed overreactions.

Sticky information is an important feature of our model. To assess the role that infrequent annual updating plays in driving observed overreactions, we focus on the frequency of Case 2 updating. Figure 3 illustrates how individual overreactions depend on q(1-p), which is the probability of Case 2 updating. As q(1-p) increases, agents increasingly find themselves updating their quarterly predictions based on news while keeping their annual outlooks the same. In this case, agents respond to news, but offset their sequence of revisions so as to preserve consistency. These excessive revisions are responsible for generating overreactions.

# 4 Model Estimation

While our model can generate overreactions among forecasters, quantifying the importance of our mechanism requires us to estimate the model parameters. We therefore discipline the model with micro data from the SPF. For our baseline results, we fit the model to real GDP growth forecasts. Of the seven parameters, we first fix the unconditional mean,  $\mu = 2.4$ , consistent with the sample mean of real-time real GDP growth over this period.

#### Figure 3: Overreaction and Updating Probabilities



Note: The figure plots the simulated BGMS coefficient as a function of the probability of Case 2 updating. The bold line reflects the estimated parameters reported in Table 5. The gray lines reflect these same point estimates for all but one parameter, where that parameter is instead set to its lower (upper) bound based on a 95% confidence interval.

We estimate the remaining six parameters via SMM as detailed in Appendix C.<sup>13</sup> The parameters to be estimated are  $\theta = (\rho \ \sigma_w \ \sigma_e \ \sigma_v \ q \ p)'$ . These parameters are chosen to match eight data moments: the covariance matrix of current-quarter and current-year forecasts, the covariance matrix of current-quarter forecast revisions and last quarter's real-time forecast error, and the mean squared real-time errors associated with current-quarter predictions and current-year predictions. Appendix C details how these moments are related to the parameters.<sup>14</sup>

<sup>&</sup>lt;sup>13</sup>We also explored an alternative strategy by first estimating the data generating process parameters via maximum likelihood estimation (MLE) using real GDP growth as our observation, and then estimating the remaining parameters via SMM. This joint MLE-SMM approach delivers quantitatively similar results to those reported in Table 5.

<sup>&</sup>lt;sup>14</sup>We do not directly target rates of micro-level inattention in our baseline estimation approach, however,

Panel A: Parameter Estimates			
	Parameter	Estimate	Standard error
Persistence of latent state	ρ	0.441	0.071
State innovation dispersion	$\sigma_w$	1.842	0.126
Public signal noise	$\sigma_{e}$	1.289	0.327
Private signal noise	$\sigma_v$	0.934	0.191
Probability of quarterly update	q	0.999	0.078
Probability of annual update	p	0.581	0.042
Panel B: Moments			
	Model moment	Data moment	t-statistic
Std(CQ forecast)	Model moment 1.682	Data moment 1.745	t-statistic 0.607
Std(CQ forecast) Corr(CQ forecast, CY forecast)	Model moment 1.682 0.687	Data moment 1.745 0.685	t-statistic 0.607 0.594
Std(CQ forecast) Corr(CQ forecast, CY forecast) Std(CY forecast)	Model moment 1.682 0.687 1.096	Data moment 1.745 0.685 1.115	t-statistic 0.607 0.594 0.349
Std(CQ forecast) Corr(CQ forecast, CY forecast) Std(CY forecast) Std(CQ revision)	Model moment 1.682 0.687 1.096 1.572	Data moment 1.745 0.685 1.115 1.589	t-statistic 0.607 0.594 0.349 0.140
Std(CQ forecast) Corr(CQ forecast, CY forecast) Std(CY forecast) Std(CQ revision) Corr(CQ revision, lagged CQ error)	Model moment 1.682 0.687 1.096 1.572 0.127	Data moment 1.745 0.685 1.115 1.589 0.138	t-statistic 0.607 0.594 0.349 0.140 0.387
Std(CQ forecast) Corr(CQ forecast, CY forecast) Std(CY forecast) Std(CQ revision) Corr(CQ revision, lagged CQ error) Std(lagged CQ error)	Model moment 1.682 0.687 1.096 1.572 0.127 1.672	Data moment 1.745 0.685 1.115 1.589 0.138 1.749	t-statistic 0.607 0.594 0.349 0.140 0.387 0.883
Std(CQ forecast) Corr(CQ forecast, CY forecast) Std(CY forecast) Std(CQ revision) Corr(CQ revision, lagged CQ error) Std(lagged CQ error) CQ RMSE	Model moment 1.682 0.687 1.096 1.572 0.127 1.672 1.688	Data moment 1.745 0.685 1.115 1.589 0.138 1.749 1.717	t-statistic 0.607 0.594 0.349 0.140 0.387 0.883 0.522

 Table 5: Model Estimation Results

Note: Panel A reports the model parameters with point estimates reported in the third column and standard errors reported in the fourth column. Panel B reports the model vs. data moments with the t-statistics of the null of equality of the two moments reported in the fourth column. 'CQ' denotes current-quarter and 'CY' denotes current-year. J-statistic is 4.256, with p-value of 0.12.

### 4.1 Estimation Results

The estimated parameters are reported in Panel A of Table 5. The underlying persistence of the latent state is estimated to be 0.44. In addition, the dispersion in state innovations is 1.84 while the dispersion of public and private noise are 1.29 and 0.93, respectively. These estimates imply a signal-to-noise ratio of about  $\frac{\sigma_w}{\sigma_e + \sigma_v} \approx 0.83$ . Furthermore, the probability of quarterly updating is about one, implying that forecasters update their quarterly predictions in every period. Lastly, the probability of annual updating is estimated to be 0.58, meaning that forecasters update their annual predictions slightly more than twice a year. This estimated probability is significantly below one, indicating that there is scope for the

in unreported results we estimate our model by targeting the share of small revisions (up to one-tenth of a percentage point) at the quarterly and annual frequencies rather than targeting the quarterly and annual mean squared errors. We obtained similar estimates when taking this approach.

 Table 6: Non-targeted Moments

	Model			Data
1. $\beta(FECQ, FRCQ)$	0.046	(0.046)	-0.2	66 (0.059)
2. $\beta(FE1Q, FR1Q)$	-0.179	(0.105)	-0.1	45 (0.073)
3. $\beta(FE2Q, FR2Q)$	-0.567	(0.115)	-0.3	34 (0.066)
4. $\beta(FE3Q, FR3Q)$	-0.905	(0.184)	-0.6	57 (0.087)
5. $\beta(FRCQ, FR1Q_{-1})$	-0.091	(0.063)	-0.1	31 (0.057)
6. $\beta(FR1Q, FR2Q_{-1})$	-0.305	(0.028)	-0.3	02 (0.055)
7. $\beta(FR2Q, FR3Q_{-1})$	-0.510	(0.027)	-0.4	24 (0.050)
8. $\beta(FEYY, FRYY)$	-0.177	(0.074)	-0.2	36  (0.137)
9. $\beta$ (FEYY, Outcome)	-0.067	(0.096)	-0.1	34 (0.070)
10. $\beta(FECQ, FECQ_{-1})$	0.148	(0.051)	0.14	47 (0.054)

Note: The table reports regression coefficients in the model as well in the data. Standard deviations and standard errors are reported in parentheses. 'FE' refers to forecast error, 'FR' refers to forecast revision, and 'CQ, 1Q, 2Q,3Q,YY' refer to current quarter, one-quarter ahead, two-quarters ahead, three-quarters ahead, and year-over-year, respectively.

model to generate overreactions. Our estimates imply that annual anchoring is a meaningful friction in the model. In the absence of infrequent annual updating, the root mean squared error for current-quarter predictions would fall by 10%.

The model is able to successfully replicate the targeted features of the data. Panel B of Table 5 reports the model-implied moments and the empirical moments, scaled to correlations and standard deviations. The fourth column of Panel B reports t-statistics which indicate that the model moments are statistically indistinguishable from their empirical counterparts. A test of overidentifying restrictions delivers a p-value of 0.12, failing to reject the null hypothesis thereby lending additional support to the validity of the estimates.

### 4.2 Non-targeted Moments

Having evaluated the estimated model and assessed its fit to the targeted moments, we next turn to analyzing its ability to replicate the overreactions observed in the data.

Table 6 reports ten non-targeted regression coefficients. Rows 1 to 4 report individual-

level regression coefficients of errors-on-revisions at the current quarter as well as one-, two-, and three-quarter ahead horizons. Rows 5 to 7 report revision autocorrelation coefficients for the current quarter as well as one- and two-quarters ahead. Row 8 reports the BGMS coefficient of errors-on-revisions. Row 9 reports the estimated coefficient from a regression of the year-over-year forecast error on the realized outcome as in Kohlhas and Walther (2021). Across these regressions, the model nearly always predicts individual overreactions.

One limitation of the estimated model is that it does not generate a negative errors-onrevisions coefficient for current-quarter forecasts (row 1 of Table 6). This is because the model assumes that the news that forecasters receive is about the present. As a result, forecasters place more importance on minimizing current quarter errors, and optimally reshuffle their future forecasts, for which the signals are less informative, to maintain annual consistency. If signals were informative about future quarters rather than the current quarter, then the model would generate a negative errors-on-revisions coefficient for current-quarter forecasts.

The final row of Panel A displays estimates of forecast error persistence. We report this estimate to highlight our model's ability to reproduce another feature of the data: positively autocorrelated individual-level errors. In a rational setting in which forecasters are able to observe past realizations of the variable of interest, errors should not exhibit persistence.<sup>15</sup> Our model is able to generate forecast error persistence precisely because annual inattention introduces lagged errors into reported forecasts. We find this to be a desirable feature of our model as it allows us to match this pattern in the data while making a more realistic assumption about the forecaster's information set.

In addition to successfully matching individual-level overreaction estimates, the estimated model is also able to match consensus-level moments. We report these in Table D10.

### 4.3 Annual Anchoring by Macroeconomic Variable

We next estimate our baseline model for various macroeconomic variables covered in the SPF as well as real GDP forecasts from the Bloomberg (BBG) and Wall Street Journal (WSJ) surveys.<sup>16</sup> To evaluate how well the model is able to account for overreactions in the

<sup>&</sup>lt;sup>15</sup>The literature sometimes implicitly assumes that forecasters never actually observe the variable of interest, thereby preserving error persistence. Here, we assume that  $x_{t-1}$  is observable.

<sup>&</sup>lt;sup>16</sup>Appendix A.5 provides further details on the BBG and WSJ surveys and shows that these surveys similarly feature robust evidence quarterly overreaction but not annual overreaction.

	BGMS (2020) Coefficient		
	Model	Data	
Real GDP	-0.177(0.074)	-0.236(0.137)	
Nominal GDP	-0.144(0.089)	-0.308(0.060)	
Real consumer spending	-0.246 (0.100)	-0.268(0.061)	
GDP deflator	-0.149 (0.080)	-0.510 $(0.062)$	
Real residential investment	-0.153(0.094)	-0.108(0.088)	
Real nonresidential investment	-0.130(-0.085)	-0.031 (0.111)	
Real federal spending	$-0.425 \ (0.137)$	$-0.512 \ (0.068)$	
Real state/local spending	-0.393 $(0.112)$	-0.494 (0.086)	
Unemployment	-0.005(0.087)	$0.312 \ (0.108)$	
Ten year bond	$-0.132 \ (0.073)$	$-0.114 \ (0.065)$	
3-month bill	-0.051(0.172)	$0.134\ (0.076)$	
Real GDP (BBG)	$-0.783 \ (0.148)$	$-0.443 \ (0.237)$	
Real GDP (WSJ)	-0.814 (0.150)	-0.587(0.111)	

Table 7: Estimates Across Macro Variables

Note: The table reports the BGMS (2020) error-on-revision coefficients in the model and Driscoll and Kraay (1998) standard errors are reported in parentheses for various macroeconomic variables covered in the SPF. Bold values are significantly negative at the 10% level.

data, Table 7 reports empirical and simulated errors-on-revisions regression estimates, our non-targeted moment of choice. In general, we find that our model is able to reproduce the negative covariance between errors and revisions observed in the data. The model is also able to generate a null result among variables for which there is no statistically significant evidence of overreactions such as investment components and unemployment.

The empirical coefficients reported in Table 7 are also consistent with some of the comparative statics observed in Figure 2. For instance, there is no evidence of overreaction in forecasts for the unemployment rate, a highly persistent aggregate.

# 5 Incorporating Non-Rational Expectations

To better understand the quantitative importance of our mechanism as a driver of overreactions, we augment our model with a behavioral friction in a supplementary exercise. We choose a leading theory of non-rational expectations, diagnostic expectations (Bordalo et al., 2019; Bianchi et al., 2021; Bordalo et al., 2021; Chodorow-Reich et al., 2021; L'Huillier et al., 2023), which is rooted in the representativeness heuristic (Kahneman and Tversky, 1972).

According to diagnostic expectations, agents form their beliefs subject to a cognitive friction in which they conflate the objective likelihood of a type in a group with its representativeness (i.e., the frequency of the type within the group *relative* to a reference group). This is formalized in Gennaioli and Shleifer (2010).

We choose to apply the formulation of diagnostic expectations presented in Bordalo et al. (2020) in which diagnostic forecasters place excessive weight on new information such that their reported current-quarter prediction is:

$$x_{t|t}^{i,\theta} = \mathbb{E}_{it}(x_t) + \theta \big[ \mathbb{E}_{it}(x_t) - \mathbb{E}_{it-1}(x_t) \big],$$

where  $\theta$  is the degree of diagnosticity. When  $\theta = 0$ , the model collapses to a rational expectations model. On the other hand, in a world of diagnostic expectations,  $\theta > 0$ .

The objective of this exercise is to jointly model two sources of overreaction: annual anchoring and diagnostic expectations, and to quantify the relative importance of our annual anchoring mechanism. To do so, we re-estimate the model with diagnostic expectations while targeting two additional moments: the *contemporaneous* covariance of current-quarter errors and revisions, and the variance of *contemporaneous* current-quarter errors. As discussed in the previous section, our baseline model cannot generate a negative correlation between current-quarter errors and revisions. Thus, we can identify  $\theta$  by targeting these two additional moments. The estimated parameters are reported in column 1 of Table D11. We estimate a degree of diagnosticity equal to 0.50 which is slightly lower than the estimate reported in Bordalo et al. (2020) that follows a similar minimum distance estimation procedure.

We examine the importance of annual smoothing relative to diagnostic expectations by running three simulated regressions. Using these parameter estimates, we first simulate a panel of forecasts and estimate regressions (1), (2), and (3). We then fix  $\theta = 0$  and repeat this exercise. Figure 4 displays three sets of stacked bars, each corresponding to one of the aforementioned regressions. The red bar denotes the contribution of our annual anchoring mechanism to the overall estimate of overreactions, while the blue bar denotes the contribution of diagnostic expectations. Based on these results, we find that annual

Figure 4: Annual Anchoring vs. Diagnostic Expectation Contributions



Note: The figure plots the contributions of annual anchoring and diagnostic expectations to three measures of overreactions for real GDP.

anchoring is a meaningful, and in this case dominant, driver of quarterly overreactions. Our results suggest that annual anchoring with quarterly-to-annual consistency can be a quantitatively important driver of overreactions.<sup>17</sup>

# 6 Implications for Information Frictions

In addition to serving as a source of observed overreactions, our model can also speak to the literature on information frictions. Since our model does not allow us to readily extract an estimate of information rigidity from a regression of consensus errors on consensus revisions (Coibion and Gorodnichenko, 2015), we simulate the estimated model in order to retrieve

<sup>&</sup>lt;sup>17</sup>Column 2 of Table D11 reports a related exercise in which we estimate a constrained (no diagnostic expectations) model with the expanded set of ten moments and compare this model with the unconstrained model (with diagnostic expectations). Figure D7 repeats the comparison of diagnostic expectation based on simulated error predictability regressions. Our results are qualitatively similar to Figure 4.

the steady state Kalman gains and to quantify the size of information frictions.

### 6.1 Model-Implied Information Frictions

Column 2 of Table 8 reports measures of implied information rigidity for SPF forecasts of real GDP and inflation based on the GDP deflator. Since our model is a hybrid sticky-noisy information model, we define the implied information friction to be:

Implied friction = 
$$[1 - Pr(update)] + Pr(update) \times (1 - \kappa_1 - \kappa_2),$$
 (9)

where Pr(update) denotes the probability of updating, which reflects the sticky information feature of the model. Based on our estimates, this probability varies across frequencies. Moreover, the role of noisy information in overall information frictions is understood through the coefficients { $\kappa_1, \kappa_2$ } which denote the Kalman gains.<sup>18</sup>

In traditional models of either sticky information or noisy information, the relevant information rigidity is governed by either the probability of updating or the Kalman gain(s). Here, the implied friction is a combination of these two objects. With some probability, forecasters do not update. In this case, they effectively place a weight of zero on new information. With some probability, forecasters do update, in which case they weigh new information based on the Kalman gains. Upon updating, the relevant information friction is one minus the sum of these optimal weights. Together, these terms capture the notion of an information friction in a hybrid sticky-noisy information model, which can be interpreted as an *expected* weight placed on new information.

In order to compare our implied information frictions to those in the literature, focus on inflation forecasts based on the GDP deflator.<sup>19</sup> At a quarterly frequency, we estimate information frictions to be about 0.19 while, for annual forecasts, we find that information frictions are higher, at 0.55. For reference, Coibion and Gorodnichenko (2015) estimate coefficients of information rigidity to be around 0.54 while Ryngaert (2017) estimates information frictions to be roughly 0.33. Importantly, whereas existing estimates imply a single information friction for all frequencies, our analysis indicates that there is a difference in

<sup>&</sup>lt;sup>18</sup>In particular,  $\kappa_1$  denotes the weight placed on the private contemporaneous signal and  $\kappa_2$  is the weight placed on the lagged realization of the macroeconomic variable.

<sup>&</sup>lt;sup>19</sup>Table D12 reports the parameter estimates and model fit.

	(1)	(2)	(3)	(4)
	Probability	Implied	Sticky info	Noisy info
	of updating	friction	$\operatorname{contribution}$	$\operatorname{contribution}$
Real GDP				
Quarterly	0.999	0.174	0%	100%
Annual	0.581	0.520	80.1%	19.4%
Inflation				
Quarterly	1.000	0.190	0%	100%
Annual	0.552	0.553	81.1%	19.0%

 Table 8: Information Frictions Across Models

Note: The table reports estimated updating probabilities, implied information frictions, and contributions of sticky and noisy information for real GDP and inflation (GDP deflator) at quarterly and annual frequencies. Implied information frictions are computed based on (9) with model-implied Kalman gains  $\{\kappa_1, \kappa_2\} = \{0.800, 0.026\}$  and  $\{0.783, 0.028\}$  for real GDP and inflation, respectively. Contributions of sticky and noisy information are computed according to (10).

frictions between quarterly and annual frequencies. We note that the average of our implied quarterly and annual information frictions resides in between these previously documented estimates.

While we have two signals in our model, it is important to note that only the contemporaneous private signal contributes to forecast dispersion. Since the lagged realization of the macroeconomic variable is a common to all, it is a public signal. Thus if  $x_{t-1}$  was the only signal, then all forecasters would make the same predictions. However, since forecasters also observe  $y_t^i$ , they will not have the same predictions.<sup>20</sup> We find that the Kalman gain from the public signal is much smaller than the one from the private signal. Hence the private signal is more informative relative to the public signal when making a new prediction. Overall, we regard the information friction defined in equation (9) as a measure of the extent of imperfect information rather than a measure of information dispersion.

<sup>&</sup>lt;sup>20</sup>Note that the sticky information friction also implies that forecasters update their information sets at different points in time.

### 6.2 Contributions of Sticky and Noisy Information

The literature on survey expectations has documented evidence consistent with both sticky and noisy information. Our results indicate that the data favor a hybrid model featuring signal extraction and frequency-specific inattention. In addition to providing estimates of information frictions based on both sticky and noisy information, our model can also quantify the relative importance of each of these channels. To do so, we normalize the implied information friction to equal one

$$1 = \underbrace{\frac{1 - \Pr(\text{update})}{\left[1 - \Pr(\text{update})\right] + \Pr(\text{update}) \times (1 - \kappa_1 - \kappa_2)}}_{\text{Sticky info contribution}} + \underbrace{\frac{\Pr(\text{update}) \times (1 - \kappa_1 - \kappa_2)}{\left[1 - \Pr(\text{update})\right] + \Pr(\text{update}) \times (1 - \kappa_1 - \kappa_2)}}_{\text{Noisy info contribution}}.$$
 (10)

The first term in the above expression quantifies the role of sticky information in the overall measured information rigidity while the second term quantifies the importance of noisy information. The final two columns of Table 8 report the contributions of each form of imperfect information to the implied friction reported in column 3. As foreshadowed by the parameter estimates in Table 5, this accounting exercise implies that noisy information is the primary contributor to information frictions at the quarterly frequency, while sticky information becomes substantially more important at the annual frequency.

# 7 Conclusion

There are many settings in which forecasts must be made simultaneously and consistently for multiple frequencies such as household budgeting, fiscal planning, and professional forecasting. In this paper, we focus on the latter by studying the updating behavior of professional forecasters.

We show that forecaster-level overreactions are prevalent at the quarterly frequency, but less so at the annual frequency. Furthermore, we show that annual forecast errors underreact to realized quarterly errors, and that forecast revisions exhibit an offsetting pattern. Motivated by these facts, we build a hybrid sticky-noisy information model featuring high and low frequency forecasts. From the lens of our model, overreactions arise because of (i) low frequency anchoring and (ii) high-to-low frequency consistency. We find that our mechanism can explain a meaningful amount of overreactions to real GDP and other aggregates.

Our results also imply that information frictions vary by frequency, and we can attribute most of the annual friction to stickiness and the quarterly friction to noisiness. This unique decomposition is in line with forecasters making major revisions of the annual predictions about twice a year while constantly updating the quarterly path to reflect new data releases.

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# Appendix A Empirics

This section provides further detail on the data used for the empirical and model estimation sections of the main text. For our baseline model results, we focus on forecasts of real GDP growth.

### A.1 Quarterly-to-Annual Consistency in SPF Forecasts

We provide descriptive, anecdotal, and empirical evidence to confirm that SPF forecasts satisfy quarterly-to-annual consistency. First, the SPF documentation (chapter 3) details how the monthly and quarterly observations are linked to the annual, and states that procedures are in place to ensure that participants adhere to these formulas. A forecaster who does not follow the specified formulas is contacted and a discussion about non-adherence ensues. Second, we gathered anecdotal evidence by speaking to several survey participants, all of whom verified the quarterly-to-annual consistency requirement. Third, we directly show that consistency is present in the data by computing implied current-year forecasts, based on the quarterly predictions, and comparing them with the current-year forecast actually issued by the respondent. In the first quarter of the calendar year, the current-year forecast should coincide with the average forecasted levels of the current-, one-, two-, and three-quarter forecasts. In the second quarter of the calendar year, the current-year forecast should coincide with the average forecasted levels of the previous-, current-, one-, and two-quarter forecasts, and so on.<sup>21</sup>

We construct implied current-year forecasts accordingly and compare them to the reported current-year forecasts, finding a 0.9999 correlation between the two as indicated by Figure A1.

### A.2 Sample selection

We apply a set cleaning filters to the raw data, before estimating the regressions. First, following Bordalo et al. (2020), for every horizon, we winsorize the observations above or below five interquartile ranges of the sample median. Second, we keep only forecasters who

 $<sup>^{21}</sup>$ As noted in footnote 6 of the SPF documentation, the previous quarter forecast is history which is observable to the forecaster and is nearly never revised.





Note: The figure displays a binned scatter plot of report current-year forecasts against implied current-year forecasts for SPF real GDP forecasts. The implied current-year forecast is computed as described in the text.

issue predictions for at least ten quarters. In addition, we drop the 1985Q1, 1986Q1, and 1990Q1 survey observations due to measurement error associated the reporting of annual forecasts as noted in the SPF documentation. In addition, we drop the survey observations in 1990Q2 because of small sample issues also noted in the SPF documentation.

As stated in the main text, we begin our sample in 1981Q3 when the SPF began to collect annual forecasts. We end our sample in 2019Q4.

## A.3 Quarterly Forecasts

Our main results utilize real GDP growth forecasts. The SPF collects predictions for the level of real GDP,  $f_t$ . We transform these to quarter-over-quarter annualized predicted real GDP growth rates,  $\hat{x}_{t+h|t}$ , as follows:

$$\widehat{x}_{t+h|t} = \left[ \left( \frac{f_{t+h}}{f_{t-1}} \right)^4 - 1 \right] \times 100$$

Table A1 reports summary statistics of real GDP forecasts, errors, and revisions across horizons, as well as real-time outcomes.

	Mean	Median	Std. deviation	25%	75%
Annualized quarterly forecasts					
Current quarter	2.314	2.500	1.948	1.700	3.287
One quarter ahead	2.593	2.655	1.566	2.025	3.300
Two quarters ahead	2.761	2.737	1.511	2.167	3.380
Three quarters ahead	2.829	2.800	1.363	2.259	3.401
$\mathrm{Q4}/\mathrm{Q4}$	2.616	2.649	1.099	2.155	3.180
Quarterly Forecast errors					
Current quarter	0.084	0.021	1.810	-1.039	1.086
One quarter ahead	-0.190	-0.196	2.168	-1.402	0.901
Two quarters ahead	-0.268	-0.244	2.397	-1.446	0.952
Three quarters ahead	-0.312	-0.323	2.395	-1.540	0.937
$\mathrm{Q4}/\mathrm{Q4}$	-0.213	-0.248	1.371	-0.976	0.573
Quarterly Forecast revisions					
Current quarter	-0.247	-0.102	1.757	-0.825	0.486
One quarter ahead	-0.139	-0.028	1.528	-0.503	0.310
Two quarters ahead	-0.088	-0.009	1.327	-0.418	0.282
Three quarters ahead	0.004	-0.00004	1.399	-0.331	0.290
$\mathrm{Q4}/\mathrm{Q4}$	-0.121	-0.056	0.798	-0.401	0.224
Real GDP					
Quarterly real-time outcome	2.392	2.464	2.234	1.386	3.521

Table A1: SPF Real GDP Summary Statistics

Note: The table reports summary statistics for the relevant variables utilized in the main text. The sample is constructed from SPF real GDP growth forecast data. The sample spans 1981Q3-2019Q4.

### A.4 Annual Forecasts

The SPF collects annual real GDP forecasts which are defined as the average level of real GDP in a given year,

$$f_Y = \frac{f_{YQ1} + f_{YQ2} + f_{YQ3} + f_{YQ4}}{4}$$

The annual growth rate of real GDP is defined on a year-over-year basis,

$$x_Y = \left(\frac{f_Y}{f_{Y-1}} - 1\right) \times 100$$

To construct current year forecasted real GDP growth, we require the most recent average level of real GDP in the prior year. We obtain this data by collecting all vintages across variables from the Real-Time Data Set for Macroeconomists from the Philadelphia Fed.

We define the forecast error for annual real GDP growth in year Y as  $x_Y - \hat{x}_{Y|Y,Q}$ , where  $\hat{x}_{Y|Y,Q}$  is the forecast of annual real GDP growth for year Y devised at time (year-quarter) Y, Q. We define the forecast revision as  $\hat{x}_{Y|Y,Q} - \hat{x}_{Y|Y,Q-1}$  for quarters 2-4 of a given year (Q > 2). For the first quarter of the calendar year, Q = 1, we define the forecast revision as  $\hat{x}_{Y|Y,Q} - \hat{x}_{Y|Y,Q-1}$  (i.e., the current-year forecast devised in the first quarter of the current calendar year minus the one year ahead forecast devised in the fourth quarter of the prior calendar year.

Table A2 reports summary statistics of real GDP forecasts, errors, and revisions across horizons, as well as real-time outcomes and data revisions.

	Mean	Median	Std. deviation	25%	75%
Current-year forecast	2.419	2.495	1.523	1.925	3.274
Current-year error	0.030	0.028	0.606	-0.209	0.237
Current-year revision	-0.019	-0.00003	0.719	-0.290	0.241
Current-year real-time outcome	2.449	2.416	1.577	1.950	3.383

Table A2: SPF Real GDP Summary Statistics

Note: The table reports summary statistics for the relevant current-year variables analyzed in the main text. The sample is constructed from SPF real GDP growth forecast data. The sample spans 1981Q3-2019Q4.

## A.5 Empirical Facts: Robustness

#### **Fixed Effects**

Table A3 report the regression estimates of equations (1), (2), and (3) with forecaster fixed effects.

	Current	quarter	One qua	rter ahead	Two quar	ters ahead	Year-o	ver-year
	(1) Error	(2) Revision	(3) Error	(4) Revision	(5) Error	(6) Revision	(7) Error	(8) Error
Revision	$-0.270^{***}$ (0.059)		$-0.160^{**}$ (0.069)		$-0.362^{***}$ (0.065)		$-0.259^{*}$ (0.137)	
Previous revision		$-0.137^{**}$ (0.058)	. ,	$-0.319^{***}$ (0.051)		$-0.394^{***}$ (0.066)	. ,	
Realization								$-0.160^{**}$ (0.062)
Forecasters	152	143	143	142	138	141	137	136
Observations	4193	3545	3566	3531	3466	3435	3199	3104

Table A3: Overreaction among Individual Forecasters

Note: The table reports panel regression results from SPF forecasts of real GDP growth based on regressions (1), (2), and (3). Standard errors are reported in parentheses. Standard errors are clustered by forecaster and time. \*\*\* denotes 1% significance, \*\* denotes 5% significance, and \* denotes 10% significance.

Table A4 reports estimates of annual version of equations (1) and (3) with forecaster fixed effects.

	(1) Annual error	(2) Annual error	(3) Annual error
Revision	-0.095		
Realization	(0.000)	0.021	
Realized quarterly error		(0.024)	$0.037^{*}$ (0.019)
Forecasters	137	137	137
Observations	4045	4049	4035

Table A4: No Annual Overreaction among Individual Forecasters

Note: The table reports panel regression results from SPF forecasts of real GDP growth based on regressions (1), (3), and (4). Standard errors are reported in parentheses. Standard errors are clustered by forecaster and time. \*\*\* denotes 1% significance, \*\* denotes 5% significance, and \* denotes 10% significance.

### Other Macroeconomic Variables

In addition to the real GDP forecasts analyzed in the main text, in this section we document our more novel empirical facts for ten other variables in the SPF. We first list the variables analyzed in this section and then report the results.

List of variables

- 1. GDP Deflator (PGDP)
- 2. Nominal GDP (NGDP)
- 3. Real consumption expenditures (RCON)
- 4. Real federal government spending (RFED)
- 5. Real state and local government spending (RSL)
- 6. Real non-residential investment (RNRES)
- 7. Real residential investment (RRES)
- 8. 3-month Treasury bill (TBILL)

9. 10-year government bond (TBOND)

### 10. Unemployment rate (UE)

Tables A5 and A6 report the estimates of annual versions of regressions (1) and (2) across different macroeconomic variables in the SPF.

	Estimate	Std. error	Forecasters	Obs
Unemployment rate	0.167	0.108	163	4151
3-month Treasury bill	$0.143^{*}$	0.082	158	3876
10-year bond	-0.052	0.073	113	3207
GDP Deflator	-0.190***	0.044	135	3700
Nominal GDP	-0.101**	0.048	159	3830
Real consumption expenditures	-0.115***	0.039	131	3713
Real federal government spending	-0.100	0.060	144	3499
Real state & local government spending	-0.338***	0.086	144	3517
Real residential investment	0.002	0.089	146	3634
Real non-residential investment	0.085	0.097	146	3663

Table A5: Annual Errors vs. Annual Revisions, by Variable

Note: The table reports estimates of the annual analog to regression (1). Standard errors are reported in parentheses. Standard errors are clustered by forecaster and time. \*\*\* denotes 1% significance, \*\* denotes 5% significance, and \* denotes 10% significance.

Table A7 reports estimates of regression (4) for different macroeconomic variables in the SPF.

	Estimate	Std. error	Forecasters	Obs
Unemployment rate	-0.025**	0.011	175	5116
3-month Treasury bill	-0.026**	0.013	172	4818
10-year bond	0.0004	0.016	114	3910
GDP deflator	-0.043**	0.022	135	4594
Nominal GDP	-0.050*	0.026	173	4771
Real consumption expenditures	0.047	0.032	134	4530
Real federal government spending	0.040	0.031	162	4380
Real state & local government spending	0.026	0.035	161	4389
Real residential investment	0.017	0.029	164	4512
Real non-residential investment	-0.072**	0.028	163	4548

Table A6: Annual Errors vs. Annual Outcome, by Variable

Note: The table reports estimates of the annual analog to regression (3). Standard errors are reported in parentheses. Standard errors are clustered by forecaster and time. \*\*\* denotes 1% significance, \*\* denotes 5% significance, and \* denotes 10% significance.

	Estimate	Std. error	Forecasters	Obs
Unemployment rate	0.361***	0.114	166	4172
3-month Treasury bill	$0.377^{***}$	0.087	158	3901
10-year bond	0.008	0.082	113	3236
GDP Deflator	0.022	0.022	135	3749
Nominal GDP	$0.044^{***}$	0.014	161	3845
Real consumption expenditures	0.006	0.018	131	3726
Real federal government spending	0.010	0.015	144	3524
Real state & local government spending	0.027	0.020	144	3532
Real residential investment	$0.062^{***}$	0.020	145	3651
Real non-residential investment	$0.048^{*}$	0.028	145	3659

Table A7: Annual Errors vs. Lagged G	Quarterly Errors,	by Variable
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Note: The table reports estimates of the annual analog to regression (3). Standard errors are reported in parentheses. Standard errors are clustered by forecaster and time. \*\*\* denotes 1% significance, \*\* denotes 5% significance, and \* denotes 10% significance.





Note: The figure plots estimates of regression (6) across different variables in the SPF. Standard errors are clustered at the forecaster and date levels





Note: The figure plots estimates of regression (6) across different variables in the SPF. Standard errors are clustered at the forecaster and date levels.

Figure A4: Offsetting interaction regression, two-quarter ahead horizon



Note: The figure plots estimates of regression (6) across different variables in the SPF. Standard errors are clustered at the forecaster and date levels.





Note: The figure plots estimates of regression (6) across different variables in the SPF. Standard errors are clustered at the forecaster and date levels.

#### Other Surveys

In this section, we show that our empirical findings arise in surveys outside of the SPF. Since our analysis requires the availability of an annual forecast and its quarter-by-quarter path, we are unable to utilize surveys such as BlueChip, Consensus Economics, or the ECB Survey of Professional Forecasters. However, we are able to exploit the Bloomberg (BBG) Survey and the Wall Street Journal (WSJ) Survey.

The BBG and WSJ surveys are non-anonymous surveys of professional forecasters. We observe the forecasters' quarterly forecasts for a given year as well as their calendar year forecasts. Our sample for the BBG survey spans 1993Q2 to 2016Q3 while our WSJ sample spans 1982Q1 to 2019Q4.

Table A8 reports the BGMS coefficient and Kohlhas and Walther (2021) coefficient across both surveys and verifies that quarterly forecasts exhibit overreaction at the individual level.

	В	BG	W	SJ
	Error	Error	Error	Error
Revision	-0.443*		-0.587***	
	(0.237)		(0.111)	
Realization		-0.387**		-0.189***
		(0.152)		(0.066)
Forecasters	33	39	84	132
Observations	151	182	544	2153

Table A8: Individual-level Quarterly Overreactions in BBG and WSJ Surveys

Note: The table reports panel regression results of (1) and (2) from BBG and WSJ forecasts. Standard errors clustered by forecaster and time are reported in parentheses. \*\*\* denotes 1% significance, \*\* denotes 5% significance, and \* denotes 10% significance.

Table A9 reports the annual analog to the regressions in Table A8, which shows that there is no evidence of annual overreaction at the forecaster level.

	BI	BG	W	SJ
	Error	Error	Error	Error
Revision	0.025		-0.025	
	(0.066)		(0.017)	
Realization		-0.102		-0.142
		(0.113)		(0.133)
Forecasters	62	57	148	144
Observations	269	228	3546	2528

Table A9: No Individual-level Annual Overreactions in BBG and WSJ Surveys

Note: The table reports panel regression results of the annual analogs of (1) and (2) from BBG and WSJ forecasts. Standard errors clustered by forecaster and time are reported in parentheses. \*\*\* denotes 1% significance, \*\* denotes 5% significance, and \* denotes 10% significance.

# Appendix B Model

In this section, we describe the multi-frequency model featuring annual smoothing in further detail. We also derive the errors-on-revisions coefficient from the perspective of the model.

## **B.1** Model Description

Suppose that in each period, professional forecasters devise predictions at some point in time,  $\ell h$ , for some future period  $\ell' h'$ . The subscript  $\ell$  represents the low frequency period while the subscript h denotes the high frequency period (within the low frequency period). For instance,  $\ell h$  can refer to a year-quarter (e.g., year 2019, quarter 1). We define H to be the total number of high frequency periods within a low frequency period. For instance, there are H = 4 quarters in a year.

Forecasters in the model wish to minimize their squared errors:

$$\min_{\{\widehat{x}_{\ell'h'|\ell h}^{i}\}} \sum_{\ell'=\ell}^{\infty} \sum_{h'=1}^{H} (x_{\ell'h'} - \widehat{x}_{\ell'h'|\ell h}^{i})^{2}, \quad \ell', \ell \in [0,\infty), \quad h', h \in [1,H],$$
(11)

where  $\widehat{x}_{\ell'h'|\ell h}^{i}$  denotes forecaster *i*'s predictions about *x* in period  $\ell'h'$  based on information in period  $\ell h$ .

When forecasters are able to freely update high and low frequency forecasts, they report the following optimal high frequency prediction:

$$\widehat{x}^{i}_{\ell'h'|\ell h} = \mathbb{E}_{i\ell h}(x_{\ell'h'}),$$

and low frequency prediction,

$$\widehat{x}^{i}_{\ell'|\ell} = \frac{1}{H} \sum_{h'=1}^{H} \widehat{x}^{i}_{\ell'h'|\ell h}.$$

If a forecaster is able to update her short-run predictions but not her long-run predictions, then she must solve the optimization problem above subject to the requirement that the updated high frequency forecasts coincide with the outdated low frequency forecast:

$$\frac{1}{H}\sum_{h'=1}^{H}\widehat{x}_{\ell'h'|\ell h}^{i} = \frac{1}{H}\sum_{h'=1}^{H}\widehat{x}_{\ell'h'|\ell h-j}^{i},$$
(12)

where  $\hat{x}^i_{\ell'h'|\ell h-j}$  denotes the period in which the annual forecast was last updated.

In this case, the forecaster solves (11) subject to (12).

The Lagrangian is

$$\mathcal{L} = \sum_{\ell'=\ell}^{\infty} \left\{ \sum_{h'=1}^{H} (x_{\ell'h'} - \widehat{x}_{\ell'h'|\ell h}^{i})^2 - \lambda \left( \frac{1}{H} \sum_{h'=1}^{H} \widehat{x}_{\ell'h'|\ell h}^{i} - \frac{1}{H} \sum_{h'=1}^{H} \widehat{x}_{\ell'h'|\ell h-j}^{i} \right) \right\}$$

The first order condition with respect to the reported forecast  $\hat{x}^i_{\ell' h' | \ell h}$  implies

$$\widehat{x}^{i}_{\ell'h'|\ell h} = \mathbb{E}_{i\ell h}(x_{\ell'h'}) + \frac{\lambda}{2H}.$$
(13)

Combining the FOC with the definition of the constraint delivers:

$$\frac{1}{H} \sum_{h'=1}^{H} \widehat{x}_{\ell'h'|\ell h-j}^{i} = \frac{1}{H} \sum_{h'=1}^{H} \left[ \mathbb{E}_{i\ell h}(x_{\ell'h'}) + \frac{\lambda}{2H} \right].$$

Rearranging, we obtain:

$$\lambda = 2H \left[ \frac{1}{H} \sum_{h'=1}^{H} \widehat{x}_{\ell'h'|\ell h-j}^{i} - \frac{1}{H} \sum_{h'=1}^{H} \mathbb{E}_{i\ell h}(x_{\ell'h'}) \right]$$

Substituting this expression for the Lagrange multiplier into the FOC for the reported forecast, we recover an intuitive expression:

$$\widehat{x}_{\ell'h'|\ell h}^{i} = \mathbb{E}_{i\ell h}(x_{\ell'h'}) + \left[\frac{1}{H}\sum_{h'=1}^{H}\widehat{x}_{\ell'h'|\ell h-j}^{i} - \frac{1}{H}\sum_{h'=1}^{H}\mathbb{E}_{i\ell h}(x_{\ell'h'})\right]$$

or, equivalently,  $^{22}$ 

$$\widehat{x}_{\ell'h'|\ell h}^{i} = \mathbb{E}_{i\ell h}(x_{\ell'h'}) + \frac{1}{H} \sum_{h'=1}^{H} \left[ \mathbb{E}_{i\ell h-j}(x_{\ell'h'}) - \mathbb{E}_{i\ell h}(x_{\ell'h'}) \right].$$
(14)

<sup>22</sup>This follows from the fact that whenever the forecaster constructed her outdated annual, she did so optimally, based on the conditional expectation as of date  $\ell h - j$ .

## **B.2** Errors-on-Revisions Coefficient

We can express the forecaster's reported forecast as:

$$\widehat{x}^{i}_{\ell h'|\ell h} = \mathbb{E}^{i}_{\ell h}(x_{\ell h'}) + \frac{1}{H} \sum_{j'=0}^{H} \left[ \mathbb{E}^{i}_{\ell h-k}(x_{\ell j'}) - \mathbb{E}^{i}_{\ell h}(x_{\ell j'}) \right]$$

where  $0 \le h - k \le h \le h' \le H$ . In other words, the forecast devised at time  $\ell h$  for future period  $\ell h'$  is equal to the conditional expectation plus a sum of revisions of x from  $\ell 0, ..., \ell H$ where the revision is taken relative to the expectation at  $\ell h - k$  which denotes the period in which the annual forecast was last updated.

We can express this more generally in order to account for the fact that  $\ell h$  can refer to any point in the calendar year. If  $\ell h$  were in, say, Q2, then the forecast would include some past errors in the summation. In other words, we can split the sum above and express the reported forecast as:

$$\widehat{x}_{\ell h'|\ell h}^{i} = \mathbb{E}_{\ell h}^{i}(x_{\ell h'}) - \frac{1}{H} \sum_{j=k}^{h-1} \left[ x_{\ell j} - \mathbb{E}_{\ell j}^{i}(x_{\ell j}) \right] - \frac{1}{H} \sum_{j'=h}^{H} \left[ \mathbb{E}_{\ell h}^{i}(x_{\ell j'}) - \mathbb{E}_{\ell h-k}^{i}(x_{\ell j'}) \right]$$

Now, the middle term reflects nowcast errors between yesterday  $(\ell h - 1)$  and when the annual forecast was last updated  $(\ell h - k)$ . We don't care about the forecast errors between  $\ell 0, ..., \ell k - 1$  because those would have already been updated at  $\ell k$  (i.e., when the annual forecast was last revised).

The forecast error is:

$$x_{\ell h'} - \widehat{x}_{\ell h'|\ell h}^{i} = x_{\ell h'} - \mathbb{E}_{\ell h}^{i}(x_{\ell h'}) + \frac{1}{H} \sum_{j=k}^{h-1} \left[ x_{\ell j} - \mathbb{E}_{\ell j}^{i}(x_{\ell j}) \right] + \frac{1}{H} \sum_{j'=h}^{H} \left[ \mathbb{E}_{\ell h}^{i}(x_{\ell j'}) - \mathbb{E}_{\ell h-k}^{i}(x_{\ell j'}) \right]$$

The forecast error is a function of: (i) the optimal forecast error, (ii) lagged nowcast error(s), and (iii) forecast revisions.

Turning to the forecast revision, if a forecaster in our model revises her quarterly forecast today, then she must either be optimally updating both her quarterly and annual forecasts, or she must be updating her quarterly forecast but not her annual forecast. In the first case, forecast errors and revisions are optimal and there is no correlation between the two. In the second case, we can get non-zero  $\beta(FE, FR)$ . Suppose that we are in the second case.

In addition, it is possible that the forecaster was able to update both the annual forecast yesterday. On the other hand, it is also possible that the forecaster was only able to update the quarterly forecast yesterday, leaving the annual the same. So there are two cases to potentially consider: (i) Case 2 updating today with Case 1 updating yesterday, and (ii) Case 2 updating today with Case 2, 3, or 4 updating yesterday. Below, we derive the errors-on-revisions coefficient assuming (i) and then show that the forecaster's reported forecast revision is the same in (ii) as it is in (i), implying that (i) and (ii) yield the same errors-on-revisions coefficient.

### (i) Case 2 updating today, Case 1 updating yesterday

If we have Case 2 updating today with Case 1 updating yesterday, then deriving the errorson-revisions coefficient is fairly straightforward. In this case, k = h - 1 so the error is:

$$\begin{aligned} x_{\ell h'} - \widehat{x}_{\ell h'|\ell h}^{i} &= x_{\ell h'} - \mathbb{E}_{\ell h}^{i}(x_{\ell h'}) + \frac{1}{H} \left[ x_{\ell h-1} - \mathbb{E}_{\ell h-1}^{i}(x_{\ell h-1}) \right] + \frac{1}{H} \sum_{j'=h}^{H} \left[ \mathbb{E}_{\ell h}^{i}(x_{\ell j'}) - \mathbb{E}_{\ell h-1}^{i}(x_{\ell j'}) \right] \\ &= x_{\ell h'} - \mathbb{E}_{\ell h}^{i}(x_{\ell h'}) + \frac{1}{H} \left[ x_{\ell h-1} - \mathbb{E}_{\ell h-1}^{i}(x_{\ell h-1}) \right] + \left( \frac{1}{H} \sum_{j'=h}^{H} \rho^{j'} \right) \left[ \mathbb{E}_{\ell h}^{i}(x_{\ell h}) - \mathbb{E}_{\ell h-1}^{i}(x_{\ell h}) \right] \end{aligned}$$

and the forecast revision is:

$$\begin{aligned} \widehat{x}_{\ell h'|\ell h}^{i} - \widehat{x}_{\ell h'|\ell h-1} &= \mathbb{E}_{\ell h}^{i}(x_{\ell h'}) - \frac{1}{H} \Big[ x_{\ell h-1} - \mathbb{E}_{\ell h-1}^{i}(x_{\ell h-1}) \Big] - \frac{1}{H} \sum_{j'=h}^{H} \Big[ \mathbb{E}_{\ell h}^{i}(x_{\ell j'}) - \mathbb{E}_{\ell h-1}^{i}(x_{\ell j'}) \Big] - \mathbb{E}_{\ell h-1}^{i}(x_{\ell h'}) \\ &= \mathbb{E}_{\ell h}^{i}(x_{\ell h'}) - \mathbb{E}_{\ell h-1}^{i}(x_{\ell h'}) - \frac{1}{H} \Big[ x_{\ell h-1} - \mathbb{E}_{\ell h-1}^{i}(x_{\ell h-1}) \Big] - \frac{1}{H} \sum_{j'=h}^{H} \Big[ \mathbb{E}_{\ell h}^{i}(x_{\ell j'}) - \mathbb{E}_{\ell h-1}^{i}(x_{\ell j'}) \Big] \\ &= \Big( \rho^{h'-h} - \frac{1}{H} \sum_{j'=h}^{H} \rho^{j'} \Big) \Big[ \mathbb{E}_{\ell h}^{i}(x_{\ell h}) - \mathbb{E}_{\ell h-1}^{i}(x_{\ell h}) \Big] - \frac{1}{H} \Big[ x_{\ell h-1} - \mathbb{E}_{\ell h-1}^{i}(x_{\ell h-1}) \Big] \end{aligned}$$

The covariance of errors and revisions is

$$Cov(FE, FR) = \frac{1}{H} \left( \rho^{h'-h} - \frac{2}{H} \sum_{j'=h}^{H} \rho^{j'} \right) Cov \left( x_{\ell h-1} - \mathbb{E}^{i}_{\ell h-1}(x_{\ell h-1}), \mathbb{E}^{i}_{\ell h}(x_{\ell h}) - \mathbb{E}^{i}_{\ell h-1}(x_{\ell h}) \right) - \left( \frac{1}{H} \right)^{2} Var \left( x_{\ell h-1} - \mathbb{E}^{i}_{\ell h-1}(x_{\ell h-1}) \right) + \left( \frac{1}{H} \sum_{j'=h}^{H} \rho^{j'} \right) \left[ \rho^{h'-h} - \frac{1}{H} \sum_{j'=h}^{H} \rho^{j'} \right] Var \left( \mathbb{E}^{i}_{\ell h}(x_{\ell h}) - \mathbb{E}^{i}_{\ell h-1}(x_{\ell h}) \right)$$

The variance of the forecast revision is:

$$\begin{aligned} Var(\hat{x}_{\ell h'|\ell h} - \hat{x}_{\ell h'|\ell h-1}) &= Var\left( \left[ \rho^{h'-h} - \frac{1}{H} \sum_{j'=h}^{H} \rho^{j'} \right] \left( \mathbb{E}_{\ell h}^{i}(x_{\ell h}) - \mathbb{E}_{\ell h-1}^{i}(x_{\ell h}) \right) - \frac{1}{H} \left[ x_{\ell h-1} - \mathbb{E}_{\ell h-1}^{i}(x_{\ell h-1}) \right] \right) \\ &= \left( \rho^{h'-h} - \frac{1}{H} \sum_{j'=h}^{H} \rho^{j'} \right)^{2} Var\left( \mathbb{E}_{\ell h}^{i}(x_{\ell h} - \mathbb{E}_{\ell h-1}^{i}(x_{\ell h}) \right) \\ &+ \left( \frac{1}{H} \right)^{2} Var\left( x_{\ell h-1} - \mathbb{E}_{\ell h-1}^{i}(x_{\ell h-1}) \right) \\ &- \frac{2}{H} \left( \rho^{h'-h} - \frac{1}{H} \sum_{j'=h}^{H} \rho^{j'} \right) Cov\left( x_{\ell h-1} - \mathbb{E}_{\ell h-1}^{i}(x_{\ell h-1}), \mathbb{E}_{\ell h}^{i}(x_{\ell h}) - \mathbb{E}_{\ell h-1}^{i}(x_{\ell h}) \right) \end{aligned}$$

Recall that  $\kappa_1$  and  $\kappa_2$  denote the Kalman gain coefficients associated with the contemporaneous signal,  $y_{\ell h}^i$  and  $x_{\ell h-1}$ , respectively. In addition, let  $\Psi_{11}$  and  $\Psi_{22}$  denote the variance of the one step ahead state estimation error,  $Var(s_{\ell h} - \mathbb{E}_{\ell h-1}^i(s_{\ell h}))$  and the lagged currentquarter state estimation error,  $Var(s_{\ell h-1} - \mathbb{E}_{\ell h-1}^i(s_{\ell h-1}))$ , where  $\Psi_{11} = \rho \Psi_{22} + \sigma_w^2$ . These variances and Kalman gains are obtained from the Kalman filter.

Using this notation, we can express the variance of the lagged current-quarter error as:

$$Var(x_{\ell h-1} - \mathbb{E}^{i}_{\ell h-1}(x_{\ell h-1})) = \Psi_{22} + \sigma_{e}^{2},$$

the variance of the revision as:

$$Var\left(\mathbb{E}_{\ell h}^{i}(x_{\ell h}) - \mathbb{E}_{\ell h-1}^{i}(x_{\ell h})\right) = \kappa_{1}^{2}(\Psi_{11} + \sigma_{v}^{2}) + \kappa_{2}^{2}(\Psi_{22} + \sigma_{e}^{2}) + 2\kappa_{1}\kappa_{2}\rho\Psi_{22},$$

and the covariance of the revision and the lagged current-quarter error as:

$$Cov\left(\mathbb{E}_{\ell h-1}^{i}(x_{\ell h}) - \mathbb{E}_{\ell h-1}^{i}(x_{\ell h-1}), x_{\ell h-1} - \mathbb{E}_{\ell h-1}^{i}(x_{\ell h-1})\right) = (\kappa_{1}\rho + \kappa_{2})\Psi_{22} + \kappa_{2}\sigma_{e}^{2}.$$

As a result, the errors-on-revisions coefficients can be expressed as:

$$\beta(FE, FR) = \frac{Cov(FE, FR)}{Var(FR)}$$

where

$$Cov(FE, FR) = \frac{1}{H} (\rho^{h'-h} - \frac{2}{H} \sum_{j'=h}^{H} \rho^{j'}) \left[ (\kappa_1 \rho + \kappa_2) \Psi_{22} + \kappa_2 \sigma_e^2 \right] - \frac{1}{H^2} (\Psi_{22} + \sigma_e^2) + \left( \frac{1}{H} \sum_{j'=h}^{H} \rho^{j'} \right) (\rho^{h'-h} - \frac{1}{H} \sum_{j'=h}^{H} \rho^{j'}) \left[ (\kappa_1^2 (\Psi_{11} + \sigma_v^2) + \kappa_2^2 (\Psi_{22} + \sigma_e^2) + 2\kappa_1 \kappa_2 \rho \Psi_{22} \right]$$

and

$$Var(FR) = (\rho^{h'-h} - \frac{1}{H} \sum_{j'=h}^{H} \rho^{j'})^2 \left[ \kappa_1^2 (\Psi_{11} + \sigma_v^2) + \kappa_2^2 (\Psi_{22} + \sigma_e^2) + 2\kappa_1 \kappa_2 \rho \Psi_{22} \right] + \frac{1}{H^2} (\Psi_{22} + \sigma_e^2) - \frac{2}{H} (\rho^{h'-h} - \frac{1}{H} \sum_{j'=h}^{H} \rho^{j'}) \left[ (\kappa_1 \rho + \kappa_2) \Psi_{22} + \kappa_2 \sigma_e^2 \right]$$

#### (ii) Case 2 updating today, no Case 1 updating yesterday

In this case, since the annual was neither updated today nor yesterday, we can denote  $\ell h - k$  as the period in which the annual was last updated. The error is:

$$FE = x_{\ell h'} - \mathbb{E}_{\ell h'}^{i} + \frac{1}{H} \sum_{j=k}^{h-1} \left[ x_{\ell j} - \mathbb{E}_{\ell j}^{i}(x_{\ell j}) \right] + \frac{1}{H} \sum_{j'=h}^{H} \left[ \mathbb{E}_{\ell h}^{i}(x_{\ell j'}) - \mathbb{E}_{\ell h-k}^{i}(x_{\ell j'}) \right]$$
$$= x_{\ell h'} - \mathbb{E}_{\ell h'}^{i} + \frac{1}{H} \sum_{j=k}^{h-1} \left[ x_{\ell j} - \mathbb{E}_{\ell j}^{i}(x_{\ell j}) \right] + \left( \frac{1}{H} \sum_{j'=h}^{H} \rho^{j'} \right) \left[ \mathbb{E}_{\ell h}^{i}(x_{\ell h}) - \mathbb{E}_{\ell h-k}^{i}(x_{\ell h}) \right]$$
$$= x_{\ell h'} - \mathbb{E}_{\ell h'}^{i} + \frac{1}{H} \sum_{j=k}^{h-2} \left[ x_{\ell j} - \mathbb{E}_{\ell j}^{i}(x_{\ell j}) \right] + \left[ x_{\ell h-1} - \mathbb{E}_{\ell h-1}^{i}(x_{\ell h-1}) \right]$$
$$+ \left( \frac{1}{H} \sum_{j'=h}^{H} \rho^{j'} \right) \left[ \mathbb{E}_{\ell h}^{i}(x_{\ell h}) - \mathbb{E}_{\ell h-k}^{i}(x_{\ell h}) \right]$$

In the last line above, we split apart the summation in the second term. As we can see, the difference in the expression of the forecast error in this case versus the previous case boils down to this case including passed errors as well,  $\frac{1}{H}\sum_{j=k}^{h-2} (x_{\ell j} - \mathbb{E}_{\ell j}^{i}(x_{\ell j}))$ .

The forecast revision is:

$$\mathbb{E}_{\ell h}^{i}(x_{\ell h'}) - \frac{1}{H} \sum_{j=k}^{h-1} \left[ x_{\ell j} - \mathbb{E}_{\ell j}^{i}(x_{\ell j}) \right] - \frac{1}{H} \sum_{j'=h}^{H} \left[ \mathbb{E}_{\ell h}^{i}(x_{\ell j'}) - \mathbb{E}_{\ell h-k}^{i}(x_{\ell j'}) \right] \\ -\mathbb{E}_{\ell h-1}^{i}(x_{\ell h'}) + \frac{1}{H} \sum_{j=k}^{h-2} \left[ x_{\ell j} - \mathbb{E}_{\ell j}^{i}(x_{\ell j}) \right] + \frac{1}{H} \sum_{j'=h}^{H} \left[ \mathbb{E}_{\ell h-1}^{i}(x_{\ell j'}) - \mathbb{E}_{\ell h-k}^{i}(x_{\ell j'}) \right]$$

Simplifying this expression, we obtain:

$$\mathbb{E}_{\ell h}^{i}(x_{\ell h'}) - \mathbb{E}_{\ell h-1}^{i}(x_{\ell h'}) - \frac{1}{H} \left[ x_{\ell h-1} - \mathbb{E}_{\ell h-1}^{i}(x_{\ell h-1}) \right] - \frac{1}{H} \sum_{j'=h}^{H} \left[ \mathbb{E}_{\ell h}^{i}(x_{\ell j'}) - \mathbb{E}_{\ell h-1}^{i}(x_{\ell j'}) \right]$$

The forecast revision here is the same as the forecast revision obtained when assuming that forecasters efficiently updated last period.

Since the revisions are identical across (i) and (ii), we know that the variance of the revision will be the same too. Will the covariance of the errors and revisions be the same

as well? Yes. The only difference is the additional term in the forecast error reflecting past errors, but this term is uncorrelated with any of the terms defining the forecast revision. This means that we will recover the exact same covariance of errors and revisions derived above. Taken together, this implies that the errors-on-revisions coefficient will also be the same as the one derived above.

# Appendix C Estimation

The model is estimated via the simulated method of moments. Operationally, this is done by simulating a balanced panel of 250 forecasters over 40 periods, consistent with the average number of quarterly forecasts that a unique forecaster contributes throughout the history of the survey.<sup>23</sup> For each iteration, the target moments are computed, averaged across simulations, and compared to their empirical analogs. The six-dimensional parameter vector,  $\theta$ , is selected to minimize the weighted distance between simulated moments and empirical moments, where the asymptotically efficient weighting matrix is specified.

Formally, we search the parameter space, using a particle swarm procedure, to find the  $\hat{\theta}$  that minimizes the following objective

$$\min_{\theta} \left( m(\theta) - m(X) \right)' W \left( m(\theta) - m(X) \right)$$

where  $m(\theta)$  denotes the simulated moments, m(X) denotes the empirical moments, and W denotes the weighting matrix. The limiting distribution of the estimated parameter vector  $\hat{\theta}$  is

$$\sqrt{N}(\widehat{\theta} - \theta) \stackrel{d}{\to} \mathcal{N}(0, \Sigma)$$

where

$$\Sigma = \left(1 + \frac{1}{S}\right) \left[ \left(\frac{\partial m(\theta)}{\partial \theta}\right)' W\left(\frac{\partial m(\theta)}{\partial \theta}\right) \right]^{-1}$$

and S = 100. Standard errors are obtained by numerically computing the partial derivative of the simulated moment vector with respect to the parameter vector.

### C.1 Identification

The eight moments jointly determine the six parameters that reside in vector  $\theta$ . Figure C6 illustrates some important comparative statics that lend support to the choice of target moments which are discussed below.

The underlying persistence of the latent state,  $\rho$ , is in part identified by the covariance between the current-quarter forecast and the current-year forecast. With a highly persistent

<sup>&</sup>lt;sup>23</sup>Similar results are obtained when mimicking the unbalanced nature of the panel data by simulating a larger set of forecasters and matching missing observations.

data generating process, the covariance between current-quarter and current-year forecasts will be strongly positive. Moreover, the updating probabilities, q and p, inform the relevant mean squared errors.

The dispersion parameters,  $\sigma_w$ ,  $\sigma_e$ , and  $\sigma_v$  require further discussion. Two of these parameters reflect noise variance ( $\sigma_e$  and  $\sigma_v$ ) while the other ( $\sigma_w$ ) reflects the variance of the latent state innovations. Recognizing the distinction between noise and signal is essential for the identification of these parameters.

First, the variance of the underlying state innovations,  $\sigma_w$ , is identified in part from the variance of the current-year forecast. Recall that the current-year forecast is:  $\frac{1}{4} \sum_{h=0}^{3} \hat{x}_{t+h|t}^i$ . As the end of the year approaches, more and more realizations of  $x_t$  within the year figure into the optimal current-year projection, replacing the filtered forecasts that are subject to private noise. For this reason, an increase in  $\sigma_w$  raises the variance of the current-year forecast.

Moreover, higher levels of public noise,  $\sigma_e$ , contribute to a larger forecast error variance. The link between common noise and the variance of errors is intuitive since the transitory component,  $e_t$ , is linear in the macroeconomic aggregate being predicted  $(x_t)$ .

Lastly, private noise variance,  $\sigma_v$ , informs the covariance between revisions and lagged errors. Based on the model, the filtered current-quarter forecast revision is:

$$x_{t|t}^{i} - x_{t|t-1}^{i} = \kappa_1(y_t^{i} - x_{t|t-1}^{i}) + \kappa_2(x_{t-1} - x_{t-1|t-1}^{i}).$$

where  $\kappa_1$  and  $\kappa_2$  denote the Kalman gains. An increase in  $\sigma_v$  reduces the Kalman gain weight placed on the private signal,  $\kappa_1$ . As  $\sigma_v$  rises, fluctuations in the current-quarter revision are increasingly driven by lagged forecast errors, thereby strengthening the covariance between the revision and the lagged error. In other words, with less informative private signals, forecasters trust  $y_t^i$  less and instead base more of their revisions on the news gleaned from yesterday's error.



### Figure C6: Comparative Statics

Note: Each panel displays a monotonic relationship between the parameter on the horizontal axis and a given moment. The vertical axis measures the percent deviation of the given moment from its estimated value in Table 5.

# Appendix D Estimation Results and Robustness

In this section, we detail estimation results reported in the main text and conduct a variety of additional model-based exercises. Section D.1 reports the non-targeted fit of the baseline model to consensus-level moments. Section D.2 augments our model with diagnostic expectations to assess the relative importance of our mechanism in generating overreactions. Section D.3 reports the estimates based SPF inflation forecasts, from which we obtain estimates of information frictions in Section 7. Section D.4 examines the role that rounding plays in the parameter estimates. Section D.5, undertakes a sub-sample analysis, estimating the baseline model before and after 1990. Finally, Section D.6 considers an alternative data generating process for the underlying state.

### D.1 Aggregate Underreactions

Whereas individual forecasters appear to overreact, consensus predictions exhibit underreaction. This inertia at the aggregate level has been of interest to the literature studying information rigidities. In this section, we explore the consensus-level analogs to the overreaction regressions in the main text and show that our baseline model is able to generate these aggregate underreactions as well. Intuitively, while annual anchoring generates offsetting and overreactions at the forecaster level, the imperfect information environment allows us to recover underreactions at the consensus level.

Table D10 reports ten moments in the data and the model-based counterparts. In general, the baseline model is also able to successfully fit the majority of these moments.

	Mo	odel	D	ata
1. $\beta(FECQ, FRCQ)$	0.446	(0.070)	0.354	(0.178)
2. $\beta(FE1Q, FR1Q)$	0.569	(0.264)	0.676	(0.314)
3. $\beta(FE2Q, FR2Q)$	-0.063	(0.532)	0.694	(0.374)
4. $\beta(FE3Q, FR2Q)$	-0.794	(0.806)	-0.464	(0.222)
5. $\beta(FRCQ, FR1Q_{-1})$	0.346	(0.152)	0.401	(0.112)
6. $\beta(FR1Q, FR2Q_{-1})$	0.042	(0.107)	0.448	(0.134)
7. $\beta(FR2Q, FR3Q_{-1})$	-0.397	(0.075)	0.135	(0.109)
8. $\beta(FEYY, FRYY)$	0.475	(0.148)	0.648	(0.275)
9. $\beta$ (FEYY, Outcome)	-0.066	(0.096)	-0.077	(0.064)
10. $\beta(FECQ, FECQ_{-1})$	0.099	(0.067)	0.084	(0.074)

Table D10: Baseline Model Fit to Consensus Moments

Note: The table reports consensus-level analogs to the simulated and empirical regression coefficients reported in Table 6. Standard deviations and Newey-West standard errors are reported in parentheses. 'FE' refers to forecast error, 'FR' refers to forecast revision, and 'CQ, 1Q, 2Q, 3Q, YY' refer to current quarter, one-quarter ahead, two-quarters ahead, three-quarters ahead, and year-over-year, respectively.

## D.2 Diagnostic Expectations

Table D11 reports the parameter estimates for the unconstrained and constrained models. These models are estimated by targeting the original eight moments listed in Table 5 as well as the covariance of contemporaneous errors and revisions and the variance of contemporaneous errors. The unconstrained model estimates the annual smoothing plus diagnostic expectations model. The constrained model estimates a version without diagnostic expectations.

		(1)	(2)
	Parameter	Unconstrained	Constrained
Persistence of latent state	ρ	0.544	0.488
		(0.058)	(0.047)
State innovation dispersion	$\sigma_w$	1.455	1.757
		(0.178)	(0.131)
Public signal noise	$\sigma_{e}$	1.093	0.774
		(0.200)	(0.194)
Private signal noise	$\sigma_v$	0.876	1.442
		(0.260)	(0.311)
Probability of quarterly update	q	0.784	1.000
		(0.102)	(0.044)
Probability of annual update	p	0.473	0.597
		(0.042)	(0.054)
Diagnosticity	heta	0.501	0.000
		(0.115)	-

Table D11: Model Estimation Results, Diagnostic Expectations

Note: The table reports parameter estimates of the model with and without diagnostic expectations. The "Unconstrained" column refers to the full model with annual inattention and diagnostic expectations. The "Constrained" column refers to the model with only annual inattention. Standard errors are reported in parentheses.

Figure D7 plots the contributions of annual anchoring and diagnostic expectations to measures of individual overreaction based on the unconstrained and constrained parameter estimates reported in Table D11. This differs from Figure 4 in that the counterfactual in Figure 4 features the same parameters as the unconstrained model, but with  $\theta$  fixed at zero.

Figure D7: Annual Smoothing vs. Diagnostic Expectation Contributions



Note: The figure plots the contributions of annual smoothing and diagnostic expectations, to three measures of overreactions.

## D.3 Inflation Forecasts

Table D12 reports model estimates using SPF inflation forecasts based on the GDP deflator.

Panel A: Parameter Estimates			
	Parameter	Estimate	Standard error
Persistence of latent state	ρ	0.585	0.081
State innovation dispersion	$\sigma_w$	1.041	0.072
Public signal noise	$\sigma_{e}$	0.950	0.109
Private signal noise	$\sigma_v$	0.566	0.149
Probability of quarterly update	q	1.000	0.152
Probability of annual update	p	0.552	0.084
Panel B: Moments			
	Model moment	Data moment	t-statistic
Standard deviation of nowcast	1.064	1.168	1.166
Correlation of nowcast with annual forecast	0.767	0.757	0.840
Standard deviation of annual forecast	0.773	0.806	0.632
Standard deviation of revision	0.908	1.118	1.775
Correlation of revision with lagged error	0.133	0.168	0.808
Standard deviation of lagged error	1.162	1.256	1.328
RMSE nowcast	1.174	1.257	1.424
RMSE annual forecast	0.748	0.819	1.167

Table D12: Model Estimation Results, Inflation Forecasts (Deflator)

Note: Panel A reports the model parameters with point estimates reported in the third column and standard errors reported in the fourth column. Panel B reports the model vs. data moments with t-statistics reported in the fourth column.

## D.4 Rounding

We report parameter estimates under the assumption that forecasters round their predictions to the nearest 0.10 percentage point. We find that this rounding assumption does not meaningfully change our parameter estimates.<sup>24</sup>

Panel A: Parameter Estimates			
	Parameter	Estimate	Standard error
Persistence of latent state	ρ	0.401	0.034
State innovation dispersion	$\sigma_w$	2.016	0.158
Public signal noise	$\sigma_{e}$	0.816	0.353
Private signal noise	$\sigma_v$	1.595	0.364
Probability of quarterly update	q	0.997	0.129
Probability of annual update	p	0.620	0.032
Panel B: Moments			
	Model moment	Data moment	t-statistic
Standard deviation of nowcast	1.656	1.719	-0.623
Correlation of nowcast with annual forecast	0.689	0.670	-0.211
Standard deviation of annual forecast	1.093	1.103	-0.178
Standard deviation of revision	1.573	1.615	-0.295
Correlation of revision with lagged error	0.242	0.143	1.603
Standard deviation of lagged error	1.644	1.720	-0.889
RMSE nowcast	1.657	1.677	-0.415
	1.007	1.011	01110

Table D13: Model Estimation Results (Rounding to nearest 0.1 pp)

Note: Panel A reports the model parameters with point estimates reported in the third column and standard errors reported in the fourth column. Panel B reports the model vs. data moments with t-statistics reported in the fourth column.

<sup>&</sup>lt;sup>24</sup>Studying more traditional Gaussian measurement error introduces an identification problem between the measurement error dispersion and private signal noise dispersion,  $\sigma_v$ . At the same time, rounding is a well understood phenomenon in survey expectations. For this reason, we focus on this form of measurement error.

### D.5 Sub-sample Analysis (Pre- and Post-2000)

The SPF, as well as broader macroeconomic dynamics, experienced important changes between 1981-2019. In this section, we estimate the model for two sub-periods: 1981-1999 (Table D14) and 2000-2019 (Table D15). Overall, we find that our headline conclusions hold across the sub-samples with the estimated parameters differing across samples as expected. For instance, we estimate the underlying state to be less persistent and more volatile in the earlier period.

We can further validate these estimates by comparing them with empirical Bordalo et al. (2020) coefficients over these sub-periods. When estimating the regression, we find that they are more negative in the earlier sub-period. While our parameter estimates indicate that q(1 - p) rises in the post-2000 period, this is largely because q is estimated to be higher, not because p falls. Furthermore, as discussed in the main text, the BGMS coefficient, from the lens of our model, depends on other model parameters. Of note, we estimate a much higher persistence of the underlying process which can explain why we observe no evidence of overreaction based on the BGMS coefficient in our post-2000 sub-sample. When simulating these coefficients for the early and later sub-periods, we arrive at estimates of -0.21 and -0.13, respectively.

Panel A: Parameter Estimates			
	Parameter	Estimate	Standard error
Persistence of latent state	ρ	0.335	0.089
State innovation dispersion	$\sigma_w$	2.081	0.438
Public signal noise	$\sigma_{e}$	1.366	0.709
Private signal noise	$\sigma_v$	0.031	0.016
Probability of quarterly update	q	0.778	0.318
Probability of annual update	p	0.501	0.067
Panel B: Moments			
	Model moment	Data moment	t-statistic
Standard deviation of nowcast	1.798	2.003	-0.933
Correlation of nowcast with annual forecast	0.592	0.560	-0.790
Standard deviation of annual forecast	1.071	1.177	-0.870
Standard deviation of revision	1.704	2.146	-1.465
Correlation of revision with lagged error	0.067	0.083	-0.443
Standard deviation of lagged error	1.828	2.035	-1.159
RMSE nowcast	1.863	1.945	-1.056
RMSE annual forecast	1.240	1.300	-0.965

## Table D14: Model Estimation Results (1981-1999)

Note: Panel A reports the model parameters with point estimates reported in the third column and standard errors reported in the fourth column. Panel B reports the model vs. data moments with t-statistics reported in the fourth column.

Panel A: Parameter Estimates			
	Parameter	Estimate	Standard error
Persistence of latent state	ρ	0.624	0.035
State innovation dispersion	$\sigma_w$	1.359	0.256
Public signal noise	$\sigma_{e}$	1.129	0.308
Private signal noise	$\sigma_v$	0.720	0.345
Probability of quarterly update	q	1.000	0.121
Probability of annual update	p	0.520	0.068
Panel B: Moments			
	Model moment	Data moment	t-statistic
Standard deviation of nowcast	1.388	1.538	-2.213
Correlation of nowcast with annual forecast	0.792	0.764	-1.040
Standard deviation of annual forecast	1.031	1.060	-0.555
Standard deviation of revision	1.152	1.225	-1.334
Correlation of revision with lagged error	0.155	0.218	-1.955
Standard deviation of lagged error	1.461	1.518	-1.269
RMSE nowcast	1.481	1.509	-0.641
RMSE annual forecast	0.960	0.969	-0.260

## Table D15: Model Estimation Results (2000-2019)

Note: Panel A reports the model parameters with point estimates reported in the third column and standard errors reported in the fourth column. Panel B reports the model vs. data moments with t-statistics reported in the fourth column.

### D.6 Alternative Data Generating Process

Whereas offsetting revisions can be an artifact of annual anchoring, these patterns could also arise under a more general data generating process. If so, then we might be erroneously attributing the empirical finding to annual anchoring. In this section, we provide results in support of our mechanism under richer dynamics.

We extend our model to feature an AR(2) process for real GDP growth. We select an AR(2) process for three reasons. First, we find that the AR(2) fits real GDP growth best in the sense that it delivers the lowest information criteria.<sup>25</sup> Second, an AR(2) is highly feasible to estimate with the baseline SMM approach as it only adds one parameter to the model. Third, an AR(2) allows us to remain consistent with others in the literature who similarly examine richer data generating processes for their models (Bordalo et al., 2020).

The key modification relative to the baseline model detailed in the main text is that the underlying latent state now evolves as follows:

$$s_t = (1 - \rho_1 - \rho_2)\mu + \rho_1 s_{t-1} + \rho_2 s_{t-2} + w_t, \quad w_t \sim N(0, \sigma_w^2)$$

where  $\rho_1$  and  $\rho_2$  govern the persistence of the state. We impose the usual assumptions on these two parameters to ensure stationarity.

There are now seven parameters to be estimated. We estimate these parameters by targeting the same eight moments described in the main text. As a result, our estimator is still an overidentified SMM estimator. The results are reported in Table D16.

All the parameters are precisely estimated and the model fits the empirical moments well. We estimate  $\rho_1 > 0$  and  $\rho_2 < 0$ , indicating that AR(2) dynamics can potentially account for some of the offsetting revisions in the data. With that said, we note that controlling for adjacent revisions, there is still evidence of offsetting revisions over longer horizons. While such patterns cannot arise with an AR(2) process, they can arise under annual anchoring.

The estimated dispersion parameters are similar to those in Table 5. The quarterly updating probability is estimated to be slightly lower than the baseline estimates, while the annual updating probability is estimated to be higher. Relative to Table 8, these estimates imply roughly similar levels of information rigidity in quarterly and annual real GDP forecasts

 $<sup>^{25}\</sup>mathrm{In}$  this unreported exercise, we considered AR(2), AR(4), ARMA(1,1), ARMA(2,1) and ARMA(2,2) models.

Panel A: Parameter Estimates			
	Parameter	Estimate	Standard error
First lag autocorrelation	$ ho_1$	0.524	0.149
Second lag autocorrelation	$ ho_2$	-0.075	0.018
State innovation dispersion	$\sigma_w$	1.828	0.231
Public signal noise	$\sigma_{e}$	1.163	0.343
Private signal noise	$\sigma_v$	1.002	0.418
Probability of quarterly update	q	0.934	0.524
Probability of annual update	p	0.618	0.045
Panel B: Moments			
	Model moment	Data moment	t-statistic
Standard deviation of nowcast	1.624	1.719	-0.926
Correlation of nowcast with annual forecast	0.702	0.670	-0.588
Standard deviation of annual forecast	1.057	1.103	-0.799
Standard deviation of revision	1.486	1.615	-0.882
Correlation of revision with lagged error	0.172	0.143	0.141
Standard deviation of lagged error	1.629	1.720	-1.060
RMSE nowcast	1.645	1.677	-0.661
RMSE annual forecast	1.077	1.098	-0.576

Table D16: Model Estimation Results, AR(2)

Note: Panel A reports the model parameters with point estimates reported in the third column and standard errors reported in the fourth column. Panel B reports the model vs. data moments with t-statistics reported in the fourth column.

(0.235 and 0.494, respectively based on (9)). The scope for overreactions, based on the probability of Case 2 updating, q(1-p), is approximately 15% lower in the AR(2) model relative to the baseline AR(1) model.