SUPPLEMENTARY MATERIALS TO OVERREACTION THROUGH ANCHORING

Appendix A Empirics

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

A.1 Sample selection

We apply a set cleaning filters to the raw data, before estimating the regressions. First, following Bordalo et al. (2020), for every horizon, we winsorize the observations above or below five interquartile ranges of the sample median. Second, we keep only forecasters who issue predictions for at least ten quarters. In addition, we drop the 1985Q1, 1986Q1, and 1990Q1 survey observations due to measurement error associated the reporting of annual forecasts as noted in the SPF documentation. In addition, we drop the survey observations in 1990Q2 because of small sample issues also noted in the SPF documentation.

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

A.2 Quarterly Forecasts

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

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

Table A1: SPF Real GDP Summary Statistics

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

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

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

A.3 Annual Forecasts

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

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

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

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

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

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

Table A2: SPF Real GDP Summary Statistics

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

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

A.4 Empirical Facts: Robustness

Fixed Effects

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

Table A3: Overreaction among Individual Forecasters

	Current quarter		One quarter ahead		Two quarters ahead		Year-over-year	
	(1) Error	(2) Revision	(3) Error	(4) Revision	(5) Error	(6) Revision	(7) Error	(8) Error
Revision	-0.270***		-0.160**		-0.362***		-0.259*	
	(0.059)		(0.069)		(0.065)		(0.137)	
Previous revision		-0.137**		-0.319***		-0.394***		
		(0.058)		(0.051)		(0.066)		
Realization								-0.160**
								(0.062)
Forecasters	152	143	143	142	138	141	137	136
Observations	4193	3545	3566	3531	3466	3435	3199	3104

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

Table A4 reports regression estimates of equation (2) with time fixed effects.

Table A4: Revision Autocorrelation with Time Fixed Effects

	Current quarter	One quarter ahead	Two quarters ahead
	(1) Revision	(2) Revision	(3) Revision
Previous revision	-0.254***	-0.387***	-0.420***
	(0.068)	(0.041)	(0.071)
Forecasters	143	142	141
Observations	3545	3531	3435
Fixed effects	Forecaster, Time	Forecaster, Time	Forecaster, Time

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

Table A5 reports estimates of annual version of equations (1) and (3) with forecaster fixed effects.

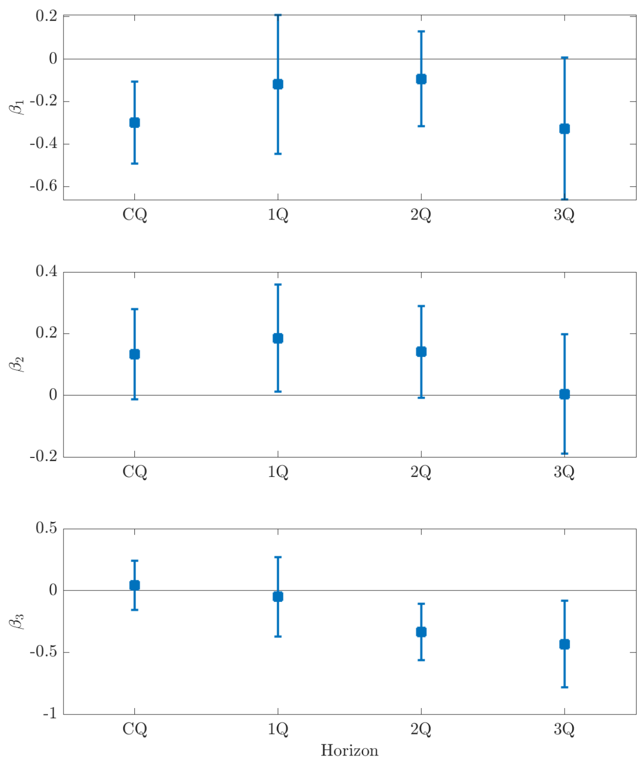
Table A5: No Annual Overreaction among Individual Forecasters

	(1) Annual error	(2) Annual error	(3) Annual error
Revision	-0.095		
	(0.058)		
Realization		0.021	
		(0.024)	
Realized quarterly error			0.039**
			(0.019)
Forecasters	137	137	137
Observations	4045	4049	4035

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

Finally, Figure A1 plots the revision offsetting interaction regression estimates when specifying forecaster fixed effects in equation (6).

Figure A1: Offsetting Drives Overreactions Over Longer Horizons



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

Other Macroeconomic Variables

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

List of variables

1. GDP Deflator (PGDP)
2. Nominal GDP (NGDP)
3. Real consumption expenditures (RCON)
4. Real federal government spending (RFED)
5. Real state and local government spending (RSL)
6. Real non-residential investment (RNRES)
7. Real residential investment (RRES)
8. 3-month Treasury bill (TBILL)
9. 10-year government bond (TBOND)
10. Unemployment rate (UE)

Tables A6 and A7 report the estimates of annual versions of regressions (1) and (2) across different macroeconomic variables in the SPF.

Table A8 reports estimates of regression (4) for different macroeconomic variables in the SPF.

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

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

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

Table A7: Annual Errors vs. Annual Outcome, by Variable

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

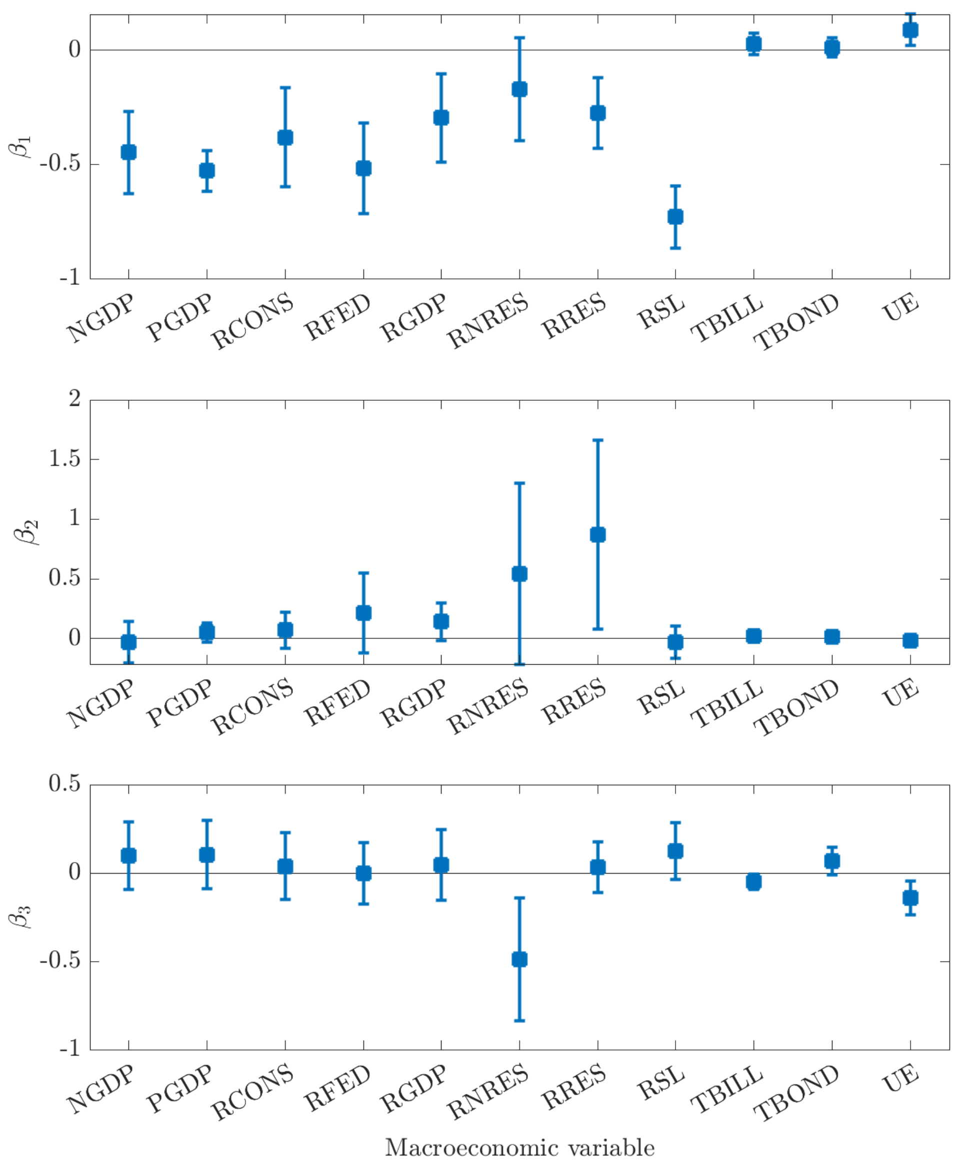
Note: The table reports estimates of the annual analog to regression (3). Standard errors are reported in parentheses. Standard errors are clustered by forecaster and time. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

Table A8: Annual Errors vs. Lagged Quarterly Errors, by Variable

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

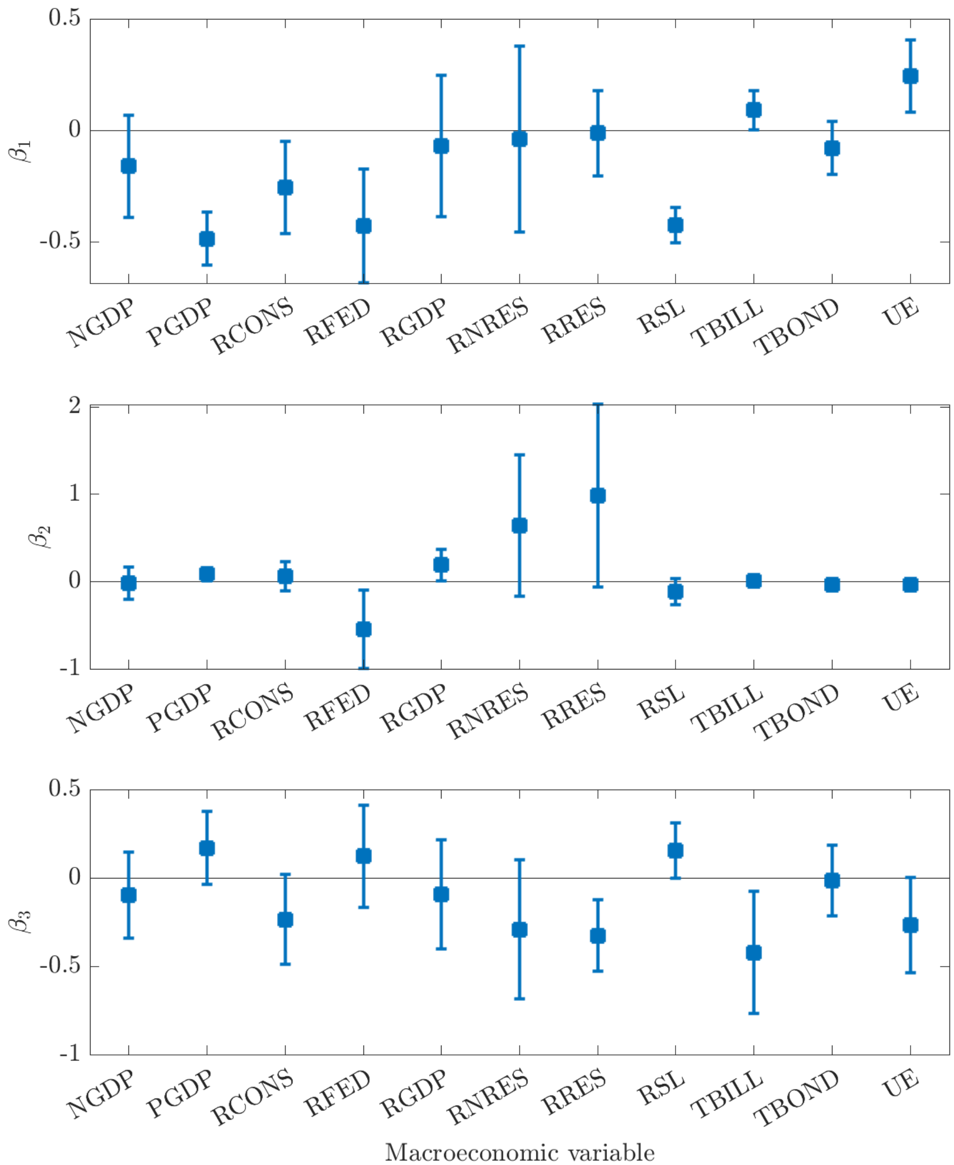
Note: The table reports estimates of the annual analog to regression (3). Standard errors are reported in parentheses. Standard errors are clustered by forecaster and time. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

Figure A2: Offsetting interaction regression, current-quarter horizon



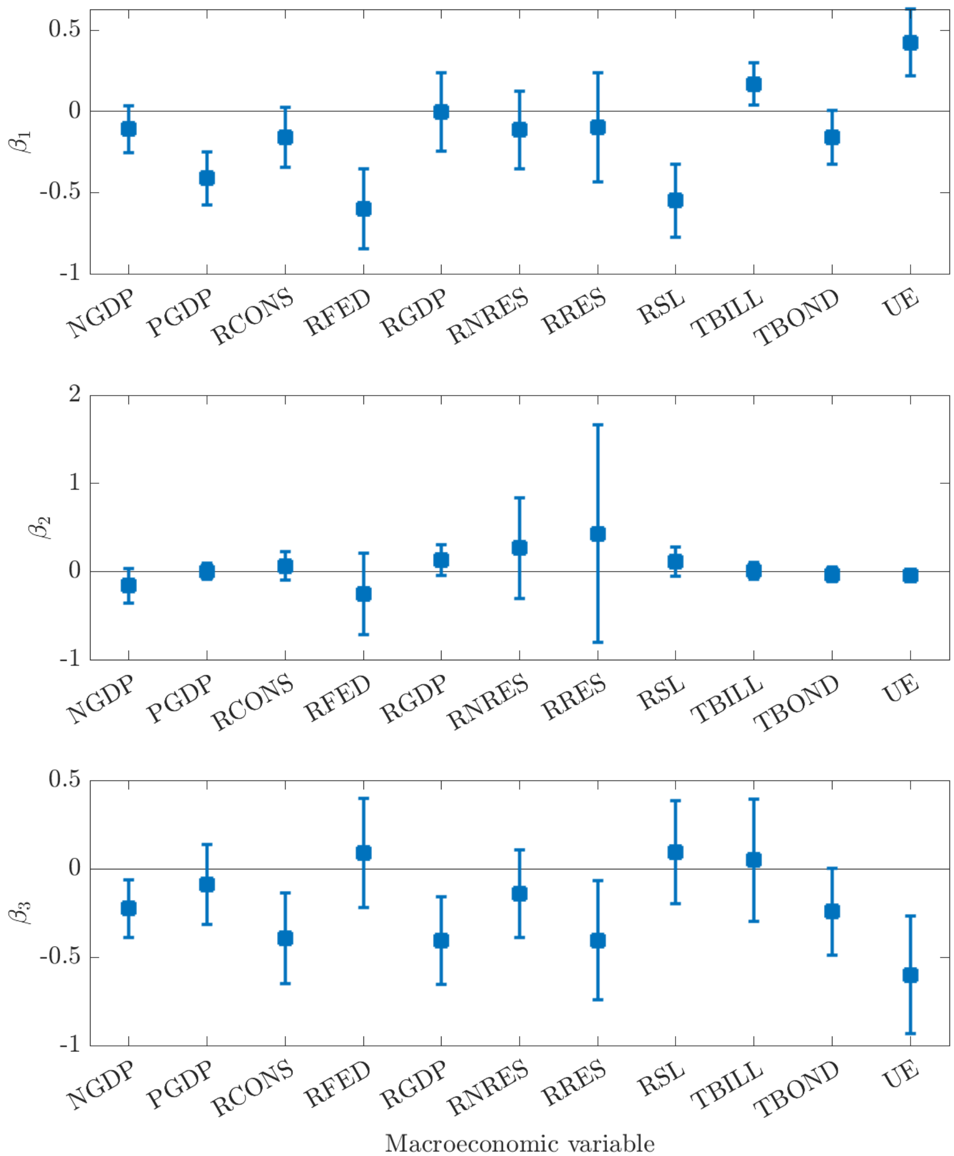
Note: The figure plots estimates of regression (6) across different variables in the SPF. Standard errors are clustered at the forecaster and date levels

Figure A3: Offsetting interaction regression, one-quarter ahead horizon



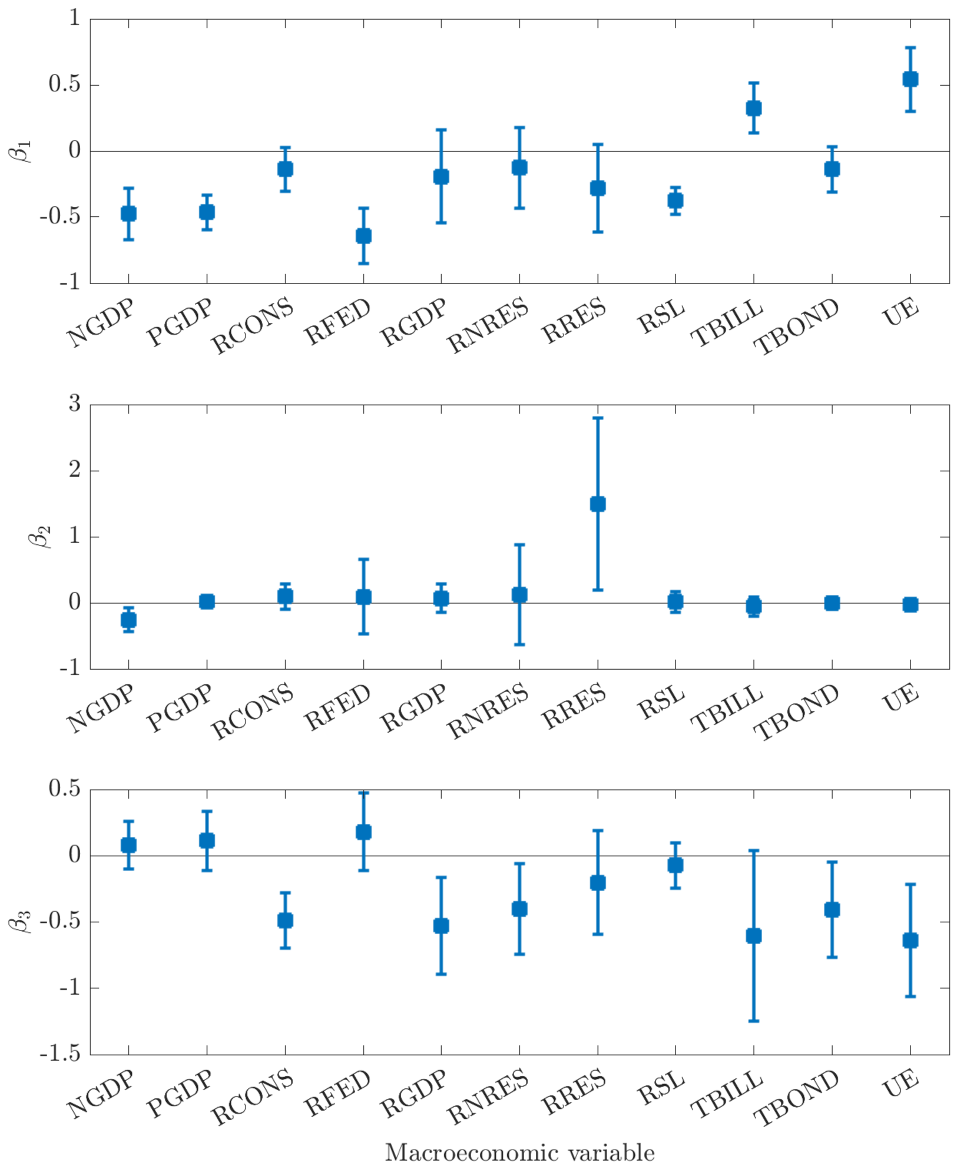
Note: The figure plots estimates of regression (6) across different variables in the SPF. Standard errors are clustered at the forecaster and date levels.

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



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

Figure A5: Offsetting interaction regression, three-quarter ahead horizon



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

Other Surveys

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

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

Table A9 reports the BGMS coefficient and Kohlhas and Walther (2021) coefficient across both surveys and verifies that quarterly forecasts exhibit overreaction at the individual level.

Table A9: Individual-level Quarterly Overreactions in BBG and WSJ Surveys

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

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

Table A10 reports the annual analog to the regressions in Table A9, which shows that there is no evidence of annual overreaction at the forecaster level.

Table A10: No Individual-level Annual Overreactions in BBG and WSJ Surveys

	BBG		WSJ	
	Error	Error	Error	Error
Revision	0.025		-0.025	
	(0.066)		(0.017)	
Realization		-0.102		-0.142
		(0.113)		(0.133)
Forecasters	62	57	148	144
Observations	269	228	3546	2528

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

Appendix B Model

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

B.1 Model Description

Suppose that in each period, professional forecasters devise predictions at some point in time, t, for some future period t'. We define H to be the total number of high frequency periods within a low frequency period. For instance, there are $H = 4$ quarters in a year.

Forecasters in the model wish to minimize their squared errors for each low frequency period:

$$\min_{\{\widehat{x}^i_{t'|t}\}} \sum_{t'=1}^{H} (x_{t'} - \widehat{x}^i_{t'|t})^2, \quad t', t \in [1, \infty), \tag{1}$$

where $\widehat{x}^i_{t'|t}$ denotes forecaster i's predictions about x in period t' based on information in period t.

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

$$\widehat{x}^i_{t'|t} = \mathbb{E}^i_t(x_{t'}),$$

and low frequency prediction,

$$\widehat{x}^i_{low'|t} = \frac{1}{H} \sum_{h'=1}^{H} \widehat{x}^i_{h'|t}.$$

So the low frequency prediction (e.g. annual) is simply the average prediction across several high frequency periods (e.g. quarters).

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

$$\frac{1}{H}\sum_{h'=1}^{H}\widehat{x}^i_{h'|t}=\frac{1}{H}\sum_{h'=1}^{H}\widehat{x}^i_{h'|t-1}. \tag{2}$$

Note that while we use the previous period in $\widehat{x}^i_{h'|t-1}$, this does not necessarily correspond to the optimal prediction for the previous period because it might have remained unchanged for several periods.

In this case, the forecaster solves (1) subject to rearranged (2).

The Lagrangian is

$$\mathcal{L}=\sum_{t'=1}^{H}\left\{(x_{t'}-\widehat{x}^i_{t'|t})^2-\lambda\left(\frac{1}{H}\sum_{h'=1}^{H}\widehat{x}^i_{h'|t}-\widehat{x}^i_{h'|t-1}\right)\right\}$$

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

$$\widehat{x}^i_{t'|t}=\mathbb{E}^i_t(x_{t'})+\frac{\lambda}{2H}. \tag{3}$$

Combining the FOC with the definition of the constraint delivers:

$$0=\frac{1}{H}\sum_{h'=1}^{H}(\mathbb{E}^i_t(x_{t'})+\frac{\lambda}{2H}-\widehat{x}^i_{h'|t-1}).$$

Rearranging, we obtain:

$$\frac{\lambda}{2H}=\frac{1}{H}\sum_{h'=1}^{H}(\widehat{x}^i_{h'|t-1}-\mathbb{E}^i_t(x_{t'}))$$

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

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

or, equivalently,[1]

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

[1]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 $t-j$.

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

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

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

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

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

where

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

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

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

C.1 Identification

The eight moments jointly determine the six parameters that reside in vector θ. Figure C1 illustrates some important comparative statics that lend support to the choice of target moments which are discussed below.

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

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

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

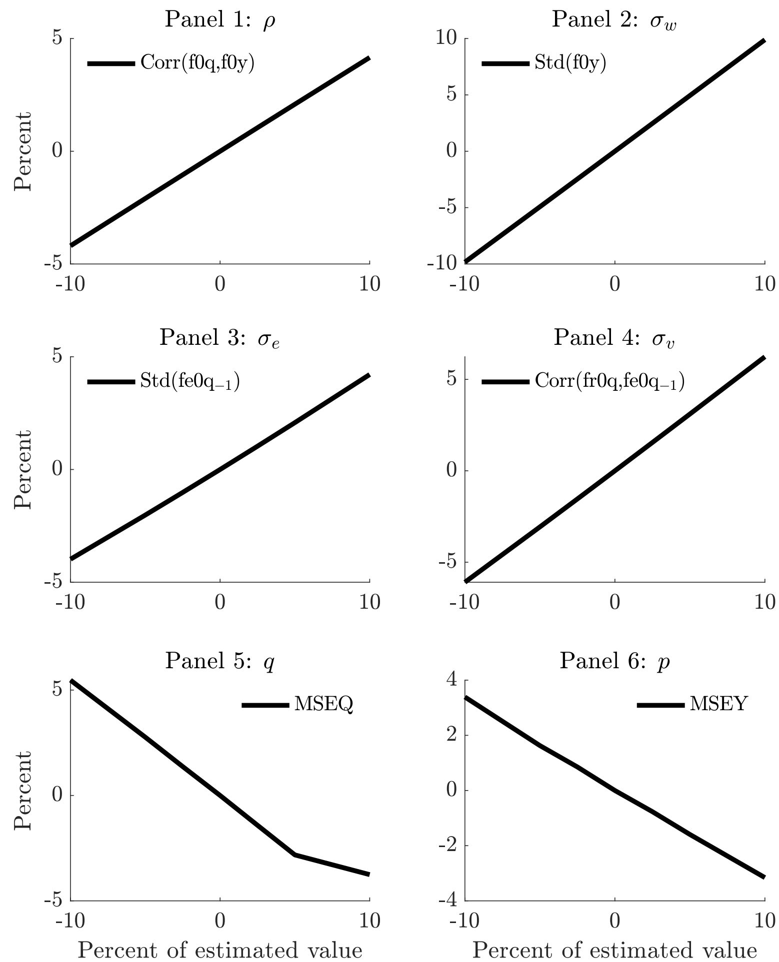
Moreover, higher levels of public noise, σ_e, contribute to a larger forecast error variance. The link between common noise and the variance of errors is intuitive since the transitory component, e_t, is linear in the macroeconomic aggregate being predicted (x_t).

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

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

where κ_1 and κ_2 denote the Kalman gains. An increase in σ_v reduces the Kalman gain weight placed on the private signal, κ_1. As σ_v rises, fluctuations in the current-quarter revision are increasingly driven by lagged forecast errors, thereby strengthening the covariance between the revision and the lagged error. In other words, with less informative private signals, forecasters trust y_t^i less and instead base more of their revisions on the news gleaned from yesterday's error.

Figure C1: Comparative Statics



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

Appendix D Estimation Results and Robustness

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

D.1 Aggregate Underreactions

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

Table D1 reports ten moments in the data and the model-based counterparts. In general, the baseline model is also able to successfully fit the majority of these moments.

Table D1: Baseline Model Fit to Consensus Moments

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

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

D.2 Diagnostic Expectations

Table D2 reports the parameter estimates for the unconstrained and constrained models. These models are estimated by targeting the original eight moments listed in Table 5 as well as the covariance of contemporaneous errors and revisions and the variance of contemporaneous errors. The unconstrained model estimates the annual smoothing plus diagnostic expectations model. The constrained model estimates a version without diagnostic expectations.

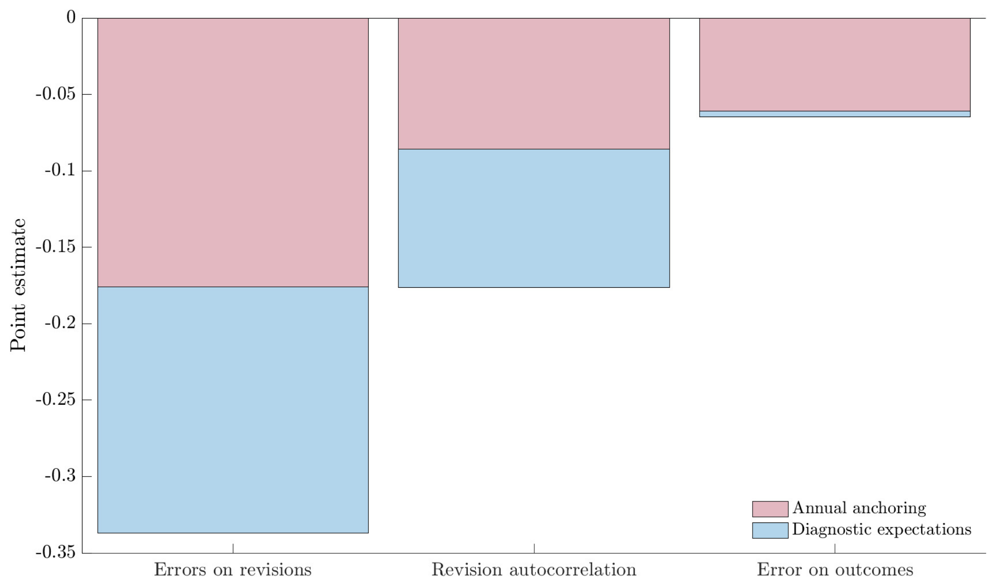
Table D2: Model Estimation Results, Diagnostic Expectations

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

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

Figure D1 plots the contributions of annual anchoring and diagnostic expectations to measures of individual overreaction based on the unconstrained and constrained parameter estimates reported in Table D2. This differs from Figure 4 in that the counterfactual in Figure 4 features the same parameters as the unconstrained model, but with θ fixed at zero.

Figure D1: Annual Smoothing vs. Diagnostic Expectation Contributions



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

D.3 Inflation Forecasts

Table D3 reports model estimates using SPF inflation forecasts based on the GDP deflator.

Table D3: Model Estimation Results, Inflation Forecasts (Deflator)

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

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

D.4 Rounding

We report parameter estimates under the assumption that forecasters round their predictions to the nearest 0.10 percentage point. We find that this rounding assumption does not meaningfully change our parameter estimates.[3]

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 lagged 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.

[3] 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.

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

The SPF, as well as broader macroeconomic dynamics, experienced important changes between 1981-2019. In this section, we estimate the model for two sub-periods: 1981-1999 (Table D5) and 2000-2019 (Table D6). Overall, we find that our headline conclusions hold across the sub-samples with the estimated parameters differing across samples as expected. For instance, we estimate the underlying state to be less persistent and more volatile in the earlier period.

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

Table D5: 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 lagged error	1.828	2.035	-1.159
RMSE nowcast	1.863	1.945	-1.056
RMSE annual forecast	1.240	1.300	-0.965

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 D6: 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 lagged error	1.461	1.518	-1.269
RMSE nowcast	1.481	1.509	-0.641
RMSE annual forecast	0.960	0.969	-0.260

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

D.6 Alternative Data Generating Process

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

We extend our model to feature an AR(2) process for real GDP growth. We select an AR(2) process for three reasons. First, we find that the AR(2) fits real GDP growth best in the sense that it delivers the lowest information criteria.[4] Second, an AR(2) is highly feasible to estimate with the baseline SMM approach as it only adds one parameter to the model. Third, an AR(2) allows us to remain consistent with others in the literature who similarly examine richer data generating processes for their models (Bordalo et al., 2020).

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

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

where 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 D7.

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

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

Table D7: 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 lagged error	1.629	1.720	-1.060
RMSE nowcast	1.645	1.677	-0.661
RMSE annual forecast	1.077	1.098	-0.576

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.

The estimated dispersion parameters are similar to those in Table 5. The quarterly updating probability is estimated to be slightly lower than the baseline estimates, while the annual updating probability is estimated to be higher. Relative to Table 8, these estimates imply roughly similar levels of information rigidity in quarterly and annual real GDP forecasts (0.235 and 0.494, respectively based on equation (9). The scope for overreactions, based on the probability of Case 2 updating, $q(1-p)$, is approximately 15% lower in the AR(2) model relative to the baseline AR(1) model.

References

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

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