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Overreaction through Anchoring

Abstract

We show that updates to macroeconomic expectations among professional forecasters exhibit an offsetting pattern where increases in current-quarter predictions lead to decreases in three quarter ahead predictions. We further document evidence of individual overreaction at the quarterly frequency and a lack of overreaction at the annual frequency. 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.

JEL-Codes: C530, D830, D840, E170, E270, E370, E470.

Keywords: information friction, consistency, SPF, inattention, overreaction.

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1 Introduction

Professional forecasters make predictable mistakes. Whereas individual forecasts exhibit overreactions (Bordalo et al., 2020; Broer and Kohlhas, 2022; Bürgi, 2016), aggregate forecasts are characterized by inertia (Coibion and Gorodnichenko, 2015; Dovern et al., 2015). Both forms of error predictability are incompatible with full information rational expectations, a benchmark assumption made in macroeconomics. Consequently, theories of non-rational expectations and models departing from full information have been devised to explain over- and underreactions (Afrouzi et al., 2021; Bordalo et al., 2020; Broer and Kohlhas, 2022; Ehrbeck and Waldmann, 1996; Fuhrer, 2018; Gabaix, 2019; Kohlhas and Walther, 2021; Kucinskas and Peters, 2022; Farmer et al., 2022; Mankiw and Reis, 2002; Sims, 2003; Woodford, 2001).

In this paper, we document a novel fact about survey expectations: individual forecast revisions exhibit an offsetting pattern. That is, an upward revision in the current-quarter prediction leads to a downward revision a few quarters out. This fact does not arise under traditional theories of expectation formation. In addition, we show that while there is robust evidence of overreaction at the quarterly frequency, there is no evidence of overreaction at the annual frequency. To explain these facts, we build and estimate a model featuring annual anchoring which generates offsetting revisions and implies relatively stronger overreaction at the quarterly frequency.

Our model is a hybrid sticky-noisy information model as in Andrade and Le Bihan (2013) with a focus on the interaction between quarterly and annual forecasts. Two key assumptions are responsible for generating offsetting and overreactions: consistency (i.e. the quarterly path of forecasts are in line with the annual forecasts) and annual inattention. Under these two assumptions, an upward revision in the near-term must be offset by a downward revision later in the year, as in the data.[1] Offsetting in our model introduces volatility into quarterly updates which ultimately generate overreactions.

We offer two potential interpretations for the quarterly offsetting pattern observed in the data and generated by our model. Both interpretations rely on forecasters issuing quarterly

[1] In the event that forecasts are rounded, quarterly updates would need to be sufficiently large to generate offsetting revisions but not so large that they lead to a full outlook revision (Baker et al., 2020). While these factors may be present in the data, we nonetheless uncover robust evidence of offsetting revisions, leading us to abstract from rounding and state dependent updating in our model.

forecasts that are consistent with the annual ones.[2] First, forecasters may have separate models for quarterly and annual outcomes that need to be reconciled. One way of doing this is to use the annual model prediction as an anchor, and to make adjustments to the quarterly predictions to achieve consistency. Assuming that forecasters are more informed about the present than the future, they would revise the present based on new information and offset these updates farther out along their projected path in order to preserve consistency. Second, since annual forecasts are often accompanied by a narrative, a change to the annual forecast may require changing the story. Forecasters may be reluctant to alter their narratives either because they are overconfident or because too many "rethinks" may signal incompetence. As a result, forecasters might engage in few annual revisions per year, and instead reshuffle their quarterly predictions as they bring in new information.

We begin by providing empirical evidence relating to offsetting and overreactions based on data from the U.S. Survey of Professional Forecasters (SPF). With regard to offsetting, we find that when a forecaster revises upward today, she simultaneously revises downward further along her projected quarterly path. We interpret this result as evidence of low frequency anchoring, and note that traditional models of expectation formation cannot account for offsetting revisions. With regard to overreactions at the quarterly frequency, we document a negative relation between quarterly errors and revisions (Bordalo et al., 2020), a negative autocorrelation of quarterly revisions (Nordhaus, 1987), and quarterly extrapolation from recent outcomes Kohlhas and Walther (2021). At the annual frequency we find no evidence of overreaction.

Motivated by these facts, we devise a noisy information model with heterogeneous updating rates by frequency. Forecasters issue quarterly and annual forecasts based on private and public signals. Quarterly and annual updating are separate activities governed by distinct Calvo-like probabilities. Furthermore, forecasters are subject to a consistency constraint which requires that a forecaster's sequence of quarterly predictions aggregates up to her average annual forecast.[3]

[2]For real GDP growth, our primary variable of interest, quarterly forecasts in the data correspond to the quarter over quarter annualized growth rate, and annual forecasts correspond to the percentage change of the average quarterly level this year relative to the average quarterly level last year. Quarterly and annual forecasts are similarly defined for the other variables that we examine.

[3]The SPF requires forecasters to issue consistent predictions, a feature of the data which we verify in Appendix A. Beyond the SPF, we also find evidence of quarterly offsetting in the Bloomberg survey as shown

Individual overreactions arise in our model because forecasters introduce past errors into their reported predictions through the annual consistency constraint.[4] These offsetting revisions in turn generate error and revision predictability as forecasters trade off accuracy with consistency. Infrequent annual updating is a key ingredient which allows our model to generate overreactions. While traditional models of forecast smoothing (Scotese, 1994) deliver individual and consensus (aggregate) underreactions, our multi-frequency approach allows us to generate individual overreactions while preserving aggregate underreactions.

We estimate the model via the simulated method of moments (SMM). In particular, we estimate the six parameters of our model by targeting eight micro moments in the panel of forecasts from the SPF. Our estimated model successfully fits both targeted and non-targeted moments in the data. We find that modeling heterogeneity in updating by frequency allows us to jointly match realistic levels of inattention and disagreement, something which is not feasible in traditional hybrid sticky-noisy information models (Andrade and Le Bihan, 2013). 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.

In an effort to quantify the importance of our mechanism relative to other theories, we estimate a version of the model with diagnostic expectations (Bordalo et al., 2018, 2019, 2020), a leading theory of non-rational expectations.[5] When we add diagnostic expectations to our model and examine different forms of error and revision predictability, we find that our mechanism can still explain more than half of the measured overreactions. This suggests that low frequency anchoring is an important contributor to overreactions, alongside other forces.

We conduct additional exercises to establish the robustness of our findings and to examine potential drivers of offsetting revisions. First, we estimate our model for the different macroeconomic variables observed in the SPF. Our estimates are able to replicate observed

in Appendix A.

[4]Similar to the apparent biases in Bürgi (2017), overreactions in our model arise among rational forecasters.

[5]Other theories of non-rational expectations can explain overreactive behavior (Daniel et al., 1998; Broer and Kohlhas, 2022). Overreactions can also arise through optimizing behavior subject to attention or memory constraints (Kohlhas and Walther, 2021; Azeredo da Silvera et al., 2020), or through learning (Farmer et al., 2022).

overreactions for a variety of SPF variables.[6] Next, we examine the updating behavior of financial and non-financial SPF forecasters, and provide evidence that the quarterly offsetting is more likely driven by model reconciliation than narrative forecasts.

Finally, we use the model to study information frictions. Our estimates reveal that the frictions 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). In addition, our model allows us to decompose the sources of imperfect information into noisy and sticky information. 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.

The rest of the paper is organized as follows. Section 2 documents empirical evidence relating to offsetting and overreactions. 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 information frictions. Section 7 concludes.

2 Facts About Offsetting and Overreactions

We first document some facts about professional forecasts, with a focus on real GDP growth. The patterns that we highlight in the data serve as motivating evidence for the model introduced in the subsequent section. Furthermore, we revisit some of these moments when assessing the estimated model's ability to explain observed overreactions.

The data that we use come from the SPF, a quarterly survey managed by the Federal Reserve Bank of Philadelphia. The survey began in 1968Q4 and provides forecasts from several forecasters across a range of macroeconomic variables over many horizons, h. The SPF reports current-year annual predictions which the survey requires to be consistent with the averages of the quarterly forecasts starting in 1981Q3.[7] In this sense, the consistency

[6] In Appendix D, we complete additional robustness exercises. We estimate the model assuming that forecasts are rounded, then across different sub-periods, then under alternative assumptions on the data generating process, and also for forecasts issued in the Bloomberg survey.

[7] For this reason, and to abstract away from the COVID-19 pandemic, our sample spans 1981Q3 to

Table 1: Offsetting Revisions, across Horizons

	(1) 3Q ahead growth	(2) 3Q ahead revision	(3) 3Q ahead forecast	(4) 3Q ahead forecast
2Q Ahead	0.488***	0.047*	0.012	0.033
	(0.097)	(0.144)	(0.121)	(0.089)
1Q Ahead	-0.008	-0.007	-0.056	-0.028
	(0.097)	(0.063)	(0.051)	(0.055)
Current Quarter	0.007	-0.077*	-0.095**	-0.079**
	(0.073)	(0.045)	(0.045)	(0.039)
Lagged 4Q ahead forecast			0.381***	0.387***
			(0.091)	(0.090)
Estimation	OLS	OLS	OLS	IV
Fixed effects	None	Time	Forecaster, Time	Forecaster, Time
Forecasters		183	183	183
Observations	194	3911	3911	3911

Note: The table reports panel regression results from SPF forecasts based on regressions (2) and (3). Driscoll and Kraay (1998) standard errors are reported in parentheses. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

constraint that we impose in our model is directly motivated by the data.

2.1 Offsetting Revisions Across Horizons

We define offsetting revisions as a sign switch within a given sequence of forecast revisions. For example, if a forecaster revises up her forecast for the first quarter of the year, and simultaneously revises down her forecast for the fourth quarter of the year, then her revisions are said to exhibit offsetting.

Before documenting evidence of offsetting revisions, we note that this pattern could naturally arise if the aggregate variable of interest exhibits certain dynamics. Suppose, for instance, that real GDP growth evolves as follows:

$$x_t = \beta_0 + \beta_1 x_{t-1} + \beta_2 x_{t-2} + \beta_3 x_{t-3} + u_t, \quad u_t \sim N(0, \sigma_u^2). \tag{1}$$

Assuming that one cannot observe x_t in real time, the conditional expectation three

2019Q4.

periods into the future would be:

$$\mathbb{E}_t(x_{t+3}) = \beta_0 + \beta_1 \mathbb{E}_t(x_{t+2}) + \beta_2 \mathbb{E}_t(x_{t+1}) + \beta_3 \mathbb{E}_t(x_t).$$

Offsetting revisions would arise in this example if $\beta_1 < 0$, $\beta_2 < 0$, and/or $\beta_3 < 0$, since forecasters would feed any news through the this AR(3) data generating process.

In column (1) of Table 1, we fit equation (1) to real-time real GDP growth and find no evidence of a significant and negative autoregressive coefficient, leading us to conclude that offsetting revisions are unlikely to be driven by the dynamics of real GDP growth. We choose to estimate an AR(3) model for symmetry since we will next document evidence of offsetting revisions over a three quarter horizon.[8]

While the autocorrelations of real GDP growth do not call for revision offsetting, we show that forecasters nonetheless offset their revisions. Exploiting the term structure of forecasts in the SPF, we begin by regressing the three-quarter ahead revision on the two-quarter ahead revision, the one-quarter ahead revision, and the current-quarter revision.

We run the following regression:

$$F_{it}(x_{t+3}) - F_{it-1}(x_{t+3}) = \delta_t + \sum_{k=0}^{2} \alpha_k \big[F_{it}(x_{t+k}) - F_{it-1}(x_{t+k}) \big] + \nu_{it}, \tag{2}$$

where $F_{it}(x_{t+h})$ denotes forecaster i's h-step ahead forecast for real GDP growth devised at time t.

The results are reported in the second column of Table 1. Based on the regression results, a one percentage point increase in the two quarter ahead revision predicts a 4.7 basis point increase in the three quarter ahead revision. However, a one percentage point increase in the current quarter revision predicts a 7.7 basis point decrease in the three quarter ahead revision. Put another way, a one standard deviation increase in the current quarter revision predicts a 6% downward revision three quarters ahead.

Under rational expectations, the forecast revision is uncorrelated with any variable re-

[8]We find similar results when fitting other AR(p) models to GDP growth. We discuss alternative assumptions about the data generating process in further detail throughout the paper. In Section 2.2, we reason through a model with permanent and transitory shocks, and, in Appendix D we estimate a latent AR(2) process for real GDP growth.

siding in the forecaster's information set. The literature on macroeconomic survey expectations, however, has documented ample evidence of error and revision predictability (Bordalo et al., 2020; Broer and Kohlhas, 2022; Nordhaus, 1987; Crowe, 2010; Dovern et al., 2015), a phenomenon which we revisit in the next section. If there is an unobserved source of over-revisions at time $t-1$, then the OLS estimate of α_0 in regression (2) will be biased upward since, by definition, this omitted variable would covary negatively with all revisions. Depending on the magnitude of this bias, one might erroneously conclude that revision offsetting is minor or not present at all in the data. To mitigate this concern, we next run the following regression:

$$F_{it}(x_{t+3}) = \delta_i + \delta_t + \beta F_{it-1}(x_{t+3}) + \sum_{k=0}^{2} \alpha_k \big[F_{it}(x_{t+k}) - F_{it-1}(x_{t+k})\big] + \nu_{it}. \tag{3}$$

Regression (3) is similar to (2) except that it relates the three-quarter ahead forecast to the two-quarter, one-quarter and current-quarter revisions, controlling for the lagged four quarter ahead forecast. A negative sign in front of α_0, α_1, or α_2 once again implies offsetting. We prefer specification (3) because it allows us to better account for potentially unobserved drivers of the three quarter ahead revision at time $t-1$. Column (3) of Table 1 reports the results from regression (3).[9] The point estimate in column (2) imply that a one percentage point increase in the current quarter revision leads to a nearly 10 basis point decrease in the three quarter ahead revision.

In the SPF, forecasters issue their revisions simultaneously for all horizons. This simultaneous determination could lead to an endogeneity issue and bias our coefficients. We thus instrument the right hand-side variables with leave-out means.[10] Based on our framework, these leave-out means are valid instruments since they reside outside of forecaster i's information set. Furthermore, these instruments are relevant as they are naturally tightly linked to the regressors. We report the instrumental variable (IV) estimates in final column of Table 1 and find that they are similar to the OLS estimates. Based on Column (4), a one percentage point increase in the current quarter revision leads to a 7.9 basis point decrease

[9] When running regression (3) with the three-quarter ahead forecast revision as the dependent variable, we obtain a point estimate for α_0 that is more negative than the estimate reported in column (1). This lends further support to our intuition behind the potential omitted variable bias.

[10] The leave-out consensus revision is defined as: $\sum_{j\neq i}^{N} \big[F_{it}(x_{t+k}) - F_{it-1}(x_{t+k})\big]$.

Table 2: Offsetting Revisions, within Calendar Year

	(1) Fourth quarter growth	(2) Fourth quarter revision	(3) Fourth quarter forecast	(4) Fourth quarter forecast
Third Quarter	0.784***	0.205***	0.084**	0.078**
	(0.174)	(0.043)	(0.034)	(0.034)
Second Quarter	0.119	0.033	-0.047	-0.055
	(0.133)	(0.075)	(0.054)	(0.061)
First Quarter	0.170	-0.170**	-0.122**	-0.193**
	(0.093)	(0.086)	(0.047)	(0.095)
Lagged fourth quarter forecast			-0.682***	-0.677***
			(0.053)	(0.047)
Estimation	OLS	OLS	OLS	IV
Fixed effects	None	Time	Forecaster, Time	Forecaster, Time
Forecasters		184	184	184
Observations	50	4020	4020	4020

Note: The table reports panel regression results from SPF forecasts based on regressions (4) and (5). Driscoll and Kraay (1998) standard errors are reported in parentheses. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

in the three quarter ahead revision.[11]

2.2 Offsetting Revisions within the Calendar Year

While the estimates reported in Table 1 reveal quarterly offsetting behavior, these regressions do not directly map to our notion of annual anchoring. With annual anchoring, quarterly offsetting should be more pronounced within a calendar year. In order to assess this, we run the following regression:

$$F_{it}(x_{Q4}) - F_{it-1}(x_{Q4}) = \delta_i + \delta_t + \sum_{k \in \{Q1,Q2,Q3\}} \alpha_k \big[F_{it}(x_k) - F_{it-1}(x_k)\big] + \omega_{it}. \tag{4}$$

The difference between (2) and (4) is that the latter focuses on a fixed event. In the first quarter of the year, the Q4 revision is $F_{it}(x_{t+3}) - F_{it-1}(x_{t+3})$ since the fourth quarter is three periods ahead. In the second quarter of the year, the Q4 revision is $F_{it}(x_{t+2}) - F_{it-1}(x_{t+2})$

[11]We provide additional evidence of revision offsetting in Appendix A.4 where we use statistical data revisions as an exogenous shock with which to trace out the response of forecast revisions at different horizons. Here too we find that forecasters revise their current quarter and three quarter ahead forecasts in opposite directions.

since the fourth quarter is now two periods ahead, and so on. We construct first, second, and third quarter calendar-year revisions in a similar way.

Importantly, as the calendar year progresses, values of real GDP are realized and forecast revisions become forecast errors. For instance, the Q1 revision in the first quarter is $F_{it}(x_t) - F_{it-1}(x_t)$, 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, $x_{t-1} - F_{it-1}(x_{t-1})$.

As in column (1) of Table 1, column (1) of Table 2 begins by examining fluctuations in real GDP growth. Rather than fitting an AR(3) to real GDP growth, here, we collect real GDP growth in the fourth quarter of each year in our sample and regress it on real GDP growth in the first, second, and third quarters of each calendar year. Similar to our AR(3) results, we find that real GDP in the first quarter does not predict real GDP in the fourth quarter of the year. These results again indicate that the offsetting present in professional forecasts is driven by something other than the underlying data generating process.

Column (2) of Table 2 reports the OLS estimates of regression (4). 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 17-basis point downward revision to the fourth quarter forecast.

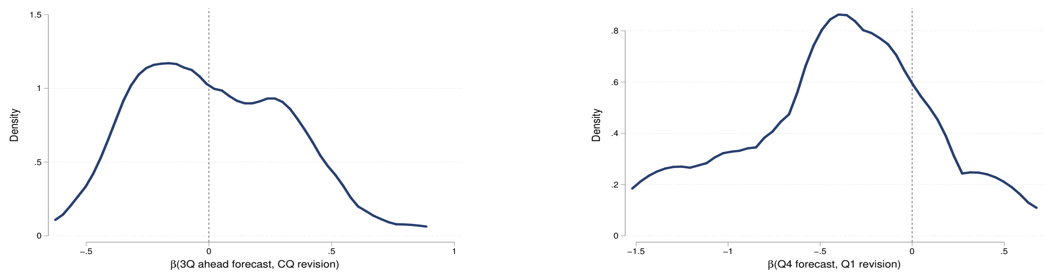
Column (3) of Table 2 reports estimates from the following regression:

$$F_{it}(x_{Q4}) = \delta_i + \delta_t + \beta F_{it-1}(x_{Q4}) + \sum_{k \in \{Q1,Q2,Q3\}} \alpha_k \big[F_{it}(x_k) - F_{it-1}(x_k)\big] + \omega_{it}. \tag{5}$$

Similar to column (3) of Table 1, column (3) of Table 2 reports a regression of the fourth quarter forecast on the first, second, and third quarter revisions, controlling for the previous fourth quarter forecast. Furthermore, column (4) reports IV estimates by again instrumenting individual revisions with leave-out consensus revisions where appropriate. Our IV estimates are similar to the OLS estimates in column (3), and imply that a one percentage point upward revision in the first quarter of the year leads to an 19-basis point downward revision in the fourth quarter of the year. Put another way, a one standard deviation increase in the first quarter revision leads to a roughly 15% downgrade to the fourth quarter revision.

Figure 1: Density of Individual Revision Offsetting Coefficients

(a) Offsetting by horizon (b) Offsetting within calendar year



Note: The figures plot a kernel density estimates of the offsetting revision coefficient from a series of forecaster-by-forecaster regressions. Regressions are only estimated for forecasters issuing at least 20 quarters worth of forecasts. Only statistically significant estimates are kept (at least at the 10% level).

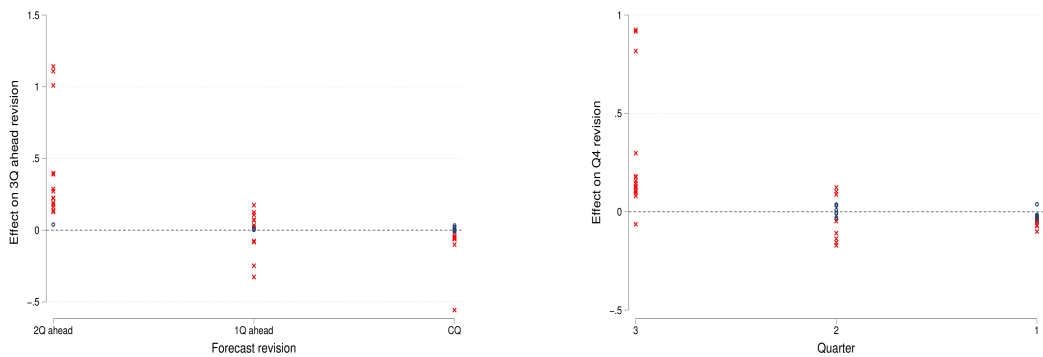
2.3 Offsetting Across Forecasters and Macroeconomic Variables

The regressions estimated above allow for only a common degree of offsetting across forecasters. As a result, our estimates could be driven by a few forecasters exhibiting a strong degree of offsetting. To explore the potential heterogeneity in offsetting patterns further, we estimate (3) and (5) forecaster-by-forecaster and non-parametrically visualize the distribution of point estimates for α_0 and α_{Q1}. Panel (a) of Figure 1 displays the density of point estimates of α_0 in regression (3) while panel (b) plots the density of point estimates of α_{Q1} in regression (5). The figures imply that most of these point estimates are negative. The share of negative point estimates are 0.53 and 0.83 for panels (a) and (b), respectively. Thus, the offsetting patterns reported in Tables 1 and 2 are present for the majority of forecasters when allowing the regressions coefficients to exhibit cross-sectional heterogeneity.

In a final exercise, we estimate (3) and (5) across 15 macroeconomic variables reported in the SPF. Figure 2 plots the estimated coefficients. Panel (a) reports the estimates for the offsetting regression by horizon while panel (b) plots the estimates for the offsetting regression by calendar year. The red 'x' in each panel denote statistically significant point estimates. Across both specifications, we find that professional forecasts exhibit offsetting for the majority of macroeconomic variables in the SPF. Similar to the pooled regressions for real GDP growth reported above, Figure 2 indicates that offsetting is non-adjacent.

Figure 2: Offsetting Across SPF Variables

(a) Offsetting by horizon (b) Offsetting within calendar year



Note: The figures estimates of the offsetting revision coefficient for a variety of macroeconomic variables in the SPF. The red 'x' symbols denote statistical significance at the 10% level and the hollow blue circles denote no statistical significance. Across both specifications, nine of the 15 variables exhibit statistically significant evidence of offsetting.

2.4 Interpreting the Results

It is not immediately obvious how offsetting revisions matter for our understanding of expectation formation. To provide further context and intuition for our results, we first review a standard rational expectations model and show that it is unable to reproduce revision offsetting. We then propose our explanation for revision offsetting which we claim is an artifact of multi-frequency forecasting under consistency constraints. Finally, we reason through a model with transitory level shocks, and explain why these dynamics are unlikely to be the primary driver of revision offsetting in the data.

Traditional rational expectations models with AR(1) dynamics do not allow for revisions to feature sign switching. To see this, note that under rational expectations and AR(1) dynamics, the forecast revision at time $t+h$ is:

$$\mathbb{E}_{it}(x_{t+h}) - \mathbb{E}_{it-1}(x_{t+h}) = \rho^h \big[\mathbb{E}_{it}(x_t) - \mathbb{E}_{it-1}(x_t)\big], \quad -1 < \rho < 1,$$

where ρ is the persistence of the fundamental variable. From the above expression, it is immediate that the path of forecast revisions will gradually converge to zero over a long horizon, but will not cross the horizontal axis.

We propose that offsetting revisions can arise in an otherwise standard AR(1) rational expectations model if forecasters have a tendency to anchor their predictions over lower frequencies. In the SPF, forecasters issue both quarterly and annual forecasts. These forecasts must be internally consistent, meaning that quarterly predictions must aggregate to the annual prediction in every period. How exactly does offsetting arise? If a forecaster receives positive news about the present, then she will wish to revise up her current quarter forecast. However, if she has anchored her annual forecast, then she will have to revise up subject to a quarterly-to-annual adding up constraint. Thus, for her newly issued quarterly predictions to reflect her unchanged annual outlook, the upward revision today must be offset by a downward revision elsewhere along her predicted path.

The explanation above requires forecasters to be more attentive to higher frequency forecasts. Forecasters might differ in their attentiveness to quarterly and annual forecasts for a variety of reasons. For instance, forecasters may employ different models for different frequencies, and update their high frequency model more often. Alternatively, forecasters might want to preserve an overarching narrative while nonetheless reacting to high frequency developments. Section 5 explores this hypothesis further by comparing the updating behavior of different types of forecasters observed in the SPF.

Aside from low frequency anchoring, offsetting revisions can arise if there are transitory shocks to the level of the macroeconomic variable. For instance, a natural disaster in one period could lead forecasters to bring down their growth forecast today and project a reversal in the next quarter. Transitory level shocks, however, imply adjacent offsetting whereas in the data, we uncover evidence of non-adjacent offsetting. While macroeconomic variables such as real GDP are likely subject to transitory level shocks, these dynamics do not appear to drive the offsetting observed in the data, as indicated by column (1) of Tables 1 and 2.

Assuming that forecasters anchor their annual predictions, and assuming that quarterly forecasts must always aggregate to the annual forecast, then overreactions can arise due to the reshuffling that occurs in order to satisfy quarterly-to-annual consistency. We next document new and existing evidence of overreaction at the forecaster level. We then present a model of offsetting revisions due to annual anchoring and study the link between offsetting and overreactions from the perspective of the model.

2.5 Individual Overreactions

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). We provide evidence of overreaction in quarterly macroeconomic expectations through error and revision predictability regressions. We then show that there is no evidence of overreaction at the annual frequency.

We estimate three regressions, all of which imply that forecasters overreact to new information. We run an errors-on-revisions regression:

$$x_{t+h} - F_{it}(x_{t+h}) = \beta_i + \beta_{1,h}\left[F_{it}(x_{t+h}) - F_{it-1}(x_{t+h})\right] + \epsilon_{it+h}, \tag{6}$$

a revision autocorrelation regression:

$$F_{it}(x_{t+h}) - F_{it-1}(x_{t+h}) = \gamma_h\left[F_{it-1}(x_{t+h}) - F_{it-2}(x_{t+h})\right] + \varepsilon_{it+h}, \tag{7}$$

and an errors-on-outcome regression:

$$x_{t+h} - F_{it}(x_{t+h}) = \alpha_i + \alpha_{1,h}x_t + \eta_{it+h}. \tag{8}$$

Regressions (6) and (7) were first introduced as tests of weak efficiency in Nordhaus (1987). The errors-on-revisions regression (6), which is widely employed in the survey expectations literature (Bordalo et al., 2020; Bürgi, 2016), relates ex-post errors on 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.

Unlike the (6), the revision autocorrelation regression, (7), does not rely on macroeconomic data. Instead, this regression relates fixed event revisions across time, projecting the current forecast revision on its previous value. We are interested in the coefficient in front of the lagged revision, γ_h. The standard rational expectations model 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.

Table 3: 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	-0.260***		-0.154**		-0.358***		-0.154**	
	(0.062)		(0.043)		(0.067)		(0.070)	
Previous revision		-0.136**		-0.319***		-0.406***		
		(0.055)		(0.065)		(0.088)		
Realization								-0.096***
								(0.019)
Forecasters	183	163	162	162	157	161	217	154
Observations	4,207	3,566	3,545	3,552	3,444	3,466	4,314	4,581

Note: Note: The table reports panel regression results from SPF forecasts of real GDP growth based on regressions (6), (7), and (8). Each set of columns refers to a different horizon, from the current quarter to two quarters ahead. Driscoll and Kraay (1998) standard errors are reported in parentheses. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

Finally, the errors-on-outcomes regression (8), studied in Kohlhas and Walther (2021), examines another form of error predictability. This regression differs from (7) 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 3 reports all of the regression results. Across horizons, we find that a one percentage point upward forecast revision predicts a roughly -0.15 to -0.35 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).

Turning to the revision autocorrelation estimates (columns 2, 4, and 6), we similarly find that forecasters overrevise their predictions. For current quarter forecasts, a one percentage point upward revision today predicts a 0.13 percentage point downward revision tomorrow. Forecasters tend to overrevise more strongly at the one- and two-quarter ahead horizons, with point estimates hovering from -0.30 to -0.40.

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).

To further examine whether there is evidence of annual anchoring in the data, we next estimate these regressions at the annual frequency. The data would be consistent with annual anchoring if the annual analogs to (6) (7), and (8) yield weaker evidence of overreaction. Put another way, if forecasters truly reshuffle their quarterly predictions due to annual anchoring, then overreactions should be relatively stronger at the quarterly frequency than the annual frequency.

There are some limitations to estimating the overreaction regressions using annual frequency forecasts. First, the mapping between quarterly and annual coefficients is, in general, 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 (7). Third, aggregating from a quarterly to an annual sample shortens the time dimension of our panel, which substantially reduces

Table 4: Error Predictability at Annual Frequency

	(1) Current year error	(2) Current year error
Current year revision	0.025	
	(0.016)	
Outcome		0.187***
		(0.051)
Fixed effects	Forecaster×variable	Forecaster×variable
Forecasters	129	131
Observations	2900	3460

Note: The table reports estimates of the annual analog to regression (6) and (8), pooling across the macroeconomic variables covered in the SPF. Driscoll and Kraay (1998) standard errors are reported in parentheses. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

our number of observations. To achieve greater power, we therefore pool across the set of macroeconomic variables featured in the SPF when running regressions (6) and (8). The results are reported in Table 4.[12]

Column (1) of Table 4 reports the annual version of regression (6) pooled across macroeconomic variables featured in the SPF. The point estimate is positive and statistically insignificant, leading to a failure to reject the null hypothesis of full information rational expectations. Column (2) reports the annual version of regression (8). The point estimate is positive and statistically significant, implying that forecasters underreact to the most recent annual realization of a given macroeconomic variable when devising their annual forecasts. These results suggest that forecasters do not overreact at the annual frequency, consistent with annual anchoring.

Taken together, professional forecasters offset their near-term revisions over their longer-term trajectories. Consistent with this finding, professional forecasters appear to overreact at the quarterly frequency but not at the annual frequency. We argue that annual anchoring with a quarterly-to-annual consistency constraint can generate quarterly offsetting which in turn causes quarterly overreactions. In the next section, we build and estimate a model that allows us to quantify the degree of annual anchoring, its quantitative importance in

[12]For these regressions, we use the annual forecasts issued in the fourth quarter of the calendar year. We provide evidence in Tables A2 and A3 that our results are insensitive to this assumption.

generating overreactions, and its implications for estimates of information frictions.

3 A Model of Offsetting Revisions

We begin by detailing our model of offsetting revisions. The model is in the spirit of Andrade and Le Bihan (2013) and features quarterly and annual forecasts, each subject to a distinct updating probability. Derivations of our results can be found in Appendix B. After outlining the model, we discuss how overreactions arise through annual inattention and quarterly-to-annual consistency. 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 professional forecasters. Forecasters issue predictions about an exogenous macroeconomic variable which in part reflects the latent state of the economy, subject to the realization of noisy signals. Forecasters issue both quarterly and annual forecasts which they may update at different points in time, subject to an adding up constraint that requires quarterly forecasts to aggregate up to the annual forecast in every period.

More formally, forecasters predict a macroeconomic 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 of the economy, s_t, follows an AR(1) process:[13]

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

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 of the economy is unobserved to forecasters and to the econometrician. However, we assume that the

[13] In Appendix D we explore a richer driving process, with little effect on our results.

parameters governing the data generating process are known to forecasters.

Forecasters are interested in predicting the quarterly and annual realizations of the macroeconomic variable, x_t. Forecaster i's quarterly k-step ahead forecast devised at time t is $\widehat{x}^i_{t+k|t}$. Her annual forecast devised at time t is $\frac{1}{4}\sum_{h=0}^{3}\widehat{x}^i_{t+h|t}$.

When updating their predictions, forecasters observe the previous realization of the macroeconomic variable, x_{t-1}, as well as a contemporaneous private signal:

$$y^i_t = s_t + v^i_t, \quad v^i_t \overset{\text{i.i.d.}}{\sim} N(0, \sigma^2_v).$$

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. Instead, in a given period, a forecaster is only able to revise her quarterly prediction with probability q, and annual prediction with probability p.[14]

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 quarterly forecast, but not the annual one. In this case, she updates the quarterly forecast based on the signals received and subject to an adding up constraint.

Case 3: With probability $(1-q)p$, the forecaster updates her annual forecast, but not the quarterly ones. We interpret this case as a scenario in which the forecaster simply "brings in" the latest macroeconomic release, x_{t-1}, and updates her annual prediction accordingly. Importantly, the forecaster does not update the rest of the quarterly forecasts.[15]

Case 4: With probability pq, the forecaster can optimally update both types of forecasts based on the signals received.

[14] In principle, it is possible for forecasters to anchor over other frequencies or horizons, and for these targets to be heterogeneous across forecasters. We abstract away from this for parsimony and due to lack of sufficiently rich survey data.

[15] 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.

3.2 Quarterly Overreactions

From the perspective of the model, quarterly overreactions are due to Case 2 updating. As a result, the probability $q(1-p)$ governs the sign and magnitudes of the coefficients reported in Table 3. For general forms of low-frequency anchoring, the reported Case 2 prediction is:

$$\widehat{x}^i_{t+k'|t+k} = \mathbb{E}_{it+k}(x_{t+k'}) + \frac{1}{H+1}\sum_{h=0}^{H}\Big[\mathbb{E}_{i,t+k-j}(x_{t+h}) - \mathbb{E}_{it+k}(x_{t+h})\Big], \tag{9}$$

where $\widehat{x}^i_{t+k'|t+k}$ denotes forecaster i's reported forecast in period $t+k$ for some future period, $t+k'$. The subscript $t+k-j$ refers to period in which the low-frequency forecast was last updated. Finally, $H+1$ refers to the length of the horizon over which forecasts are anchored. The reported forecast is the sum of the optimal conditional expectation and a term capturing the gap between the path of the outdated forecast and what it should be based on the latest information.

Because our central focus is on quarterly and annual updating, we set the relevant horizon length to be $H=3$. Note, however, that as $H\to\infty$, the second term in (9) vanishes and the reported forecast converges to the conditional expectation. This is intuitive: as the horizon over which a forecaster anchors her predictions expands, the forecaster has more degrees of freedom along which to adjust the trajectory in order to preserve quarterly-to-annual consistency. As a result, she is more flexibly able to report a prediction that is consistent with the optimal forecast.

We can rearrange (9) in order to more transparently characterize the source of overreactions:

$$\widehat{x}^i_{t+k'|t+k} = \underbrace{\frac{3}{4}\mathbb{E}_{it+k}(x_{t+k'}) + \frac{1}{4}\mathbb{E}_{t+k-j}(x_{t+k'})}_{\text{Traditional smoothing motive}} + \underbrace{\frac{1}{4}\sum_{h\neq k'}\left[\mathbb{E}_{it+k-j}(x_{t+h}) - \mathbb{E}_{t+k}(x_{t+h})\right]}_{\text{Source of overreactions}}.$$

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. The last term is responsible for generating overreactions in our model. This sum reflects the differences in the conditional expectations between $t+k$ and $t+k-j$ for the other quarters that comprise the annual path. As current-year events unfold, this sum incorporates past forecast errors.

To see this, note that (9) can be re-written as:

$$\widehat{x}^{i}_{t+k'|t+k} = \mathbb{E}_{it+k}(x_{t+k'}) + \frac{1}{4}\sum_{h=0}^{k-1}\big[\mathbb{E}_{it+k-j}(x_{t+h}) - x_{t+h}\big] + \frac{1}{4}\sum_{h=k}^{3}\big[\mathbb{E}_{it+k-j}(x_{t+h}) - \mathbb{E}_{it+k}(x_{t+h})\big],$$

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

Overreactions arise because annual inattention and quarterly-to-annual consistency introduce past mistakes into the reported prediction. Suppose, for simplicity, that forecasters last updated their predictions in the previous period so that $j = 1$. Then, the above expression becomes:

$$\widehat{x}^{i}_{t+k'|t+k} = \mathbb{E}_{it+k}(x_{t+k'}) + \frac{1}{4}\big[\mathbb{E}_{it+k-1}(x_{t+k-1}) - x_{t+k-1}\big] + \frac{1}{4}\sum_{h=k}^{3}\big[\mathbb{E}_{it+k-j}(x_{t+h}) - \mathbb{E}_{it+k}(x_{t+h})\big].$$

Based on the second term, if x_{t+k-1} comes in higher than expected, then forecasters will mark down their forecasts in order to preserve consistency. 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. The trade-off between accuracy and consistency is therefore responsible for producing overreactions in our model.[16]

3.3 Analyzing the Model

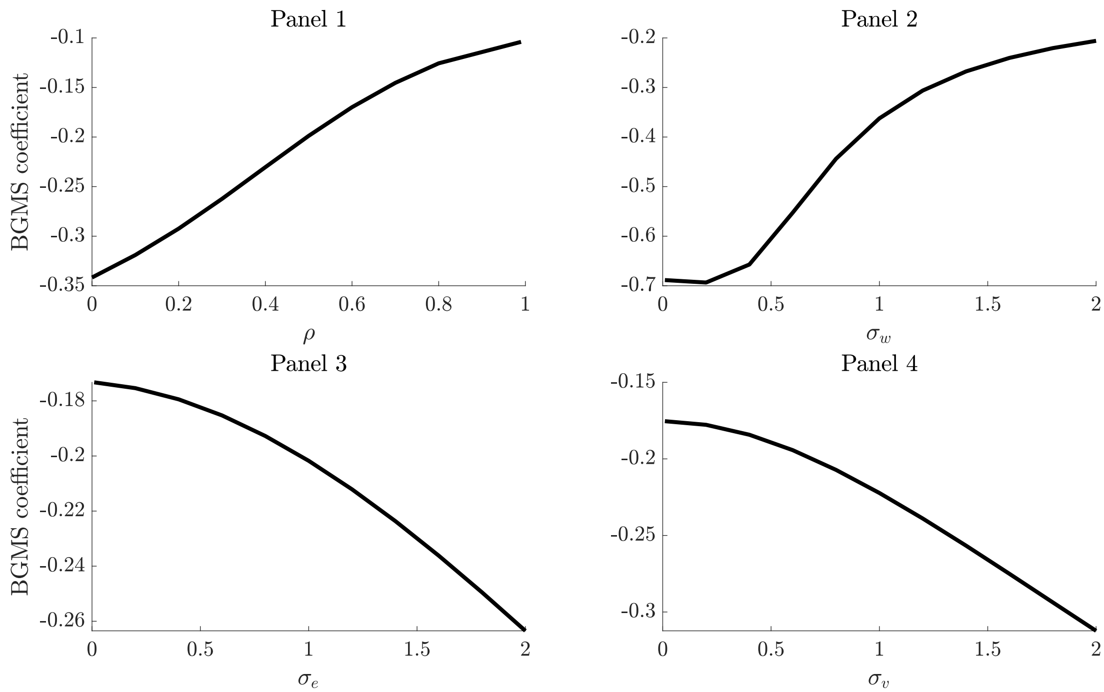
The model features rich dynamics across horizon and frequency. As a result, the coefficients studied in Section 2 are nonlinear functions of the underlying model parameters. To provide intuition for the model's ability to generate overreactions, we therefore rely on simulated comparative statics.

We focus on the Bordalo et al. (2020) (BGMS) coefficient, which regresses year-over-year errors on year-over-year revisions. We note, however, that the same qualitative findings arise with the other coefficients. Figure 3 plots simulated BGMS coefficients across a range of different parameter values collectively governing the state and signals.

Panels 1 and 2 display the relationship between the BGMS coefficient and the parameters

[16] In Appendix A.5, we provide empirical evidence consistent with the forecasting rule defined in equation (9). We show that the current year forecast is negatively related to the current-quarter error while past realizations are positively related to the current-quarter error.

Figure 3: Overreaction and Model Parameters

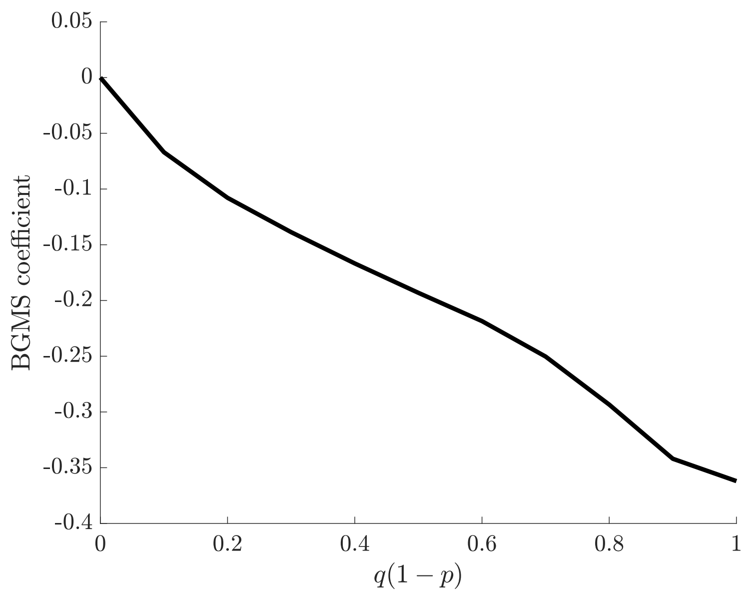


Note: The figure plots the BGMS coefficient as a function of each model parameter, holding the other parameters fixed.

governing the latent state. Based on Panel 1, as the underlying process approaches a unit root, we find that 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 ρ. From the lens of our model, a more persistent target variable reduces the magnitude of the forecast errors thereby minimizing the scope for past forecast errors to influence current predictions through the consistency constraint. 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 reduces the volatility of offsetting.

On the other hand, Panels 3 and 4 show that the forecaster-level coefficients are decreasing in public and private noise. All else equal, higher noise variances mean that forecast errors

Figure 4: Overreaction and Updating Probabilities



Note: The figure plots the simulated BGMS coefficient as a function of the probability of Case 2 updating.

are increasingly driven by transitory shocks. Since the transitory shocks are short-lived, forecasters 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 4 illustrates how individual overreactions depend on $q(1-p)$, which is the probability of Case 2 updating. As $q(1-p)$ increases, forecasters increasingly find themselves updating their quarterly predictions based on news while keeping their annual outlooks the same. In this case, forecasters respond to news, but offset their sequence of revisions so as to preserve consistency. The excessive revising that occurs along the annual path is responsible for generating overreactions.

4 Model Estimation

While our model can generate overreactions among forecasters, 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 Appendix C.[17] 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.

4.1 Identification

As with any other estimation approach, a discussion of identification is necessary. Here, there is a joint mapping between parameters and moments, however, some moments are especially important for identifying certain parameters. Figure C4 illustrates some important comparative statics that lend support to the choice of target moments.

The underlying persistence of the latent state, ρ, is in part identified by the covariance between the current-quarter forecast and the current-year forecast. With a highly persistent 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, σ_w, σ_e, and σ_v require further discussion. Two of these parameters reflect noise variance (σ_e and σ_v) while the other (σ_w) reflects the variance of the latent state innovations. Recognizing the distinction between noise and signal is essential for the identification of these parameters.

[17] 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.

First, the variance of the underlying state innovations, σ_w, is identified in part from the variance of the current-year forecast. Recall that the current-year forecast is: $\frac{1}{4}\sum_{h=0}^{3}\widehat{x}^{i}_{t+h|t}$. 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 σ_w raises the variance of the current-year forecast.

Moreover, higher levels of public noise, σ_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, σ_v, informs the covariance between revisions and lagged errors. Based on the model, the filtered current-quarter forecast revision is:

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

where κ_1 and κ_2 denote the Kalman gains. An increase in σ_v reduces the Kalman gain weight placed on the private signal, κ_1. As σ_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^{i}_{t} less and instead base more of their revisions on the news gleaned from yesterday's error.

4.2 Estimation Results

The parameters estimated via SMM are precisely estimated and 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 model to generate overreactions. Our estimates imply that annual anchoring is a meaningful friction in the model. In the absence of infre-

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 t-statistics 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.

quent 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.

Table 6: Non-targeted Moments

	Model		Data	
1. $\beta(FECQ, FRCQ)$	0.046	(0.046)	-0.260	(0.062)
2. $\beta(FE1Q, FR1Q)$	-0.179	(0.105)	-0.154	(0.076)
3. $\beta(FE2Q, FR2Q)$	-0.567	(0.115)	-0.358	(0.067)
4. $\beta(FE3Q, FR2Q)$	-0.905	(0.184)	-0.657	(0.087)
5. $\beta(FRCQ, FR1Q_{-1})$	-0.091	(0.063)	-0.136	(0.055)
6. $\beta(FR1Q, FR2Q_{-1})$	-0.305	(0.028)	-0.319	(0.065)
7. $\beta(FR2Q, FR3Q_{-1})$	-0.510	(0.027)	-0.406	(0.088)
8. $\beta(FEYY, FRYY)$	-0.177	(0.074)	-0.154	(0.078)
9. β(FEYY, Outcome)	-0.067	(0.096)	-0.096	(0.019)
10. $\beta(FECQ, FECQ_{-1})$	0.148	(0.051)	0.113	(0.048)

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.

5 Annual Anchoring and Overreactions

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. We then discuss two robustness exercises and explore potential drivers of offsetting revisions.

5.1 Simulated Regression Coefficients

The model is able to successfully replicate several moments 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-on-revisions coefficient for current-quarter forecasts (row 1 of Table 6). This is because the model assumes that the news 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.[18] 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 D8.

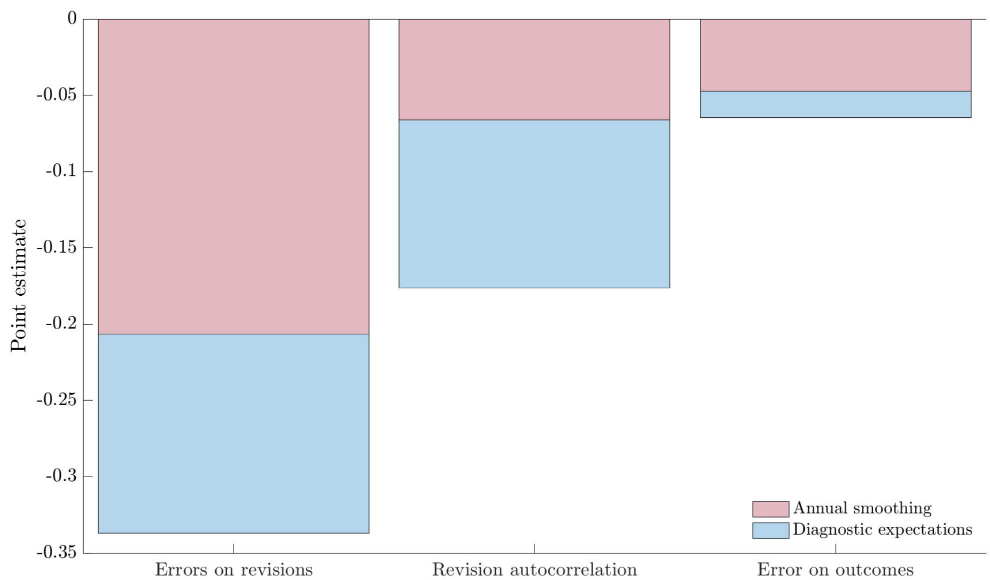
5.2 Incorporating Non-Rational Expectations

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), which draws from the representativeness heuristic (Tversky and Kahneman, 1974). In particular, diagnostic forecasters place excessive weight on new information such that their reported current-quarter prediction is:

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

[18] 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.

Figure 5: Annual Anchoring vs. Diagnostic Expectation Contributions



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

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 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 above, the baseline model cannot generate a negative correlation between current-quarter errors and revisions. Thus, we can identify θ by targeting these two additional moments. The estimated parameters are reported in column 1 of Table D9. We estimate a degree of diagnosticity equal to 0.50 which is close to the estimate of 0.60 reported in Bordalo et al. (2020) which uses a similar minimum distance estimation approach.

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 (6), (7), and (8). We then fix $\theta = 0$ and repeat this exercise. Figure 5 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]

5.3 Annual Anchoring by Macroeconomic Variable

We next estimate our baseline model for 15 macroeconomic variables covered in the SPF. 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 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 3. For instance, there is no evidence of overreaction in forecasts for the unemployment rate, a highly persistent aggregate.

5.4 Examining Potential Explanations for Offsetting Revisions

In the introduction, we offered two potential explanations for the annual anchoring and offsetting pattern observed in the data. Namely, we discussed the possibility that forecasters have two distinct models: one for their quarterly predictions and another one for their annual predictions. The reconciliation of these two models can lead to the offsetting revisions. Alternatively, forecasters could have a narrative attached to their annual prediction which

[19] Column 2 of Table D9 reports a related exercise in which we re-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 D5 repeats the comparison of diagnostic expectation based on simulated error predictability regressions. Our results are qualitatively unchanged from Figure 5.

Table 7: Estimates Across SPF Variables

	BGMS (2020) Coefficient	
	Model	Data
Real GDP	**-0.177 (0.074)**	**-0.154 (0.078)**
Nominal GDP	**-0.144 (0.089)**	**-0.308 (0.060)**
Real consumer spending	**-0.246 (0.100)**	**-0.266 (0.078)**
GDP deflator	**-0.149 (0.080)**	**-0.215 (0.100)**
Real residential investment	-0.153 (0.094)	-0.107 (0.103)
Real nonresidential investment	-0.130 (-0.085)	-0.034 (0.135)
Real federal spending	**-0.425 (0.137)**	**-0.510 (0.058)**
Real state/local spending	**-0.393 (0.112)**	**-0.495 (0.062)**
Employment	-0.067 (0.088)	0.307 (0.305)
Industrial production	**-0.195 (0.098)**	-0.014 (-0.091)
CPI	**-0.353 (0.108)**	**-0.327 (0.108)**
Unemployment	-0.005 (0.087)	0.214 (0.131)
Ten year bond	**-0.132 (0.073)**	**-0.111 (0.057)**
3-month bill	-0.051 (0.172)	0.091 (0.095)
Housing starts	**-0.194 (0.085)**	**-0.501 (0.048)**

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

they are reluctant to change. If, at the same time, they want to reflect new information quickly, then they will reshuffle their quarterly predictions. In this section, we examine these two explanations and their implications in further detail. While we anticipate that both explanations are present in the survey, a closer look may reveal their relative importance.

To do so, we exploit the SPF classifications of different forecaster types. In 1990, the SPF began collecting information on respondents' industries of employment. A respondent is labeled as either a financial service provider, a non-financial service provider, or neither. Financial service providers include asset managers, investment bankers, and insurance companies while non-financial forecasters include academics employed at universities, manufacturers, and consulting firms.[20]

[20] A full list is provided on page 33 of the SPF documentation: https://www.philadelphiafed.org/-/media/frbp/assets/surveys-and-data/survey-of-professional-forecasters/spf-documentation.pdf

We posit that financial forecasters are more likely to exhibit offsetting, and hence overreactions, in order to preserve a narrative rather than to reconcile two models. Financial service providers often have research departments that produce daily, weekly, and monthly publications in which they advertise their forecasts. Since these reports should always be up to date, revising separate annual and quarterly models for every report would require them to engage in costly model reconciliation each time new information is released.

At the same time, forecasters working in the financial sector are closely following the financial market news cycle, which includes economic data releases due to their market impact.[21] The regular publication cycle and closeness to financial markets can lead forecasters to build narratives around their forecasts. Upon first issuing their predictions, forecasters try to persuade clients of their story. By reinforcing these narratives through regular newsletters and reports, forecasters may find it costly to change their stories since doing so might signal incompetence. These characteristics, which are specific to financial forecasters, make it unlikely for them to maintain separate annual and quarterly models that they repeatedly reconcile.

On the other hand, we posit that non-financial forecasters are more likely to engage in offsetting due to model reconciliation rather than preserving a narrative. Non-financial forecasters, particularly academic forecasters, might only update their predictions at predetermined intervals (e.g. semiannually) since they are further away from financial markets and the the macroeconomic news cycle.[22] Though they might also have a narrative attached to their predictions, non-financial are unlikely to repeat this narrative in reports as frequently as financial forecasters. At the same time, being further removed from the economic release cycle makes model reconciliation easier, making it more likely for non-financial forecasters to operate with separate annual and quarterly models.

We thus assume that offsetting and overreactions are driven by different factors for different types of forecasters. By comparing updating behavior across the two groups, we can assess whether one of the two potential explanations is dominant in the data. If financial forecasters exhibit stronger overreactions than non-financial forecasters, then narrative fore-

[21] E.g. see Scotti (2016) where the market impact of several economic news releases is compared.

[22] While not a part of the SPF, international organizations such as the IMF, the World Bank, and the OECD, issue public forecasts only a few times per year. We believe that non-financial forecasters behave more like these institutions than financial forecasters.

Table 8: Overreaction by Forecaster Type

	Interaction term	
	Estimate	Standard error
1. $\beta(FECQ, FRCQ)$	0.013	0.053
2. $\beta(FE1Q, FR1Q)$	-0.045	0.091
3. $\beta(FE2Q, FR2Q)$	-0.254*	0.151
4. $\beta(FE3Q, FR3Q)$	-0.196	0.144
5. $\beta(FRCQ, FR1Q_{-1})$	-0.157*	0.089
6. $\beta(FR1Q, FR2Q_{-1})$	-0.059	0.100
7. $\beta(FR2Q, FR3Q_{-1})$	-0.246*	0.147
8. $\beta(FEYY, FRYY)$	-0.154*	0.092

Note: The table reports panel regression results from SPF forecasts of real GDP growth based on regressions (10) and (11). 'FE' refers to forecast error and 'FR' refers to forecast revision. 'CQ, 1Q, 2Q, 3Q' and 'YY' refer to current quarter, one-quarter ahead, two-quarters ahead, three-quarters ahead, and year-over-year, respectively. Driscoll and Kraay (1998) standard errors are reported in parentheses. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

casting is likely the more important driver of our offsetting results. On the other hand, if non-financial forecasters exhibit stronger overreactions, then model reconciliation is likely the more important driver of our offsetting results.

To assess which of the two explanations is more likely, we re-run regressions (6) and (7), with interaction terms to test for differences in the overreaction between financial and non-financial forecasts. Specifically, we run regressions of the following form:

$$FE_{it,t+h} = \beta_1 FR_{it,t+h} + \beta_2 \text{nonfinancial}_{it} + \beta_3 \left[FR_{it,t+h} \times \text{nonfinancial}_{it}\right] + \epsilon_{it,t+h} \tag{10}$$

$$FR_{it,t+h} = \gamma_1 FR_{it-1,t+h} + \gamma_2 \text{nonfinancial}_{it} + \gamma_3 \left[FR_{it-1,t+h} \times \text{nonfinancial}_{it}\right] + \eta_{it,t+h}. \tag{11}$$

We are interested in the estimates of β_3 and γ_3, which, if negative and statistically significant, tell us that non-financial forecasters exhibit stronger overreactions than financial forecasters.

Table 8 reports estimates of β_3 and γ_3. The results suggest that non-financial forecasters overreact more than financial forecasters since $\widehat{\beta}_3$ is negative and significant at the 10% level for half of the regressions. The point estimate is negative in nearly all of the regressions, and there is no statistically significant evidence that non-financial forecasters exhibit less overreaction than financial forecasters.

To supplement these results, we estimate a version of our model which allows for heterogeneity in updating frequencies across financial and non-financial forecasters. We define group-specific quarterly and annual updating probabilities, and estimate this extended model. The parameter estimates and the model fit are reported in Table D10 in the appendix.[23] We recover a higher annual updating probability for financial forecasters, in line with the results in Table 8. Taken together, our results imply that financial forecasters exhibit less overreaction than non-financial forecasters.

While there is evidence of overreaction in both groups, suggesting that both potential explanations for offsetting are present in the data, we find that non-financial forecasts exhibit stronger overreactions than financial forecasts. This suggests that the reconciliation between distinct annual and quarterly models might explain a larger share of revision offsetting.

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 9 reports measures of implied information rigidity for SPF forecasts of real GDP and inflation. Since our model is a hybrid sticky-noisy information model, we define the implied information friction to be:

$$\text{Implied friction} = \big[1 - \Pr(\text{update})\big] + \Pr(\text{update}) \times (1 - \kappa_1 - \kappa_2), \tag{12}$$

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.

[23] We also estimated a version of this model which allows for potentially different signal noise dispersion across groups. Our conclusions do not change based on the estimates from this version of the model.

Table 9: 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 at quarterly and annual frequencies. Implied information frictions are computed based on (12) with model-implied Kalman gains $\{0.800, 0.026\}$ and $\{0.783, 0.028\}$ for real GDP and inflation, respectively. Contributions of sticky and noisy information are computed according to (13).

Moreover, the role of noisy information in overall information frictions is understood through the coefficients $\{\kappa_1, \kappa_2\}$ which denote the Kalman gains.[24]

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 interpreted as an *expected* weight placed on new information.

In order to compare our implied information frictions to those in the literature, we also report model estimates using inflation forecasts based on the GDP deflator.[25] At a quarterly frequency, we estimate information frictions to be about 0.19 while, for annual forecasts, we

[24]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.

[25]Table D12 reports the parameter estimates and model fit.

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

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

$$1 = \underbrace{\frac{1 - \Pr(\text{update})}{[1 - \Pr(\text{update})] + \Pr(\text{update}) \times (1 - \kappa_1 - \kappa_2)}}_{\text{Sticky info contribution}} + \underbrace{\frac{\Pr(\text{update}) \times (1 - \kappa_1 - \kappa_2)}{[1 - \Pr(\text{update})] + \Pr(\text{update}) \times (1 - \kappa_1 - \kappa_2)}}_{\text{Noisy info contribution}}. \tag{13}$$

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 9 report the contributions of each form of imperfect information to the implied friction reported in column 3. The results from this accounting exercise suggest that noisy information is the primary contributor to estimated information frictions among quarterly forecasts, while sticky information becomes substantially more important at the annual frequency.

7 Conclusion

We show that professional forecasts exhibit an offsetting pattern where increases in short horizon predictions lead to decreases in longer horizon predictions such that the annual prediction remains anchored. We further document evidence of individual overreaction at the quarterly frequency and lack of overreaction at the annual frequency. Motivated by these facts, we build a hybrid sticky-noisy information model with quarterly and annual forecasts. From the lens of our model, overreactions arise because of annual anchoring and quarterly-to-annual consistency. The trade-off between minimizing errors and satisfying consistency can explain a substantial amount of overreactions to real GDP as well as other aggregates, while not requiring overreactions at the annual frequency.

While we cannot firmly exclude one explanation for annual anchoring and offsetting over the other, we provide evidence that favors one of the two. Specifically, it appears to be more driven by a reconciliation between separate models for annual and quarterly predictions, rather than by forecasters having a narrative attached to the annual prediction that forecasters are reluctant change while having quarterly predictions that are fully up to date with the latest data releases. Further research might be able to better pinpoint to what extent these two theories and others are driving the observed pattern.

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 twice a year while constantly updating the quarterly path to reflect new data releases.

References

Afrouzi, H., Kwon, S., Landier, A., Ma, Y., and Thesmar, D. (2021). Overreaction in Expectations: Evidence and Theory. Working Paper.

Andrade, P. and Le Bihan, H. (2013). Inattentive Professional Forecasters. *Journal of Monetary Economics*, 60:967–982.

Angeletos, G.-M., Huo, Z., and Sastry, K. A. (2020). Imperfect Macroeconomic Expectations; Evidence and Theory. *NBER Macroeconomics Annual 2020*, 35.

Azeredo da Silvera, R., Sung, Y., and Woodford, M. (2020). Optimally Imprecise Memory and Biased Forecasts. NBER Working Paper 28075.

Baker, S. R., McElroy, T. S., and Sheng, X. S. (2020). Expectation formation following large, unexpected shocks. *Review of Economics and Statistics*, 102(2):287–303.

Bianchi, F., Ilut, C., and Saijo, H. (2021). Diagnostic Business Cycles. NBER Working Paper 28604.

Bordalo, P., Gennaioli, N., Ma, Y., and Shleifer, A. (2020). Overreaction in Macroeconomic Expectations. *American Economic Review*, 110:2748–2782.

Bordalo, P., Gennaioli, N., Porta, R. L., and Shleifer, A. (2019). Diagnostic Expectations and Stock Returns. *The Journal of Finance*, 74(6):2839–2874.

Bordalo, P., Gennaioli, N., Schleifer, A., and Terry, S. (2021). Real Credit Cycles. NBER Working Paper 28416.

Bordalo, P., Gennaioli, N., and Shleifer, A. (2018). Diagnostic Expectations and Credit Cycles. *Journal of Finance*.

Broer, T. and Kohlhas, A. (2022). Forecaster (Mis-)Behavior. *Review of Economics and Statistics*, pages 1–45.

Bürgi, C. R. S. (2016). What Do We Lose When We Average Expectations? Working Papers 2016-013, The George Washington University, Department of Economics, H. O. Stekler Research Program on Forecasting.

Bürgi, C. R. S. (2017). Bias, rationality and asymmetric loss functions. *Economics Letters*, 154:113–116.

Chodorow-Reich, G., Guren, A. M., and McQuade, T. J. (2021). The 2000s Housing Cycle with 2020 Hindsight: A Neo-Kindlebergerian View. NBER Working Paper 29140.

Coibion, O. and Gorodnichenko, Y. (2015). Information rigidity and the expectations formation process: A simple framework and new facts. *American Economic Review*, 109:465–490.

Crowe, C. (2010). Consensus Forecasts and Inefficient Information Aggregation. Working Paper.

Daniel, K., Hirshleifer, D., and Subrahmanyam, A. (1998). Investor Psychology and Security Market Under- and Overreactions. *Journal of Finance*, 53:1839–1885.

Dovern, J., Fritsche, U., Loungani, P., and Tamirisa, N. (2015). Information Rigidities: Comparing Average and Individual Forecasts for a Large International Panel. *International Journal of Forecasting*, 31:144–154.

Driscoll, J. C. and Kraay, A. C. (1998). Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data. *The Review of Economics and Statistics*, 80:549–560.

Ehrbeck, T. and Waldmann, R. (1996). Why Are Professional Forecasters Biased? Agency Versus Behavioral Explanations. *The Quarterly Journal of Economics*, 111(1):21–40.

Farmer, L., Nakamura, E., and Steinsson, J. (2022). Learning About the Long Run. NBER Working Paper 29495.

Fuhrer, J. (2018). Intrinsic Expectations Persistence: Evidence from Professional and Household Survey Expectations. Working Paper.

Gabaix, X. (2019). Chapter 4 - behavioral inattention. In Bernheim, B. D., DellaVigna, S., and Laibson, D., editors, *Handbook of Behavioral Economics - Foundations and Applications 2*, volume 2 of *Handbook of Behavioral Economics: Applications and Foundations 1*, pages 261–343. North-Holland.

Kohlhas, A. N. and Walther, A. (2021). Asymmetric Attention. *American Economic Review*, 111:2879–2925.

Kucinskas, S. and Peters, F. (2022). Measuring Under- and Overreaction in Expectation Formation. *Review of Economics and Statistics*, pages 1–45.

Mankiw, G. and Reis, R. (2002). Sticky Information Versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve. *Quarterly Journal of Economics*, 117:1295–1328.

Nordhaus, W. D. (1987). Forecasting Efficiency: Concepts and Applications. *The Review of Economics and Statistics*, 69:667–674.

Ryngaert, J. (2017). What Do (and Don't) Forecasters Know About U.S. Inflation? Working Paper.

Scotese, C. A. (1994). Forecast Smoothing and the Optimal Under-utilization of Information at the Federal Reserve. *Journal of Macroeconomics*, 16:653–670.

Scotti, C. (2016). Surprise and uncertainty indexes: Real-time aggregation of real-activity macro-surprises. *Journal of Monetary Economics*, 82:1–19.

Sims, C. (2003). The Implications of Rational Inattention. *Journal of Monetary Economics*, 50:665–690.

Tversky, A. and Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science*, 185:1124–1131.

Woodford, M. (2001). Imperfect Common Knowledge and the Effects of Monetary Policy. *Knowledge, Information, and Expectations in Modern Macroeconomics: In Honor of Edmund Phelps.*

Appendix A Empirics

This section describes in further detail 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.[26]

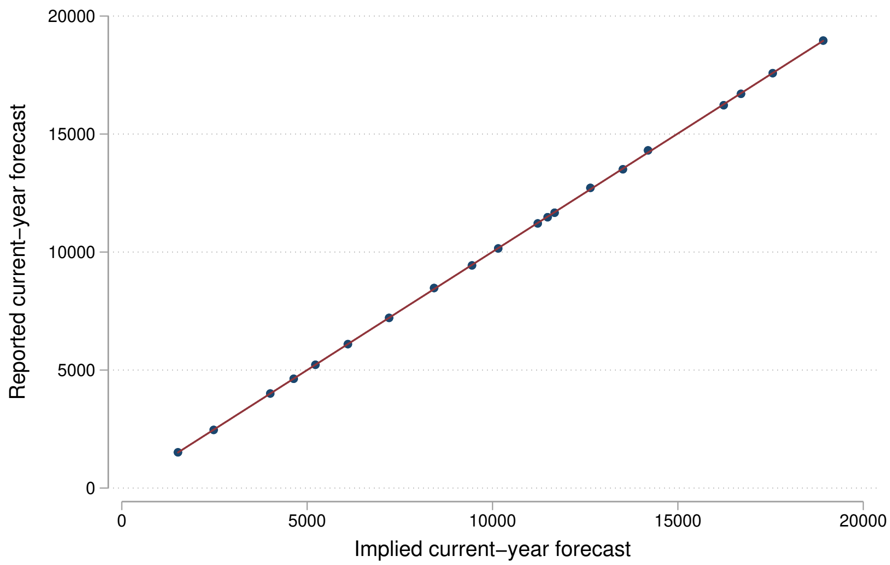
We construct implied current-year forecasts accordingly and compare them to the reported current-year forecasts, finding a 0.9999 correlation between the two as indicated by Figure A1.

A.2 Summary Statistics

We use data from the SPF spanning 1981Q3-2019Q4. Table A1 report summary statistics of real GDP forecasts, errors, and revisions across horizons, as well as real-time outcomes and data revisions.

[26]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.

Figure A1: Reported vs. Implied Current-Year Forecasts



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.

Table A1: SPF Real GDP Summary Statistics

	Mean	Median	Std. deviation	25%	75%
Forecasts					
Current quarter	2.280	2.500	1.966	1.687	3.256
One quarter ahead	2.581	2.635	1.585	2.014	3.296
Two quarters ahead	2.750	2.727	1.503	2.155	3.359
Current year	2.354	2.482	1.625	1.780	3.285
Forecast errors					
Current quarter	0.097	0.021	1.822	-1.038	1.111
One quarter ahead	-0.231	-0.211	2.233	-1.427	0.909
Two quarters ahead	-0.595	-0.291	3.927	-1.542	0.926
Forecast revisions					
Current quarter	-0.258	-0.107	1.743	-0.828	0.471
One quarter ahead	-0.144	-0.033	1.518	-0.503	0.302
Two quarters ahead	-0.100	-0.015	1.325	-0.424	0.266
Real GDP					
Real-time outcomes	2.373	2.458	2.251	1.373	3.521
Data revisions	-0.001	-0.034	0.529	-0.272	0.312

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 unbalanced panel spans 1981Q3-2019Q4.

A.3 Annual Error Predictability Regressions

To supplement the results in Table 4, we estimate additional errors-on-revisions and revisions-on-outcomes regressions at the annual frequency.

In column (1) of Table 4 in the main text, we estimate:

$$x_{jy} - \widehat{x}_{ijy|yq4} = \beta\left[\widehat{x}_{ijy|yq4} - \widehat{x}_{ijy|y-1q4}\right] + \delta_{ij} + \varepsilon_{ijyq4},$$

which is the relevant annual analog to regression (6). Here, j denotes a specific macroeconomic variable, i denotes the forecaster, y is year and q is quarter within the year ($q = q1, q2, q3$, or $q4$).

Rather than defining the revision as the annual forecast devised in Q4 of the current year minus the annual one year-ahead forecast in Q4 of the previous year, we can alternatively define the revision as the change in the current year annual forecast within the current year:

$$x_{jy} - \widehat{x}_{ijy|yq} = \beta\left[\widehat{x}_{ijy|yq} - \widehat{x}_{imy|yq-1}\right] + \delta_{ij} + \varepsilon_{ijyq},$$

Table A2 reports estimates of the above regression for different specifications of q.

Table A2: Errors-on-Revisions at Annual Frequency

	Annual error	Annual error	Annual error
Annual revision ($q = q2$)	-0.111		
	(0.131)		
Annual revision ($q = q3$)		-0.007	
		(0.065)	
Annual revision ($q = q4$)			0.076
			(0.050)
Fixed effects	Forecaster×variable	Forecaster×variable	Forecaster×variable
Forecasters	109	111	113
Observations	3287	3263	3241

Note: The table reports panel regression results from SPF forecasts of errors on revisions (6) at an annual frequency. Driscoll and Kraay (1998) standard errors are reported in parentheses. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

Moreover, in column (2) of Table 4, we define the annual forecast as the annual prediction reported in Q4 of the current year. We can alternatively specify the annual forecast as the one that is reported in earlier quarters of the year. Table A3 reports the results of these alternative specifications.

Table A3: Errors-on-Outcomes at Annual Frequency

	Annual error	Annual error	Annual error
Realized outcome ($q = 1$)	0.299***		
	(0.073)		
Realized outcome ($q = 2$)		0.299***	
		(0.063)	
Realized outcome ($q = 3$)			0.212***
			(0.055)
Fixed effects	Forecaster×variable	Forecaster×variable	Forecaster×variable
Forecasters	122	122	123
Observations	3601	3596	3527

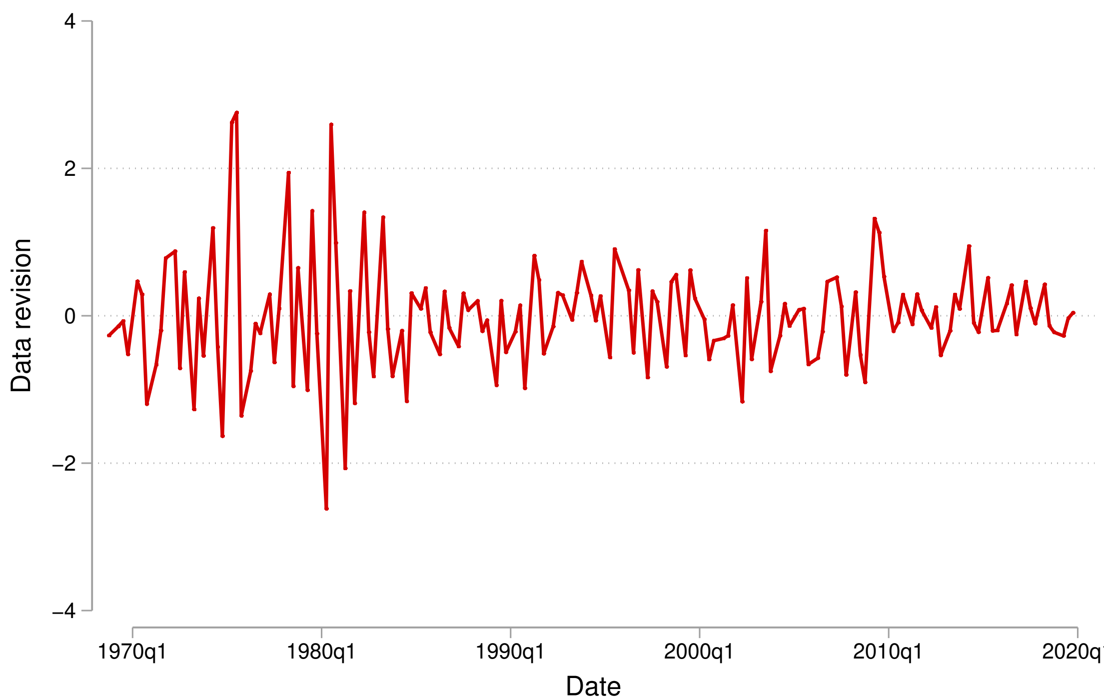
Note: The table reports panel regression results from SPF forecasts of errors on outcomes (8) at an annual frequency. Driscoll and Kraay (1998) standard errors are reported in parentheses. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

A.4 Offsetting Based on Macroeconomic Surprises

To lend further support to the offsetting revisions discussed in Section 2, we dig deeper by examining exogenous surprises. In particular, we analyze the response of forecast revisions of real GDP growth to a surprise in real GDP, proxied by statistical data revisions. Macroeconomic variables are subject to frequent data revisions that are made by statistical agencies.[27]

We construct a series of real GDP data revisions by computing the difference across vintages: $d_t = x_t^{\text{new}} - x_t^{\text{old}}$. Figure A2 plots the time series of measured real GDP data revisions.

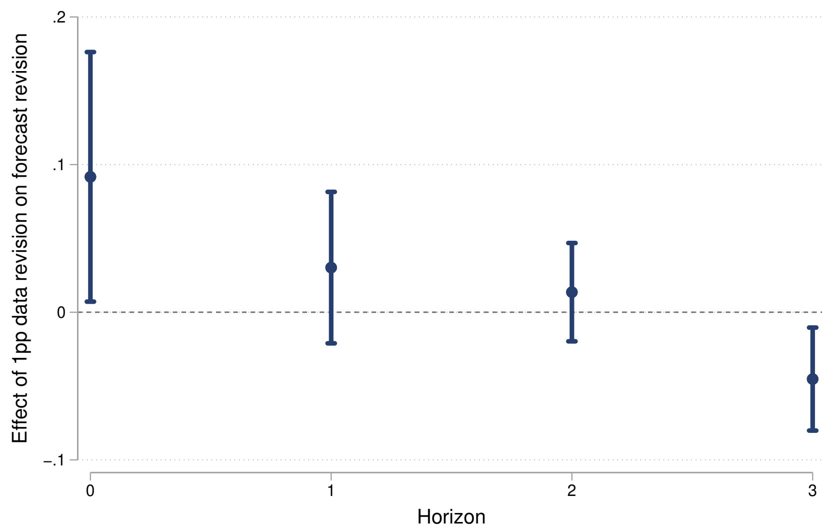
Figure A2: Real GDP Data Revision Series



For each horizon, we regress forecast revisions devised at time t on realized data revisions

[27]We focus on data revision "shocks" because they represent exogenous changes in the target variable which typically do not require widespread model revisions. If revisions are state dependent, then other more fundamental shocks would likely mask the presence of offsetting.

Figure A3: Effect of Data Revisions on Forecast Revisions



Note: The figure reports 95% confidence estimates of the α_1 coefficient in regression (14) across four horizons. Driscoll and Kraay (1998) standard errors are specified in the regressions.

observed at time t:

$$F_{it}(x_{t+h}) - F_{it-1}(x_{t+h}) = \alpha d_t + \varepsilon_{it}. \tag{14}$$

Figure A3 plots the point estimates across horizons, with 95% confidence intervals. The estimates indicate that an upward revision to real GDP induces forecasters to revise their current-quarter predictions upward and concurrently revise their three-quarter ahead predictions downward. This figure accords with the estimates reported in Table 1, and indicates that forecast revisions exhibit an offsetting behavior consistent with long-horizon smoothing.

A.5 Additional Evidence Consistent with the Offsetting Model

The offsetting model implies that a forecaster's reported prediction is the sum of a rational forecast and the deviation between an outdated annual forecast and an updated annual forecast as expressed in equation (8). Below, we document additional support for our model by regressing the forecast error on the annual forecast, the cumulative realizations of real GDP growth, and forecast revisions. Consistent with our model, the forecaster's annual forecast enters with a negative coefficient while the cumulative calendar year realizations of output, which factor into the updated annual forecast in equation (8) enters with a positive coefficient. Furthermore, as shown by the final two columns, the scope for overreaction based on the traditional errors-on-revisions regression decreases when controlling for the current-year forecast and the cumulative calendar year realizations of real GDP growth.

Table A4: Offsetting and Overreaction

	CQ error	CQ error	CQ error
CY forecast	-0.125***	-0.099**	
	(0.044)	(0.046)	
Cumulative realizations	0.010**	0.078*	
	(0.046)	(0.047)	
CQ Revision		-0.168**	-0.257***
		(0.064)	(0.076)
Fixed effects	Forecaster	Forecaster	Forecaster
Forecasters	162	161	161
Observations	2769	2757	2757

A.6 Bloomberg Real GDP Forecasts

Tables A5 and A6 document additional evidence of offsetting revisions from the Bloomberg survey of real GDP forecasts, a non-anonymous survey.

Table A5: Offsetting Revisions in the Bloomberg Survey

	Three quarter ahead revision	Three quarter ahead forecast
Two quarter ahead revision	0.401***	0.382***
	(0.063)	(0.058)
One quarter ahead revision	0.005	-0.045*
	(0.029)	(0.025)
Current quarter revision	-0.050**	-0.043**
	(0.019)	(0.016)
Lagged four quarter ahead forecast		0.731***
		(0.038)
Fixed effects	Time	Forecaster, Time
Forecasters	132	132
Observations	857	857

Note: The table reports panel regression results from SPF forecasts based on regression (2). The sample spans 1993Q2 to 2016Q3. Driscoll and Kraay (1998) standard errors are reported in parentheses. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

Table A6: Offsetting Calendar Year Revisions in the Bloomberg Survey

	Fourth quarter revision	Fourth quarter forecast
Third quarter revision	0.307***	0.184***
	(0.024)	(0.026)
Second quarter revision	-0.023	-0.064***
	(0.019)	(0.023)
First quarter revision	-0.059***	-0.056**
	(0.021)	(0.022)
Lagged fourth quarter forecast		0.586***
		(0.040)
Fixed effects	Time	Forecaster, Time
Forecasters	223	223
Observations	3123	3090

Note: The table reports panel regression results from SPF forecasts based on regression (4). The sample spans 1993Q2 to 2016Q3. Driscoll and Kraay (1998) standard errors are reported in parentheses. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

Appendix B Model

Suppose that in each period, professional forecasters devise predictions across a number of horizons, H. Forecasters in the model wish to minimize the sum of their mean square errors:

$$\min_{\{\widehat{x}^i_{t+h|t|t+k}\}} \sum_{h=0}^{H} (x_{t+h} - \widehat{x}^i_{t+h|t+k})^2, \tag{15}$$

where $\widehat{x}^i_{t+h|t+k}$ denote forecaster i's predictions about x_t h-steps into the future, based on information at time $t+k$.

When forecasters are able to freely update quarterly and annual forecasts, they report

$$\widehat{x}^i_{t+k'|t+k} = \mathbb{E}_{it+k}(x_{t+k'}) \ \forall k' \in [0, H], \quad \text{and} \quad \frac{1}{H+1}\sum_{h=0}^{H} \widehat{x}^i_{t+h|t+k}$$

as their quarterly and annual forecasts, respectively.

If the 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 quarterly forecasts coincide with the outdated annual forecast:

$$\frac{1}{H+1}\sum_{h=0}^{H} \widehat{x}^i_{t+h|t+k} = \frac{1}{H+1}\sum_{h=0}^{H} \widehat{x}^i_{t+h|t+k-j}, \tag{16}$$

where j denotes the period in which the annual forecast was last updated. In this case, the forecaster solves (15) subject to (16).

The Lagrangian is

$$\mathcal{L} = \sum_{h=0}^{H} (x_{t+h} - \widehat{x}^i_{t+h|t+k})^2 - \lambda\left(\frac{1}{H+1}\sum_{h=0}^{H} \widehat{x}^i_{t+h|t+k} - \frac{1}{H+1}\sum_{h=0}^{H} \widehat{x}^i_{t+h|t+k-j}\right)$$

The first order condition with respect to the reported forecast $\widehat{x}^i_{t+k'|t+k}$ implies

$$\widehat{x}^i_{t+k'|t+k} = \mathbb{E}_{it+k}(x_{t+k'}) + \frac{\lambda}{2(H+1)}. \tag{17}$$

Combining the FOC with the definition of the constraint delivers:

$$\frac{1}{H+1}\sum_{h=0}^{H}\widehat{x}^{i}_{t+h|t+k-j} = \frac{1}{H+1}\sum_{h=0}^{H}\left[\mathbb{E}_{it+h}(x_{t+k'}) + \frac{\lambda}{2(H+1)}\right].$$

Rearranging, we obtain:

$$\lambda = 2(H+1)\left[\frac{1}{H+1}\sum_{h=0}^{H}\widehat{x}^{i}_{t+h|t+k-j} - \frac{1}{H+1}\sum_{h=0}^{H}\mathbb{E}_{it+k}(x_{t+k'})\right]$$

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

$$\widehat{x}^{i}_{t+k'|t+k} = \mathbb{E}_{it+k}(x_{t+k'}) + \left[\frac{1}{H+1}\sum_{h=0}^{H}\widehat{x}^{i}_{t+k'|t+k-j} - \frac{1}{H+1}\sum_{h=0}^{H}\mathbb{E}_{it+k}(x_{t+k'})\right]$$

or, equivalently,[28]

$$\widehat{x}^{i}_{t+k'|t+k} = \mathbb{E}_{it+k}(x_{t+k'}) + \frac{1}{H+1}\sum_{h=0}^{H}\left[\mathbb{E}_{it+k-j}(x_{t+k'}) - \mathbb{E}_{it+k}(x_{t+k'})\right]. \tag{18}$$

[28] 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 $t+k-j$.

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.[29] For each iteration, the target moments are computed, averaged across simulations, and compared to their empirical analogs. The six-dimensional parameter vector, θ, 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 $\widehat{\theta}$ that minimizes the following objective

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

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 $\widehat{\theta}$ is

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

where

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

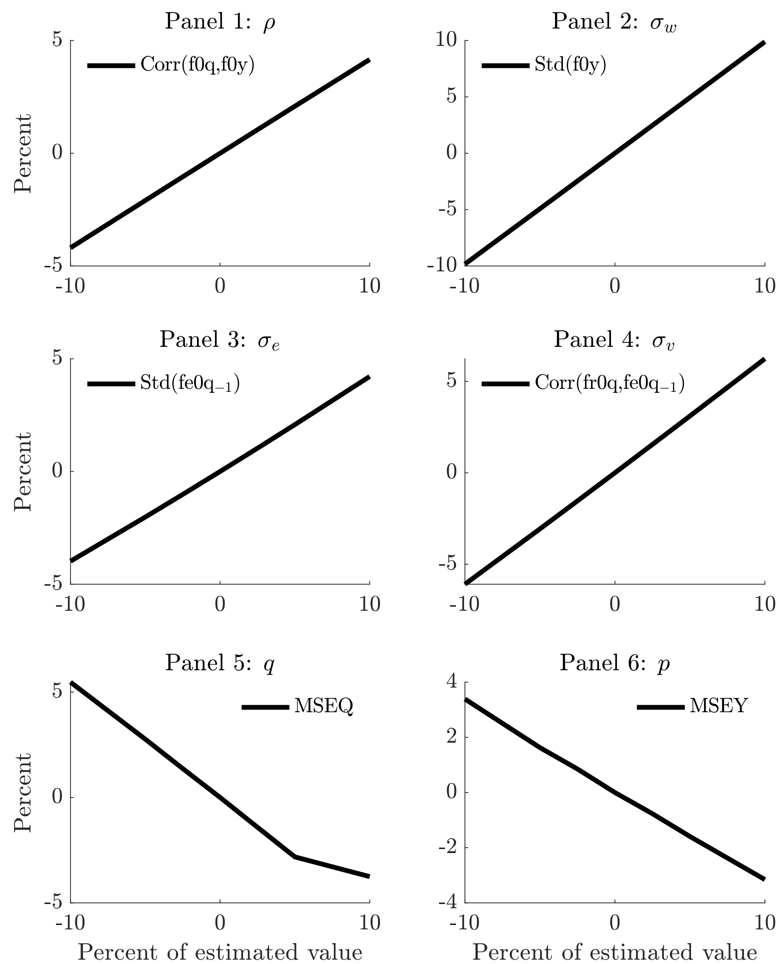
and $S = 100$. Standard errors are obtained by numerically computing the partial derivative of the simulated moment vector with respect to the parameter vector.

C.1 Identification

The eight moments jointly determine the six parameters that reside in vector θ. Figure C4 visualizes the monotonic relationships between parameters and moments discussed in the main text.

[29] Similar results are obtained when mimicking the unbalanced nature of the panel data by simulating a larger set of forecasters and matching missing observations.

Figure C4: 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 Robustness

In this section, we conduct a variety of additional model-based exercises. First, we examine the role that rounding plays in the parameter estimates. We then report the non-targeted fit of the baseline model to consensus-level moments. Next, we augment our model with diagnostic expectations to assess the relative importance of our mechanism in generating overreactions. We then report estimates of the extended model in which updating rates vary by forecaster type. We then report the estimates based on real GDP forecasts from the Bloomberg Survey as well as SPF inflation forecasts. Following this, we undertake a sub-sample analysis, estimating the baseline model before and after 1990. Finally, we consider an alternative data generating process for the underlying state.

D.1 Rounding

We first 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 (see Table D7).[30]

[30]Studying more traditional Gaussian measurement error introduces an identification problem between the measurement error dispersion and private signal noise dispersion, σ_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.

Table D7: Model Estimation Results (Rounding to nearest 0.1 pp)

Panel A: Parameter Estimates			
	Parameter	Estimate	Standard error
Persistence of latent state	ρ	0.401	0.034
State innovation dispersion	σ_w	2.016	0.158
Public signal noise	σ_e	0.816	0.353
Private signal noise	σ_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 lag error	1.644	1.720	-0.889
RMSE nowcast	1.657	1.677	-0.415
RMSE annual forecast	1.095	1.098	-0.100

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.2 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 regression 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 noisy information environment allows us to recover underreactions at the consensus level.

Table D8 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.

Table D8: Baseline Model Fit to Consensus Moments

	Model		Data	
1. $\beta(FECQ, FRCQ)$	0.446	(0.070)	0.177	(0.108)
2. $\beta(FE1Q, FR1Q)$	0.569	(0.264)	0.711	(0.292)
3. $\beta(FE2Q, FR2Q)$	-0.063	(0.532)	0.972	(0.334)
4. $\beta(FE3Q, FR2Q)$	-0.794	(0.806)	-0.599	(0.156)
5. $\beta(FRCQ, FR1Q_{-1})$	0.346	(0.152)	0.292	(0.128)
6. $\beta(FR1Q, FR2Q_{-1})$	0.042	(0.107)	0.459	(0.149)
7. $\beta(FR2Q, FR3Q_{-1})$	-0.397	(0.075)	-0.326	(0.203)
8. $\beta(FEYY, FRYY)$	0.475	(0.148)	0.648	(0.275)
9. β(FEYY, Outcome)	-0.066	(0.096)	-0.077	(0.064)
10. $\beta(FECQ, FECQ_{-1})$	0.099	(0.067)	0.076	(0.075)

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.3 Diagnostic Expectations

Table D9 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.

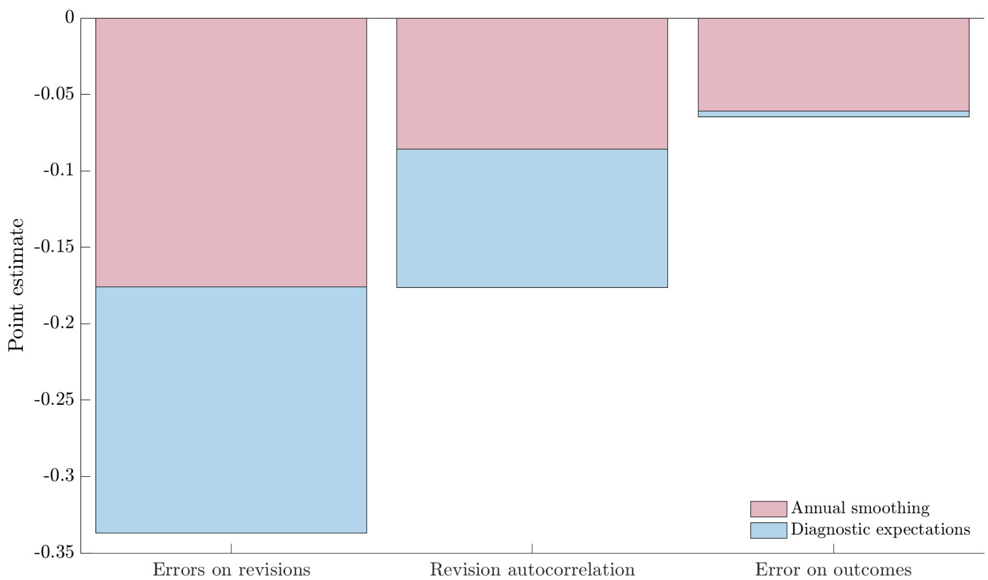
Table D9: Model Estimation Results, Diagnostic Expectations

	Parameter	(1) Unconstrained	(2) Constrained
Persistence of latent state	ρ	0.544	0.488
		(0.058)	(0.047)
State innovation dispersion	σ_w	1.455	1.757
		(0.178)	(0.131)
Public signal noise	σ_e	1.093	0.774
		(0.200)	(0.194)
Private signal noise	σ_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	θ	0.501	0.000
		(0.115)	-

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 D5 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 D9. This differs from Figure 5 in that the counterfactual in Figure 5 features the same parameters as the unconstrained model, but with θ fixed at zero.

Figure D5: Annual Smoothing vs. Diagnostic Expectation Contributions



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

D.4 Financial vs. Non-Financial Forecasters

Table D10 reports parameter estimates for real GDP predictions made by financial and non-financial forecasters, respectively. We estimate eight parameters by targeting 16 moments (the original eight moments, but for financial and non-financial forecasters separately).

Table D10: Model Estimation Results

Panel A: Parameter Estimates			
	Parameter	Estimate	Standard error
Persistence of latent state	ρ	0.517	0.037
State innovation dispersion	σ_w	1.492	0.105
Public signal noise	σ_e	1.088	0.119
Private signal noise	σ_v	0.978	0.176
Probability of quarterly update	q^F	1.000	0.085
Probability of quarterly update	q^{NF}	1.000	0.093
Probability of annual update	p^F	0.668	0.094
Probability of annual update	p^{NF}	0.524	0.058
Panel B: Financial Forecaster Moments			
	Model moment	Data moment	t-statistic
Std(CQ forecast)	1.406	1.500	1.370
Corr(CQ forecast, CY forecast)	0.739	0.756	0.584
Std(CY forecast)	1.005	0.971	-0.790
Std(CQ revision)	1.268	1.170	-1.670
Corr(CQ revision, lagged CQ error)	0.197	0.195	-0.339
Std(lagged CQ error)	1.473	1.489	0.288
CQ RMSE	1.489	1.531	0.732
CY RMSE	0.926	0.976	0.904
Panel C: Non-Financial Forecaster Moments			
Std(CQ forecast)	1.362	1.857	3.061
Corr(CQ forecast, CY forecast)	0.721	0.661	3.202
Std(CY forecast)	0.959	1.181	2.651
Std(CQ revision)	1.225	1.764	2.716
Corr(CQ revision, lagged CQ error)	0.174	0.124	0.416
Std(lagged CQ error)	1.528	1.867	2.679
CQ RMSE	1.547	1.803	3.342
CY RMSE	0.995	1.170	3.244

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.5 Bloomberg Real GDP Forecasts

Table D11 reports the the model estimates from the Bloomberg survey.

Table D11: Model Estimation Results, Bloomberg Survey

Panel A: Parameter Estimates			
	Parameter	Estimate	Standard error
Persistence of latent state	ρ	0.683	0.029
State innovation dispersion	σ_w	1.216	0.091
Public signal noise	σ_e	0.771	0.097
Private signal noise	σ_v	0.020	0.004
Probability of quarterly update	q	0.717	0.074
Probability of annual update	p	0.305	0.037
Panel B: Moments			
	Model moment	Data moment	t-statistic
Standard deviation of nowcast	1.228	1.583	5.482
Correlation of nowcast with annual forecast	0.780	0.762	4.398
Standard deviation of annual forecast	0.939	1.142	4.001
Standard deviation of revision	0.908	1.037	3.396
Correlation of revision with lagged error	0.138	0.160	1.235
Standard deviation of lag error	1.302	1.257	-1.633
RMSE nowcast	1.346	1.339	-0.285
RMSE annual forecast	1.002	1.000	-0.074

Note: 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 Inflation Forecasts

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

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

Panel A: Parameter Estimates			
	Parameter	Estimate	Standard error
Persistence of latent state	ρ	0.585	0.081
State innovation dispersion	σ_w	1.041	0.072
Public signal noise	σ_e	0.950	0.109
Private signal noise	σ_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 lag error	1.162	1.256	1.328
RMSE nowcast	1.174	1.257	1.424
RMSE annual forecast	0.748	0.819	1.167

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.7 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 D13) and 2000-2019 (Table D14). 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.

Table D13: Model Estimation Results (1981-1999)

Panel A: Parameter Estimates			
	Parameter	Estimate	Standard error
Persistence of latent state	ρ	0.335	0.089
State innovation dispersion	σ_w	2.081	0.438
Public signal noise	σ_e	1.366	0.709
Private signal noise	σ_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 lag error	1.828	2.035	-1.159
RMSE nowcast	1.863	1.945	-1.056
RMSE annual forecast	1.240	1.300	-0.965

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.

Table D14: Model Estimation Results (2000-2019)

Panel A: Parameter Estimates			
	Parameter	Estimate	Standard error
Persistence of latent state	ρ	0.624	0.035
State innovation dispersion	σ_w	1.359	0.256
Public signal noise	σ_e	1.129	0.308
Private signal noise	σ_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 lag error	1.461	1.518	-1.269
RMSE nowcast	1.481	1.509	-0.641
RMSE annual forecast	0.960	0.969	-0.260

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.8 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.[31] Second, an AR(2) is highly feasible to estimate with the current 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 ρ_1 and ρ_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 D15.

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 9, these estimates imply roughly similar levels of information rigidity in quarterly and annual real GDP forecasts

[31] In this unreported exercise, we considered AR(2), AR(4), ARMA(1,1), ARMA(2,1) and ARMA(2,2) models.

Table D15: Model Estimation Results, AR(2)

Panel A: Parameter Estimates			
	Parameter	Estimate	Standard error
First lag autocorrelation	ρ_1	0.524	0.149
Second lag autocorrelation	ρ_2	-0.075	0.018
State innovation dispersion	σ_w	1.828	0.231
Public signal noise	σ_e	1.163	0.343
Private signal noise	σ_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 lag error	1.629	1.720	-1.060
RMSE nowcast	1.645	1.677	-0.661
RMSE annual forecast	1.077	1.098	-0.576

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 (12)). 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.