Overreaction Through Anchoring*

Constantin Bürgi[†] Julio L. Ortiz[‡]

August 2025

Abstract

Quarterly-frequency macroeconomic expectations among professional forecasters robustly exhibit overreactions at the forecaster level. Much of the literature has interpreted this as unambiguous evidence that forecasters place uniformly too much weight on new information. However, we document that forecasters partially offset their quarterly revisions within the calendar year. We then propose a model of annual anchoring in which forecasters reshuffle quarterly predictions to become consistent with annual predictions. We estimate our model to fit survey expectations and show that it provides a unified explanation for the above empirical facts. This suggests a more limited role for uniform overreactions to new information.

JEL: C53, D83, D84, E17, E27, E37, E47
Keywords: Kalman Filter, Consistency, Macroeconomic forecasting, Inattention, Overreaction.

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*We would like to thank Philippe Andrade, Natsuki Arai, Chris Carroll, Simon Sheng, Tara Sinclair, and Emre Yoldas for their helpful comments and discussions. We would also like to thank the seminar participants at UCD, American University, UIBE, GWU, and the EEA, SNDE, T2M, MMF, and CEF conferences. Declarations of interest: none.

[†]*Email: constantin.burgi@ucd.ie, School of Economics, University College Dublin, Belfield, Dublin 4, Ireland*

[‡] *Email: julio.l.ortiz@frb.gov*, Federal Reserve Board, 20th and Constitution Avenue NW, Washington DC 20551. The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of any other person associated with the Federal Reserve System.

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 typically attributed to overreaction to new information (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. We argue that these empirical patterns arise because forecasters reshuffle their predictions within the calendar year. For instance, a forecaster may offset an upward revision to her current-quarter 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 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.

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.[1] 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.[2] Two key assumptions are responsible for generating offsetting and overreactions

[1]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.

[2]The SPF requires forecasters to issue predictions where the quarterly path matches the annual prediction. For real GDP growth, our primary variable of interest, quarterly (high frequency) forecasts in the data

in our model: 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.

Individual-level high frequency overreactions arise in our model because agents introduce past high frequency errors into their predictions through the consistency constraint.[3] 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.[4] 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 on its own can explain the overreaction at the quarterly frequency found in the data without the need of overreaction to new information. We next augment our model to allow for general overreaction in the form of diagnostic expectations. We show that annual anchoring accounts for a substantial part of the observed quarterly overreaction across a range of measures and is the clearly dominant factor for some. The estimated model can also generate empirically

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. In Supplementary Materials A.2 and A.3, we provide further details of the variable definitions.

[3] Similar to the apparent biases in Bürgi (2017) and Elliott et al. (2008), overreactions in our model arise among rational forecasters.

[4] 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.

relevant degrees of underreaction in consensus forecasts.[5]

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, 2025; Goldstein, 2023). 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.

A longstanding literature on expectation formation has studied forecast error predictability (Zarnowitz, 1985; Nordhaus, 1987; 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). 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;

[5] Our model features inattention in the form of infrequent updating which generates aggregate underreaction at both frequencies.

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 multi-frequency 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., 2023; Bordalo et al., 2020; Broer and Kohlhas, 2022; Kohlhas and Walther, 2021; Farmer et al., 2024). 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 Quarterly and Annual Overreaction

2.1 Data

The data that we use for our 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 began collecting current-year forecasts, so that we can assess whether forecasters indeed produce annual predictions that are consistent with the associated quarterly forecasts.[6]

Though we primarily focus on SPF forecasts for real GDP growth, we show below that our model can capture overreactions of 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. 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; 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:

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

[6] To abstract away from the COVID-19 pandemic, our sample ends in 2019Q4. Also, while the survey reports the forecasts for some variables in terms of levels, this might not be the way they are forecasted since survey participants can provide forecasts in levels or growth rates.

Table 1: Overreaction among Individual Forecasters

	Current quarter		One quarter ahead		Two quarters ahead		Year-over-year	
	(1) Error	(2) Revision	(3) Error	(4) Revision	(5) Error	(6) Revision	(7) Error	(8) Error
Revision	-0.266***		-0.145**		-0.334***		-0.236*	
	(0.059)		(0.073)		(0.066)		(0.137)	
Previous revision		-0.131**		-0.302***		-0.424***		
		(0.057)		(0.055)		(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

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.

a revision autocorrelation regression:

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

and an errors-on-outcome regression:

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

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), 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, γ_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 γ_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). 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 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.

Table 2: No Annual Overreaction among Individual Forecasters

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

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.

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).[7] The results are reported in Table 2.

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.

[7]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, 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.

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

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

where $F^i_{Y,Q}(x_Y)$ denotes forecaster i's forecast of the annual variable x_Y devised in year Y and quarter Q. Similarly, $F^i_{Y,Q-1}(x_{Y,Q-1})$ 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 β_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. Indeed, a one percentage point increase in the quarterly error increases the annual error

Table 3: Underreaction to Realized Quarterly Error

	(1) Annual error	(2) Annual error
Realized quarterly error	0.053***	0.039**
	(0.019)	(0.019)
Fixed effects	None	Forecaster
Forecasters	137	137
Observations	3832	3832

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.

by 0.039-0.053 percentage points. 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 at the quarterly frequency but not at the annual frequency. In addition, forecasters underreact to past 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:

$$\begin{aligned} F^i_{Y,Q4}(x_{Y,Q4}) - F^i_{Y,Q3}(x_{Y,Q4}) = \alpha_{Q3}\big[F^i_{Y,Q3}(x_{Y,Q3}) - F^i_{Y,Q2}(x_{Y,Q3})\big] \\ + \alpha_{Q2}\big[F^i_{Y,Q2}(x_{Y,Q2}) - F^i_{Y,Q1}(x_{Y,Q2})\big] \\ + \alpha_{Q1}\big[F^i_{Y,Q1}(x_{Y,Q1}) - F^i_{Y-1,Q4}(x_{Y,Q1})\big] + \nu^i_{Q4}, \end{aligned} \tag{5}$$

where $F^i_{YQ}(x_{YQ})$ denotes forecaster i's forecast of real GDP growth in year-quarter YQ.

We construct these calendar year variables as follows. In the first quarter of the year, the

Table 4: Offsetting Real GDP Revisions Within Calendar Year

	(1) Fourth quarter revision	(2) Fourth quarter revision	(3) Fourth quarter revision	(4) Fourth quarter 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

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.

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. 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. The positive and significant third quarter revision indicates that calendar year offsetting does not (fully) happen in consecutive quarters.

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 growth.

Intuitively, this pattern could be explained as follows: forecasters think GDP approximately follows an AR(1) process (but with a lower AR coefficient than the actual data). As new information comes in, they have anchored their annual prediction and need to offset changes to the quarterly path. The information received is most valuable for short horizon quarters and so the far horizon quarters are used to offset.

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:

$$FE^i_{t+h} = \beta_0 + \beta_1 FR^i_{t+h} + \beta_2 \text{offset}^i_t + \beta_3 \left[FR^i_{t+h} \times \text{offset}^i_t\right] + \varepsilon^i_t. \tag{6}$$

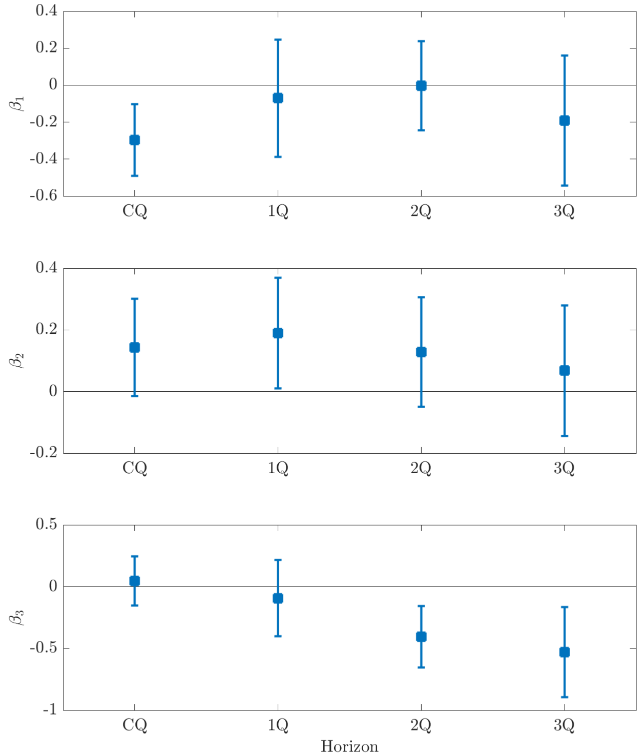
Note that regression (6) is a generalization of the error-on-revision regression (1), where FE denotes the forecast error and FR denotes the forecast revision, for notational convenience. If offsetting is not important, then we would expect $\beta_2 = \beta_3 = 0$ and $\beta_1 < 0$, consistent with the results in Table 1. The coefficient β_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 $\beta_1 + \beta_3 \times \text{offset}^i_t$.

Because the SPF data features variation across forecasters, time, and horizon, we can measure offsetting in the data by constructing a forecaster-quarter specific dummy variable that equals one whenever a forecaster's sequence of revisions across horizons exhibits a sign switch. For example, the dummy equals one in period t if a forecaster i revises up her current-quarter and one-quarter ahead forecasts, but revises down her two-quarter ahead forecast. On the other hand, the dummy equals zero if the entire projected path, from the current-quarter to three-quarters ahead, is revised up. 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 β_1, the middle panel displays estimates of β_2, and the bottom panel displays estimates of β_3.

At the current-quarter (CQ) and one-quarter ahead (1Q) horizons, we find that offsetting does not drive overreactions since β_3 is statistically indistinguishable from zero while β_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 β_3. In other words, overreactions at these horizons are concentrated among forecasters who offset their revisions.

In general, finding a statistically significant estimate of β_3 at any horizon suggests a role for offsetting in explaining overreactions. In this case, β_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.

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.

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 Supplementary Materials 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 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.[8] 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:

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

The underlying state, s_t, follows an AR(1) process:[9]

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

with unconditional mean μ, persistence ρ, and variance $\frac{\sigma_w^2}{1-\rho^2}$. The transitory component, e_t, is normally distributed and centered at zero with variance σ_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 updat-

[8]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.

[9]In Supplementary Materials D.6 we explore a richer driving process which delivers qualitatively similar results to those reported in the subsequent sections.

ing their predictions, forecasters observe the previous realization of the variable, x_{t-1}. In addition, we assume that forecasters observe a contemporaneous private signal:

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

In this linear Gaussian setting, an optimal forecast would be obtained by employing the Kalman filter. However, 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.[10]

We assume exogenous Calvo-like updating probabilities in our model in order to align with the literature (Andrade and Le Bihan, 2013) and for tractability. As noted in the introduction, forecasters may smooth their annual forecasts for various reasons such as to reconcile quarterly and annual models or because there are resource or reputation costs associated with revising annual forecasts. We find that we would obtain a similar forecasting rule to the one implied by our model if we instead assumed that forecasters update their forecasts every period subject to a convex cost to revising annual forecasts.

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

[10]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.

higher frequency forecasts.[11]

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. For simplicity, we will denote everything in terms of the higher frequency (quarterly predictions) and assume that the low frequency prediction is equal to the average of several higher frequency predictions (e.g. annual prediction).[12] We can express the Case 2 prediction, in general, as:

$$\widehat{x}^i_{t'|t} = \mathbb{E}^i_t(x_{t'}) + \frac{1}{H}\sum_{h'=1}^{H}\Big[\mathbb{E}^i_{t-j}(x_{h'}) - \mathbb{E}^i_t(x_{h'})\Big], \tag{7}$$

where H is the number of high frequency periods in one low frequency period (e.g., the number of quarters in a year). Furthermore, $\widehat{x}^i_{t'|t}$ denotes agent i's reported prediction in period t for some future high frequency period, t'. The subscript $t-j$ refers to the (high frequency) period 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 overreac-

[11] 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.

[12] In practice, some variables are forecasted in levels while others are forecasted in growth rates. When estimating the model in the next section, we calculate the targeted annual moments as averages of quarterly growth rates to align with our model. We regard this approach as suitable since we apply the same quarterly-to-annual arithmetic to the data and the model.

tions:

$$\widehat{x}^i_{t'|t} = \underbrace{\frac{H-1}{H}\mathbb{E}^i_t(x_{t'}) + \frac{1}{H}\mathbb{E}^i_{t-j}(x_{t'})}_{\text{Traditional smoothing motive}} + \underbrace{\frac{1}{H}\sum_{h' \neq t'}^{H}\left[\mathbb{E}^i_{t-j}(x_{h'}) - \mathbb{E}^i_t(x_{h'})\right]}_{\text{Source of overreactions}}.$$

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 t and $t-j$ 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:

$$\widehat{x}^i_{t'|t} = \mathbb{E}^i_t(x_{t'}) - \frac{1}{H}\sum_{h'=t-k}^{h-1}\left[x_{h'} - \mathbb{E}^i_{t-j}(x_{h'})\right] - \frac{1}{H}\sum_{h'=h}^{H-(t-k)}\left[\mathbb{E}^i_t(x_{h'}) - \mathbb{E}^i_{t-j}(x_{h'})\right], \qquad (8)$$

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

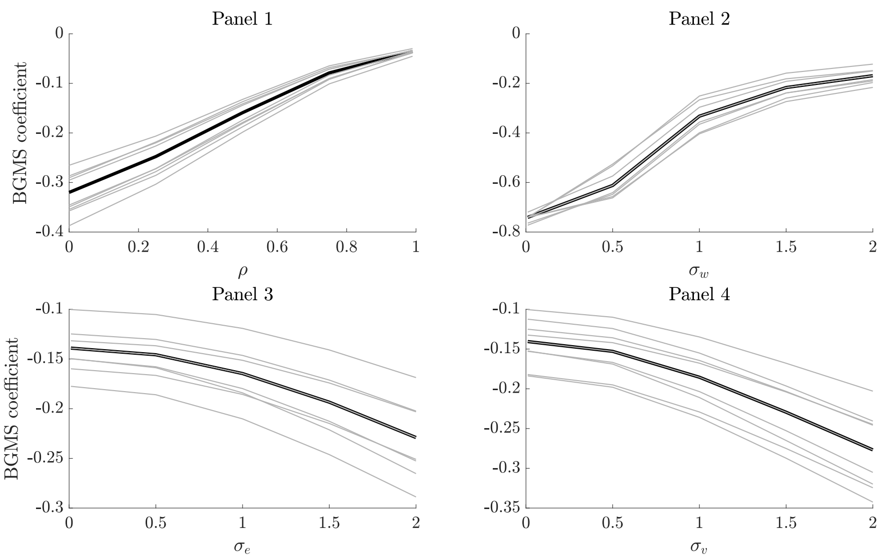
Overreactions arise because low-frequency inattention and high-to-low frequency consistency, together, introduce past rational mistakes into the reported prediction. Based on the second term in (8), if x_{t-1} comes in above expectations, then the forecaster will mark down her current forecast in order to preserve consistency.[13] 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.

3.3 Analyzing the Model

We concentrate on the Bordalo et al. (2020) (BGMS) coefficient, which regresses year-over-year errors on year-over-year revisions. We note, however, that similar findings arise with the

[13]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.

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.[14] 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

[14]We derive the errors-on-revisions coefficient implied by the model in Supplementary Materials B.2.

Afrouzi et al. (2023) who find that overreactions are decreasing in ρ. 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, σ_w. Similar to Panel 1, here we find that the scope for overreactions is decreasing in σ_w. As σ_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.

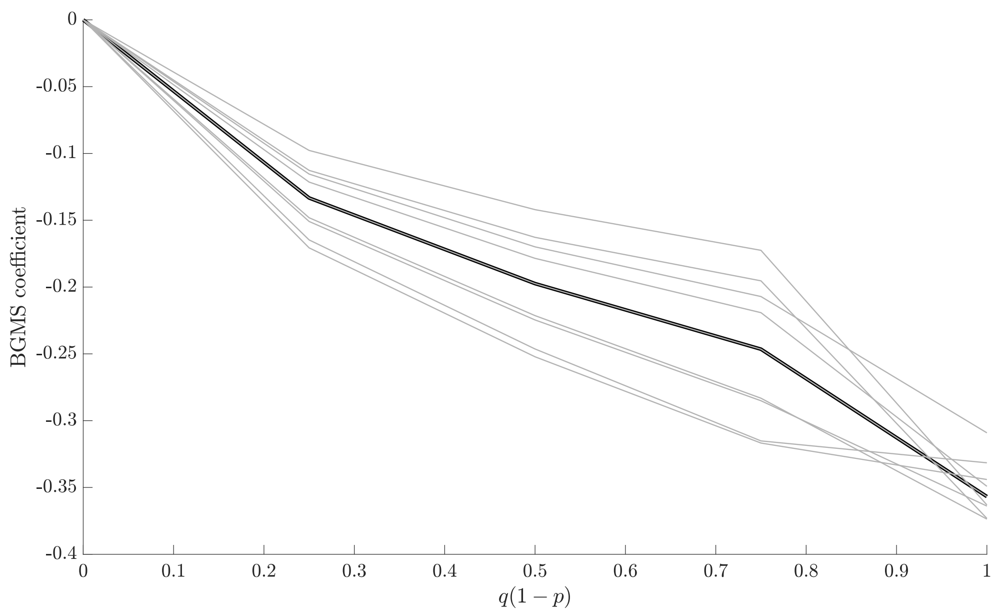
Sticky information is an important feature of our model. To assess the role that infrequent annual updating plays in driving observed overreactions, we focus on the frequency of Case 2 updating. Figure 3 illustrates how individual overreactions depend on $q(1-p)$, which is the probability of Case 2 updating. 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.

We estimate the remaining six parameters via SMM as detailed in Supplementary Mate-

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.

rials C.[15] 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. Supplementary Materials C details how these moments are related to the parameters.[16]

[15] We explored an alternative strategy by first estimating the data generating process parameters via maximum likelihood estimation using real GDP growth as our observation, and then estimating the remaining parameters via SMM. This approach delivers quantitatively similar results to those in Table 5.

[16] We do not directly target rates of micro-level inattention in our baseline estimation approach, however, in unreported results we estimate our model by targeting the share of small revisions (up to one-tenth of a

Table 5: Model Estimation Results

Panel A: Parameter Estimates			
	Parameter	Estimate	Standard error
Persistence of latent state	ρ	0.441	0.071
State innovation dispersion	σ_w	1.842	0.126
Public signal noise	σ_e	1.289	0.327
Private signal noise	σ_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)	1.682	1.745	0.607
Corr(CQ forecast, CY forecast)	0.687	0.685	0.594
Std(CY forecast)	1.096	1.115	0.349
Std(CQ revision)	1.572	1.589	0.140
Corr(CQ revision, lagged CQ error)	0.127	0.138	0.387
Std(lagged CQ error)	1.672	1.749	0.883
CQ RMSE	1.688	1.717	0.522
CY RMSE	1.102	1.109	0.157

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.

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.

This estimated probability is significantly below one, indicating that there is scope for the 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 and with a magnitude similar to the data.

One limitation of the estimated model is that it does not generate a negative errors-on-revisions 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

Table 6: Non-targeted Moments

		Model		Data	
1.	$\beta(FECQ, FRCQ)$	0.046	(0.046)	-0.266	(0.059)
2.	$\beta(FE1Q, FR1Q)$	-0.179	(0.105)	-0.145	(0.073)
3.	$\beta(FE2Q, FR2Q)$	-0.567	(0.115)	-0.334	(0.066)
4.	$\beta(FE3Q, FR3Q)$	-0.905	(0.184)	-0.657	(0.087)
5.	$\beta(FRCQ, FR1Q_{-1})$	-0.091	(0.063)	-0.131	(0.057)
6.	$\beta(FR1Q, FR2Q_{-1})$	-0.305	(0.028)	-0.302	(0.055)
7.	$\beta(FR2Q, FR3Q_{-1})$	-0.510	(0.027)	-0.424	(0.050)
8.	$\beta(FEYY, FRYY)$	-0.177	(0.074)	-0.236	(0.137)
9.	β(FEYY, Outcome)	-0.067	(0.096)	-0.134	(0.070)
10.	$\beta(FECQ, FECQ_{-1})$	0.148	(0.051)	0.147	(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.

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 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.[17] 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

[17]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.

Table 7: Estimates Across Macro Variables

	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)**

Note: The table reports the BGMS (2020) error-on-revision coefficients, controlling for forecaster fixed effects, in the model and in the data for various macroeconomic variables covered in the SPF. Standard errors are reported in parentheses. Bold values are significantly negative at the 10% level.

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.

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.[18] To evaluate how well the model is able to account for overreactions in the data, Table 7 reports empirical and simulated errors-on-revisions regression estimates, our

[18]Estimates of the over-/underreaction for the quarterly and annual predictions of the other variables and surveys are available from the authors upon request. They similarly feature robust evidence quarterly overreaction but not annual overreaction.

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. In turn, our model does not produce overreactions for variables that do not show overreaction empirically either such as unemployment. In terms of magnitudes, the model-based estimates are generally in line with their empirical counterparts with the exception of the GDP deflator which exhibits stronger overreaction in the data than in the model.

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

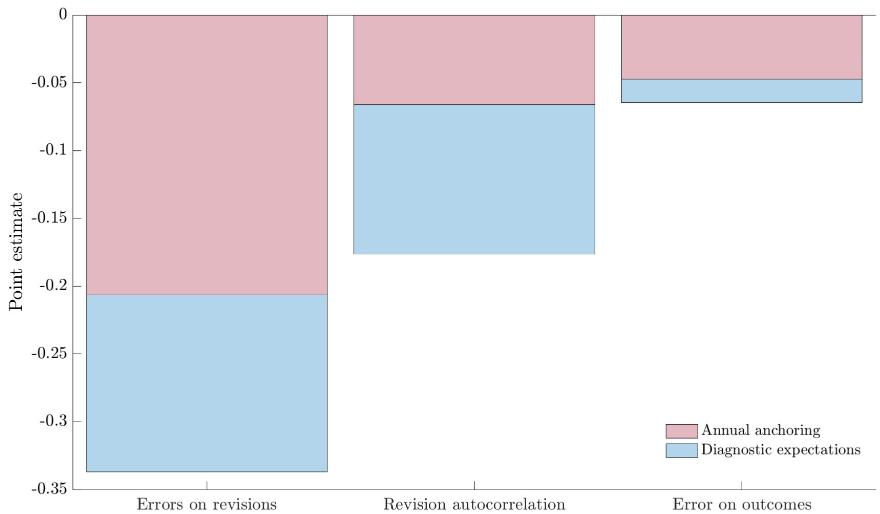
To better understand the quantitative importance of our mechanism as a driver of overreactions, we augment our model with a behavioral friction in a supplementary exercise. We choose a leading theory of non-rational expectations, diagnostic expectations (Bordalo et al., 2019; Bianchi et al., 2024; Bordalo 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:

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

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.

where θ 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 θ by targeting these two additional moments. 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 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 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.[19]

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 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

[19] In the Supplementary Materials, we perform 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). Table D2 reports the estimated parameters and Figure D1 repeats the comparison of diagnostic expectation based on simulated error predictability regressions. Our results are qualitatively similar to Figure 4.

information model, we define the implied information friction to be:

$$\text{Implied friction} = \big[1 - \Pr(\text{update})\big] + \Pr(\text{update}) \times (1 - \kappa_1 - \kappa_2), \tag{9}$$

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.[20]

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, we focus on real GDP growth forecasts and inflation forecasts based on the GDP deflator.[21] At a quarterly frequency, we estimate information frictions to be about 0.17 for real GDP growth and 0.19 for inflation. For annual forecasts, we find that information frictions are higher, at 0.52 for real GDP growth and 0.55 for inflation. For reference, Goldstein (2023) estimates real GDP growth information frictions to be about 0.34 at the current-quarter horizon. Turning to inflation forecasts based on the GDP deflator, Coibion and Gorodnichenko (2015) estimate

[20]In particular, κ_1 denotes the weight placed on the private contemporaneous signal and κ_2 is the weight placed on the lagged realization of the macroeconomic variable.

[21]Table D3 of the Supplementary Materials reports the parameter estimates and model fit.

Table 8: Information Frictions Across Models

	(1)	(2)	(3)	(4)
	Probability of updating	Implied friction	Sticky info contribution	Noisy info 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%

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).

coefficients of information rigidity to be around 0.54 while Ryngaert (2025) 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 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.[22] 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

[22]Note that the sticky information friction also implies that forecasters update their information sets at different points in time.

regard the information friction defined in equation (9) as a measure of the extent of imperfect information rather than a measure of information dispersion.

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

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

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

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. These findings are inconsistent with general overreaction to new information; a frequently used explanation for the quarterly overreaction found in the data. Motivated by these facts, we build a hybrid sticky-noisy information model featuring high and low frequency forecasts. We find that our mechanism can explain a substantial amount of overreactions to macroeconomic aggregates. While not all the overreaction at the quarterly frequency can be explained by our model, it substantially reduces the role of general overreaction to news as the driver and provides an alternative mechanism. Future research might be able to determine the relative importance of these mechanisms outside professional forecasters.

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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