# Overreaction Through Anchoring[*]

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**Abstract**

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

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# 1 Introduction

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

We start by documenting a novel fact about survey expectations: individual forecast revisions exhibit an offsetting pattern. That is, an upward revision to the current-quarter forecast leads to a downward revision in the three-quarter ahead forecast. We document evidence for this fact using data from the U.S. Survey of Professional Forecasters (SPF) as well as other surveys, and argue that offsetting 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 (Bordalo et al., 2020; Nordhaus, 1987; Kohlhas and Walther, 2021), there is no evidence of overreaction at the annual frequency.

To explain these facts, we build and estimate a model of multi-frequency forecasting. Our model is a hybrid sticky-noisy information model as in Andrade and Le Bihan (2013) with heterogeneous updating rates by frequency. Forecasters issue high and low frequency forecasts based on private and public signals. High and low frequency updating are separate activities governed by distinct Calvo-like probabilities. Furthermore, forecasters are subject to a consistency constraint which requires a forecaster's sequence of high frequency predictions aggregate up to her low frequency prediction.[1] Two key assumptions are responsible for generating offsetting and overreactions: consistency (i.e. high frequency forecasts aggregate up to the low frequency forecast) and low frequency inattention. Under these two

[1] The SPF requires forecasters to issue consistent predictions, a feature of the data which we verify in Appendix A. For real GDP growth, our primary variable of interest, quarterly (high frequency) forecasts in the data correspond to the quarter over quarter annualized growth rate, and annual (low frequency) forecasts correspond to the percentage change of the average quarterly level this year relative to the average quarterly level last year. Quarterly and annual forecasts are similarly defined for the other variables that we examine.

assumptions, an upward revision in the near-term must be offset by a downward revision, as in the data.

We offer two explanations for the offsetting pattern observed in the data and generated by our model. First, agents may have separate frequency-specific models that need to be reconciled. One way of doing this is to use the lower frequency prediction as an anchor and adjust the higher frequency forecasts to achieve consistency. Assuming that agents are more informed about the short run, they would optimally revise the near term based on new information and offset these updates further out along their projected path. Second, forecasters may publicly commit to their lower frequency forecasts. Examples of such commitment can be found in different settings such as when professional forecasters attach narratives to their lower frequency forecasts, when managers issue longer-run guidance, and when individuals plan major life events. In such cases, revising the lower frequency forecast may be costly. As a result, agents might engage in few revisions of lower frequency predictions, and instead reshuffle their higher frequency forecasts as they bring in new information.[2] Though we are unable to discern between these two explanations in the data, both can account for the observed overreactions documented in the literature.

Individual overreactions arise in our model because agents introduce past errors into their reported predictions through the consistency constraint.[3] Because of the trade off between accuracy and consistency, agents offset their revisions which in turn generates error and revision predictability. Low frequency inattention is therefore 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, consistent with the data.

We specify our model to fit quarterly (high frequency) and annual (low frequency) forecasts and estimate its parameters via the simulated method of moments (SMM) by targeting micro moments in the SPF. Our estimated model successfully fits both targeted and

[2]We talked to a number of professional forecasters contributing to the surveys used here and these two explanations are consistent with how they devise their forecasts. There is thus anecdotal evidence of this updating behavior in the professional forecasting context.

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

non-targeted moments. Overall, our estimates imply that annual anchoring can explain a meaningful share of observed overreactions across a range of measures. The estimated model can also generate empirically-relevant degrees of underreaction in consensus forecasts.

To quantify the relative importance of our mechanism, we estimate a version of the model with diagnostic expectations (Bordalo et al., 2018, 2019, 2020), a leading theory of non-rational expectations.[4] When we add diagnostic expectations into our model and examine different forms of error and revision predictability, we find that our mechanism can still explain more than half of measured overreactions. This suggests that low frequency anchoring can be an important contributor to overreactions, alongside other forces.

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

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

A longstanding literature on expectation formation has studied forecast error predictability (Nordhaus, 1987; Clements, 1997; Pesaran and Weale, 2006; Patton and Timmermann, 2012; Coibion and Gorodnichenko, 2015). Recent evidence suggests that, at the individual level, forecasters overreact to news (Bordalo et al., 2020; Broer and Kohlhas, 2022; Bürgi, 2016). In this paper, we study three specific measures of overreaction (Bordalo et al., 2020; Nordhaus and Durlauf, 1984; Kohlhas and Walther, 2021). Furthermore, we document novel

[4]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).

evidence that forecasters partially offset their revisions, and we show that this pattern can generate observed overreactions.

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

Following on these seminal sticky and noisy information models, which can only generate aggregate underreaction, a strand of the literature has proposed novel theories to explain the aforementioned evidence of overreactions (Afrouzi et al., 2021; Bordalo et al., 2020; Broer and Kohlhas, 2022; Gabaix, 2019; Kohlhas and Walther, 2021; Farmer et al., 2022). We offer a new explanation by building a model in which overreactions emanate from consistency constraints that arise under multi-frequency forecasting. Our model can jointly explain offsetting, overreactions, and underreactions.

The rest of the paper is organized as follows. Section 2 documents empirical evidence relating to offsetting. Section 3 reviews evidence on observed overreactions at the forecaster level. Section 4 presents the offsetting revisions model. Section 5 discusses the estimation strategy and results. Section 6 quantifies the extent to which low-frequency anchoring can explain higher-frequency overreactions. Section 7 discusses the implications for estimates of information frictions. Section 8 concludes.

# 2 Facts About Offsetting

We start by documenting a novel fact 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.

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 collects quarterly predictions across a range of macroeconomic variables over many horizons. We begin our sample in 1981Q3 when the SPF started to collect current-year forecasts and required them to be consistent with the associated quarterly forecasts.[5] In this sense, the consistency constraint that we impose in our model is directly motivated by the data.[6]

## 2.1 Offsetting Revisions Across Horizons

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

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.[7] We run the following regression:

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

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 Table 1. Columns (1) and (2) report the regression results across different fixed effects specifications. Our preferred specification is reported in column (2). We prefer introducing time fixed effects because larger fluctuations in real GDP growth may lead forecasters to implement widespread model revisions which could mask offsetting behavior since the annual forecast would no longer be anchored. We do not specify fore-

[5]To abstract away from the COVID-19 pandemic, our sample spans 1981Q3 to 2019Q4.

[6]Our pre-1981Q3 offsetting estimates are smaller in magnitude relative to the post-1981Q3 sample. One could view this as lending support to our hypothesis that offsetting is due to quarterly-to-annual consistency. We cannot, however, rule out the possibility that forecasters were issuing quarterly-to-annual-consistent forecasts prior to 1981Q3.

[7]We are unable to complete this exercise over longer horizons since it requires a full sequence of forecast revisions. While the SPF provides longer-term forecasts, we do not observe the sequence of forecasts from which to construct revisions and run this regression.

Table 1: Offsetting Revisions across Horizons

| | (1) 3Q ahead revision | (2) 3Q ahead revision | (3) 3Q ahead growth |
|---|---|---|---|
| 2Q Ahead | 0.147** | 0.118* | 0.508*** |
| | (0.064) | (0.062) | (0.103) |
| 1Q Ahead | 0.059 | 0.042 | -0.012 |
| | (0.068) | (0.072) | (0.105) |
| Current Quarter | -0.061* | -0.062** | 0.047 |
| | (0.032) | (0.029) | (0.098) |
| Fixed effects | None | Time | None |
| Forecasters | 205 | 205 | |
| Observations | 4143 | 4143 | 154 |

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

caster fixed effects in these regressions because permanent differences across forecasters are differenced out when constructing revisions. Based on the regression results, a one percentage point increase in the two quarter ahead revision predicts a roughly 12 to 15 basis point increase in the three quarter ahead revision. However, a one percentage point increase in the current quarter revision predicts a 6 basis point decrease in the three quarter ahead revision. Put another way, a one standard deviation increase in the current quarter revision predicts a 7% downward revision three quarters ahead.[8]

Offsetting revisions could naturally arise if the aggregate variable of interest exhibits certain dynamics. To examine this, we estimate equation (1) using real-time real GDP growth:

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

and report the results in column (3) of Table 1. Based on our estimates, we find no evidence of a negative and significant autoregressive coefficient leading us to conclude that offsetting

[8] 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.

Table 2: Offsetting Revisions within Calendar Year

| | (1) Fourth quarter revision | (2) Fourth quarter revision | (3) Fourth quarter revision | (4) Fourth quarter growth |
|---|---|---|---|---|
| Third Quarter | 0.279*** | 0.236*** | 0.236*** | 0.716** |
| | (0.060) | (0.046) | (0.048) | (0.276) |
| Second Quarter | 0.046 | 0.046 | 0.038 | 0.109 |
| | (0.044) | (0.060) | (0.064) | (0.263) |
| First Quarter | -0.058** | -0.103** | -0.103** | 0.009 |
| | (0.029) | (0.046) | (0.050) | (0.133) |
| Fixed effects | None | Time | Forecaster, Time | None |
| Forecasters | 205 | 205 | 185 | |
| Observations | 4254 | 4254 | 4234 | 39 |

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

revisions are unlikely to be driven by the dynamics of real GDP growth.

## 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:

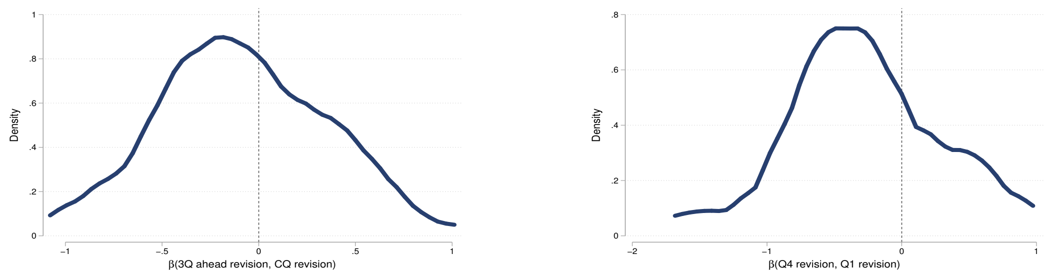
$$F_{it}(x_{Q4}) - F_{it-1}(x_{Q4}) = \delta_t + \sum_{k \in \{Q1,Q2,Q3\}} \alpha_k \big[F_{it}(x_k) - F_{it-1}(x_k)\big] + \omega_{it}. \tag{3}$$

The difference between (1) and (3) 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 $F_{it}(x_{t+2}) - F_{it-1}(x_{t+2})$ 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

Figure 1: Density of Individual Revision Offsetting Coefficients

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




Note: The figures plot kernel density estimates of $\alpha_0$ and $\alpha_{Q1}$ in regressions (1) and (3), estimated for each individual forecaster. Regressions are only estimated for forecasters issuing at least 25 quarter-long spells of forecasts. Only statistically significant estimates are kept (at least at the 10% level).

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, $x_{t-1} - F_{it-1}(x_{t-1})$.

Columns (1) through (3) of Table 2 report OLS estimates of (3) for different fixed effect specifications. Because the calendar year revisions that we construct are in part composed forecast errors, column (3) also reports a version of regression (3) with forecaster fixed effects. 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 6 to 10 basis point downward revision to the fourth quarter forecast.

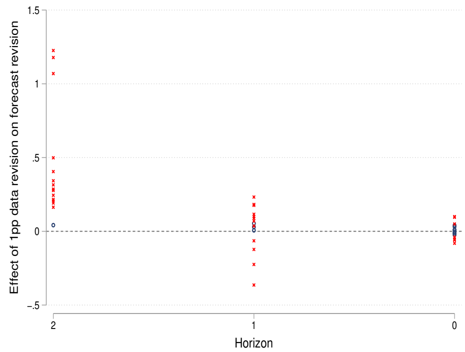
As in column (3) of Table 1, column (4) of Table 2 examines fluctuations in real GDP growth. Similar to our results for offsetting across horizons, we find that real GDP in the first quarter does not predict real GDP in the fourth quarter of the year. These results again indicate that the offsetting present in professional forecasts is driven by something other than the underlying data generating process.

## 2.3 Offsetting Across Forecasters and Macroeconomic Variables

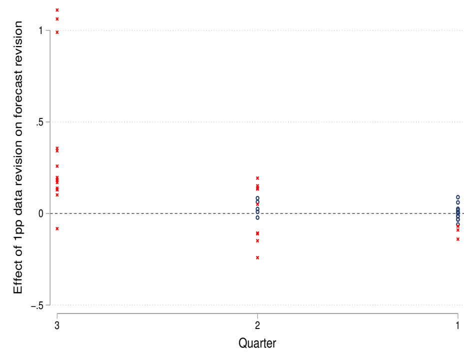
The regressions estimated above allow for only a common degree of offsetting across forecasters. As a result, our estimates could be driven by a few forecasters exhibiting a strong

Figure 2: Offsetting Across SPF Variables

(a) Offsetting by horizon




(b) Offsetting within calendar year




Note: The figures display estimated coefficients of regressions (1) and (3), respectively, 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, six of the 15 variables exhibit statistically significant evidence of offsetting.

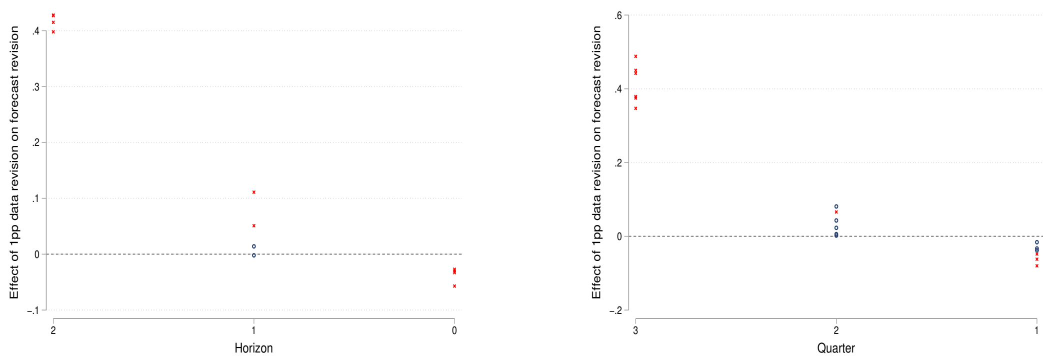
degree of offsetting. To explore the potential heterogeneity in offsetting patterns further, we estimate (1) and (3) forecaster-by-forecaster and non-parametrically visualize the distribution of point estimates for $\alpha_0$ and $\alpha_{Q1}$. Panel (a) of Figure 1 displays the density of point estimates of $\alpha_0$ in regression (1) while panel (b) plots the density of point estimates of $\alpha_{Q1}$ in regression (3). The figures imply that most of the statistically significant point estimates are negative. The share of negative point estimates are 0.62 and 0.71 for panels (a) and (b), respectively.[9] Thus, the offsetting patterns reported in Tables 1 and 2 are present for a majority of forecasters when allowing the regressions coefficients to exhibit cross-sectional heterogeneity.

We also estimate (1) and (3) for other 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 a substantial number 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.

[9]We obtain similar shares when including all point estimates.

Figure 3: Offsetting in BBG and WSJ Surveys

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




Note: The figures display estimated coefficients of regressions (1) and (3), respectively, for the BBJ and WSJ surveys. The red 'x' symbols denote statistical significance at the 10% level and the hollow blue circles denote no statistical significance.

## 2.4 Robustness: Other Surveys

Our results have so far focused on the SPF. Since our analysis requires the availability of an annual forecast and its quarter-by-quarter path, we are unable to utilize surveys such as BlueChip, Consensus Economics, or the ECB Survey of Professional Forecasters. However, we are able to exploit the Bloomberg (BBG) Survey and the Wall Street Journal (WSJ) Survey.

The BBG and WSJ surveys are non-anonymous surveys of professional forecasters. We observe the forecasters' quarterly forecasts for a given year as well as their calendar year forecasts. Our sample for the BBG survey spans 1993Q2 to 2016Q3 while our WSJ sample spans 2004Q1 to 2019Q4.

Figure 3 documents additional evidence of offsetting revisions from the Bloomberg and WSJ surveys of real GDP forecasts based on regressions (1) and (3) reported in panels (a) and (b), respectively. Each panel reflects the different fixed effects specifications for each of the two surveys, corresponding to the specifications in Tables 1 and 2. While these surveys do not require consistency between the annual and quarterly surveys, we still find ample evidence of offsetting behavior.

## 2.5 Interpreting the Results

It is not immediately apparent how offsetting revisions matter for our understanding of expectation formation. We provide further context and intuition for our results below.

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 $\rho$ 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 agents 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 aggregation 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.[10]

The explanation above requires forecasters to be more attentive to their 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.

Aside from low frequency anchoring, offsetting revisions can arise if there are transitory

[10] Since the forecaster is likely less informed about the future than the present, she will find it optimal to revise today based on new information, and then offset farther out along her projected path, where signals may be noisier.

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 subject to transitory level shocks, these dynamics do not appear to drive the offsetting observed in the data, as indicated by column (3) of Table 1 and column (4) of Table 2.

# 3 Facts About Overreaction

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.[11]

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

## 3.1 Quarterly Overreaction

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

$$x_{t+h} - F_{it}(x_{t+h}) = \beta_i + \beta_{1,h}\big[F_{it}(x_{t+h}) - F_{it-1}(x_{t+h})\big] + \epsilon_{it+h}, \tag{4}$$

a revision autocorrelation regression:

$$F_{it}(x_{t+h}) - F_{it-1}(x_{t+h}) = \gamma_h\big[F_{it-1}(x_{t+h}) - F_{it-2}(x_{t+h})\big] + \varepsilon_{it+h}, \tag{5}$$

[11] 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, the robust evidence of offsetting revisions that we uncover leads us to abstract from rounding and state dependent updating in our model. We more explicitly address the rounding issue in Appendix D.4.

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 | 4207 | 3566 | 3545 | 3552 | 3444 | 3466 | 4314 | 4581 |

Note: The table reports panel regression results from SPF forecasts of real GDP growth based on regressions (4), (5), and (6). Driscoll and Kraay (1998) standard errors are reported in parentheses. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

and an errors-on-outcome regression:

$$x_{t+h} - F_{it}(x_{t+h}) = \alpha_i + \alpha_{1,h} x_t + \eta_{it+h}. \tag{6}$$

Regressions (4) and (5) were first introduced as tests of weak efficiency in Nordhaus and Durlauf (1984) and Nordhaus (1987).[12] The errors-on-revisions regression (4), which is widely employed in the survey expectations literature (Bordalo et al., 2020; Bürgi, 2016), relates ex-post errors to ex-ante revisions. If $\beta_{1,h} < 0$, then an upward revision predicts a more negative subsequent forecast error, implying that forecasters overreact to new information when updating their predictions.

Equation (5) does not rely on macroeconomic data and instead relates fixed event revisions across time. Here we are interested in the coefficient in front of the lagged revision, $\gamma_h$. Rational expectations implies that forecasters use their information efficiently so that $\gamma_h = 0$. In other words, revisions are not serially correlated since yesterday's information set is a subset of today's information set. A negative value of $\gamma_h$ indicates that an upward forecast revision today predicts a downward forecast revision tomorrow.

Finally, the errors-on-outcomes regression (6), studied in Kohlhas and Walther (2021), examines another form of error predictability. This regression differs from (5) 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). Furthermore, in columns (2), (4), and (6), we find that forecasters overrevise their predictions. Forecasters tend to overrevise more strongly at the one- and two-quarter ahead horizons, with point estimates hovering 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

[12] Note that (5) is different from the offsetting revision regressions estimated in the previous section since the offsetting revisions regressions relate *contemporaneous* revisions to one another.

et al. (2020) while the final column reports the errors-on-outcomes regression estimated in Kohlhas and Walther (2021).

## 3.2 No Annual Overreaction

To further examine whether there is evidence of annual anchoring in the data, we next estimate these regressions at the annual frequency. If forecasters reshuffle their quarterly predictions due to annual anchoring, then overreactions should be relatively stronger at the quarterly frequency than the annual frequency. Hence, the data would be consistent with annual anchoring if the annual analogs to (4) (5), and (6) yield weaker evidence of overreaction.

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 (5). Third, aggregating from a quarterly to an annual sample shortens the time dimension of our panel, which substantially reduces our number of observations. To achieve greater power, we therefore pool across the set of macroeconomic variables featured in the SPF when running regressions (4) and (6). The results are reported in Table 4.[13]

Column (1) of Table 4 reports the annual version of regression (4) 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 (6). 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.

[13]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.

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 (4) and (6), 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.

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.

# 4 A Model of Offsetting Revisions

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

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

## 4.1 Model Setup

The model is populated by forecasters that issue predictions about an exogenous variable which in part reflects a latent state $s_t$, subject to the realizations of noisy signals.[14] Forecasters issue high and low frequency forecasts which they may update at different points in time, subject to an aggregation constraint that requires the high frequency forecast to aggregate up to the low frequency forecast in every period.

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

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

The underlying state, $s_t$, follows an AR(1) process:[15]

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

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

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

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

In this linear Gaussian 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 prediction for the higher frequency with probability $q$, and her prediction for the lower frequency with probability $p$.[16]

[14] While our focus is on professional forecasters, this model can be applied to other decision makers such as households or firms by suitably modifying the objective function and by adding additional constraints.

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

[16] In principle, it is possible for forecasters to anchor over different frequencies. We abstract away from this for parsimony and due to lack of sufficiently rich survey data.

The Calvo-like probabilities, $q$ and $p$, give rise to four distinct cases:
**Case 1:** With probability $(1-q)(1-p)$, the forecaster does not update at all.
**Case 2:** With probability $q(1-p)$, the forecaster updates the higher frequency forecast, but not the lower frequency forecast. In this case, she updates her higher frequency prediction based on the signals received and subject to the consistency constraint.
**Case 3:** With probability $(1-q)p$, the forecaster updates her lower frequency forecast, but not the higher frequency forecast. We interpret this case as a scenario in which the forecaster simply "brings in" the latest release, $x_{t-1}$, and updates her prediction at the lower frequency accordingly. Importantly, the agent does not update the rest of the sequence of higher frequency forecasts.[17]
**Case 4:** With probability $pq$, the forecaster can optimally update predictions for both frequencies based on the signals received.

## 4.2 High Frequency Overreactions

From the perspective of the model, higher frequency overreactions are due to Case 2 updating. As a result, the probability $q(1-p)$ governs the signs and magnitudes of the coefficients reported in Table 3. Since any point in time can be defined by its low and high frequency pair (e.g., year-quarter), we will denote time $t$ by its low $\ell$ and high $h$ frequency correspondence (i.e., $t = \ell h$). We can express the Case 2 prediction, in general, as:

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

where $H$ is the number of high frequency periods in one low frequency period (e.g., the number of quarters in a year). Furthermore, $\widehat{x}^i_{\ell' h'|\ell h}$ denotes agent $i$'s reported prediction in period $\ell h$ for some future period, $\ell' h'$. The subscript $\ell h - j$ refers to period in which the lower frequency prediction was last updated. The reported forecast is the sum of the optimal conditional expectation and a term capturing the gap between the path of the outdated forecast and what it should be based on the latest information.

Note that as $H$ increases, the second term in (7) gets smaller and the reported forecast

[17] 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.

approaches to the conditional expectation. This is intuitive: as the intervals within the low frequency period shrink, the forecaster has more degrees of freedom along which to adjust the trajectory in order to preserve consistency. As a result, she is more flexibly able to report a prediction that is consistent with the optimal forecast.

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

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

The first two terms on the right-hand side of the above expression reflect averaging between current and past forecasts that arises in standard revision smoothing models. The last term is responsible for generating overreactions in our model. This sum reflects the differences in the conditional expectations between $\ell h$ and $\ell h - j$ for the other periods over which the forecaster smooths her forecast. As events unfold through the low frequency period, this sum incorporates past forecast errors.

To see this, note that (7) can be re-written as:

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

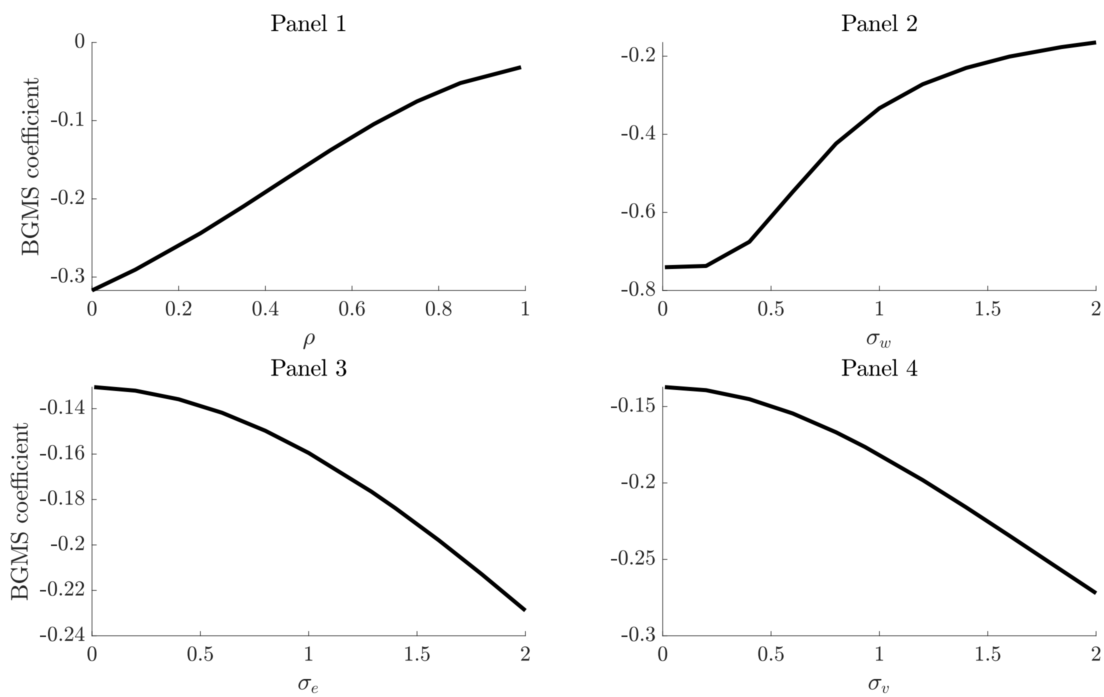
where the second term on the right hand side reflects past forecast errors.

Overreactions arise because inattention at the lower frequency and high-to-low frequency consistency, together, introduce past mistakes into the reported prediction. Suppose for simplicity that a forecaster last updated her predictions in the previous period so that $j = 1$. Then, the above expression becomes:

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

Based on the second term, if $x_{\ell h-1}$ comes in above expectations, then the forecaster will mark down her current forecast 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

Figure 4: Overreaction and Model Parameters




Note: The figure plots the BGMS coefficient as a function of each model parameter, holding the other parameters fixed at their estimated levels according to Table 5.

period, generating observed overreactions. The trade-off between accuracy and consistency is therefore responsible for producing overreactions in our model.[18]

## 4.3 Analyzing the Model

The model features rich dynamics across horizons and frequencies. As a result, the coefficients studied in Section 2 are nonlinear functions of the underlying model parameters. To provide intuition for the model's ability to generate overreactions, we therefore rely on simulated comparative statics. As stated earlier, we will focus on quarterly and annual forecasts

[18] In Appendix A, we provide empirical evidence consistent with the forecasting rule defined in equation (7). 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.

(i.e., $H = 4$).

We concentrate on the Bordalo et al. (2020) (BGMS) coefficient, which regresses year-over-year errors on year-over-year revisions. We note, however, that similar findings arise with the other coefficients. Figure 4 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 governing the latent state. Based on Panel 1, as the underlying process approaches a unit root, the scope for overreactions declines. This is consistent with Bordalo et al. (2020) and Afrouzi et al. (2021) who find that overreactions are decreasing in $\rho$. From the lens of our model, a more persistent 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, $\sigma_w$. Similar to Panel 1, here we find that the scope for overreactions is decreasing in $\sigma_w$. As $\sigma_w$ rises, forecast errors are increasingly driven by the persistent shock which reduces the volatility of offsetting.

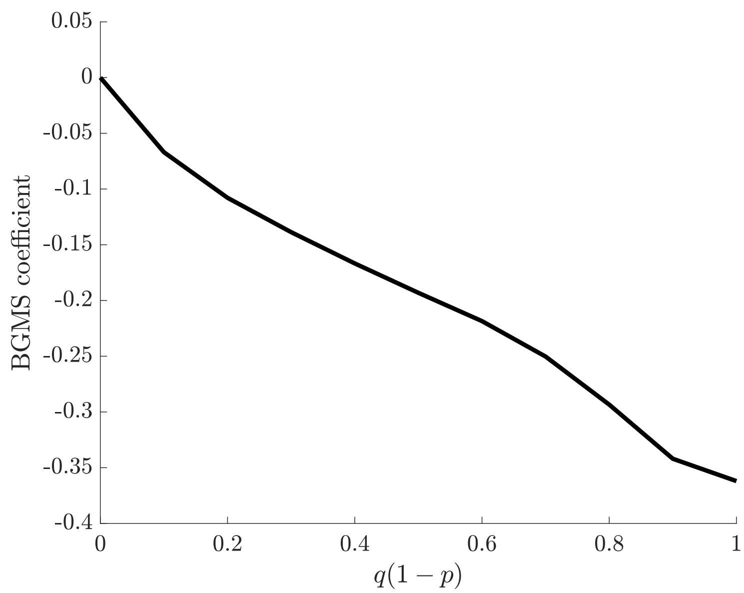
On the other hand, Panels 3 and 4 show that the BGMS coefficient is decreasing in public and private noise. All else equal, higher noise variances mean that forecast errors are increasingly driven by transitory shocks. Since these shocks are short lived, agents find themselves often changing the manner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

Sticky information is an important feature of our model. To assess the role that infrequent annual updating plays in driving observed overreactions, we focus on the frequency of Case 2 updating. Figure 5 illustrates how individual overreactions depend on $q(1-p)$, which is the probability of Case 2 updating. As $q(1-p)$ increases, agents increasingly find themselves updating their quarterly predictions based on news while keeping their annual outlooks the same. In this case, agents respond to news, but offset their sequence of revisions so as to preserve consistency. These excessive revisions are responsible for generating overreactions.

# 5 Model Estimation

While our model can generate overreactions among forecasters, quantifying the importance of our mechanism requires us to estimate the model parameters. We therefore discipline the

Figure 5: Overreaction and Updating Probabilities




Note: The figure plots the simulated BGMS coefficient as a function of the probability of Case 2 updating, holding the other parameters fixed at their estimated levels according to Table 5.

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.[19] The parameters to be estimated are $\theta = (\rho\ \sigma_w\ \sigma_e\ \sigma_v\ q\ p)'$. These parameters are chosen to match eight data moments: the covariance matrix of current-quarter and current-year forecasts, the covariance matrix of current-quarter forecast revisions and last quarter's real-time forecast error, and the mean squared real-time errors associated with current-quarter predictions and current-year predictions. Appendix C details how these moments are related to

[19]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.

Table 5: Model Estimation Results

| *Panel A: Parameter Estimates* | | | |
|---|---|---|---|
| | Parameter | Estimate | Standard error |
| Persistence of latent state | $\rho$ | 0.441 | 0.071 |
| State innovation dispersion | $\sigma_w$ | 1.842 | 0.126 |
| Public signal noise | $\sigma_e$ | 1.289 | 0.327 |
| Private signal noise | $\sigma_v$ | 0.934 | 0.191 |
| Probability of quarterly update | $q$ | 0.999 | 0.078 |
| Probability of annual update | $p$ | 0.581 | 0.042 |
| *Panel B: Moments* | | | |
| | Model moment | Data moment | t-statistic |
| Std(CQ forecast) | 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.

the parameters.[20]

## 5.1 Estimation Results

The estimated parameters are reported in Panel A of Table 5. The underlying persistence of the latent state is estimated to be 0.44. In addition, the dispersion in state innovations is 1.84 while the dispersion of public and private noise are 1.29 and 0.93, respectively. These estimates imply a signal-to-noise ratio of about $\frac{\sigma_w}{\sigma_e+\sigma_v} \approx 0.83$. Furthermore, the probability of quarterly updating is about one, implying that forecasters update their quarterly predic-

[20]We do not directly target rates of micro-level inattention in our baseline estimation approach, however, in unreported results we estimate our model by targeting the share of small revisions (up to one-tenth of a percentage point) at the quarterly and annual frequencies rather than targeting the quarterly and annual mean squared errors. We obtained similar estimates when taking this approach.

tions 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 infrequent annual updating, the root mean squared error for current-quarter predictions would fall by 10%.

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

## 5.2 Non-targeted Moments

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

Table 6 reports ten non-targeted regression coefficients. Rows 1 to 4 report individual-level regression coefficients of errors-on-revisions at the current quarter as well as one-, two-, and three-quarter ahead horizons. Rows 5 to 7 report revision autocorrelation coefficients for the current quarter as well as one- and two-quarters ahead. Row 8 reports the BGMS coefficient of errors-on-revisions. Row 9 reports the estimated coefficient from a regression of the year-over-year forecast error on the realized outcome as in Kohlhas and Walther (2021). Across these regressions, the model nearly always predicts individual overreactions.

One limitation of the estimated model is that it does not generate a negative errors-on-revisions coefficient for current-quarter forecasts (row 1 of Table 6). This is because the model assumes that the news that forecasters receive is about the present. As a result, forecasters place more importance on minimizing current quarter errors, and optimally reshuffle their 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

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. | $\beta$(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.

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.[21] 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 D5.

Table 7: Estimates Across Macro 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)** |
| Real GDP (BBG) | **-0.783 (0.148)** | **-0.539 (0.224)** |
| Real GDP (WSJ) | **-0.814 (0.150)** | -0.186 (0.391) |

Note: The table reports the BGMS (2020) error-on-revision coefficients in the model and Driscoll and Kraay (1998) standard errors are reported in parentheses for various macroeconomic variables covered in the SPF. Since the BBG and WSJ surveys do not have a sufficiently rich term structure from which to estimate year-on-year regressions, we report regressions of the three quarter ahead error on the three quarter ahead revision. Bold values are significantly negative at the 10% level.

## 5.3 Annual Anchoring by Macroeconomic Variable

We next estimate our baseline model for 15 macroeconomic variables covered in the SPF and real GDP forecasts from the BBG and WSJ surveys. 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

[21] 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.

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 4. For instance, there is no evidence of overreaction in forecasts for the unemployment rate, a highly persistent aggregate.

# 6 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:

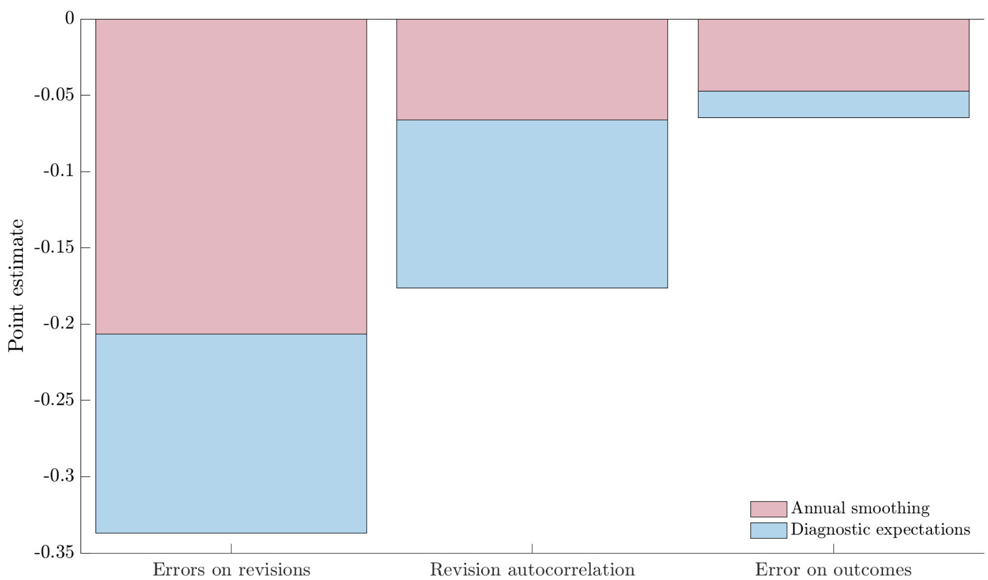
$$x_{t|t}^{i,\theta} = \mathbb{E}_{it}(x_t) + \theta\big[\mathbb{E}_{it}(x_t) - \mathbb{E}_{it-1}(x_t)\big],$$

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

The objective of this exercise is to jointly model two sources of overreaction: annual anchoring and diagnostic expectations, and to quantify the relative importance of our annual anchoring mechanism. To do so, we re-estimate the model with diagnostic expectations while targeting two additional moments: the *contemporaneous* covariance of current-quarter errors and revisions, and the variance of *contemporaneous* current-quarter errors. As discussed in the previous section, the baseline model cannot generate a negative correlation between current-quarter errors and revisions. Thus, we can identify $\theta$ by targeting these two additional moments. The estimated parameters are reported in column 1 of Table D6. We estimate a degree of diagnosticity equal to 0.50 which is smaller than the estimate 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

Figure 6: Annual Anchoring vs. Diagnostic Expectation Contributions




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

a panel of forecasts and estimate regressions (4), (5), and (6). We then fix $\theta = 0$ and repeat this exercise. Figure 6 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.[22]

[22]Column 2 of Table D6 reports a related exercise in which we estimate a constrained (no diagnostic expectations) model with the expanded set of ten moments and compare this model with the unconstrained model (with diagnostic expectations). Figure D5 repeats the comparison of diagnostic expectation based on simulated error predictability regressions. Our results are qualitatively similar to Figure 6.

# 7 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.

## 7.1 Model-Implied Information Frictions

Column 2 of Table 8 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:

$$\text{Implied friction} = \big[1 - \Pr(\text{update})\big] + \Pr(\text{update}) \times (1 - \kappa_1 - \kappa_2), \tag{8}$$

where Pr(update) denotes the probability of updating, which reflects the sticky information feature of the model. Based on our estimates, this probability varies across frequencies. Moreover, the role of noisy information in overall information frictions is understood through the coefficients $\{\kappa_1, \kappa_2\}$ which denote the Kalman gains.[23]

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

In order to compare our implied information frictions to those in the literature, we also

[23] In particular, $\kappa_1$ denotes the weight placed on the private contemporaneous signal and $\kappa_2$ is the weight placed on the lagged realization of the macroeconomic variable.

Table 8: Information Frictions Across Models

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

Note: The table reports estimated updating probabilities, implied information frictions, and contributions of sticky and noisy information for real GDP and inflation at quarterly and annual frequencies. Implied information frictions are computed based on (8) 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 (9).

report model estimates using inflation forecasts based on the GDP deflator.[24] At a quarterly frequency, we estimate information frictions to be about 0.19 while, for annual forecasts, we find that information frictions are higher, at 0.55. For reference, Coibion and Gorodnichenko (2015) estimate coefficients of information rigidity to be around 0.54 while Ryngaert (2017) estimates information frictions to be roughly 0.33. Importantly, whereas existing estimates imply a single information friction for all frequencies, our analysis indicates that there is a difference in 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.

## 7.2 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

[24] Table D7 reports the parameter estimates and model fit.

information friction to equal one

$$1 = \underbrace{\frac{1 - \Pr(\text{update})}{[1 - \Pr(\text{update})] + \Pr(\text{update}) \times (1 - \kappa_1 - \kappa_2)}}_{\text{Sticky info contribution}} + \underbrace{\frac{\Pr(\text{update}) \times (1 - \kappa_1 - \kappa_2)}{[1 - \Pr(\text{update})] + \Pr(\text{update}) \times (1 - \kappa_1 - \kappa_2)}}_{\text{Noisy info contribution}}. \quad (9)$$

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

# 8 Conclusion

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

We show that forecast revisions 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 featuring high and low frequency forecasts. From the lens of our model, overreactions arise because of (i) anchoring of the lower frequency forecast and (ii) high-to-low frequency consistency. The trade-off between minimizing errors and satisfying consistency can explain a meaningful amount of overreactions to real GDP and other aggregates.

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

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# Appendix A Empirics

This section 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.[25]

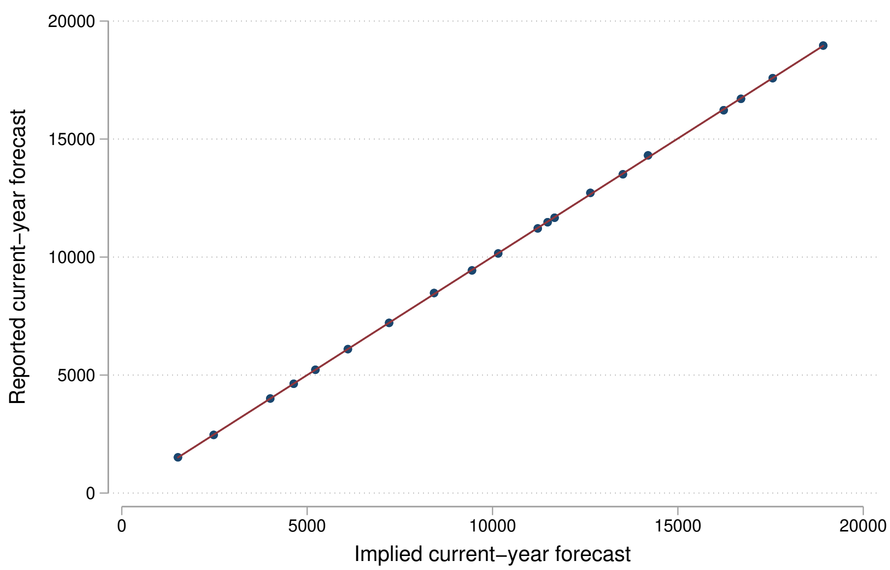
We construct implied current-year forecasts accordingly and compare them to the reported current-year forecasts, finding a 0.9999 correlation between the two as indicated by Figure A1.

## 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.

[25] 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:

$$x_{jy} - \widehat{x}_{ijy|\ell h4} = \beta\left[\widehat{x}_{ijy|\ell h4} - \widehat{x}_{ijy|y-1q4}\right] + \delta_{ij} + \varepsilon_{ij\ell h4},$$

which is the relevant annual analog to regression (4). Here, $j$ denotes a specific macroeconomic variable, $i$ denotes the forecaster, $y$ is year and $k$ 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:

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

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 (4) 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 |

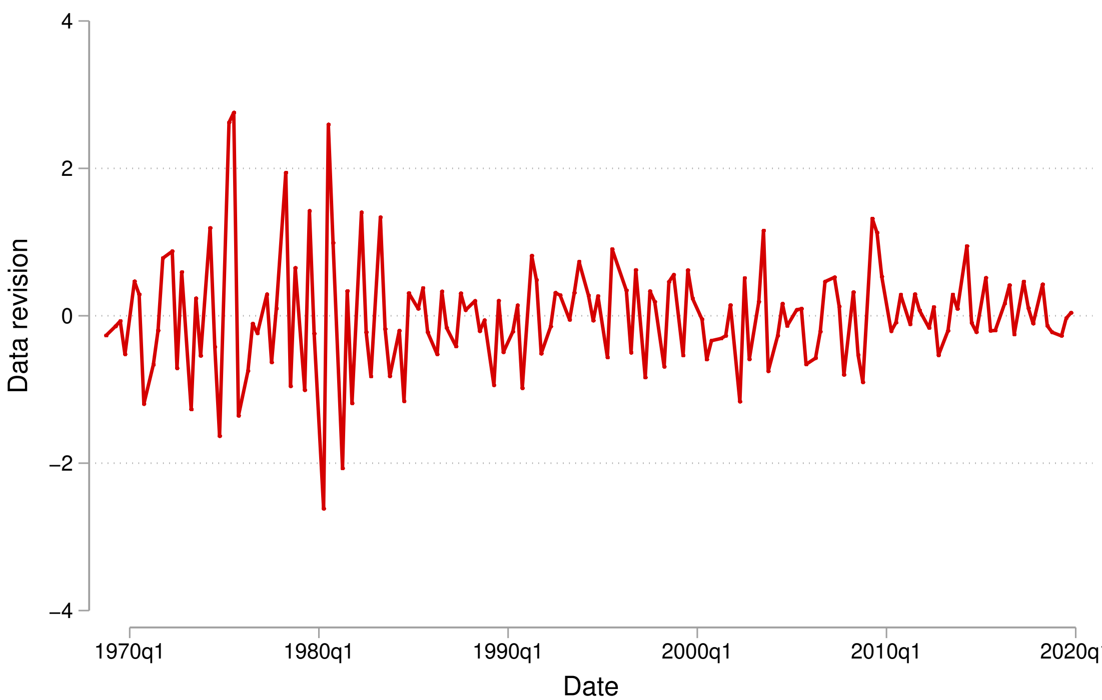
Note: The table reports panel regression results from SPF forecasts of errors on outcomes (6) at an annual frequency. Driscoll and Kraay (1998) standard errors are reported in parentheses. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

## 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.[26]

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.

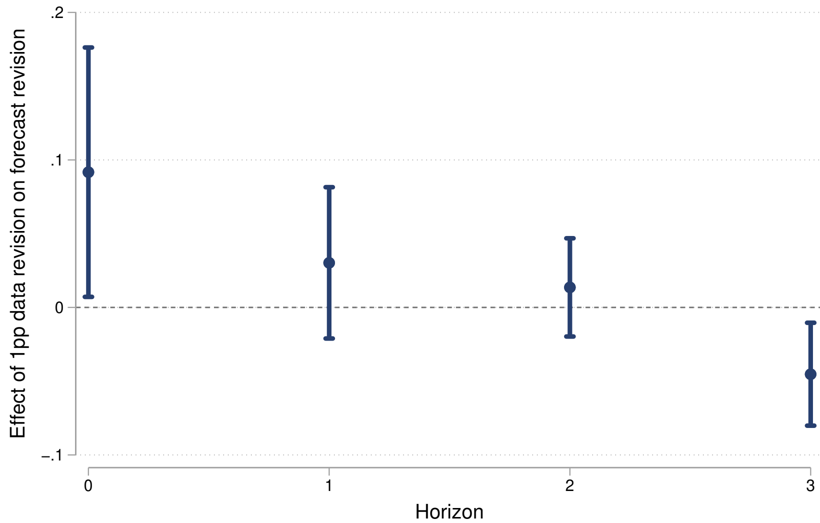
Figure A2: Real GDP Data Revision Series




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

[26]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 $\alpha_1$ coefficient in regression (10) across four horizons. Driscoll and Kraay (1998) standard errors are specified in the regressions.

observed at time $t$:

$$F_{it}(x_{t+h}) - F_{it-1}(x_{t+h}) = \alpha d_t + \varepsilon_{it}. \tag{10}$$

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 up-to-date annual forecast as expressed in equation (6). 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 (6) 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 |

Note: The table reports panel regression results from SPF forecasts of errors on outcomes (6). 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 at some point in time, $\ell h$, for some future period $\ell' h'$. The subscript $\ell$ represents the low frequency period while the subscript $h$ denotes the high frequency period (within the low frequency period). For instance, $\ell h$ can refer to a year-quarter (e.g., year 2019, quarter 1). We define $H$ to be the total number of high frequency periods within a low frequency period. For instance, there are $H = 4$ quarters in a year.

Forecasters in the model wish to minimize their squared errors:

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

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

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

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

and low frequency prediction,

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

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

$$\frac{1}{H} \sum_{h'=1}^{H} \widehat{x}^i_{\ell' h' | \ell h} = \frac{1}{H} \sum_{h'=1}^{H} \widehat{x}^i_{\ell' h' | \ell h - j}, \tag{12}$$

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

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

The Lagrangian is

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

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

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

Combining the FOC with the definition of the constraint delivers:

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

Rearranging, we obtain:

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

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

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

or, equivalently,[27]

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

[27]This follows from the fact that whenever the forecaster constructed her outdated annual, she did so optimally, based on the conditional expectation as of date $\ell h - j$.

# 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.[28] For each iteration, the target moments are computed, averaged across simulations, and compared to their empirical analogs. The six-dimensional parameter vector, $\theta$, is selected to minimize the weighted distance between simulated moments and empirical moments, where the asymptotically efficient weighting matrix is specified.

Formally, we search the parameter space, using a particle swarm procedure, to find the $\widehat{\theta}$ 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 $\theta$. Figure C4 illustrates some important comparative statics that lend support to the choice of target moments which are discussed below.

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

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

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

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

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

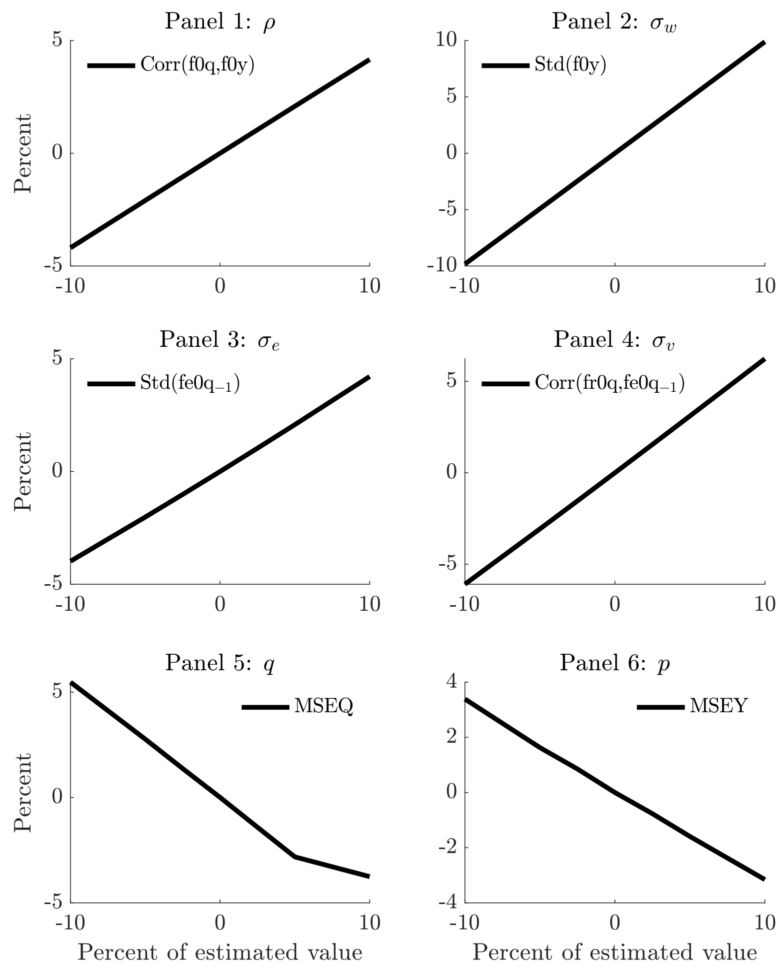
Moreover, higher levels of public noise, $\sigma_e$, contribute to a larger forecast error variance. The link between common noise and the variance of errors is intuitive since the transitory component, $e_t$, is linear in the macroeconomic aggregate being predicted ($x_t$).

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

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

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

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 Estimation Results and Robustness

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

## D.1 Aggregate Underreactions

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

Table D5 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 D5: 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. $\beta$(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.2 Diagnostic Expectations

Table D6 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.

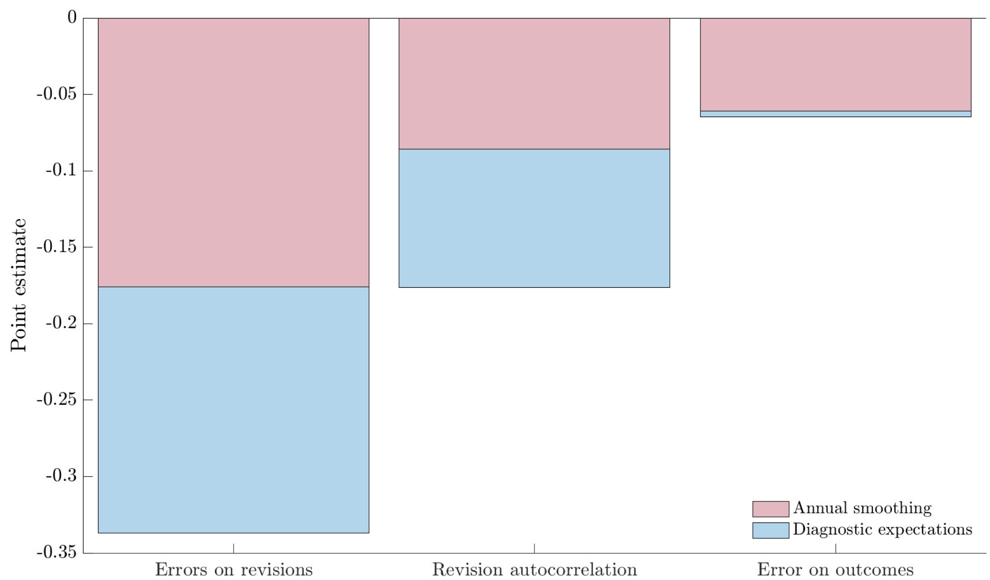
Table D6: Model Estimation Results, Diagnostic Expectations

| | Parameter | (1) Unconstrained | (2) Constrained |
|---|---|---|---|
| Persistence of latent state | $\rho$ | 0.544 | 0.488 |
| | | (0.058) | (0.047) |
| State innovation dispersion | $\sigma_w$ | 1.455 | 1.757 |
| | | (0.178) | (0.131) |
| Public signal noise | $\sigma_e$ | 1.093 | 0.774 |
| | | (0.200) | (0.194) |
| Private signal noise | $\sigma_v$ | 0.876 | 1.442 |
| | | (0.260) | (0.311) |
| Probability of quarterly update | $q$ | 0.784 | 1.000 |
| | | (0.102) | (0.044) |
| Probability of annual update | $p$ | 0.473 | 0.597 |
| | | (0.042) | (0.054) |
| Diagnosticity | $\theta$ | 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 D6. This differs from Figure 6 in that the counterfactual in Figure 6 features the same parameters as the unconstrained model, but with $\theta$ 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.3 Inflation Forecasts

Table D7 reports model estimates using SPF inflation forecasts based on the GDP deflator.

Table D7: Model Estimation Results, Inflation Forecasts (Deflator)

| *Panel A: Parameter Estimates* | | | |
|---|---|---|---|
| | Parameter | Estimate | Standard error |
| Persistence of latent state | $\rho$ | 0.585 | 0.081 |
| State innovation dispersion | $\sigma_w$ | 1.041 | 0.072 |
| Public signal noise | $\sigma_e$ | 0.950 | 0.109 |
| Private signal noise | $\sigma_v$ | 0.566 | 0.149 |
| Probability of quarterly update | $q$ | 1.000 | 0.152 |
| Probability of annual update | $p$ | 0.552 | 0.084 |
| *Panel B: Moments* | | | |
| | Model moment | Data moment | t-statistic |
| Standard deviation of nowcast | 1.064 | 1.168 | 1.166 |
| Correlation of nowcast with annual forecast | 0.767 | 0.757 | 0.840 |
| Standard deviation of annual forecast | 0.773 | 0.806 | 0.632 |
| Standard deviation of revision | 0.908 | 1.118 | 1.775 |
| Correlation of revision with lagged error | 0.133 | 0.168 | 0.808 |
| Standard deviation of 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.4 Rounding

We report parameter estimates under the assumption that forecasters round their predictions to the nearest 0.10 percentage point. We find that this rounding assumption does not meaningfully change our parameter estimates.[29]

Table D8: Model Estimation Results (Rounding to nearest 0.1 pp)

| *Panel A: Parameter Estimates* | | | |
|---|---|---|---|
| | Parameter | Estimate | Standard error |
| Persistence of latent state | $\rho$ | 0.401 | 0.034 |
| State innovation dispersion | $\sigma_w$ | 2.016 | 0.158 |
| Public signal noise | $\sigma_e$ | 0.816 | 0.353 |
| Private signal noise | $\sigma_v$ | 1.595 | 0.364 |
| Probability of quarterly update | $q$ | 0.997 | 0.129 |
| Probability of annual update | $p$ | 0.620 | 0.032 |
| *Panel B: Moments* | | | |
| | Model moment | Data moment | t-statistic |
| Standard deviation of nowcast | 1.656 | 1.719 | -0.623 |
| Correlation of nowcast with annual forecast | 0.689 | 0.670 | -0.211 |
| Standard deviation of annual forecast | 1.093 | 1.103 | -0.178 |
| Standard deviation of revision | 1.573 | 1.615 | -0.295 |
| Correlation of revision with lagged error | 0.242 | 0.143 | 1.603 |
| Standard deviation of 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.

[29]Studying more traditional Gaussian measurement error introduces an identification problem between the measurement error dispersion and private signal noise dispersion, $\sigma_v$. At the same time, rounding is a well understood phenomenon in survey expectations. For this reason, we focus on this form of measurement error.

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

The SPF, as well as broader macroeconomic dynamics, experienced important changes between 1981-2019. In this section, we estimate the model for two sub-periods: 1981-1999 (Table D9) and 2000-2019 (Table D10). 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 D9: Model Estimation Results (1981-1999)

| *Panel A: Parameter Estimates* | | | |
|---|---|---|---|
| | Parameter | Estimate | Standard error |
| Persistence of latent state | $\rho$ | 0.335 | 0.089 |
| State innovation dispersion | $\sigma_w$ | 2.081 | 0.438 |
| Public signal noise | $\sigma_e$ | 1.366 | 0.709 |
| Private signal noise | $\sigma_v$ | 0.031 | 0.016 |
| Probability of quarterly update | $q$ | 0.778 | 0.318 |
| Probability of annual update | $p$ | 0.501 | 0.067 |
| *Panel B: Moments* | | | |
| | Model moment | Data moment | t-statistic |
| Standard deviation of nowcast | 1.798 | 2.003 | -0.933 |
| Correlation of nowcast with annual forecast | 0.592 | 0.560 | -0.790 |
| Standard deviation of annual forecast | 1.071 | 1.177 | -0.870 |
| Standard deviation of revision | 1.704 | 2.146 | -1.465 |
| Correlation of revision with lagged error | 0.067 | 0.083 | -0.443 |
| Standard deviation of 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 D10: Model Estimation Results (2000-2019)

| *Panel A: Parameter Estimates* | | | |
|---|---|---|---|
| | Parameter | Estimate | Standard error |
| Persistence of latent state | $\rho$ | 0.624 | 0.035 |
| State innovation dispersion | $\sigma_w$ | 1.359 | 0.256 |
| Public signal noise | $\sigma_e$ | 1.129 | 0.308 |
| Private signal noise | $\sigma_v$ | 0.720 | 0.345 |
| Probability of quarterly update | $q$ | 1.000 | 0.121 |
| Probability of annual update | $p$ | 0.520 | 0.068 |
| *Panel B: Moments* | | | |
| | Model moment | Data moment | t-statistic |
| Standard deviation of nowcast | 1.388 | 1.538 | -2.213 |
| Correlation of nowcast with annual forecast | 0.792 | 0.764 | -1.040 |
| Standard deviation of annual forecast | 1.031 | 1.060 | -0.555 |
| Standard deviation of revision | 1.152 | 1.225 | -1.334 |
| Correlation of revision with lagged error | 0.155 | 0.218 | -1.955 |
| Standard deviation of 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.6 Alternative Data Generating Process

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

We extend our model to feature an AR(2) process for real GDP growth. We select an AR(2) process for three reasons. First, we find that the AR(2) fits real GDP growth best in the sense that it delivers the lowest information criteria.[30] Second, an AR(2) is highly feasible to estimate with the baseline SMM approach as it only adds one parameter to the model. Third, an AR(2) allows us to remain consistent with others in the literature who similarly examine richer data generating processes for their models (Bordalo et al., 2020).

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

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

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

There are now seven parameters to be estimated. We estimate these parameters by targeting the same eight moments described in the main text. As a result, our estimator is still an overidentified SMM estimator. The results are reported in Table D11.

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

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

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

Table D11: Model Estimation Results, AR(2)

| *Panel A: Parameter Estimates* | | | |
|---|---|---|---|
| | Parameter | Estimate | Standard error |
| First lag autocorrelation | $\rho_1$ | 0.524 | 0.149 |
| Second lag autocorrelation | $\rho_2$ | -0.075 | 0.018 |
| State innovation dispersion | $\sigma_w$ | 1.828 | 0.231 |
| Public signal noise | $\sigma_e$ | 1.163 | 0.343 |
| Private signal noise | $\sigma_v$ | 1.002 | 0.418 |
| Probability of quarterly update | $q$ | 0.934 | 0.524 |
| Probability of annual update | $p$ | 0.618 | 0.045 |
| *Panel B: Moments* | | | |
| | Model moment | Data moment | t-statistic |
| Standard deviation of nowcast | 1.624 | 1.719 | -0.926 |
| Correlation of nowcast with annual forecast | 0.702 | 0.670 | -0.588 |
| Standard deviation of annual forecast | 1.057 | 1.103 | -0.799 |
| Standard deviation of revision | 1.486 | 1.615 | -0.882 |
| Correlation of revision with lagged error | 0.172 | 0.143 | 0.141 |
| Standard deviation of 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 (8)). 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.