Overreaction Through Expectation Smoothing*

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Abstract

Updates to macroeconomic expectations among professional forecasters are: (i) negatively serially correlated at the individual level, (ii) positively serially correlated at the aggregate level, and (iii) exhibit an offsetting pattern. To explain these facts, we estimate a hybrid sticky-noisy information model featuring quarterly and annual inattention, and a quarterly-to-annual aggregation constraint. Relative to existing theories, our model provides a unified explanation for the three facts as well as previously documented evidence of over- and underreaction. Furthermore, our estimates suggest that annual forecasts exhibit more information rigidity than quarterly forecasts, with a larger role for sticky information relative to noisy information.

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1 Introduction

Professional forecasters make predictable mistakes. Whereas individual predictions exhibit overreactions (Bordalo et al., 2020; Broer and Kohlhas, 2019; Bürgi, 2016), aggregate forecasts are characterized by inertia (Coibion and Gorodnichenko, 2015; Dovern et al., 2015). Both forms of error predictability are incompatible with full information rational expectations, a benchmark assumption made in macroeconomics. Consequently, theories of non-rational expectations as well as models of imperfect information have been devised to explain over- and underadjustments.[1]

In this paper, we document three key facts relating to survey expectations. First, fixed-event revisions are negatively serially correlated among individual forecasters. Second, fixed-event revisions are positively serially correlated at the consensus-level. Third, individual forecast revisions exhibit an offsetting pattern. The third fact, which has not been previously documented in the literature, cannot be reconciled with traditional theories of expectation formation. We develop a model of long-run smoothing that can reproduce all of these empirical patterns.

Our model is a version of a hybrid sticky-noisy information model as in Andrade and Le Bihan (2013) with a focus on the interaction between quarterly and annual forecasts. Two key assumptions are responsible for generating overreactions: temporal consistency (i.e. quarterly forecasts aggregate up to annual forecasts) and smoothing of annual expectations. With these two assumptions, an upward revision in the near-term must be offset by a downward revision later in the year, as in the data.[2] These overrevisions introduce volatility to quarterly updates which generates overreactions.

[1] Bordalo et al. (2020) for instance develop a model of diagnostic expectations while Woodford (2001), Sims (2003), and Mankiw and Reis (2002) present theories of imperfect information.

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

We begin by providing empirical evidence relating to overreactions, underreactions, and annual smoothing based on data from the U.S. Survey of Professional Forecasters (SPF). With regard to overadjustments, we document a robust negative autocorrelation of revisions (Nordhaus, 1987). We repeat this exercise at the aggregate level, documenting a positive autocorrelation of consensus revisions.[3] Finally, we find that when a forecaster revises upward today, she simultaneously revises downward further along her forecasted annual path. We interpret this result as evidence of annual smoothing and note that existing models of expectation formation cannot flexibly account for offsetting revisions.

Motivated by these facts, we devise a noisy information model with heterogeneous updating rates by frequency. Forecasters issue quarterly and annual forecasts based on private and public signals. Quarterly and annual updating are separate activities governed by distinct Calvo-like probabilities. Furthermore, forecasters are subject to a consistency constraint which requires that a forecaster's sequence of quarterly predictions aggregate up to her annual forecast.[4]

Annual inattention can reflect deeper real-world features of forecasting. For instance, reputational considerations can generate annual smoothing.[5] Alternatively, time and resource constraints associated with widespread model revisions can result in infrequent annual updating. In both of these settings, forecasters could find it optimal to revise high frequency forecasts while keeping their low frequency outlooks fixed.

The source of overreactions in our model comes from forecasters introduc-

[3]We focus on revision autocorrelation as these over- and underadjustments can be determined ex ante. However, our results also hold for alternative ex post measures like errors on revisions (Nordhaus, 1987; Coibion and Gorodnichenko, 2015; Bordalo et al., 2020) or errors on outcomes (Kohlhas and Walther, 2021) as shown in the main text and appendix.

[4]The SPF requires forecasters to issue consistent predictions, a feature of the data which we verify in Appendix A. Beyond the SPF, we also find evidence consistent with annual smoothing in the Bloomberg survey as shown in Appendix D.

[5]Ways to model such reputational considerations include adjustment costs as in Kucinskas and Peters (2021) or the game theory framework in Ehrbeck and Waldmann (1996).

ing past errors into their reported predictions through the annual consistency constraint.[6] Suppose, for instance, that a forecaster periodically makes full updates to her GDP forecast and story. In between these full updates, she replaces the quarterly predictions with realized outcomes, and then offsets the prediction error to ensure annual consistency and to preserve her accompanying narrative. These offsetting revisions in turn generate a negative autocorrelation of fixed-event updates as forecasters trade off accuracy with consistency.

Annual smoothing is a key ingredient which allows our model to generate individual overadjustments. While traditional models of forecast smoothing (Scotese, 1994) deliver individual and aggregate underreactions, our multi-frequency approach allows us to match individual overreactions while preserving aggregate underreactions.

We estimate the model using a minimum distance approach. In particular, we estimate the six parameters of our model by targeting eight micro moments in the panel of real GDP forecasts from the SPF. Our estimated model successfully fits both targeted and non-targeted moments in the data. We find that modeling heterogeneity in updating by frequency allows us to jointly match realistic levels of inattention and disagreement, something which is not feasible in traditional hybrid sticky-noisy information models (Andrade and Le Bihan, 2013). Overall, our estimates imply that sticky long-run expectations can explain meaningful share of observed overadjustments across a range of measures. The estimated model can also replicate underreactions in consensus forecasts.

In an effort to quantify the importance of our mechanism relative to other theories, we estimate a version of the model with diagnostic expectations Bordalo et al. (2020).[7] When we add diagnostic expectations to our model and examine different forms of error and revision predictability, we find that our

[6]Similar to the explanation for an apparent forecast bias at the individual level in Bürgi (2017), the overreaction here is consistent with standard forecasting methods.

[7]Several alternative theories of non-rational expectations can explain overreactive behavior (Daniel et al., 1998; Broer and Kohlhas, 2019). At the same time, overreactions can 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).

mechanism can still explain more than half of measured overreactions. This indicates that annual smoothing is an important contributor to overreactions, alongside other forces.

We conduct additional exercises to establish the robustness of our findings and to examine a potential driver of annual smoothing. First, we estimate our model across the many macroeconomic variables for which SPF forecasters issue predictions. Our estimates are able to replicate observed overreactions for a variety of SPF variables.[8] Next, we estimate our model for financial and non-financial SPF forecasters, and provide evidence suggesting that time or resource costs associated with frequent model revisions can explain annual inattention.

Finally, we use the model to study information rigidities. Our estimates reveal that information frictions differ across frequencies and are more pervasive at the annual level. When averaging across the two frequencies, we recover implied information frictions similar to estimates previously documented in the literature (Coibion and Gorodnichenko, 2015; Ryngaert, 2017). In addition, our model allows us to decompose the sources of information rigidities into noisy and sticky information. We find that noisy information is the dominant source of information frictions at the quarterly frequency while sticky information is the main driver of information frictions at the annual frequency.

The rest of the paper is organized as follows. Section 2 documents motivating empirical evidence relating to overadjustments, underadjustments, and annual smoothing. Section 3 presents the hybrid sticky-noisy information model with differential rates of updating. Section 4 discusses the estimation approach and results. Section 5 quantifies the extent to which long-run rigidity can explain short-run overadjustments. Section 6 discusses the implications for information frictions. Section 7 concludes.

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

2 Facts About Over- and Underreactions

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

The data that we use come from the SPF, a quarterly survey managed by the Federal Reserve Bank of Philadelphia. The survey began in 1968Q4 and provides forecasts from several forecasters across a range of macroeconomic variables over many horizons, h. The SPF reports current-year annual predictions which the survey requires to be consistent with the averages of the quarterly forecasts starting in 1981Q3.[9] In this sense, the consistency constraint that we impose in our model is directly motivated by the data.

2.1 Individual Overreactions

First, professional forecasters exhibit overreactive behavior. To show this, we run two sets of panel regressions: revisions on past revisions and errors on revisions.[10] Both regressions were first introduced as tests of weak efficiency in Nordhaus (1987). Let x_{t+h} denote real GDP growth at time $t+h$. Furthermore, let $F_{it}(x_{t+h})$ denote forecaster i's prediction for x_{t+h} devised at time t. With this notation defined, the revision autocorrelation regression is:

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

In words, we focus on a fixed-event and project the current forecast revision on its previous value. We are interested in the coefficient in front of the lagged revision, γ_h. A negative value of γ_h indicates that an upward forecast revision

[9] For this reason, and to abstract away from the COVID-19 pandemic, our sample spans 1981Q3 to 2019Q4.

[10] We provide an additional estimate of overreactions based on Kohlhas and Walther (2021) in Appendix A.

Table 1: Overreaction Among Individual Forecasters

	$h = 0$		$h = 1$		$h = 2$	
	Revision	Error	Revision	Error	Revision	Error
Previous revision	-0.132**		-0.316***		-0.397***	
	(0.056)		(0.064)		(0.089)	
Revision		-0.269***		-0.156**		-0.355***
		(0.061)		(0.077)		(0.064)
Forecasters	164	184	163	165	162	161
Observations	3,384	3,605	3,573	3,532	3,477	3,384

Note: The table reports panel regression results from SPF forecasts of real GDP growth based on regressions (1) and (2). Each set of columns refers to a different horizon, from the current quarter to two quarters ahead. Driscoll and Kraay (1998) standard errors are reported in parentheses. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

today predicts a downward forecast revision tomorrow.

Table 1 reports the results across three horizons which imply that forecasters overrevise their predictions. For current quarter forecasts, a one percentage point upward revision today predicts a 0.13 percentage point downward revision tomorrow. Forecasters tend to overrevise more strongly at the one- and two-quarter ahead horizons, with point estimates hovering from -0.30 to -0.40.

The second set of results, also reported in Table 1, relate to errors-on-revisions. We run the following regression:

$$x_{t+h} - F_{it}(x_{t+h}) = \beta_i + \beta_{1,h}\big[F_{it}(x_{t+h}) - F_{it-1}(x_{t+h})\big] + \epsilon_{it+h}. \tag{2}$$

When $\beta_{1,h} < 0$, an upward revision predicts a more negative subsequent forecast error, implying that forecasters overreact to new information when updating their predictions. Table 1 reproduces these estimates in our sample. 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 are in line with the estimates in Bordalo et al. (2020) and Bürgi (2016).

Table 2: Underreaction in Consensus Forecasts

	$h = 0$		$h = 1$		$h = 2$	
	Revision	Error	Revision	Error	Revision	Error
Previous revision	0.368**		0.462***		-0.085***	
	(0.150)		(0.118)		(0.026)	
Revision		0.136		0.724**		1.093***
		(0.121)		(0.299)		(0.294)
Observations	150	151	150	150	150	150

Note: The table reports time series regression results from SPF forecasts of real GDP growth akin to (1) and (2). Each set of columns refers to a different horizon, from zero steps ahead (current quarter) to two steps ahead. Newey-West standard errors are reported in parentheses. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

2.2 Aggregate Underreactions

Whereas individual forecasters appear to overreact, consensus predictions exhibit underadjustments. This inertia at the aggregate level has been of interest to the literature studying information rigidities. Table 2 reports the results based on time series analogs of (1) and (2), where, instead of specifying individual forecasts, we focus on consensus forecasts.

The estimates in Table 2 provide some evidence of underadjustments at the aggregate-level. For instance based on a simple noisy information model (Coibion and Gorodnichenko, 2015), the estimated errors-on-revisions coefficient at the one-quarter ahead horizon implies that forecasters place a weight of $\frac{0.724}{1+0.724} \approx 0.42$ on their prior when updating their prediction. These estimated underreactions are consistent with Coibion and Gorodnichenko (2012), Coibion and Gorodnichenko (2015), Bürgi (2016), and Bordalo et al. (2020).

2.3 Offsetting Revisions

Having reported the presence of over- and underreactions in the survey data, we turn to providing motivating evidence for our mechanism. If forecasters have a tendency to smooth their annual predictions, then multi-horizon revisions should exhibit an offsetting pattern. For instance, if a forecaster receives positive news today, then she will wish to revise her forecast upward. However, if she is inattentive to her annual forecast, then she will have to revise upward subject to a quarterly-to-annual adding up constraint. In order 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.

Before proceeding, we briefly reason through an alternative source of revision offsetting as well as an alternative approach to checking for annual inattention in the data.

First, aside from annual smoothing, offsetting revisions can arise if there are transitory shocks to the level of the macroeconomic variable. For instance, a large natural disaster in one period could lead forecasters to project a growth reversal in the following period. These transitory level shocks typically imply adjacent offsetting which is not required for annual smoothing. As a result, adjacent offsetting could be due to either annual smoothing or to transitory level shocks, while non-adjacent offsetting is much more likely due to annual smoothing. In our results, we document evidence of non-adjacent offsetting.

Moreover, an alternative way to check for annual smoothing in the data would be to run Bordalo et al. (2020) regressions with annual forecasts and to compare them with the quarterly estimates. This approach is potentially problematic because the current year horizon changes with every survey and reduces the sample substantially. For this reason, we provide evidence of offsetting revisions, devise a model in which annual smoothing is the mechanism through which offsetting revisions arise, and demonstrate that such a model can better fit the data than a model without annual smoothing.[11]

We now provide evidence of offsetting revisions in real GDP forecasts across horizons as well as within the calendar year.[12] First, we show that an upward

[11] Nevertheless, Appendix A estimates current year errors-on-revisions regressions which we find to be consistent with annual smoothing.

[12] Appendix A provides additional evidence of revision offsetting based on exogenous statistical data revisions.

Table 3: Offsetting Revisions By Horizon

	Three quarter ahead revision
Two quarter ahead revision	0.153***
	(0.048)
One quarter ahead revision	0.048
	(0.058)
Current quarter revision	-0.044*
	(0.024)
Fixed effects	Time
Observations	4,191

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.

revision in the current quarter forecast predicts a contemporaneous downward revision to the three-quarter ahead forecast. Second, focusing on a specific calendar year, we show that an upward revision to the start-of-year forecast predicts a downward revision to the end-of-year forecast.

We begin by regressing the three-quarter ahead revision devised at time t on the current-quarter revision, controlling for the one- and two-quarter ahead revisions and time fixed effects:

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

The results are reported in Table 3. Based on the regression results, a one percentage point increase in the two quarter ahead revision predicts a 15-basis point increase in the three quarter ahead revision. However, a one percentage point increase in the current quarter revision predicts a 4-basis point decrease in the three quarter ahead revision. Put another way, a one standard deviation increase in the current quarter revision predicts a 6% downward revision three quarters ahead.

Next, we consider calendar year revisions in order to motivate the annual

Table 4: Offsetting Revisions Within Calendar Year

	Fourth quarter revision
Third quarter revision	0.222***
	(0.043)
Second quarter revision	0.053
	(0.064)
First quarter revision	-0.163**
	(0.076)
Fixed effects	Time
Observations	4261

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

smoothing assumption that we make in the next section. We run the following regression:

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

The difference between (4) and (3) is that the former focuses on a fixed event. In the first quarter of the year, the Q4 revision is $F_{it}(x_{t+3}) - F_{it-1}(x_{t+3})$. In the second quarter of the year, the Q4 revision is $F_{it}(x_{t+2}) - F_{it-1}(x_{t+2})$, and so on. The first, second, and third quarter revisions are constructed in a similar way. Importantly, as the calendar year progresses, values of real GDP are realized and forecast revisions become forecast errors. For instance, the Q1 revision in the first quarter is $F_{it}(x_t) - F_{it-1}(x_t)$, but when we enter into the second quarter of the year, Q1 real GDP is known and the forecaster "brings in" this news so that the Q1 revision becomes the lagged current quarter error: $x_{t-1} - F_{it-1}(x_{t-1})$.

Table 4 reports the regression results. The estimates once again imply that forecasters offset their revisions. In particular, a one percentage point increase in the first quarter revision implies a 16-basis point downward revision to the fourth quarter forecast. In other words, a one standard deviation increase in the first quarter revision predicts a 13% decrease in the fourth quarter revision.

The empirical results indicate that current-quarter revisions covary negatively with future revisions across non-adjacent periods. In standard rational expectations models, forecasters optimally revise their predicted trajectories, with the magnitude of the revision over longer horizons regulated by the persistence of the driving process. Under traditional AR(1) dynamics, therefore, revisions would not exhibit an offsetting pattern. An exception would be an AR(1) model with transitory level shocks, as previously discussed. However, such a model would imply adjacent offsetting which is not borne out by the data, as indicated in Table 3 and Table 4.

Taken together, professional forecasts exhibit overreactions and inertia. Furthermore, forecasters offset near-term revisions over their longer-term trajectories. We argue that the latter finding can explain some of the observed overreactions in the data, and explicitly model offsetting revisions in the next section.

3 A Model of Offsetting Revisions

We begin by detailing our hybrid sticky-noisy information model. The model is in the spirit of Andrade and Le Bihan (2013) and features quarterly and annual forecasts, each subject to a distinct updating probability. Derivations of our results can be found in Appendix B. After outlining the model, we discuss how overreactions arise through annual smoothing and temporal consistency. Finally, we analyze a series of comparative statics in order to examine the ways in which the regression coefficients estimated in the previous section depend on the model parameters.

3.1 Model Setup

The model is populated by professional forecasters. Forecasters issue predictions about an exogenous macroeconomic variable, which in part reflects the latent state of the economy, subject to the realization of noisy signals. Forecasters issue both quarterly and annual forecasts which they update at different rates, subject to an adding up constraint that requires quarterly forecasts to aggregate up to the annual forecast in every period.

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

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

The underlying state of the economy, s_t, follows an AR(1) process:[13]

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

with unconditional mean μ, persistence ρ, and variance $\frac{\sigma_w^2}{1-\rho^2}$. The state of the economy is unobserved to forecasters and to the econometrician. The transitory component, e_t, is normally distributed and centered at zero with variance σ_e^2.

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

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

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

In this linear Gaussian set up, an optimal forecast (consistent with the conditional expectation) would be obtained by employing the Kalman filter. However, forecasters cannot flexibly update their forecasts every period. Instead, in a given period, a forecaster is only able to revise her quarterly prediction with probability q, and annual outlook with probability p.

[13]In Appendix D we explore a richer driving process under which offsetting revisions would arise, with little effect on our results.

Infrequent annual updating ($p < 1$) can be motivated by institutional, reputational, or economic considerations. Anecdotally, forecasting institutions avoid revising their annual figures in each month or quarter, opting instead to implement model revisions a couple of times per year. At the same time, infrequent annual updating can reflect the value of sticking to a particular "story" to narrate to clients rather than revising in potentially different directions each period. Finally, a probability $p < 1$ can be attributed to time or resource constraints associated with undertaking more frequent model revisions. For our purposes, all of these explanations are embedded in the probability p.[14]

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

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

Case 2: With probability $q(1-p)$, the forecaster updates the quarterly forecast, but not the annual. In this case, she updates the quarterly forecast based on the signals received and subject to an adding up constraint.

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

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

3.2 Quarterly Overreactions

From the perspective of the model, quarterly overreactions are due to Case 2 updating. As a result, the probability $q(1-p)$ governs the signs and magnitudes of the coefficients reported in Table 1. For general forms of long-run smoothing,

[14] After reporting our baseline results, we explore a potential driver of annual smoothing by re-estimating our model for different forecaster types based on their respective industries.

[15] This scenario does not play an important role in our findings. The estimated baseline model in the next section implies that Case 3 occurs only 4% of the time. In addition, in unreported results, we find that a version of this model which assumes flexible quarterly updating, $q = 1$, delivers similar conclusions about overreaction, underreaction, and revision offsetting.

the reported Case 2 prediction is:

$$\widehat{x}^{i}_{t+k'|t+k} = \mathbb{E}_{it+k}(x_{t+k'}) + \frac{1}{H+1}\sum_{h=0}^{H}\left[\mathbb{E}_{i,t+k-j}(x_{t+h}) - \mathbb{E}_{it+k}(x_{t+h})\right], \qquad (5)$$

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

Because our central focus is on quarterly and annual updating, we set the relevant horizon length to be $H = 3$. Note, however, that as $H \to \infty$, the second term in (5) vanishes and the reported forecast converges to the conditional expectation. This is intuitive: as the horizon over which a forecaster smooths her predictions expands, the forecaster has more degrees of freedom along which to adjust the trajectory in order to preserve temporal consistency. As a result, she is more flexibly able to report a prediction that is consistent with the optimal forecast.

We can rearrange (5) in order to more transparently characterize the source of overreactions:

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

The first two terms on the right-hand side of the above expression reflect averaging between current and past forecasts that arises in standard revision smoothing models. The last term is responsible for generating overreactions in our model. This sum reflects the differences in the conditional expectations between $t+k$ and $t+k-j$ for the other quarters that comprise the annual path. As current-year events unfold, this sum incorporates past forecast errors.

To see this, note that (5) can be re-written as:

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

where the middle term now reflects past forecast errors.

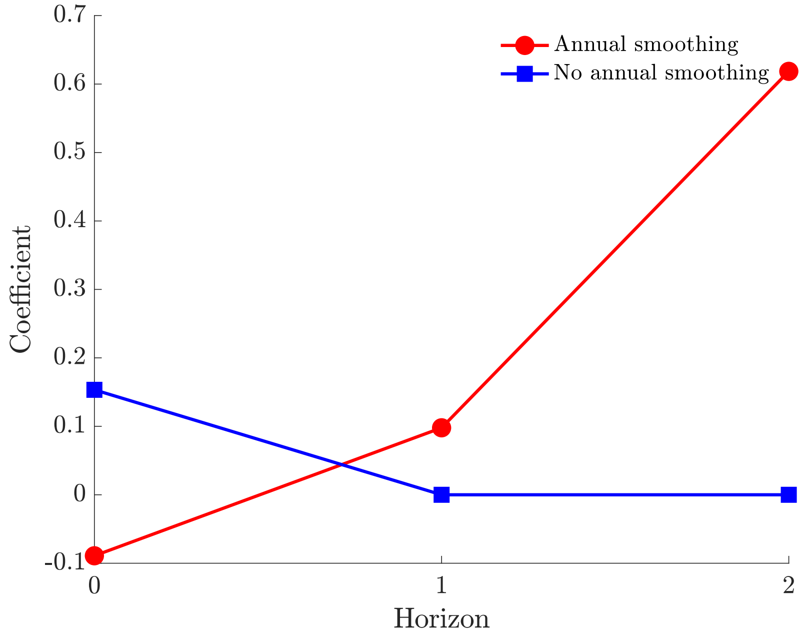
Overreactions arise because annual inattention and temporal consistency introduce past mistakes into the reported prediction. Suppose, for simplicity, that forecasters last updated their predictions in the previous period so that $j = 1$. Then, the above expression becomes:

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

Based on the second term, if x_{t+k-1} comes in higher than expected, then forecasters will tend to mark down their forecasts in order to preserve consistency. As a result, a positive rational expectations error today predicts a positive ex-post forecast error tomorrow. These erroneous revisions are later corrected as new and relevant information arrives in the next period, generating negatively autocorrelated revisions. The trade-off between accuracy and consistency is therefore responsible for producing overreactions in our model.

Figure 1 highlights the key distinction between a model with annual smoothing and temporal consistency relative to a traditional model of imperfect information. The figure plots regression coefficients estimated from simulated data in the two models based on (3). According to a standard imperfect information model, the three-quarter ahead forecast revision is positively related to the current-quarter revision. Furthermore, after controlling for the current-quarter revision, the one- and two-quarter ahead revisions hold no predictive power over the three-quarter ahead revision. Intuitively, in a model with Bayesian

Figure 1: Offsetting Revisions with and without Annual Smoothing

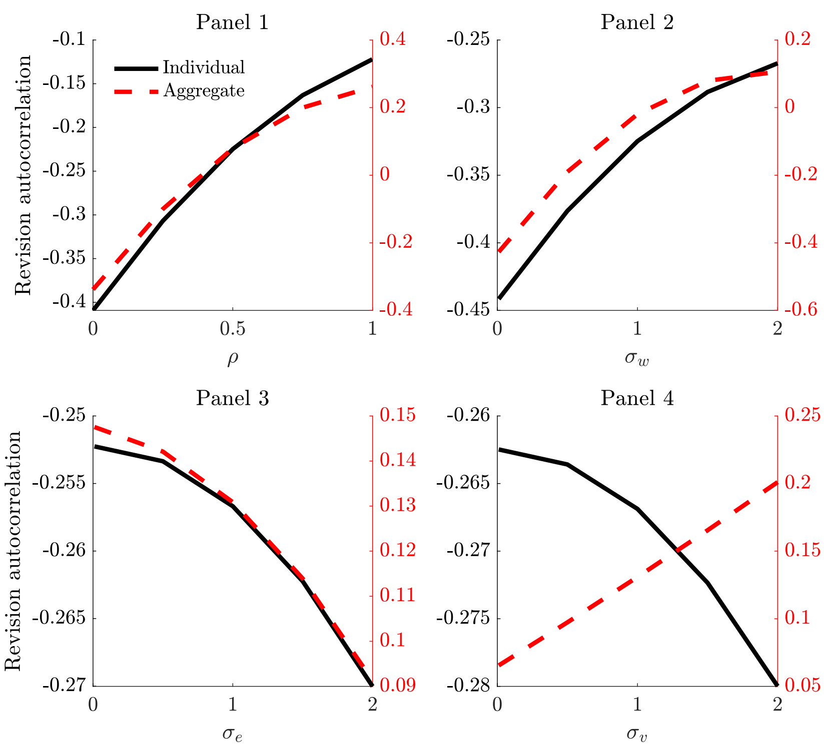


Note: The figure plots the estimated coefficients from simulated regressions based on (3). The red line denotes the model with annual smoothing and the blue line denotes a model without annual smoothing.

updating, the k-quarter ahead revision is equal to the current-quarter revision, scaled by the persistence of the driving process, raised to a power. In fact, in the absence of annual smoothing, the offsetting revisions regression suffers a collinearity problem as two of the regressors are linear combinations of the third.

On the other hand, with annual smoothing, the model is able to generate a negative relation between the three-quarter ahead revision and the current-quarter revision, and a positive relation between the three-quarter ahead revision and the two-quarter ahead revision. This offsetting pattern will be responsible for producing quarterly overreactions in our model.

Figure 2: Revision Autocorrelation and Model Parameters



Note: The figure plots comparative statics of one-quarter ahead revision autocorrelation to each model parameter. The black line (left axis) plots the individual pooled autocorrelation of revisions while the dashed red line (right axis) plots the consensus-level autocorrelation coefficient.

3.3 Analyzing the Model

The model features rich dynamics across horizon, frequency, and level of aggregation. As a result, the coefficients studied in Section 2 are complex functions of the underlying model parameters. To provide intuition from the model, we therefore rely on simulated comparative statics.

We focus on the autocorrelation of revisions, though we note that the same qualitative findings arise when simulating the errors-on-revisions coefficient. Figure 2 plots revision autocorrelation coefficients across a range of different parameter values collectively governing the state and signals. For each panel, the left axis plots the individual-level coefficient while the right axis plots the consensus-level coefficient.

Panel 1 displays results for the persistence of the state. As the underlying process approaches a unit root, we find that the scope for overreactions declines. This is consistent with Bordalo et al. (2020) and Afrouzi et al. (2021) who find that overreactions are decreasing in ρ. From the lens of our model, a more persistent target variable will reduce the magnitude of the forecast errors thereby reducing the scope for past forecast errors to influence current predictions through the consistency constraint. Furthermore, the aggregate autocorrelation of revisions rises as the state becomes more persistent. At the consensus-level, a more persistent driving process generates more sluggish aggregate beliefs in an imperfect information environment.

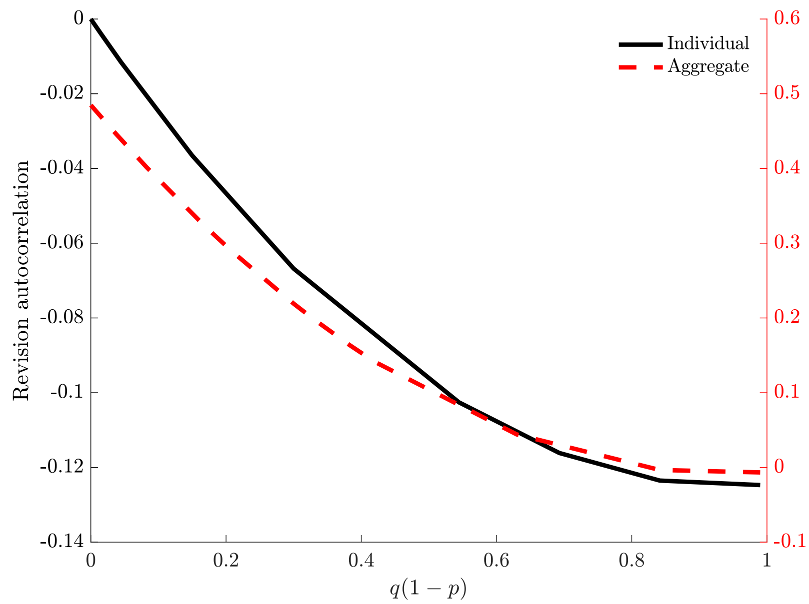
Panel 2 reports the results for the state volatility, σ_w. Here, we find that the scope for overreactions is decreasing in σ_w. Consistent with the intuition discussed for Panel 1, the rate of learning is increasing in the variance of the latent state. As information becomes more precise, there is less scope of overreactions. We also find that the autocorrelation coefficient increases at the aggregate level as the volatility of the state increases.[16]

On the other hand, Panels 3 and 4 show that the forecaster-level coefficients are decreasing in public and private noise. This is because, at the individual level, additional noise raises the variance of the forecast error and reduces the rate of learning. As a result, annual forecast smoothing promotes over-adjustments. At the aggregate level, however, the autocorrelation of revisions depends on the type of noise. In particular, the aggregate autocorrelation coefficient falls as common noise becomes more pervasive.[17] Private noise, however,

[16]We uncover similar results when simulating the consensus errors-on-revisions regression coefficient. Our interpretation is therefore different from Coibion and Gorodnichenko (2015) which finds that a larger coefficient at the consensus-level is indicative of greater information frictions. Here, the opposite is the case since the Kalman gain is increasing in the volatility of the state.

[17]This is consistent with the discussion in Coibion and Gorodnichenko (2015) on the bias in the OLS errors-on-revisions coefficient under a common noise assumption.

Figure 3: Revision Autocorrelation and Updating Probabilities



Note: The figure plots the simulated revision autocorrelation coefficients as a function of the probability of Case 2 updating. The left axis plots the individual-level coefficient while the right axis plots the aggregate coefficient.

washes out in the cross-section, so the aggregate autocorrelation coefficient actually rises with elevated levels of σ_v. The standard noisy information logic applies here: higher private noise variance reduces the signal-to-noise ratio and the Kalman gains thereby generating inertia in expectation formation.

3.4 Updating Probabilities

Sticky information is an important feature of our model. To assess the role that infrequent annual updating plays in driving observed overreactions, we focus on the frequency of Case 2 updating.

Figure 3 illustrates how individual overadjustments depend on the quarterly and annual updating probabilities. On the left axis, the figure plots simulated estimates of the autocorrelation of individual forecast revisions. The right axis plots the aggregate revision autocorrelation coefficient. Finally, the horizontal axis plots the probability of Case 2 updating.

Focusing first on the individual autocorrelation coefficient, we see that as the probability of Case 2 updating rises, forecasters' quarterly predictions overreact more strongly. The sharper overreaction occurs because forecasters increasingly find themselves in a scenario in which they wish to update based on news they receive, but cannot adjust their annual outlooks. In this case, forecasters respond to news, but offset their sequence of revisions so as to preserve temporal consistency. The excessive revising that occurs along the annual path is responsible for generating overreactions. Turning to the right axis, we note that the simulated aggregate autocorrelation coefficient is also decreasing in the probability of Case 2 updating. As more forecasters engage in Case 2 updating, the amount of inertia in quarterly expectations diminishes.

4 Model Estimation

Having analyzed the model's ability to reproduce over- and underreactions, we next turn to estimating the model with micro data from the SPF. For our baseline results, we fit the model to real GDP growth forecasts. Of the seven parameters, we first fix the unconditional mean, $\mu = 2.4$, consistent with the sample mean of real-time real GDP growth over this period.

We estimate the remaining six parameters via a minimum distance estimation approach. 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 forecast error, and the mean squared errors associated with current quarter predictions and current year predictions.

4.1 Identification

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

The underlying persistence of the latent state, ρ, is in part identified by the covariance between the current-quarter forecast and the current-year forecast. With a highly persistent data generating process, the covariance between current-quarter and current-year forecasts will be strongly positive. Moreover, the updating probabilities, q and p, inform the relevant mean squared errors.

The dispersion parameters, σ_w, σ_e, and σ_v require further discussion. Two of these parameters reflect noise variance (σ_e and σ_v) while the other (σ_w) reflects the variance of the latent state innovations. The distinction between noise and signal is crucial for the identification of these parameters.

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

Moreover, elevated levels of public signal noise, σ_e, contribute to a larger forecast error variance. The link between common noise and the variance of errors is intuitive since the transitory component, e_t, is linear in the macroeconomic variable being predicted.

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

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

where κ_1 and κ_2 denote the Kalman gains. An increase in σ_v reduces the

Kalman gain weight placed on the private signal, κ_1. As σ_v rises, fluctuations in the current-quarter revision are increasingly driven by lagged forecast errors, thereby strengthening the covariance between the revision and the lagged error. In other words, with less informative private signals, forecasters trust y_t^i less and instead base more of their revisions on the news gleaned from yesterday's error.[18]

4.2 Estimation Results

The parameters estimated via the minimum distance approach are precisely estimated and are reported in Panel A of Table 5. The underlying persistence of the latent state is estimated to be 0.46. In addition, the dispersion in state innovations is 1.92 while the dispersions of public and private noise are 1.07 and 1.13, respectively. These estimates imply a signal-to-noise ratio of about $\frac{\sigma_w}{\sigma_e+\sigma_v} \approx 0.87$. Furthermore, the probability of quarterly updating is about 0.94, indicating that forecasters update their quarterly predictions nearly 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 both over- and underadjustments. Our estimates imply that annual smoothing 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 0.49, failing to reject the null hypothesis thereby lending additional support to the validity of the estimates.

[18]Figure C5 in Appendix C helps assess the sources of identification by reporting the sensitivity of each of the six parameters to changes in a given moment, based on Andrews

Table 5: Model Estimation Results

Panel A: Parameter Estimates			
	Parameter	Estimate	Standard error
Persistence of latent state	ρ	0.460	0.040
State innovation dispersion	σ_w	1.920	0.179
Public signal noise	σ_e	1.072	0.276
Private signal noise	σ_v	1.127	0.272
Probability of quarterly update	q	0.938	0.081
Probability of annual update	p	0.584	0.037
Panel B: Moments			
	Model moment	Data moment	t-statistic
Standard deviation of nowcast	1.630	1.719	-0.873
Correlation of nowcast with annual forecast	0.701	0.670	-0.512
Standard deviation of annual forecast	1.062	1.103	-0.714
Standard deviation of revision	1.512	1.615	-0.712
Correlation of revision with lagged error	0.174	0.143	0.228
Standard deviation of lag error	1.633	1.720	-1.008
RMSE nowcast	1.650	1.677	-0.555
RMSE annual forecast	1.081	1.098	-0.461

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.

5 Annual Smoothing and Overadjustments

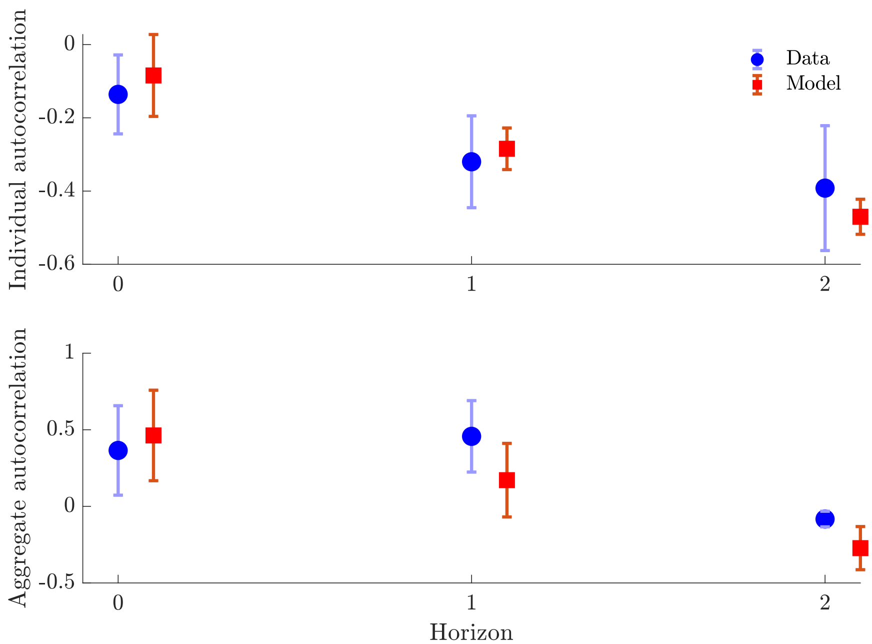
Having evaluated the estimated model and assessed its fit to the targeted moments, we next turn to analyzing its ability to replicate the patterns of over- and underadjustments observed in the data. We then discuss two robustness exercises and study a potential driver of annual inattention.

5.1 Simulated Regression Coefficients

The model is able to successfully replicate the negative autocorrelation of revisions observed in the data. Figure 4 plots the autocorrelation of revisions across horizons both in the data and in the model. The simulated model-based estimates nearly always lie within the 95% confidence interval of the estimated

et al. (2017). These figures confirm the intuition laid out above.

Figure 4: Model Fit to Revision Autocorrelation



Note: The figure plots the empirical and model-implied autocorrelation of revisions. The top panel plots the individual autocorrelation coefficient, and the bottom panel plots the consensus-level autocorrelation coefficient. 95% confident intervals are displayed with each point estimate.

coefficients, both at the individual (top panel) and aggregate (bottom panel) levels.

Table 6 reports ten additional non-targeted moments. Panel A reports individual-level regression coefficients of errors-on-revisions at the current quarter as well as one- and two-quarter ahead horizons (rows 1 to 3). The fourth row of the panel reports the estimated coefficient from a regression of the annual (Q4/Q4) forecast error on the realized outcome as in Kohlhas and Walther (2021). Across these four regressions, the model almost always predicts individual overreactions as in the top panel of Figure 4.[19]

[19] The model does not generate a negative errors-on-revisions coefficient for current-quarter forecasts. This is because the model assumes that the news forecasters receive is about today. As a result, forecasters place more importance on minimizing current quarter errors, and

Table 6: Additional Non-targeted Moments

Panel A: Individual-Level	Model		Data	
$\beta(FECQ, FRCQ)$	0.044	(0.039)	-0.269	(0.061)
$\beta(FE1Q, FR1Q)$	-0.182	(0.098)	-0.156	(0.077)
$\beta(FE2Q, FR2Q)$	-0.564	(0.113)	-0.355	(0.064)
β(Annual FE, Outcome)	-0.058	(0.094)	-0.064	(0.023)
$\beta(FE1Q, FE1Q_{-1})$	0.197	(0.061)	0.190	(0.063)
Panel B: Aggregate-Level	Model		Data	
$\beta(FECQ, FRCQ)$	0.644	(0.061)	0.136	(0.121)
$\beta(FE1Q, FR1Q)$	0.765	(0.277)	0.724	(0.299)
$\beta(FE2Q, FR2Q)$	0.109	(0.598)	1.093	(0.294)
β(Annual FE, Outcome)	-0.136	(0.216)	0.149	(0.095)
$\beta(FE1Q, FE1Q_{-1})$	0.188	(0.125)	0.286	(0.080)

Note: The table reports additional 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' refer to current quarter, one-quarter ahead, and two-quarters ahead, respectively.

The final row of Panel A displays estimates of forecast error persistence. We report this estimate to highlight our model's ability to reproduce another feature of the data: positively autocorrelated individual-level errors. In a rational setting in which forecasters are able to observe past realizations of the variable of interest, errors should not exhibit persistence.[20] Our model is able to generate error persistence precisely because annual smoothing 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

instead reshuffle their future forecasts, for which the signals are less informative, to maintain annual consistency. If instead 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.

[20]The literature often assumes that forecasters never observe the variable of interest, thereby preserving error persistence. Here, we assume that x_{t-1} is observable.

more realistic assumption about the forecaster's information set.

Panel B of Table 6 reports the aggregate analogs to the estimates in Panel A. The first three rows in particular, indicate that consensus forecasts exhibit inertia. Taken together, the results demonstrate that the model is successful in producing empirically relevant magnitudes of over- and underadjustments.

5.2 Incorporating Non-Rational Expectations

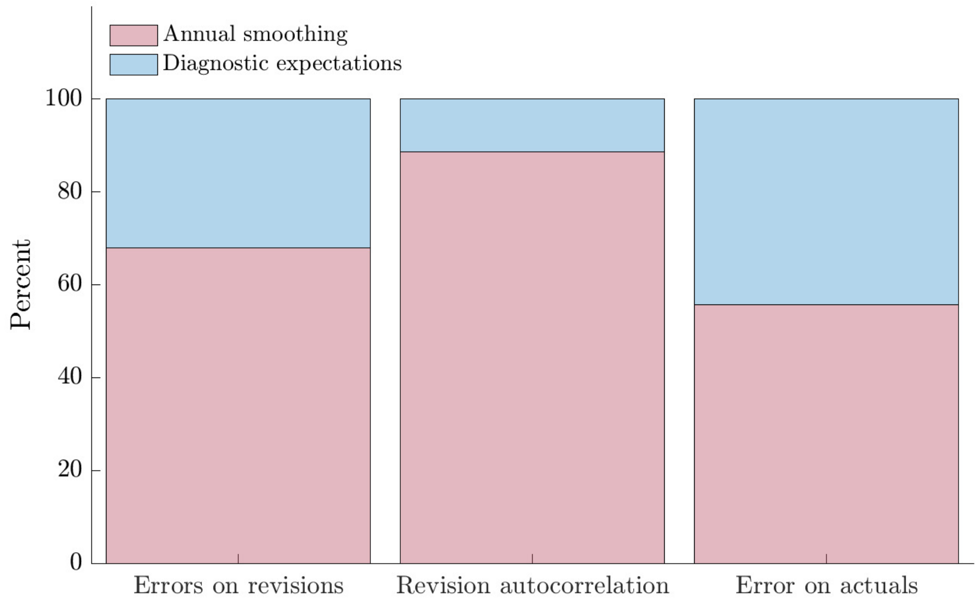
To better understand the quantitative importance of our mechanism as a driver of overadjustments, we augment our model with a behavioral friction in a supplementary exercise. We choose a leading theory of non-rational expectations, diagnostic expectations (Bordalo et al., 2019; Bianchi et al., 2021; Bordalo et al., 2021; Chodorow-Reich et al., 2021), which draws from the representativeness heuristic (Tversky and Kahneman, 1974). In particular, diagnostic forecasters place excess 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 θ is the degree of diagnosticity. When $\theta = 0$, the model collapses to a rational expectations model. On the other hand, in a world of diagnostic expectations, $\theta > 0$.

The objective of this exercise is to model two channels of overreaction: (i) our annual smoothing mechanism and (ii) diagnostic expectations, and to quantify the relative importance of our mechanism. To do so, we re-estimate the model with and without diagnostic expectations while targeting two additional moments: the *contemporaneous* covariance of errors and revisions, and the variance of *contemporaneous* errors. We add these moments to the estimation procedure in order to ensure that the model fits a well-known measure of overreactions, the coefficient of errors on revisions, as closely as possible. We estimate unconstrained (with θ) and constrained (without θ) versions of our model while targeting this expanded set of ten moments. The results are reported in Table D5.

Figure 5: Annual Smoothing vs. Diagnostic Expectation Contributions



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

The constrained model, without diagnostic expectations, implies that the probability of Case 2 updating, $q(1-p)$, is about 0.41. In the unconstrained model, which features diagnostic expectations, this probability falls by roughly 35%. At the same time, our estimate of diagnosticity is 0.50 which is similar to though slightly lower than the estimate obtained in Bordalo et al. (2020) who use the same data and estimation approach. Overall, our results indicate that annual smoothing and temporal consistency can explain a meaningful amount of observed overreactions, even in the presence of a non-rational belief friction.

In a second exercise, we examine the importance of annual smoothing relative to diagnostic expectations by running three simulated regressions. Using our unconstrained parameter estimates, we first simulate a panel of forecasts and run an errors-on-revisions regression, a revision autocorrelation regression, and an errors-on-outcomes regression. We then fix $\theta = 0$ and repeat this exercise. Figure 5 displays three sets of stacked bars, each corresponding to one of the aforementioned regressions. The red bar denotes the contribution of our annual smoothing mechanism to the overall estimate of overadjustments in the unconstrained model, while the blue bar denotes the contribution of diagnostic expectations. Once again, we find that annual smoothing is a meaningful, and in this case dominant, driver of quarterly overreactions. While there are a number of other plausible sources of overadjustments, these results suggest that annual smoothing can be a quantitatively important driver of overreactions.

5.3 Annual Smoothing Across SPF Variables

We next estimate our baseline model for a range of macroeconomic variables covered in the SPF. Table 7 reports empirical and simulated estimates of revision autocorrelation, our non-targeted moment of choice. In general, we find that our model is broadly successful in reproducing the negatively autocorrelated revisions observed in the data.

5.4 Examining Potential Sources of Annual Smoothing

Annual inattention can arise due to reputational considerations or time and resource constraints associated with frequent model updating. The reputational considerations hypothesis is unlikely to explain annual smoothing in the data since the SPF is an anonymous survey. We therefore proceed to examine the plausibility of resource constraints. To do so, we exploit the SPF classifications of different forecaster types.

In 1990, the SPF began collecting information on respondents' industries of employment. A respondent is labeled as either a financial service provider, a non-financial service provider, or neither. Financial service providers include asset managers, investment bankers, and insurance companies while non-financial forecasters include academics employed at universities, manu-

Table 7: Estimates Across SPF Variables

	Revision Autocorrelation	
	Model	Data
Real GDP	**-0285 (0.029)**	**-0.202 (0.027)**
Nominal GDP	**-0.250 (0.027)**	**-0.303 (0.050)**
Real consumer spending	**-0.325 (0.027)**	**-0.281 (0.047)**
GDP deflator	**-0.261 (0.031)**	**-0.253 (0.053)**
Real residential investment	**-0.178 (0.027)**	**-0.171 (0.035)**
Real nonresidential investment	**-0.155 (0.027)**	**-0.265 (0.025)**
Real federal spending	**-0.203 (0.030)**	**-0.222 (0.028)**
Real state/local spending	**-0.178 (0.035)**	**-0.203 (0.041)**
Industrial production	**-0.209 (0.025)**	**-0.242 (0.035)**
CPI	**-0.447 (0.019)**	**-0.336 (0.047)**
Unemployment	-0.010 (0.038)	**-0.284 (0.029)**
Ten year bond	**-0.422 (0.019)**	**-0.280 (0.028)**
3-month bill	**-0.229 (0.045)**	**-0.254 (0.025)**
Housing starts	-0.010 (0.035)	**-0.261 (0.021)**

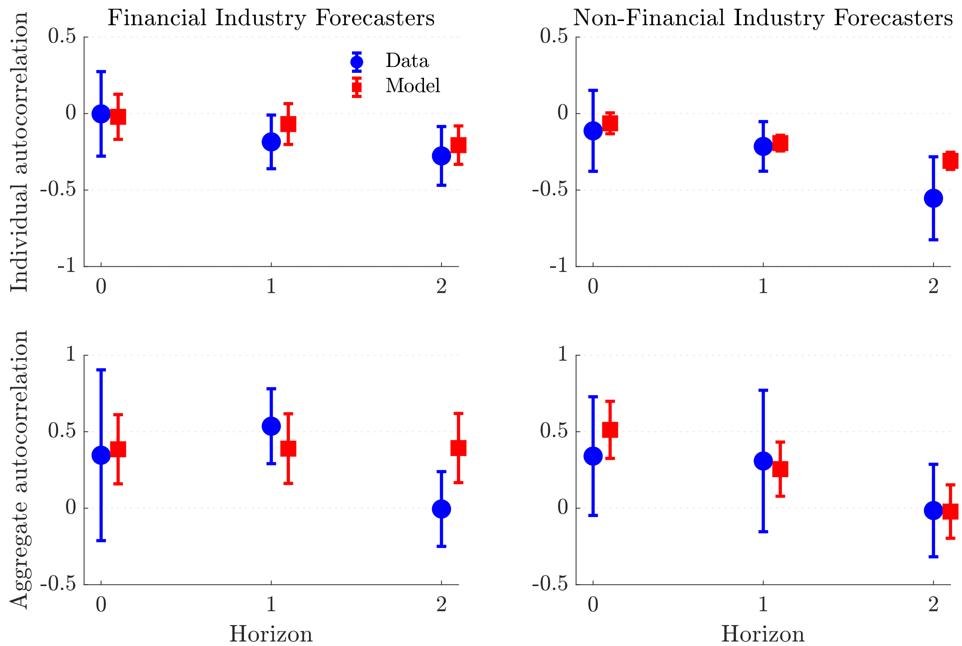
Note: The table reports one-quarter ahead revision autocorrelation coefficients in the model and the data for various macroeconomic variables covered in the SPF. Bold values are significantly negative at the 5% level.

facturers, and consulting firms.[21] In general, a forecaster is able to switch across categories over time.

We hypothesize that annual smoothing is weaker among financial service providers. Inattention is plausibly costlier among these types of forecasters because client demands require them to operate with up-to-date information. On the other hand, non-financial service providers likely complete other tasks on a regular basis that do not require highly updated information on macroeconomic developments. To assess this hypothesis, we re-estimate the baseline model for financial and non-financial forecasters separately and find the strongest evidence of annual smoothing among non-financial service

[21] A full list is provided on page 33 of the SPF documentation: https://www.philadelphiafed.org/-/media/frbp/assets/surveys-and-data/survey-of-professional-forecasters/spf-documentation.pdf?la=en&hash=F2D73A2CE0C3EA90E71A363719588D205

Figure 6: Model Fit to Revision Autocorrelation, by Forecaster Type



Note: The figure plots the empirical and model-implied autocorrelation of revisions. The top two panels plot the individual autocorrelation coefficient, and the bottom two panels plot the consensus-level autocorrelation coefficient. The first column of panels refers to the financial industry forecaster subsample while the second column of panels refers to non-financial forecasters. 95% confident intervals are displayed with each point estimate.

providers.[22]

Figure 6 displays the non-targeted fit of the estimated models to the autocorrelation of revisions. Overall, our estimated models are able to match the autocorrelation of revisions across either type of forecaster, which are more strongly negative among non-financial forecasters. In addition, the estimated probability of Case 2 updating is higher among non-financial forecasters. These results favor a time or resource-based interpretation of annual inattention.

[22]The estimation results are reported in Table D6.

6 Implications for Information Frictions

In addition to serving as a source of observed overadjustments, our model can also speak to the literature on information frictions. Since our model does not allow us to readily extract a coefficient of information rigidity from an OLS regression, we simulate the estimated model in order to retrieve the steady state Kalman gains and to quantify the size of information frictions.

6.1 Model-Implied Information Rigidities

Column 3 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:

$$\text{Implied friction} = \big[1 - \Pr(\text{update})\big] + \Pr(\text{update}) \times (1 - \kappa_1 - \kappa_2), \tag{6}$$

where Pr(update) denotes the probability of updating, which reflects the sticky information feature of the model. Based on our estimates in the previous sections, 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 interpreted as an *expected* weight placed on new information.

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

Table 8: Information Frictions Across Models

	Probability of updating	Implied friction	Sticky info contribution	Noisy info contribution
Panel A: Real GDP				
Quarterly	0.934	0.248	25.0%	75.0%
Annual	0.584	0.532	78.2%	21.8%
Panel B: Inflation				
Quarterly	0.997	0.256	1.0%	99.0%
Annual	0.571	0.574	74.7%	25.3%

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 (6) with model-implied Kalman gains $\{0.749, 0.052\}$ and $\{0.685, 0.061\}$ for real GDP and inflation, respectively. Contributions of sticky and noisy information are computed according to (7).

In order to compare our implied information frictions to those in the literature, we also report model estimates using inflation forecasts based on the GDP deflator. At a quarterly frequency, we estimate information frictions to be about 0.26 while, for annual forecasts, we find that information frictions are higher, at 0.57. 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 information rigidities across quarterly and annual frequencies. We note that the average of our quarterly and annual information frictions hover around these previously documented estimates.

6.2 Contributions of Sticky and Noisy Information

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

$$1 = \underbrace{\frac{1 - \Pr(\text{update})}{[1 - \Pr(\text{update})] + \Pr(\text{update}) \times (1 - \kappa_1 - \kappa_2)}}_{\text{Sticky info contribution}} + \underbrace{\frac{\Pr(\text{update}) \times (1 - \kappa_1 - \kappa_2)}{[1 - \Pr(\text{update})] + \Pr(\text{update}) \times (1 - \kappa_1 - \kappa_2)}}_{\text{Noisy info contribution}}. \tag{7}$$

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. The results from this accounting exercise suggest that noisy information is the primary contributor to estimated information frictions among quarterly forecasts, while sticky information becomes substantially more important at the annual frequency.

7 Conclusion

We show that professional forecasters exhibit over- and underadjustments, and they offset their updates. Motivated by these facts, we build a hybrid sticky-noisy information model with quarterly and annual forecasts. From the lens of our model, overreactions arise because of annual smoothing and temporal consistency. When faced with new information, forecasters offset their current updates further along their annual trajectories. The trade-off between minimizing errors and satisfying consistency can explain a meaningful amount of overreactions to real GDP as well as other variables.

Our results also imply that information frictions vary by frequency, and attribute most of the annual friction to stickiness and the quarterly friction to noisiness. Future research might be able to provide a deeper microfoundation for annual smoothing, be it rational or behavioral. For policymakers, the result that quarterly predictions are updated almost every quarter and are partly contaminated by overadjustments due to annual smoothing, implies that they should focus on managing more stable medium- and long-term expectations.

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APPENDIX: FOR ONLINE PUBLICATION

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.

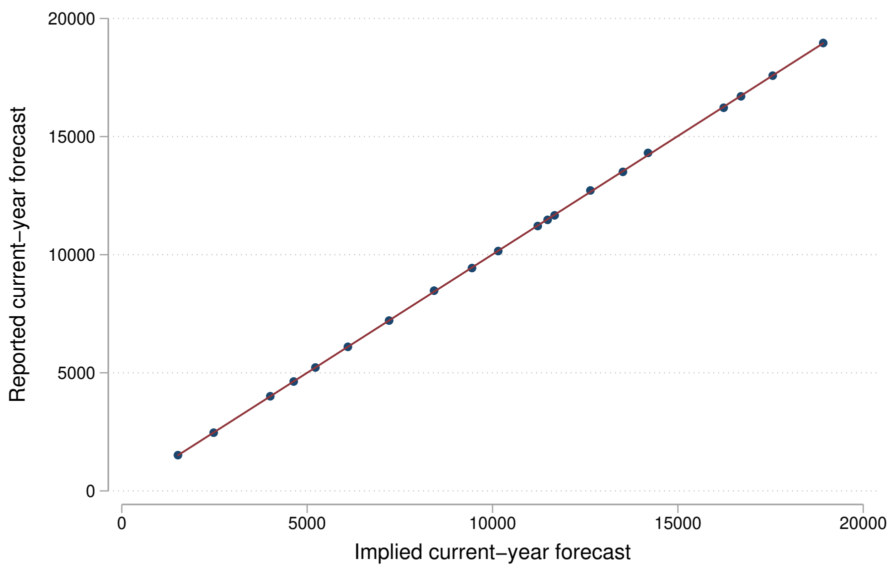
A.1 Quarterly-to-Annual Consistency in SPF Forecasts

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.[24]

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.

[24]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.

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.

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 and consists of 251 unique forecasters.

A.3 Errors on Outcomes

In addition to the regression results presented Section 2, Kohlhas and Walther (2021) provide an additional measure of overreaction based on regressing ex-post forecast errors on outcomes. Table A2 reports the results from this regression based on our sample.

Table A2: Overreaction to Realized Output

	Annual error	Annual error
Realized outcome	-0.023	-0.064***
	(0.021)	(0.023)
Fixed effects	None	Forecaster
Observations	3,402	3,384

Note: The table reports panel regression results from SPF forecasts of real GDP based on the regression of errors on realized output in Kohlhas and Walther (2021). *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

A.4 Annual Errors on Annual Revisions

Based on our theory of annual smoothing, overreactions should be less apparent at the annual frequency. We explore this further by studying annual error predictability at the forecaster-level. We regress current year forecast errors on current year forecast revisions in the second quarter of the year. We focus on the second quarter so that forecasters issue their current-year forecasts roughly halfway through the year, similar to the quarterly forecasts which are surveyed halfway through the quarter.

Table A3 reports the regression results which provide no statistically significant evidence of overreaction. Furthermore, the point estimates are closer to zero than most of the quarterly point estimates. Taken together, this is consistent with the notion under annual smoothing, quarterly forecasts should exhibit stronger overreactions than annual forecasts.

Table A3: Error Predictability at the Annual Frequency

	Current year error	Current year error
Current year revision	-0.099	-0.180
	(0.118)	(0.137)
Fixed effects	None	Forecaster
Observations	714	666

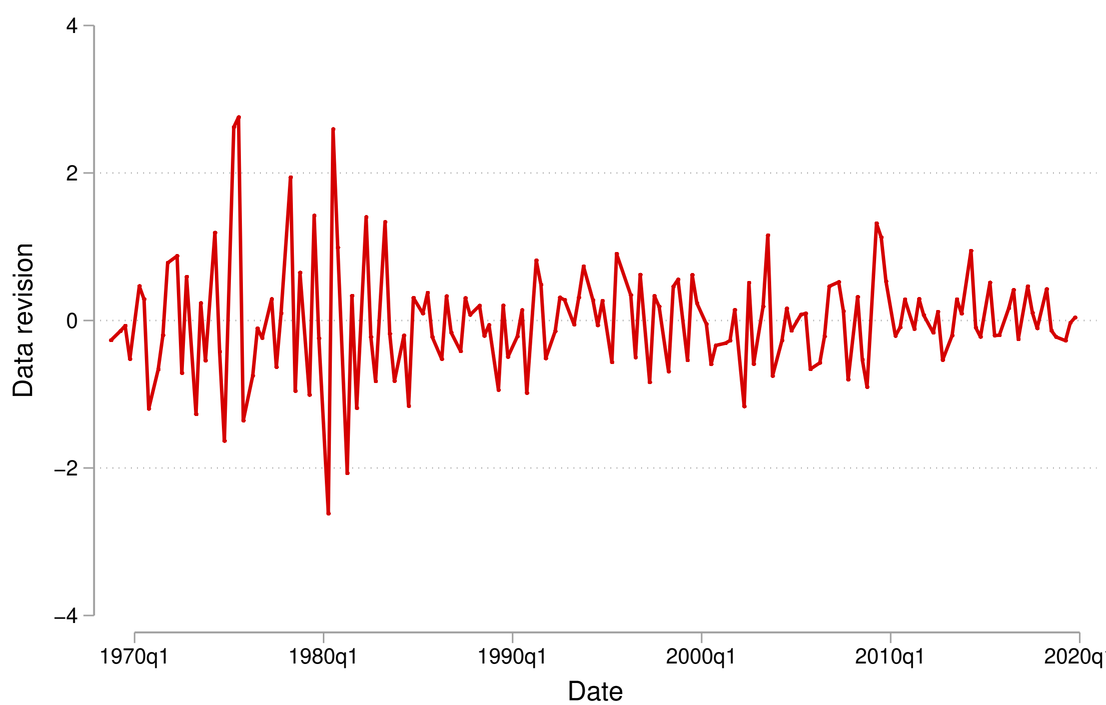
Note: The table reports panel regression results from SPF forecasts of real GDP based on the regression of errors on revisions Coibion and Gorodnichenko (2015); Bordalo et al. (2020) at an annual frequency. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

A.5 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 real GDP revisions 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.[25]

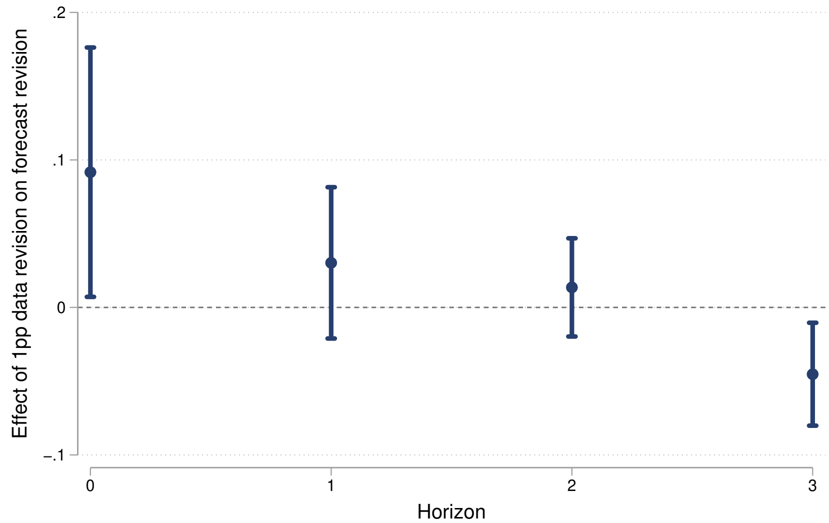
We construct a series of real GDP data revisions by computing the difference across vintages: $d_t = x_t^{\text{new}} - x_t^{\text{old}}$. Figure A2 plots the time series of measured real GDP data revisions.

Figure A2: Real GDP Data Revision Series



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

Figure A3: Effect of Data Revisions on Forecast Revisions



Note: The figure reports 95% confidence estimates of the α_1 coefficient in regression (8) across four horizons. Driscoll and Kraay (1998) standard errors are specified in the regressions.

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

$$F_{it}(x_{t+h}) - F_{it-1}(x_{t+h}) = \alpha d_t + \varepsilon_{it}. \tag{8}$$

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 3, and indicates that forecast revisions exhibit an offsetting behavior consistent with long-horizon smoothing.

Appendix B Model

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

$$\min_{\{\widehat{x}^i_{t+h|t|t+k}\}} \sum_{h=0}^{H} (x_{t+h} - \widehat{x}^i_{t+h|t+k})^2, \tag{9}$$

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

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

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

as their quarterly and annual forecasts, respectively.

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

$$\frac{1}{H+1}\sum_{h=0}^{H} \widehat{x}^i_{t+h|t+k} = \frac{1}{H+1}\sum_{h=0}^{H} \widehat{x}^i_{t+h|t+k-j}, \tag{10}$$

where j denotes the period in which the annual forecast was last updated. In this case, the forecaster solves (9) subject to (10).

The Lagrangian is

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

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

$$\widehat{x}^i_{t+k'|t+k} = \mathbb{E}_{it+k}(x_{t+k'}) + \frac{\lambda}{2(H+1)}. \tag{11}$$

Combining the FOC with the definition of the constraint delivers:

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

Rearranging, we obtain:

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

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

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

or, equivalently,[26]

$$\widehat{x}^i_{t+k'|t+k} = \mathbb{E}_{it+k}(x_{t+k'}) + \frac{1}{H+1}\sum_{h=0}^{H}\left[\mathbb{E}_{it+k-j}(x_{t+k'}) - \mathbb{E}_{it+k}(x_{t+k'})\right]. \tag{12}$$

[26]This follows from the fact that whenever the forecaster constructed her outdated annual, she did so optimally, based on the conditional expectation as of date $t+k-j$.

Appendix C Estimation

The model is estimated via the simulated method of moments. Operationally, this is done by simulating a balanced panel of 250 forecasters over 40 periods, consistent with the average number of quarterly forecasts that a unique forecaster contributes throughout the history of the survey.[27] For each iteration, the target moments are computed, averaged across simulations, and compared to their empirical analogs. The six-dimensional parameter vector, θ, is selected to minimize the weighted distance between simulated moments and empirical moments, where the asymptotically efficient weighting matrix is specified.

Formally, we search the parameter space to find the $\widehat{\theta}$ that minimizes the following objective

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

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

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

where

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

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

C.1 Identification

The eight moments jointly determine the six parameters that reside in vector θ. To supplement the discussion on monotone relationships reported in Figure C4,

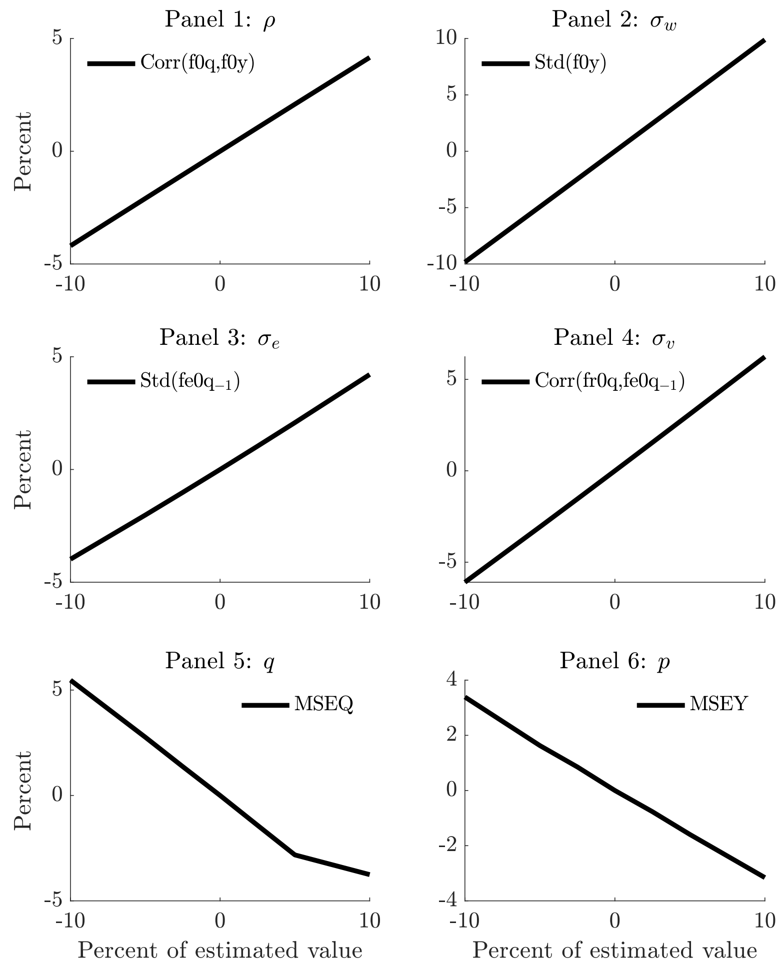
[27] Similar results are obtained when mimicking the unbalanced nature of the panel data by simulating a larger set of forecasters and matching missing observations.

we additionally report the sensitivity of each of the parameters to changes in each of the moments in Figure C5. These sensitivities are an implementation of Andrews et al. (2017). In particular, the sensitivity of $\widehat{\theta}$ to $m(\theta)$ is

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

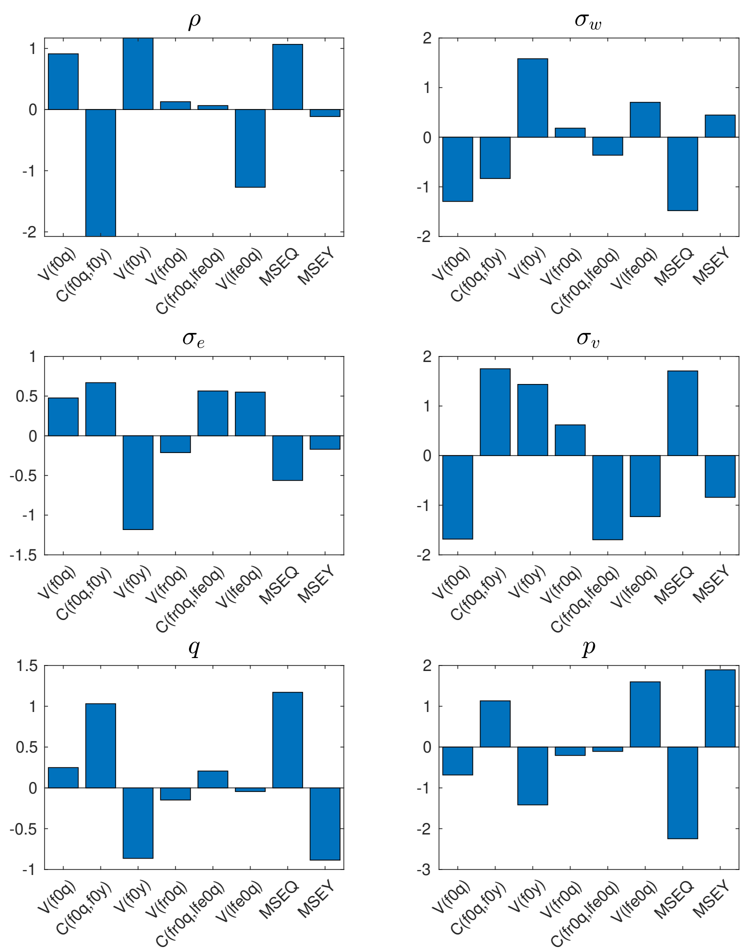
We transform this matrix so that the estimates can be interpreted as elasticities of the parameters with respect to moments.

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.

Figure C5: Sensitivity



Note: The figure computes the elasticities of estimated parameters to moments as in Andrews et al. (2017).

Appendix D Robustness

In this section, we consider a variety of robustness checks. First, we examine the role that rounding plays in the parameter estimates. We then augment our model with diagnostic expectations to assess the relative importance of our mechanism in generating overadjustments. Next, we report the results for across forecaster types, and then report the estimates based on real GDP forecasts from the Bloomberg Survey as well as SPF inflation forecasts. Following this, we undertake a sub-sample analysis, estimating the baseline model before and after 1990. Finally, we consider an alternative data generating process for the underlying state.

D.1 Rounding

We first report parameter estimates under the assumption that forecasters round their predictions to the nearest 0.10 percentage point. We find that this rounding assumption does not meaningfully change our parameter estimates (see Table D4).[28]

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

Table D4: Model Estimation Results (Rounding to nearest 0.1 pp)

Panel A: Parameter Estimates			
	Parameter	Estimate	Standard error
Persistence of latent state	ρ	0.401	0.034
State innovation dispersion	σ_w	2.016	0.158
Public signal noise	σ_e	0.816	0.353
Private signal noise	σ_v	1.595	0.364
Probability of quarterly update	q	0.997	0.129
Probability of annual update	p	0.620	0.032
Panel B: Moments			
	Model moment	Data moment	t-statistic
Standard deviation of nowcast	1.656	1.719	-0.623
Correlation of nowcast with annual forecast	0.689	0.670	-0.211
Standard deviation of annual forecast	1.093	1.103	-0.178
Standard deviation of revision	1.573	1.615	-0.295
Correlation of revision with lagged error	0.242	0.143	1.603
Standard deviation of lag error	1.644	1.720	-0.889
RMSE nowcast	1.657	1.677	-0.415
RMSE annual forecast	1.095	1.098	-0.100

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

D.2 Diagnostic Expectations

Table D5 reports the parameter estimates for the unconstrained and constrained models. These models are estimated by targeting the original eight moments described in the main text 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 D5: Model Estimation Results, Diagnostic Expectations

	Parameter	Unconstrained	Constrained
Persistence of latent state	ρ	0.512	0.566
		(0.037)	(0.039)
State innovation dispersion	σ_w	1.726	1.521
		(0.103)	(0.130)
Public signal noise	σ_e	0.306	1.062
		(0.081)	(0.161)
Private signal noise	σ_v	1.252	0.973
		(0.231)	(0.167)
Probability of quarterly update	q	0.577	0.999
		(0.061)	(0.101)
Probability of annual update	p	0.542	0.592
		(0.032)	(0.058)
Diagnosticity	θ	0.498	0.000
		(0.105)	-

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.

D.3 Financial vs. Non-Financial Forecasters

Table D6 reports parameter estimates for real GDP predictions made by financial and non-financial forecasters, respectively. These industry identifiers are recorded in the SPF beginning in 1990.

Table D6: Model Estimation Results, By Forecaster Type

	Parameter	Financial Industry	Non-financial Industry
Persistence of latent state	ρ	0.491	0.617
		(0.114)	(0.060)
State innovation dispersion	σ_w	1.365	1.339
		(0.137)	(0.120)
Public signal noise	σ_e	1.162	0.958
		(0.240)	(0.239)
Private signal noise	σ_v	1.015	1.130
		(0.142)	(0.123)
Probability of quarterly update	q	1.000	1.000
		(0.113)	(0.527)
Probability of annual update	p	0.986	0.435
		(0.432)	(0.173)

Note: The table reports parameter estimates of the baseline model, estimated separately over a sample of financial industry forecasters and non-financial industry forecasters, respectively.

D.4 Bloomberg Real GDP Forecasts

Tables D7 and D8 document additional evidence of offsetting revisions from the Bloomberg survey of real GDP forecasts. Table D9 reports the the model estimates from the Bloomberg survey.

Table D7: Offsetting Revisions in the Bloomberg Survey

	Three quarter ahead revision
Two quarter ahead revision	0.398***
	(0.057)
One quarter ahead revision	0.014
	(0.034)
Current quarter revision	-0.057**
	(0.024)
Fixed effects	Time
Observations	857

Note: The table reports panel regression results from SPF forecasts based on regression (3). The sample spans 1993Q2 to 2016Q3. Driscoll and Kraay (1998) standard errors are reported in parentheses. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

Table D8: Offsetting Calendar Year Revisions in the Bloomberg Survey

	Fourth quarter revision
Third quarter revision	0.307***
	(0.024)
Second quarter revision	-0.023
	(0.019)
First quarter revision	-0.059***
	(0.021)
Fixed effects	Time
Observations	3124

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

Table D9: Model Estimation Results, Bloomberg Survey

Panel A: Parameter Estimates			
	Parameter	Estimate	Standard error
Persistence of latent state	ρ	0.717	0.016
State innovation dispersion	σ_w	1.202	0.043
Public signal noise	σ_e	0.899	0.048
Private signal noise	σ_v	0.322	0.039
Probability of quarterly update	q	0.751	0.048
Probability of annual update	p	0.370	0.034
Panel B: Moments			
	Model moment	Data moment	t-statistic
Standard deviation of nowcast	1.320	1.540	-6.088
Correlation of nowcast with annual forecast	0.816	0.805	-4.220
Standard deviation of annual forecast	1.160	1.213	-3.311
Standard deviation of revision	0.967	0.997	-1.059
Correlation of revision with lagged error	0.180	0.240	-3.148
Standard deviation of lag error	1.399	1.411	-0.529
RMSE nowcast	1.442	1.497	-2.110
RMSE annual forecast	1.030	1.021	0.403

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

D.5 Inflation Forecasts

Table D10 reports model estimates using SPF inflation forecasts based on the GDP deflator.

Table D10: Model Estimation Results, Inflation Forecasts (Deflator)

Panel A: Parameter Estimates			
	Parameter	Estimate	Standard error
Persistence of latent state	ρ	0.523	0.040
State innovation dispersion	σ_w	1.159	0.177
Public signal noise	σ_e	0.876	0.192
Private signal noise	σ_v	0.808	0.195
Probability of quarterly update	q	0.997	0.165
Probability of annual update	p	0.571	0.045
Panel B: Moments			
	Model moment	Data moment	t-statistic
Standard deviation of nowcast	1.022	1.096	-1.002
Correlation of nowcast with annual forecast	0.730	0.727	-0.952
Standard deviation of annual forecast	0.711	0.757	-0.959
Standard deviation of revision	0.922	1.102	-1.678
Correlation of revision with lagged error	0.173	0.197	-0.709
Standard deviation of lag error	1.176	1.253	-1.172
RMSE nowcast	1.408	1.535	-1.009
RMSE annual forecast	0.531	0.606	-1.209

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 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 D11) and 2000-2019 (Table D12). 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 D11: Model Estimation Results (1981-1999)

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

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

Table D12: Model Estimation Results (2000-2019)

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

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

D.7 Alternative Data Generating Process

Whereas offsetting revisions can be an artifact of annual smoothing, 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 smoothing. 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.[29] Second, an AR(2) is highly feasible to estimate with the current SMM approach as it only adds one parameter to the model. Third, an AR(2) allows us to remain consistent with others in the literature who similarly examine richer data generating processes for their models (Bordalo et al., 2020).

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

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

where ρ_1 and ρ_2 govern the persistence of the state. We impose the usual assumptions on these two parameters to ensure stationarity.

There are now seven parameters to be estimated. We estimate these parameters by targeting the same eight moments described in the main text. As a result, our estimator is still an overidentified SMM estimator. The results are reported in Table D13.

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 smoothing and temporal

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

Table D13: Model Estimation Results, AR(2)

Panel A: Parameter Estimates			
	Parameter	Estimate	Standard error
First lag autocorrelation	ρ_1	0.524	0.149
Second lag autocorrelation	ρ_2	-0.075	0.018
State innovation dispersion	σ_w	1.828	0.231
Public signal noise	σ_e	1.163	0.343
Private signal noise	σ_v	1.002	0.418
Probability of quarterly update	q	0.934	0.524
Probability of annual update	p	0.618	0.045
Panel B: Moments			
	Model moment	Data moment	t-statistic
Standard deviation of nowcast	1.624	1.719	-0.926
Correlation of nowcast with annual forecast	0.702	0.670	-0.588
Standard deviation of annual forecast	1.057	1.103	-0.799
Standard deviation of revision	1.486	1.615	-0.882
Correlation of revision with lagged error	0.172	0.143	0.141
Standard deviation of lag error	1.629	1.720	-1.060
RMSE nowcast	1.645	1.677	-0.661
RMSE annual forecast	1.077	1.098	-0.576

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

consistency.

Moreover, estimates of the state innovation and public noise variances are similar to those in Table 5. The private signal noise variance and the quarterly updating probability are estimated to be 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 (0.235 and 0.494, respectively). The scope for overreactions, based on the probability of Case 2 updating, $q(1-p)$, is approximately 8% lower in the AR(2) model relative to the baseline AR(1) model.