Online Appendix: Lumpy Forecasts

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Contents

A Data

A.1 Inflation approximation

We provide details on the approximation of annual inflation with the sum of monthly inflation and derive conditions under which the approximation works well.

Derivation From Section 2.1, recall that average annual inflation in year t equals $\pi_t = \frac{\overline{cpi}_t - \overline{cpi}_{t-1}}{\overline{cpi}_{t-1}} \approx \log(\overline{cpi}_t) - \log(\overline{cpi}_{t-1})$ where $\overline{cpi}_t = \frac{1}{12}\sum_{m=1}^{12} cpi_{t,m}$ be the average cpi in year t and $cpi_{t,m}$ is one of the twelve monthly CPI values of year t.

$$
\begin{aligned}
\pi_t &= \log(\overline{cpi}_t) - \log(\overline{cpi}_{t-1}) \\
&= \log\left(\frac{1}{12}\sum_{m=1}^{12} cpi_{t,m}\right) - \log\left(\frac{1}{12}\sum_{m=1}^{12} cpi_{t-1,m}\right) \\
&\approx^{Jensen} \frac{1}{12}\sum_{m=1}^{12}\left(\log\left(cpi_{t,m}\right) - \log\left(cpi_{t-1,m}\right)\right) \\
&= \frac{1}{12}\sum_{h=12}^{1}\left(\log\left(cpi_{t,h}\right) - \log\left(cpi_{t-1,h+12}\right)\right) \\
&= \sum_{h=12}^{1} \underbrace{\frac{1}{12}\left(\log\left(cpi_{t,h}\right) - \log\left(cpi_{t-1,h+12}\right)\right)}_{x_{t,h}} \\
&= \sum_{h=12}^{1} x_{t,h}
\end{aligned}
\tag{A.1}
$$

Condition for approximation's accuracy Next, we derive a condition under which annual inflation is well approximated by the cumulative sum of year-on-year monthly inflation. We then empirically verify that this condition holds in our sample period. We also check that approximating annual inflation in percentage points with log differences is innocuous.

Let p denote the CPI index and consider a second-order Taylor approximation of $\log(p)$ around $\mathbb{E}[p]$, which yields:

$$
\log(p) \approx \log(\mathbb{E}[p]) + \frac{1}{\bar{p}}(p - \mathbb{E}[p]) - \frac{1}{2\mathbb{E}[p]^2}(p - \mathbb{E}[p])^2 \tag{A.2}
$$

Applying expectations on both sides (note that $\mathbb{E}[p]$ is a constant):

$$
\mathbb{E}[\log(p)] \approx \log(\mathbb{E}[p]) - \frac{\mathbb{V}ar[p]}{2\mathbb{E}[p]^2} = \log(\mathbb{E}[p]) - \frac{\mathbb{CV}^2[p]}{2} \tag{A.3}
$$

Consider p, p' to be the CPI in consecutive years. The definition of annual inflation and (A.3) implies

$$\text{(A.4)} \quad \pi = \log(\mathbb{E}[p']) - \log(\mathbb{E}[p]) = \underbrace{\mathbb{E}[\log(p') - \log(p)]}_{\text{average year-on-year inflation } \mathbb{E}[x]} + \underbrace{\frac{\mathbb{CV}^2[p'] - \mathbb{CV}^2[p]}{2}}_{\text{differences in within-year dispersion}}$$

Hence, we obtain a good approximation $\pi \approx \mathbb{E}[x]$ when two consecutive years feature similar within-year price dispersion ($\mathbb{CV}^2[p] \approx \mathbb{CV}^2[p']$).

Empirical checks of approximation We now provide the empirical counterpart of the definitions discussed in the previous Section A.1. As discussed we approximate the annual inflation at year t as $\pi_t = \sum_{h=1}^{12} x_{t,h}$, where we extend our previous definition to accommodate $x_{t,h}$, the year-on-year monthly inflation during months $h = 1, \ldots, 12$ of the targeted year t. Figure Ia in the main text shows the time series evolution of $x_{t,h}$ over the entire sample period. As observed, $x_{t,h}$ resembles a stationary process with a non-zero mean.

Through $x_{t,h}$, we can validate the empirical approximation for the annual inflation in the US. The yearly inflation for each year can be computed precisely by $\pi_t^e = \frac{\overline{cpi}_t - \overline{cpi}_{t-1}}{\overline{cpi}_{t-1}}$. We label the annual inflation computed using this method as π_t^e, i.e., the exact approximation. With our approximation, we aim to characterize such a variable measured at a very low frequency (annual) through a sum of variables observed at a relatively higher frequency (monthly), $\pi_t = \sum_{h=1}^{12} x_{t,h}$. We plot the discrepancy between the annual inflation calculated using the exact method and our approximation, i.e., $\pi_t^e - \pi_t$, for each targeted year in our sample. We quantify the discrepancies in percentage points.

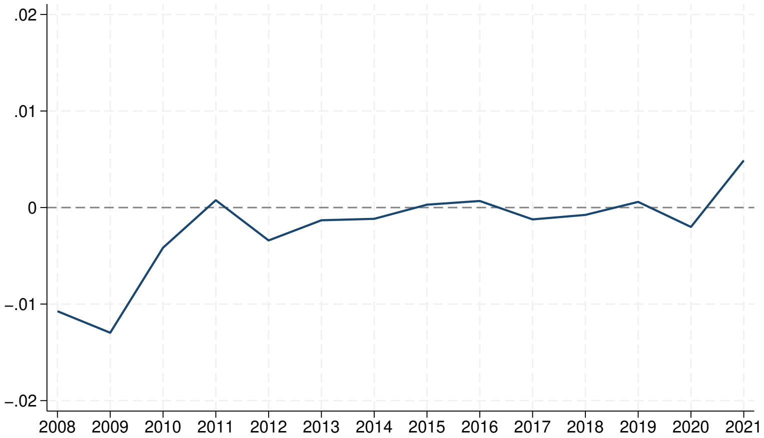


Figure A.1 – Approximation error between exact method and monthly sum. The figure shows the difference between the annual inflation computed using the exact method, $\pi_t^e = \frac{\overline{cpi}_t - \overline{cpi}_{t-1}}{\overline{cpi}_{t-1}}$ with respect to our year-on-year monthly approximation $\pi_t = \sum_{h=1}^{12} x_{t,h}$. The plot shows such differences $(\pi_t^e - \pi_t)$ for each year in our sample, and it is measured in percentage points.

The evidence in Figure A.1 validates our theoretical approximation. Throughout the sample, the difference between the two measures is almost zero, except for 2008 and 2009, the years of the Great Recession, and 2021 in the aftermath of the surge in inflation after the pandemic. As discussed, and given the observed evolution of $x_{h,t}$ in Figure Ia, during these periods, the within-price dispersion was different between consecutive years. Nevertheless, as the difference $\pi_t^e - \pi_t$ is measured in percentage points, we argue that the approximation error is still negligible even for these years.

A.2 Summary Statistics for a Longer Sample

Table A.1 provides the descriptive statistics of forecast revisions for an extended sample that includes two "turbulent" periods (2008-2009 & 2020-2021). Although inflation volatility is remarkably different across turbulence and normal years, these statistics suggest the presence of lumpy revisions with an average revision frequency of roughly 50%. Notably, and probably as an implication of the higher degree of inflation volatility, the magnitude of revisions is significantly higher during turbulent episodes. Motivated by these two features, Baley and Turen (2025) studies the implications of such lumpy behavior in economic forecasting while accounting for different dynamics of inflation volatility.

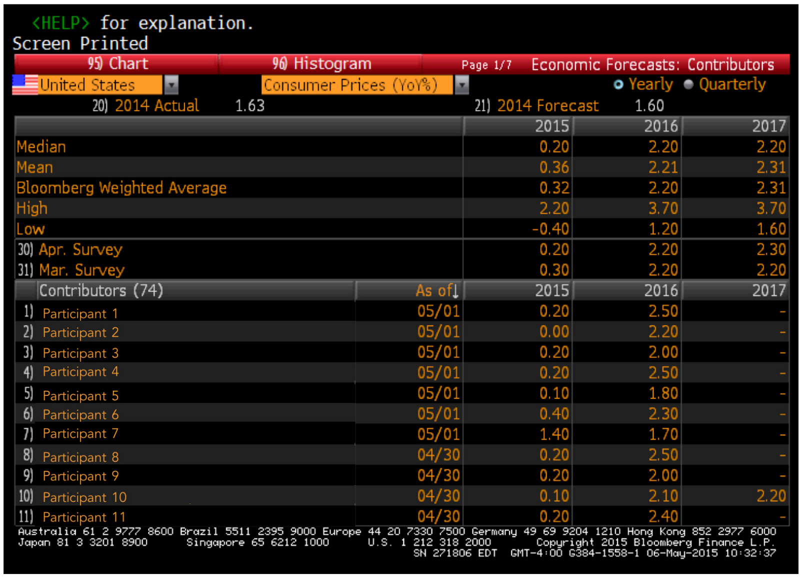
Table A.1 – Summary Statistics of Forecast Revisions

		All	**Turbulent**	**Normal**
Average	$\mathbb{E}(\Delta f)$	-0.002	0.028	-0.013
Size	$\mathbb{E}(abs(\Delta f) \mid \Delta f \neq 0)$	0.307	0.453	0.247
Dispersion	$\mathbb{V}ar(\Delta f)$	0.104	0.227	0.055
Number of revisions	$count(\Delta f \neq 0)$	5.204	5.602	5.059
Duration (months)	$\mathbb{E}(\tau)$	1.497	1.231	1.594
Inaction rate	$\Pr(\Delta f = 0)$	0.523	0.392	0.569
Frequency	$\Pr(\Delta f \neq 0)$	0.444	0.492	0.427
Upward	$\Pr(\Delta f) > 0$	0.228	0.318	0.196
Downward	$\Pr(\Delta f) < 0$	0.216	0.173	0.231
Spike rate	$abs(\Delta f / f) > 0.2$	0.081	0.231	0.028
Serial correlation (all)	$corr(\Delta f, \Delta f_{-1})$	-0.035	-0.035	-0.043
Serial correlation (non-zero)	$corr(\Delta f, \Delta f_{-1})$	-0.085	-0.078	-0.107
Inflation Average	$\mathbb{E}[\pi]$	1.896	2.175	1.795
Inflation Volatility	$\mathbb{V}ar[\pi]$	1.621	0.622	4.267
Observations	N	12,619	3,363	9,256

Notes: Bloomberg data. Notes: Normal years = 2010-2019. Turbulent years = 2008-2009 and 2020-21. Numbers are averages across forecasters, years, and horizons.

A.3 Bloomberg Survey

We specifically care about validating our approximation for the annual inflation π_t in the US, as this is the variable that survey participants are asked to predict. To further show this, Figure A.2 shows a snapshot of the ECFC Survey from the Bloomberg terminal. As noted in the upper part of the screenshot, participants are asked for their predictions about the Consumer Price (YoY%) for the US measured at the *yearly* frequency, i.e., the (average) annual inflation.



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Economic Forecasts: Contributors

United States

Consumer Prices (YoY%)

● Yearly ○ Quarterly

20) 2014 Actual 1.63

21) 2014 Forecast 1.60

	2015	2016	2017
Median	0.20	2.20	2.20
Mean	0.36	2.21	2.31
Bloomberg Weighted Average	0.32	2.20	2.31
High	2.20	3.70	3.70
Low	-0.40	1.20	1.60
30) Apr. Survey	0.20	2.20	2.30
31) Mar. Survey	0.30	2.20	2.20

Contributors (74)	As of↓	2015	2016	2017
1) Participant 1	05/01	0.20	2.50	-
2) Participant 2	05/01	0.00	2.20	-
3) Participant 3	05/01	0.20	2.00	-
4) Participant 4	05/01	0.20	2.50	-
5) Participant 5	05/01	0.10	1.80	-
6) Participant 6	05/01	0.40	2.30	-
7) Participant 7	05/01	1.40	1.70	-
8) Participant 8	04/30	0.20	2.50	-
9) Participant 9	04/30	0.20	2.00	-
10) Participant 10	04/30	0.10	2.10	2.20
11) Participant 11	04/30	0.20	2.40	-

Australia 61 2 9777 8600 Brazil 5511 2395 9000 Europe 44 20 7330 7500 Germany 49 69 9204 1210 Hong Kong 852 2977 6000
Japan 81 3 3201 8900 Singapore 65 6212 1000 U.S. 1 212 318 2000 Copyright 2015 Bloomberg Finance L.P.
SN 271806 EDT GMT-4:00 G384-1558-1 06-May-2015 10:32:37

Figure A.2 – Bloomberg's ECFC Survey: A Snapshot. The figure shows how the ECFC Survey looks in the Bloomberg terminal. Although the names of the participating institutions are also displayed as part of the survey, we have removed the specific names as requested by Bloomberg. The same Snapshot was presented by Giacomini, Skreta and Turen (2020).

Figure A.3 illustrates the behavior of three forecasters in 2019. The gray dashed line represents the actual inflation rate for that year, $\pi = 1.8\%$. Forecasts are more dispersed early in the year and more aligned with the actual value towards the end, which is natural given the releases of public information. Still, some participants keep their prediction unchanged across horizons, especially towards the end.

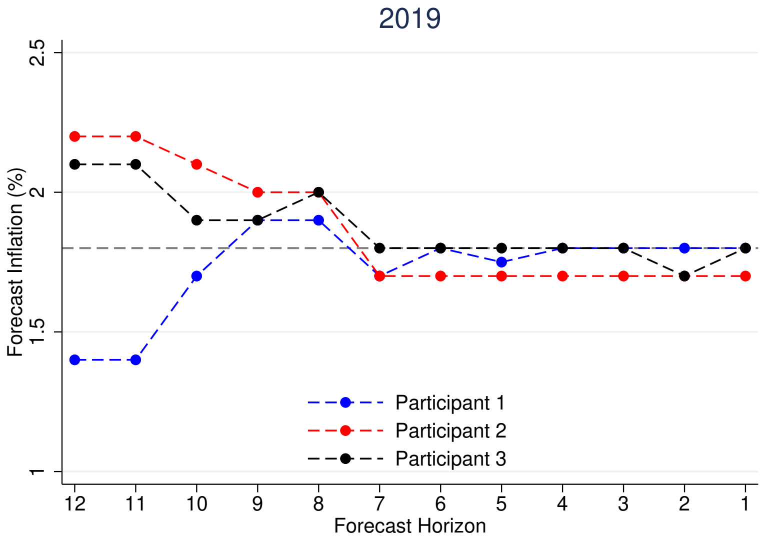
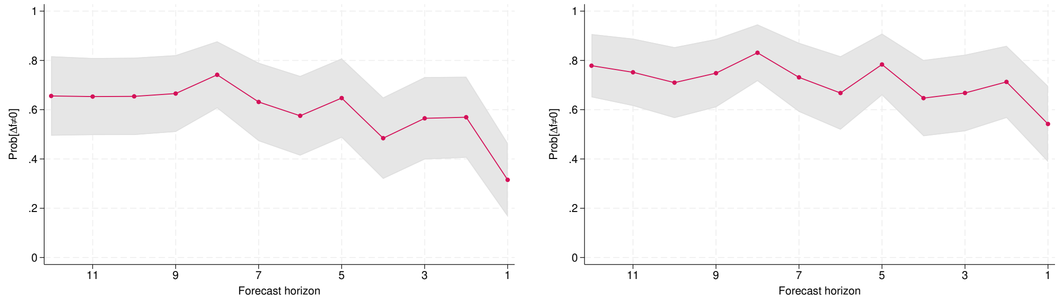


Figure A.3 – Illustration of Fixed-Event Forecasting. The figure illustrates how fixed-event forecasts work. The fixed event is the annual inflation π. All forecasts f_h^i refer to that fixed event. Although the survey is not anonymous, we remove the names of the institutions to disclose their actual forecasts.

A.4 Extensive and Intensive Margin - Consensus Economics Survey

We examine the robustness of our results using the *Consensus Economics Survey of Professional Forecasters*. We examine individual expectations at a monthly frequency for annual inflation between 1995 and 2016 in the US. We have repeated the analysis as in our baseline data over the years. One of the key differences between Consensus and the Bloomberg survey is that in the former, participants can report predictions *up to 3 decimal points*. Thus, we will contrast the dynamics of the extensive and intensive margins using the raw forecasts (No Rounding) with those rounded up to the first decimal point (Rounding). Figure A.4 shows the evolution of the adjustment probability.

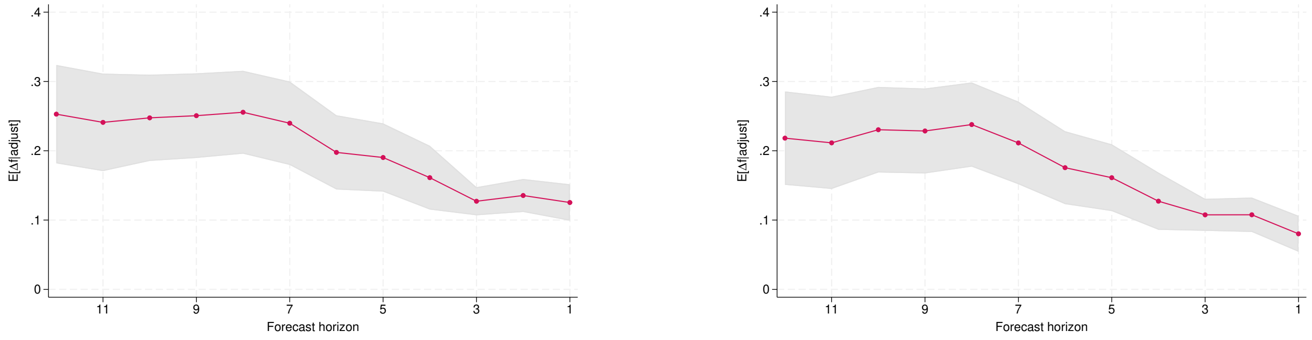


(a) Rounding

(b) No Rounding

Figure A.4 – Extensive Margin in Consensus Economics. Own calculations based on inflation expectations collected from *Consensus Economics Survey of Professional Forecasters* between 1995 and 2016

When we rely on three decimal predictions, the evidence still supports average inaction and a drop in the frequency of non-rounded forecast revisions, consistent with our data. When we round the predictions up to the first decimal, the evolution of the extensive margin resembles the dynamics of the Bloomberg data. Figure A.5 reports the evolution of the magnitude of revisions across the horizons. Again, there are no significant differences relative to our original results.



(a) Rounding

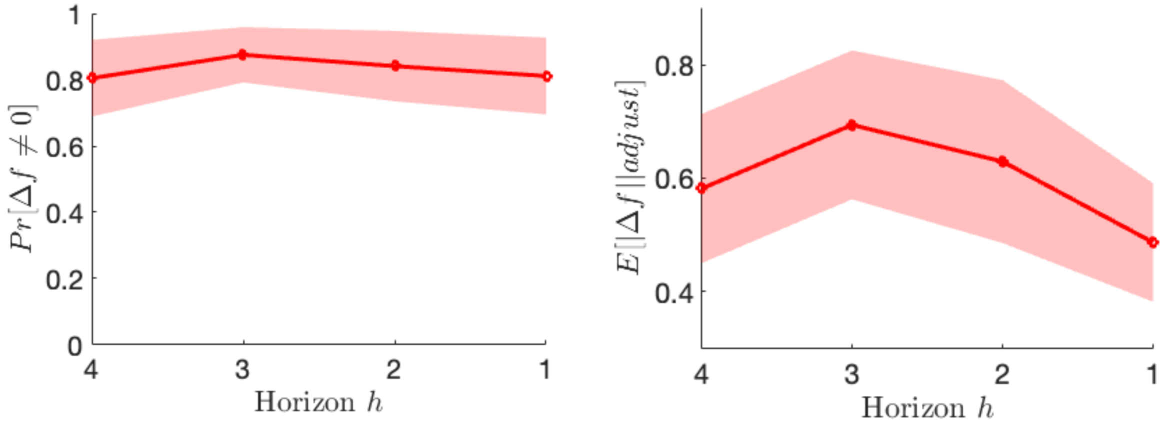
(b) No Rounding

Figure A.5 – Intensive Margin - Consensus Economics Survey. Own calculations based on inflation expectations collected from *Consensus Economics Survey of Professional Forecasters* during 1995 and 2016.

A.5 Cross-sectional Statistics for Survey of Professional Forecasters

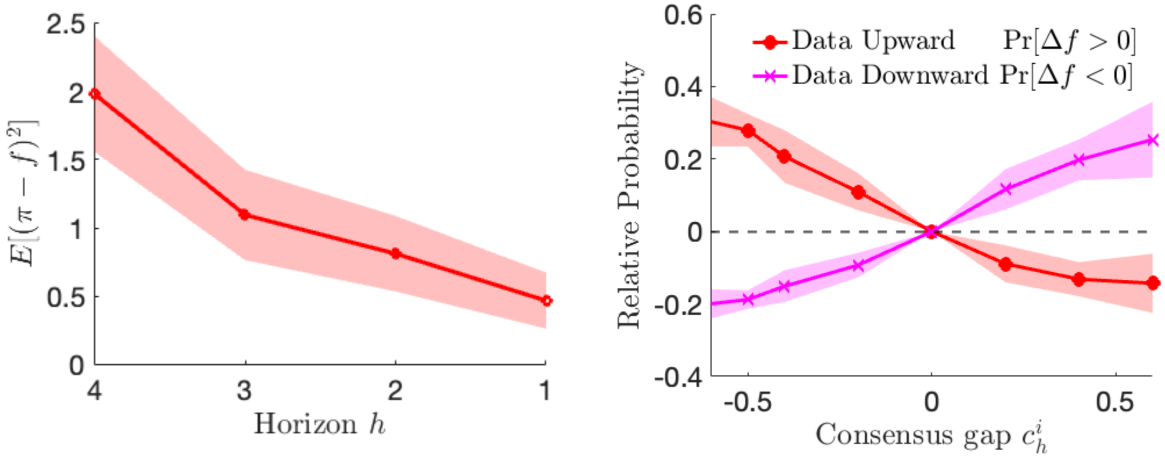
In this section, we analyze the Survey of Professional Forecasters (SPF), using fixed-event forecasts data from 1981 to 2024. Using this survey, we replicate our analysis and compute the average frequency of forecast revisions across horizons, the size of revisions (conditioning on updaters), and the MSFE for the targeted variable. In the case of the SPF, forecasters are asked about their predictions for inter-annual inflation, measured as the percentage change in the CPI for the last term of the corresponding year relative to the previous year. As noted, with respect to lumpy behavior, inaction remains large with an average of roughly 20% of forecasters choosing not to adjust their predictions between consecutive quarters. These numbers are well aligned with evidence about the probability of updating using the European SPF, as documented by Andrade and Le Bihan (2013). Moreover, and in line with the fact that more relevant information accumulates at the quarterly frequency, the magnitude of revisions is higher compared to Bloomberg, but also exhibits the same decreasing patterns as the release date approaches. Finally, and as expected, average accuracy improves as more information is released during the year, consistent with a fixed-event forecasting scheme.

We also repeat the estimation for the strategic concerns, as in equation 5, with the only difference that we define the gap to the consensus as $c^i_h = f^i_{h+1} - F_{h+1}$, since the consensus is observed with delay in the SPF. The bins are defined in the same way as in the baseline regression using the Bloomberg data. As noted, the evidence still points to the presence of strategic concerns at the individual level, but interestingly, the magnitude by which the gaps correlate with the adjustment probabilities is attenuated. We claim that this is driven by the fact that in the SPF, forecasters are anonymous, which potentially reduces the strategic concerns.



(a) Frequency of revisions

(b) Size of revisions



(c) MSFE

(d) Effect of gap on extensive margin

Figure A.6 – Cross-sectional statistics for the SPF

B Proofs

B.1 Inflation process

Demeaned monthly inflation We begin with the AR(1) process for monthly inflation:

$$x_h \;=\; c_x \;+\; \phi_x x_{h+1} \;+\; \varepsilon^x_h, \qquad \varepsilon^x_h \sim \mathcal{N}(0, \sigma^2_x). \tag{B.1}$$

This process has unconditional mean of $\frac{c_x}{1-\phi_x}$ and unconditional variance of $\frac{\sigma^2_x}{1-\phi^2_x}$. For any h, we can rewrite (B.1) as deviations from the unconditional mean:

$$x_h - \frac{c_x}{1-\phi_x} \;=\; \phi_x\left(x_{h+1} - \frac{c_x}{1-\phi_x}\right) \;+\; \varepsilon^x_h. \tag{B.2}$$

Annual inflation Annual inflation π is approximately equal to the sum of the twelve realizations of monthly inflation x_h within each target year $\pi = \sum_{h=1}^{12} x_h$. Without loss of generality, we can derive π as a function of the initial value of monthly inflation x_{12}:

$$\begin{aligned}
x_1 &= \frac{c_x}{1-\phi_x} + \phi_x^{11}\left(x_{12} - \frac{c_x}{1-\phi_x}\right) + \sum_{j=0}^{10} \phi_x^j \varepsilon^x_{j+1} \\
\dots \\
x_{10} &= \frac{c_x}{1-\phi_x} + \phi_x^{2}\left(x_{12} - \frac{c_x}{1-\phi_x}\right) + \phi_x \varepsilon^x_{11} + \varepsilon^x_{10} \\
x_{11} &= \frac{c_x}{1-\phi_x} + \phi_x\left(x_{12} - \frac{c_x}{1-\phi_x}\right) + \varepsilon^x_{11},
\end{aligned}$$

Summing up the monthly values $x_1, x_2, \dots, x_{12}$ we get an expression for annual inflation at horizon $h = 12$:

$$\pi \;=\; 12\left(\frac{c_x}{1-\phi_x}\right) \;+\; \frac{1-\phi_x^{12}}{1-\phi_x}\left(x_{12} - \frac{c_x}{1-\phi_x}\right) \;+\; \sum_{j=1}^{11} \frac{1-\phi_x^j}{1-\phi_x}\varepsilon^x_j. \tag{B.3}$$

Similarly, for any h within the year, we can derive an expression for π. Importantly, as h shrinks (as we get closer to the release date), we start summing the actual lagged values of inflation starting at $h = 12$ until h. At the same time, we project the remaining months of the year using the last piece of available information x_h. In particular, annual inflation at any given horizon $h = 12, 11, \dots, 1$ can be written as follows:

$$\pi \;=\; h\left(\frac{c_x}{1-\phi_x}\right) \;+\; \frac{(1-\phi_x^h)}{1-\phi_x}\left(x_h - \frac{c_x}{1-\phi_x}\right) \;+\; \sum_{i=h+1}^{12} x_j \;+\; \sum_{j=1}^{h-1} \frac{1-\phi_x^j}{1-\phi_x}\varepsilon^x_j, \tag{B.4}$$

where $\sum_{i=h+1}^{12} x_j = 0$ for $i = 12$. If $h = 1$ then $\pi = \sum_{h=1}^{12} x_h$. The unconditional mean and variance of annual inflation are:

$$\mathbb{E}[\pi] = \frac{12c_x}{1-\phi_x} \tag{B.5}$$

$$\mathbb{V}ar[\pi] = \sigma_x^2 \sum_{j=1}^{h-1} \left(\frac{1-\phi_x^j}{1-\phi_x}\right)^2. \tag{B.6}$$

To compute annual inflation from the perspective of $h = 13$, we use the fact that

$$x_{12} - \frac{c_x}{1-\phi_x} = \phi_x \left(x_{13} - \frac{c_x}{1-\phi_x}\right) + \varepsilon_{12}^x. \tag{B.7}$$

Thus, when summing up the monthly values $x_1, x_2, \dots, x_{12}$, we get

$$\pi = 12\left(\frac{c_x}{1-\phi_x}\right) + \phi_x \frac{1-\phi_x^{12}}{1-\phi_x}\left(x_{13} - \frac{c_x}{1-\phi_x}\right) + \sum_{j=1}^{12} \frac{1-\phi_x^j}{1-\phi_x}\varepsilon_j^x. \tag{B.8}$$

B.2 Annual inflation beliefs

At each horizon, forecasters form annual inflation beliefs $\pi|\mathcal{I}_h^i \sim \mathcal{N}(\hat{\pi}_h^i, \Sigma_h^\pi)$ by projecting their monthly beliefs using the AR(1) structure. In turn, the monthly beliefs are constructed using the AR(1) one-period ahead prediction and the private signal $\widetilde{x}_h^i = x_h + \zeta_{ih}$. In addition, the historical values of lagged monthly inflation are observed without noise. Thus, the forecasters information set at each horizon $\mathcal{I}_h^i = \{\widetilde{x}_h^i, x_{h+1}, x_{h+2}, \dots\}$.

Conditional mean Taking the conditional expectation of equation (B.4), given information up to horizon h, delivers the conditional mean $\hat{\pi}_h^i \equiv \mathbb{E}[\pi|\mathcal{I}_t^i]$:

$$\hat{\pi}_h^i = h\left(\frac{c_x}{1-\phi_x}\right) + \frac{1-\phi_x^h}{1-\phi_x}\left(\hat{x}_h^i - \frac{c_x}{1-\phi_x}\right) + \sum_{i=h+1}^{12} x_j \qquad \text{for } h = 12, \dots, 1 \tag{B.9}$$

which corresponds to equation (13) in the text.

Conditional variance To compute the conditional variance, we first define forecast errors as the difference between annual inflation π in (B.4) and the conditional mean $\varepsilon_h^i \equiv \pi - \hat{\pi}_h^i$ in (B.9):

$$\varepsilon_h^i = \pi - \hat{\pi}_h^i = \frac{1-\phi_x^h}{1-\phi_x}((1-\alpha)\varepsilon_h^x + \alpha\zeta_{ih}) + \sum_{j=1}^{h-1} \frac{1-\phi_x^j}{1-\phi_x}\varepsilon_j^x \qquad \forall h \tag{B.10}$$

Where $\alpha \equiv \frac{\sigma_\zeta^{-2}}{\sigma_x^{-2}+\sigma_\zeta^{-2}}$ as discussed in the main text. Squaring and taking expectations, we obtain the variance of the forecast error $\Sigma_h^\pi \equiv \mathbb{E}[(\varepsilon_h^i)^2]$ at each horizon h:

$$\text{(B.11)} \qquad \Sigma_h^\pi = \left(\frac{1-\phi_x^h}{1-\phi_x}\right)^2 ((1-\alpha)^2\sigma_x^2 + \alpha^2\sigma_\zeta^2) + \frac{\sigma_x^2}{(1-\phi_x)^2}\sum_{j=1}^{h-1}(1-\phi_x^j)^2 \qquad \forall h$$

where we used that shocks are i.i.d $\varepsilon_h^x \overset{\text{iid}}{\sim} \mathcal{N}(0,\sigma_x^2)$, $\zeta_h^i \overset{\text{iid}}{\sim} \mathcal{N}(0,\sigma_\zeta^2)$, $\eta_h \overset{\text{iid}}{\sim} \mathcal{N}(0,\sigma_\eta^2)$ and uncorrelated $\mathbb{E}[\zeta_h^i,\eta_h] = 0$. We simplify the last term with the sum as follows:

$$\begin{aligned}
\sum_{j=1}^{h-1}(1-\phi_x^j)^2 &= (1-\phi_x)^2 + (1-\phi_x^2)^2 + \ldots + (1-\phi^{h-1})^2 \\
&= (h-1) - 2(\phi_x + \phi_x^2 + \cdots + \phi_x^{h-1}) + (\phi_x^2 + \phi_x^4 + \ldots + \phi^{2(h-1)}) \\
&= (h-1) - \frac{2\phi_x(1-\phi_x^{h-1})}{1-\phi_x} + \frac{\phi_x^2(1-\phi_x^{2(h-1)})}{1-\phi_x^2}
\end{aligned}$$

Substituting back into (B.11), we obtain the expression for the signal variance in

$$\begin{aligned}
\Sigma_h^\pi &= [(1-\alpha)^2\sigma_x^2 + \alpha^2\sigma_\zeta^2]\left(\frac{1-\phi^h}{1-\phi}\right)^2 \\
\text{(B.12)} \qquad &+ \frac{\sigma_x^2}{(1-\phi)^2}\left[(h-1) - \frac{2\phi(1-\phi^{h-1})}{1-\phi} + \frac{\phi^2(1-\phi^{2(h-1)})}{1-\phi^2}\right].
\end{aligned}$$

The conditional variance is common across forecasters; thus, we denote it as $\Sigma_{z,h}$.

B.3 Relationship between individual vs. aggregate beliefs

To construct individual belief about yearly inflation $\hat{\pi}_h^i$ in (13), forecasters combines the past release x_{h+1} with their noisy private signal $\widetilde{x}_h^i$ to generate a monthly belief $\hat{x}_h^i$, which is then projected to obtain the yearly forecast

$$\text{(B.13)} \qquad \hat{\pi}_h^i = h\left(\frac{c_x}{1-\phi_x}\right) + \frac{1-\phi_x^h}{1-\phi_x}\left(\hat{x}_h^i - \frac{c_x}{1-\phi_x}\right) + \sum_{j=h+1}^{12} x_j.$$

In contrast, the public belief about yearly inflation z_h in (15) only projects the past release x_{h+1} to obtain the yearly forecast (note the extra ϕ_x in the second term of the expression reflecting the timing of the information):

$$\text{(B.14)} \qquad z_h = h\left(\frac{c_x}{1-\phi_x}\right) + \frac{\phi_x(1-\phi_x^h)}{1-\phi_x}\left(x_{h+1} - \frac{c_x}{1-\phi_x}\right) + \sum_{j=h+1}^{12} x_j.$$

Next, we establish a useful relationship between the private and public beliefs about yearly inflation. Starting from (B.13), we substitute the expression for $\hat{x}_h^i = (1-\alpha)x_h^{AR} + \alpha\widetilde{x}_h^i$. Then, we substitute $x_h^{AR} = \mathbb{E}[x_h|\mathcal{I}_h] = c_x + \phi_x x_{h+1}$ and the noisy signal $\widetilde{x}_h^i = x_h + \zeta_h^i$. We also use $x_h = x_h^{AR} + \varepsilon_h^x$. Lastly, we define the noise term $\nu_h^i \equiv \frac{1-\phi_x^h}{1-\phi_x}\alpha(\varepsilon_h^x + \zeta_h^i)$, which includes idiosyncratic signal noise and the one-period ahead forecasting error arising from the different timing in the use of information.

$$
\begin{aligned}
\hat{\pi}_h^i &= h\left(\frac{c_x}{1-\phi_x}\right) + \frac{1-\phi_x^h}{1-\phi_x}\left(x_h^{AR} - \frac{c_x}{1-\phi_x} + \alpha(x_h - x_h^{AR}) + \alpha\zeta_h^i\right) + \sum_{j=h+1}^{12} x_j \\
&= h\left(\frac{c_x}{1-\phi_x}\right) + \frac{1-\phi_x^h}{1-\phi_x}\left(\phi_x\left(x_{h+1} - \frac{c_x}{1-\phi_x}\right) + \alpha(\varepsilon_h^x + \zeta_h^i)\right) + \sum_{j=h+1}^{12} x_j \\
&= \underbrace{h\left(\frac{c_x}{1-\phi_x}\right) + \frac{1-\phi_x^h}{1-\phi_x}\left(\phi_x\left(x_{h+1} - \frac{c_x}{1-\phi_x}\right)\right) + \sum_{j=h+1}^{12} x_j}_{z_h} + \underbrace{\frac{1-\phi_x^h}{1-\phi_x}\alpha(\varepsilon_h^x + \zeta_h^i)}_{\nu_h^i} \\
&= z_h + \nu_h^i, \quad \text{where} \quad \nu_h^i \sim \mathcal{N}\left(0, \left[\frac{1-\phi_x^h}{1-\phi_x}\right]^2 \alpha^2(\sigma_x^2 + \sigma_\zeta^2)\right),
\end{aligned}
$$

where α is the weight on private signals: $\alpha \equiv \sigma_\zeta^{-2}/(\sigma_x^{-2} + \sigma_\zeta^{-2})$. We can further simplify the noise term since:

$$
\alpha^2(\sigma_x^2 + \sigma_\zeta^2) = \left(\frac{\sigma_\zeta^{-2}}{\sigma_x^{-2} + \sigma_\zeta^{-2}}\right)^2 (\sigma_x^2 + \sigma_\zeta^2) = \left(\frac{\frac{1}{\sigma_\zeta^2}}{\frac{1}{\sigma_x^2} + \frac{1}{\sigma_\zeta^2}}\right)^2 (\sigma_x^2 + \sigma_\zeta^2) \tag{B.15}
$$

$$
= \left(\frac{\frac{1}{\sigma_\zeta^2}}{\frac{\sigma_\zeta^2 + \sigma_x^2}{\sigma_\zeta^2 \sigma_x^2}}\right)^2 (\sigma_x^2 + \sigma_\zeta^2) = \frac{\sigma_x^4}{\sigma_\zeta^2 + \sigma_x^2} \tag{B.16}
$$

Therefore, individual beliefs are decomposed as:

$$
\hat{\pi}_h^i = z_h + \nu_h^i, \quad \text{where} \quad \nu_\eta^i \sim \mathcal{N}\left(0, \left[\frac{1-\phi_x^h}{1-\phi_x}\right]^2 \frac{\sigma_x^4}{\sigma_\zeta^2 + \sigma_x^2}\right). \tag{B.17}
$$

When signal noise is considerable ($\sigma_\zeta^2 \to \infty$), the idiosyncratic component of beliefs has zero dispersion because private signals are ignored. When signal noise is tiny ($\sigma_\zeta^2 \to 0$), the idiosyncratic component of beliefs has dispersion equal to σ_x^2. Beliefs become perfectly correlated, and the remaining noise arises from projecting x_{h+1} rather than x_h.

B.4 Martingale property of beliefs

We show that beliefs follow a martingale: the expectation of future belief at $h-1$ equals the current belief at h, i.e., $\mathbb{E}[\hat{\pi}^i_{h-1}|\mathcal{I}^i_h] = \hat{\pi}^i_h$. First, we use the relationship between public and private beliefs in (B.15) to set the expectation of future individual noise ν to zero.

$$\mathbb{E}[\hat{\pi}^i_{h-1}|\mathcal{I}^i_h] \;=\; \mathbb{E}[z_{h-1} + \nu^i_{h-1}|\mathcal{I}^i_h] \;=\; \mathbb{E}[z_{h-1}|\mathcal{I}^i_h]. \tag{B.18}$$

Second, we show that the expected public belief equals current public belief. Substituting in the expression for z_{h-1} in (15) and applying the expectation conditional on $\mathcal{I}^i_h$, we get:

$$\mathbb{E}[z_{h-1}|\mathcal{I}^i_h] \;=\; (h-1)\frac{c_x}{1-\phi_x} \;+\; \frac{\phi_x(1-\phi_x^{h-1})}{1-\phi_x}\left(\widehat{x}^i_h - \frac{c_x}{1-\phi_x}\right) \;+\; \widehat{x}^i_h \;+\; \sum_{j=h+1}^{12} x_j.$$

In the last sum, we separate $\widehat{x}^i_h \equiv \mathbb{E}[x_h|\mathcal{I}^i_h]$ that is not yet released from the rest of the known values for $h = 12, ..., h+1$. Finally, we rearrange the expression to recover the expression for individual beliefs $\hat{\pi}^i_h$ plus three summands that cancel out:

$$\begin{aligned}\mathbb{E}[z_{h-1}|\mathcal{I}^i_h] \;&=\; \underbrace{h\frac{c_x}{1-\phi_x} + \frac{1-\phi_x^h}{1-\phi_x}\left(\widehat{x}^i_h - \frac{c_x}{1-\phi_x}\right) + \sum_{j=h+1}^{12} x_j}_{=\,\hat{\pi}^i_h} \\ &-\; \underbrace{\frac{c_x}{1-\phi_x} - \frac{1-\phi_x}{1-\phi_x}\left(\widehat{x}^i_h - \frac{c_x}{1-\phi_x}\right) + \widehat{x}^i_h}_{=\,0}.\end{aligned}$$

We conclude that $\mathbb{E}[z_{h-1}|\mathcal{I}^i_h] = \hat{\pi}^i_h$. As data on monthly inflation arrives, forecasters add the new observations to their dataset and update their estimates. Belief changes tend to be very persistent, even if the shocks that caused the beliefs to change are transitory. As a result, any changes in beliefs induced by new information are approximately permanent (Kozlowski, Veldkamp and Venkateswaran, 2020a,b).

B.5 Proof of Proposition 1

First, using the law of iterated expectations, we condition payoffs on the horizon-specific information sets:

$$\mathbb{E}\left[\sum_{h=12}^{1} \mathbb{E}[(f^i_h - \pi)^2|\mathcal{I}^i_h] \;+ r\; \mathbb{E}[(f^i_h - F_h)^2|\mathcal{I}^i_h] \;+\; \kappa \mathbb{1}_{\{f^i_h \neq f^i_{h+1}\}} \middle| \mathcal{I}^i_0\right]$$

Second, we add and subtract beliefs $\hat{\pi}_h^i \equiv \mathbb{E}[\pi|\mathcal{I}_h^i]$ and $\hat{F}_h^i \equiv \mathbb{E}[F_h|\mathcal{I}_h^i]$ and open the squares:

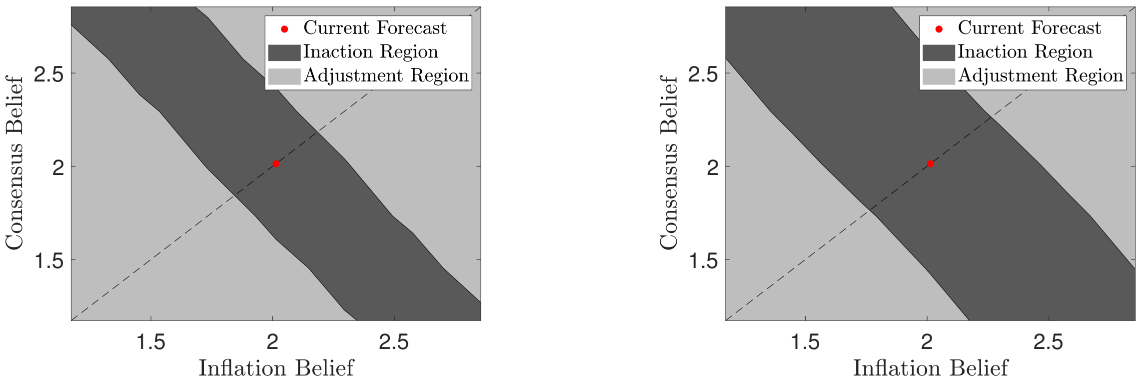
$$\begin{aligned}
& \mathbb{E}\left[\sum_{h=12}^{1} \ \mathbb{E}[(f_h^i - \hat{\pi}_h^i + \hat{\pi}_h^i - \pi)^2|\mathcal{I}_h^i] \ + r\ \mathbb{E}[(f_h^i - \hat{F}_h^i + \hat{F}_h^i - F_h)^2|\mathcal{I}_h^i] \ + \ \kappa \mathbb{1}_{\left\{f_h^i \neq f_{h+1}^i\right\}} \middle| \mathcal{I}_0^i\right] \\
= \ & \mathbb{E}\left[\sum_{h=12}^{1} \ \mathbb{E}[(f_h^i - \hat{\pi}_h^i)^2|\mathcal{I}_h^i] + \mathbb{E}[(\hat{\pi}_h^i - \pi)^2|\mathcal{I}_h^i] + 2\mathbb{E}[(f_h^i - \hat{\pi}_h^i)(\hat{\pi}_h^i - \pi)|\mathcal{I}_h^i] \middle| \mathcal{I}_0^i\right] \\
+ \ & r\mathbb{E}\left[\sum_{h=12}^{1} \mathbb{E}[(f_h^i - \hat{F}_h^i)^2|\mathcal{I}_h^i] + \mathbb{E}[(\hat{F}_h^i - F_h)^2|\mathcal{I}_h^i] \ + \ 2\mathbb{E}[(f_h^i - \hat{F}_h^i)(\hat{F}_h^i - F_h)|\mathcal{I}_h^i] \middle| \mathcal{I}_0^i\right] \\
+ \ & \kappa\mathbb{E}\left[\sum_{h=12}^{1} \mathbb{1}_{\left\{f_h^i \neq f_{h+1}^i\right\}} \middle| \mathcal{I}_0^i\right]
\end{aligned}$$

Third, we rewrite using conditional variances $\Sigma_h^\pi \equiv \mathbb{E}[(\hat{\pi}_h^i - \pi)^2|\mathcal{I}_h^i]$ and $\Sigma_h^F \equiv \mathbb{E}[(\hat{F}_h^i - F_h)^2|\mathcal{I}_h^i]$ and the fact that beliefs are unbiased $\mathbb{E}[(\hat{\pi}_h^i - \pi)|\mathcal{I}_h^i] = \mathbb{E}[(\hat{F}_h^i - F_h)|\mathcal{I}_h^i] = 0$:

$$\sum_{h=12}^{1} \Sigma_h^\pi \ + \ r\Sigma_h^F \ + \ (f_h^i - \hat{\pi}_h^i)^2 \ + \ r(f_h^i - \hat{F}_h^i)^2 \ + \ \kappa \mathbb{1}_{\left\{f_h^i \neq f_{h+1}^i\right\}}.$$

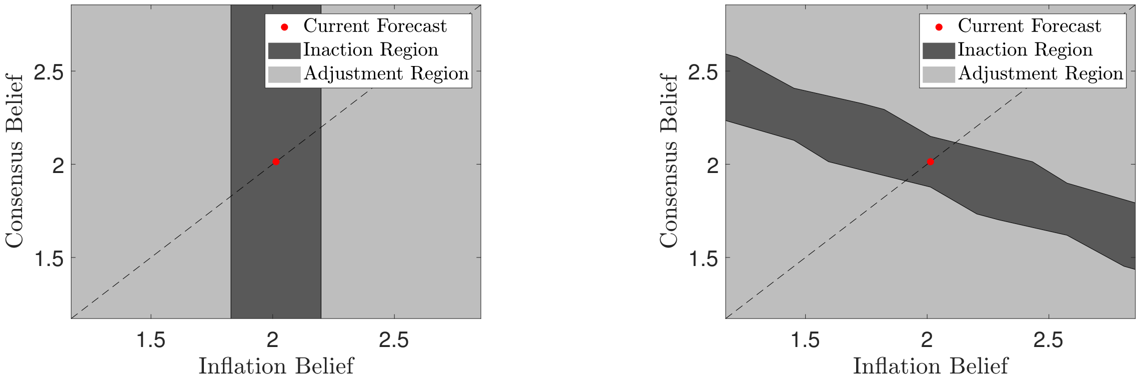
C Comparative statics

A higher fixed revision cost makes the inaction band wider. Strategic concerns shape the slope of the inaction region.



(a) small κ **(b)** large κ

Figure C.7 – Comparative Statics for Fixed Costs



(a) $r = 0$ **(b)** large r

Figure C.8 – Comparative Statics for Strategic Concerns

D Calibration

D.1 Consistency of consensus process

We validate the consistency of the consensus's assumed random walk. The perceived law of motion for consensus is $F_h = F_{h+1} + \varepsilon_h^F$ with $\varepsilon_h^F \sim \mathcal{N}(0, 0.13^2)$. Thus, the perceived process is

$$\hat{F}_t = \hat{F}_{t-1} + \varepsilon_t^{\hat{F}}, \qquad \varepsilon_h^F \sim \mathcal{N}(0, 0.13^2) \tag{D.19}$$

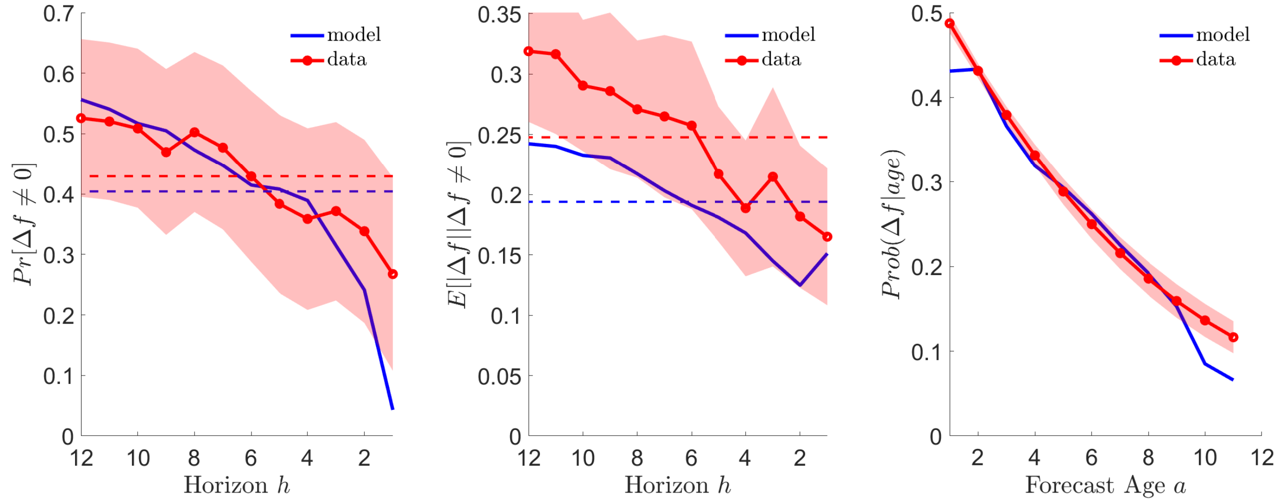
The actual law of motion is

$$F_h = -0.03 + 1.01 F_{h+1} + \varepsilon_h^F, \qquad \varepsilon_h^F \sim \mathcal{N}(0, 0.13^2). \tag{D.20}$$

We run a Dickey-Fuller test on the simulated series of the actual consensus process F to test the null hypothesis that a unit root is present. The estimate of interest is ρ in the expression $F_{t+1} = \alpha + \rho F_t + \varepsilon_{t+1}$. The estimation uses N_{years} randomly drawn from the model. We cannot reject the null with 95% confidence that the consensus process F_{t+1} follows a unit root process ($\rho = 1$) with $N_{years} \in \{1, ..., 10\}$.

D.2 Untargetted Term Structures

Figure D.9 shows the term structure of the revisions frequency, size, and hazard rate. While we only targeted the average values (dashed line), the model can replicate the downward-sloping patterns of these three moments.

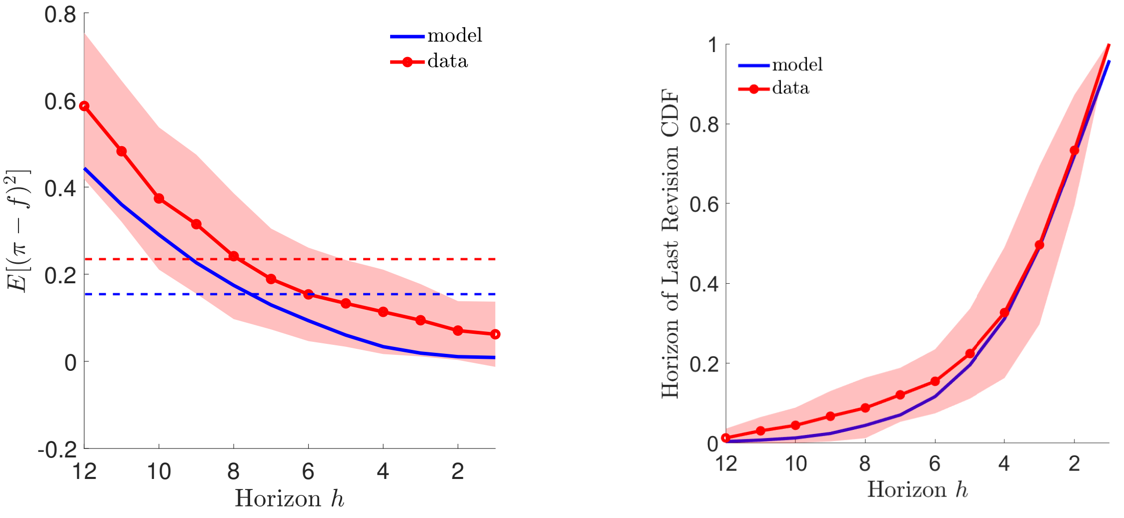


(a) Frequency of revisions **(b)** Size of revisions **(c)** Hazard rate

Figure D.9 – Cross-sectional statistics across horizons. Cross-sectional moments obtained from the model's simulation under the benchmark calibration.

D.3 Other Untargetted Moments

Panel (a) in Figure D.10 shows mean squared forecast errors $\mathbb{E}[(\pi - f_h^i)^2]$, which are closely matched on average (0.15 in the model and 0.23 in the data) and in the horizon profile. Panel (b) shows the distribution of the final revision date. To compute it, we find the forecasters' average fraction (across years) that provides their final revision at horizon h. In the data, on average, 40% of participants do their last revision four months before the release date. The model matches the same qualitative pattern, suggesting that our theory can characterize the marginal benefits of waiting for an extra release of information relative to the revision costs throughout the horizons.



(a) Mean Squared Error **(b)** Distribution of Final Revision

Figure D.10 – Untargetted Forecast Errors and Final Revision Date. Cross-sectional moments obtained from the model's simulation under the benchmark calibration.

Figure D.11 illustrates the performance of the untargeted model in terms of the consensus gap. Panel (a) examines how the consensus gap c_h^i impacts the extensive margin of adjustment. The patterns are qualitatively consistent with the data. The model also quantitatively replicates the reductions in revision probability. Still, the increases in revision probability are more responsive in the model.[21] Panel (b) examines how the consensus gap c_h^i impacts the intensive margin of adjustment. In this case, the model qualitatively matches the magnitude of adjustments in the data. Quantitatively, we also observe a slightly larger responsiveness in the model.

D.4 On the role of fixed costs and strategic concerns

We study the role that fixed costs and strategic considerations play in generating empirical patterns. For this exercise, we shut down κ and r one at a time, and recalibrate the model through

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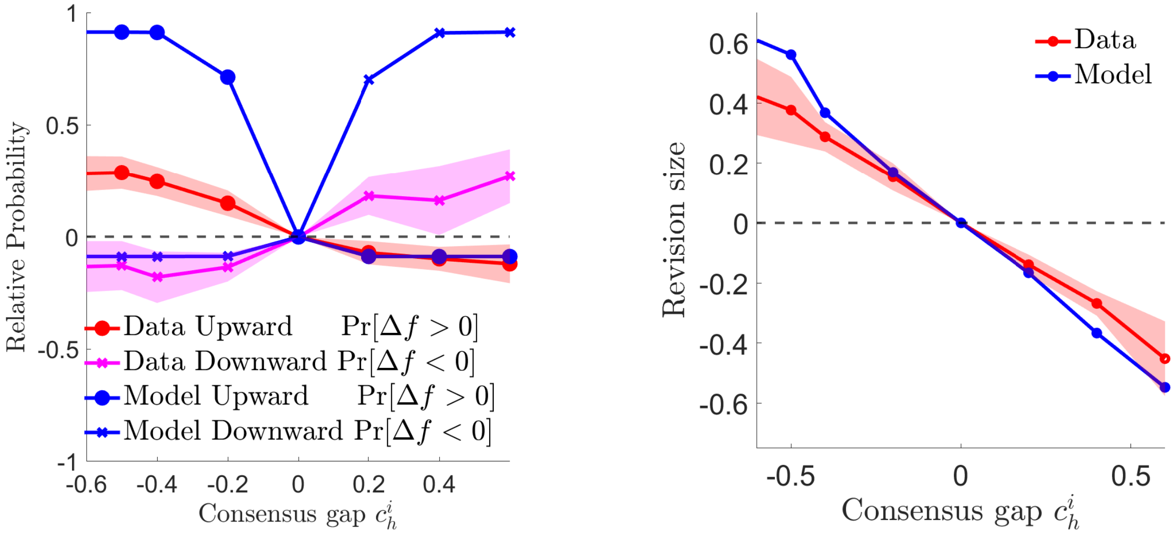
[21] Introducing free adjustment opportunities in the spirit of the CalvoPlus model, which combines state and time-dependent adjustment, or a generalized hazard could bring the consensus response closer to data.



(a) Extensive Margin **(b)** Intensive Margin

Figure D.11 – Untargetted Extensive and Intensive Margins. Estimated coefficients are obtained by running equation (5), using model simulated data.

the SMM procedure to match a subset of moments. The results are shown in Table D.2. Estimated parameters are shown in the first four rows, and targets are in the last three. Targeted moments are marked with stars. Columns (1) and (2) repeat the information in Table I with the data targets and the baseline calibration for reference.

Table D.2 – Shutting down frictions

	(1) Data	**(2) Baseline**	**(3) Only strategic** ($\kappa = 0$)	**(4) Only fixed costs** ($r = 0$)
Parameters				
κ		0.06	0.00	0.07
r		0.75	-0.43	0.00
σ_ζ^2		0.09	0.03	0.09
σ_F^2		0.12	0.23	0.18
Targets				
Frequency	0.43	0.40^*	1.00	0.38^*
Size	0.25	0.19^*	0.25^*	0.30^*
Hazard Slope	-0.04	-0.04^*	∞	-0.01^*

Notes: In the Table * denotes a targeted moment.

Column (3) shows the results when the fixed costs ($\kappa = 0$) are shut down. Without fixed costs, forecasters continuously revise; thus, we cannot match the adjustment frequency and hazard slope. We estimate r to match the average size of non-zero revisions. Interestingly, we find a negative value of $r = -0.43$, indicating that strategic diversification is necessary to match the size of adjustments. In other words, including fixed costs shifts the data's implications for r from positive (strategic complements) to negative (strategic substitutes).

Column (4) shows the results when shutting down strategic complementarities ($r = 0$), and we set κ and σ_η^2 to match the size and the hazard's slope. This configuration is less effective in matching the frequency of revisions relative to our baseline. Moreover, the hazard rate is almost flat. The fact that the probability of revisions becomes less "age-dependent" is a direct implication of removing the strategic concerns. Empirically, an "older" forecast is less likely to be revised than a recently updated prediction. Intuitively, this makes the consensus forecast more persistent as a function of age. When agents stop caring about the relative distance between their predictions and the consensus, the updating probability becomes less sensitive to age. This is precisely the result we get in this case.

E Computational strategy

Solving the problem requires computing expectations of future beliefs. Since all random variables are normal, this amounts to knowing the first two moments of these distributions. Next, we characterize these moments. Afterward, we use these moments to compute expectations.

E.1 Initial forecast

At the beginning of each year, we assume initial forecasts equal the 13-month-ahead belief, which is optimal without frictions ($\kappa = r = 0$):

$$f^i_{13} \;=\; \hat{\pi}^i_{13} \;=\; z_{13} \;+\; \nu^i_{13}, \qquad \nu^i_{13} \sim \mathcal{N}(0, \sigma^2_{13}) \tag{E.21}$$

where z_{13} is constructed using the projection formula in (15)

$$z_{13} \;=\; 12\left(\frac{c_x}{1-\phi_x}\right) \;+\; \phi_x \frac{1-\phi_x^{12}}{1-\phi_x}\left(\hat{x}_{13} - \frac{c_x}{1-\phi_x}\right) \tag{E.22}$$

and the monthly belief equals $\hat{x}^i_{13} \;=\; \alpha[c_x + \phi_x x_{14}] + (1-\alpha)\tilde{x}^i_{13}$.

E.2 Distributions of expected beliefs

The law of motion of individual states implies the following values at $h-1$:

$$\hat{\pi}^i_{h-1} \;=\; \left(\frac{\Sigma_{z,h-1}}{\sigma_o^2 + \Sigma_{z,h-1}}\right)\mu_o \;+\; \left(1 - \frac{\Sigma_{z,h-1}}{\sigma_o^2 + \Sigma_{z,h-1}}\right)\; \hat{\pi}^i \hat{\pi}^i_{h-1} \tag{E.23}$$

$$\hat{F}_{h-1} \;=\; c_F \;+\; \phi_F F_h \tag{E.24}$$

Expected consensus beliefs The mean and variance of the distribution of expected consensus beliefs at $h-1$, from the perspective of horizon h (with knowledge up to F_{h+1}), are:

$$\mathbb{E}[\hat{F}_{h-1}|\mathcal{I}_h^i] = c_F + \phi_F \mathbb{E}[F_h|\mathcal{I}_h^i] = c_F(1+\phi_F) + \phi_F^2 F_{h+1} \tag{E.25}$$

$$\mathbb{V}ar[\hat{F}_{h-1}^i|\mathcal{I}_h^i] = \phi_F^2 \mathbb{V}ar[F_h|\mathcal{I}_h^i] = \phi_F^2 \sigma_F^2 \tag{E.26}$$

Expected inflation beliefs The mean and variance of the distribution of expected inflation beliefs at $h-1$, from the perspective of horizon h, are:

$$\mathbb{E}[\hat{\pi}_{h-1}^i|\mathcal{I}_h^i] = \left(\frac{\Sigma_{z,h-1}}{\sigma_o^2 + \Sigma_{z,h-1}}\right)\mu_o + \left(1 - \frac{\Sigma_{z,h-1}}{\sigma_o^2 + \Sigma_{z,h-1}}\right)\mathbb{E}[\hat{\pi}_{h-1}^i|\mathcal{I}_h^i] \tag{E.27}$$

$$\mathbb{V}ar[\hat{\pi}_{h-1}^i|\mathcal{I}_h^i] = \left(\frac{\sigma_o^2\Sigma_{z,h-1}}{\sigma_o^2 + \Sigma_{z,h-1}}\right)^2 \mathbb{V}ar[\hat{\pi}_{h-1}^i|\mathcal{I}_h^i] \tag{E.28}$$

Now we compute the mean $\mathbb{E}[\hat{\pi}_{h-1}^i|\mathcal{I}_h^i]$ and variance $\mathbb{V}ar[\hat{\pi}_{h-1}^i|\mathcal{I}_h^i]$ of the idiosyncratic signal from the perspective of horizon h—inputs into the formulas above.

Expected signals We evaluate the formula for $\hat{\pi}_h^i$ in (B.17) at $h-1$, and separate the observation x_h from the sum yields:

$$\hat{\pi}_{h-1}^i = (h-1)\left(\frac{c_x}{1-\phi_x}\right) + \frac{1-\phi_x^{h-1}}{1-\phi_x}\left(\widetilde{x}_{h-1}^i - \frac{c_x}{1-\phi_x}\right) + x_h + \sum_{j=h+1}^{12} x_j. \tag{E.29}$$

Then, we take the expectation conditional on $\mathcal{I}_h^i$:

$$\mathbb{E}[\hat{\pi}_{h-1}^i|\mathcal{I}_h^i] = (h-1)\left(\frac{c_x}{1-\phi_x}\right) + \frac{1-\phi_x^{h-1}}{1-\phi_x}\left(\mathbb{E}[\widetilde{x}_{h-1}^i|\mathcal{I}_h^i] - \frac{c_x}{1-\phi_x}\right) + \mathbb{E}[x_h|\mathcal{I}_h^i] + \sum_{j=h+1}^{12} x_j \tag{E.30}$$

Next, we use the fact that $\mathbb{E}[\widetilde{x}_{h-1}^i|\mathcal{I}_h^i] = \mathbb{E}[x_{h-1}|\mathcal{I}_h^i]$ (because public and private noise have zero mean) and $\mathbb{E}[x_{h-1}|\mathcal{I}_h^i] = c_x + \phi_x \mathbb{E}[x_h|\mathcal{I}_h^i]$ (by the AR(1) assumption). Substituting into the previous expression:

$$\mathbb{E}[\hat{\pi}_{h-1}^i|\mathcal{I}_h^i] = (h-1)\left(\frac{c_x}{1-\phi_x}\right) + \frac{1-\phi_x^{h-1}}{1-\phi_x}\left(c_x + \phi_x \mathbb{E}[x_h|\mathcal{I}_h^i] - \frac{c_x}{1-\phi_x}\right) + \mathbb{E}[x_h|\mathcal{I}_h^i] + \sum_{j=h+1}^{12} x_j$$

Rearranging, we obtain:

$$\mathbb{E}[\hat{\pi}_{h-1}^i|\mathcal{I}_h^i] = h\left(\frac{c_x}{1-\phi_x}\right) + \phi_x \frac{1-\phi_x^{h-1}}{1-\phi_x}\left(\frac{\mathbb{E}[x_h|\mathcal{I}_h^i] - c_x}{1-\phi_x}\right) + \mathbb{E}[x_h|\mathcal{I}_h^i] - \frac{c_x}{1-\phi_x} + \sum_{j=h+1}^{12} x_j$$

Lastly, we substitute the AR(1) assumption $\mathbb{E}[x_h|\mathcal{I}^i_h] = c_x + \phi_x x_{h+1}$:

$$\text{(E.31)} \qquad \mathbb{E}[\hat{\pi}^i_{h-1}|\mathcal{I}^i_h] \;=\; h\left(\frac{c_x}{1-\phi_x}\right) \;+\; \phi_x^2 \frac{1-\phi_x^{h-1}}{(1-\phi_x)^2} x_{h+1} \;+\; \phi_x\left(x_{h+1} - \frac{c_x}{1-\phi_x}\right) + \sum_{j=h+1}^{12} x_j .$$

For the variance, we apply the variance operator to (E.29) and note that the terms in the sum disappear because they are known at h. Thus we are left with two terms.

$$\begin{aligned}
\mathbb{V}ar[\hat{\pi}^i_{h-1}|\mathcal{I}^i_h] &= \left(\frac{1-\phi_x^{h-1}}{1-\phi_x}\right)^2 \mathbb{V}ar[\widetilde{x}^i_{h-1}|\mathcal{I}^i_h] \;+\; \mathbb{V}ar[x_h|\mathcal{I}^i_h] \\
&= \left(\frac{1-\phi_x^{h-1}}{1-\phi_x}\right)^2 \left(\phi_x^2 \mathbb{V}ar[x_h|\mathcal{I}^i_h] + \sigma_x^2 + \sigma_\zeta^2 + \sigma_\eta^2\right) \;+\; \mathbb{V}ar[x_h|\mathcal{I}^i_h] \\
&= \left(\frac{1-\phi_x^{h-1}}{1-\phi_x}\right)^2 \left(\phi_x^2 \sigma_x^2 + \sigma_x^2 + \sigma_\zeta^2 + \sigma_\eta^2\right) \;+\; \sigma_x^2
\end{aligned}$$

where we use $\mathbb{V}ar[x_h|\mathcal{I}^i_h] = \sigma_x^2$, the signal structure and the AR(1) assumption to write

$$\text{(E.32)} \qquad \widetilde{x}^i_{h-1} \;=\; x^i_{h-1} + \zeta^i_{h-1} + \eta_{h-1} \;=\; c_x + \phi_x x_h + \varepsilon^x_{h-1} + \zeta^i_{h-1} + \eta_{h-1}.$$

E.3 Computing expectations

We approximate the expected continuation value of the value of action and inaction derived in Proposition 2 as follows

$$\text{(E.33)} \qquad \mathbb{E}[\mathcal{V}_{h-1}(\hat{\pi}^i_{h-1}, \hat{F}_{h-1}, f^i_{h+1})|\mathcal{I}^i_h] = \sum_{\hat{\pi}^i_{h-1}} \sum_{\hat{F}_{h-1}} \mathcal{V}_{h-1}(\hat{\pi}^i_{h-1}, \hat{F}_{h-1}, f^i_{h+1}) \omega(\hat{\pi}^i) \omega(\hat{F})$$

where weights $\{\omega(\hat{\pi}^i), \omega(\hat{F})\}$ are constructed with Gaussian quadrature over grids for $\hat{\pi}^i$ and $\hat{F}$. Integration weights $\omega_{\hat{F}}$ are such that $\hat{F}_{h-1}|\mathcal{I}^i_h \;\sim\; \mathcal{N}(\mathbb{E}[\hat{F}_{h-1}|\mathcal{I}^i_h], \mathbb{V}ar[\hat{F}^i_{h-1}|\mathcal{I}^i_h])$

$$\mathbb{E}[\hat{F}_{h-1}|\mathcal{I}^i_h] \;=\; F_{h+1} \qquad \mathbb{V}ar[\hat{F}^i_{h-1}|\mathcal{I}^i_h] \;=\; \sigma_F^2$$

Integration weights $\omega_{\hat{\pi}^i}$ are such that $\hat{\pi}^i_{h-1}|\mathcal{I}^i_h \sim \mathcal{N}\left(\mathbb{E}[\hat{\pi}^i_{h-1}|\mathcal{I}^i_h], \mathbb{V}ar[\hat{\pi}^i_{h-1}|\mathcal{I}^i_h]\right)$, with

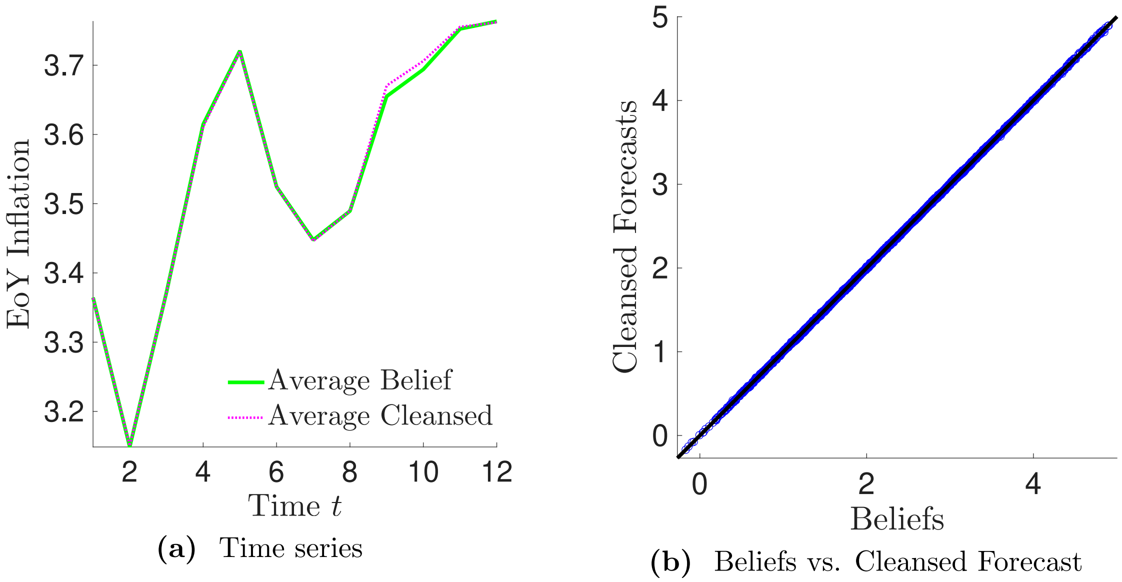
$$\begin{aligned}
\mathbb{E}[\hat{\pi}^i_{h-1}|\mathcal{I}^i_h] &= h\left(\frac{c_x}{1-\phi_x}\right) + \phi_x^2 \frac{1-\phi_x^{h-1}}{(1-\phi_x)^2} x_{h+1} + \phi_x\left(x_{h+1} - \frac{c_x}{1-\phi_x}\right) + \sum_{j=h+1}^{12} x_j \\
\mathbb{V}ar[\hat{\pi}^i_{h-1}|\mathcal{I}^i_h] &= \sigma_x^2 + \left(\frac{1-\phi_x^{h-1}}{1-\phi_x}\right)^2 \left(\phi_x^2 \sigma_x^2 + \sigma_x^2 + \sigma_\zeta^2\right).
\end{aligned}$$

F Features of Cleansed Forecasts

We present additional evidence of various features of our cleansing procedure, utilizing both actual data from the Bloomberg Survey and simulated data from our calibrated model.

F.1 Validating Cleasing Procedure

Building on the discussion in Section 5.1, we compute the consensus belief $\widetilde{F}_h$ and the consensus cleansed forecast $\mathbb{E}[\hat{\pi}^i_{h,t}]$ as cross-sectional averages across simulated forecasters for each horizon and year. Figure F.12a illustrates the time series evolution of both measures, while Figure F.12b displays their scatter plot. The two series are remarkably aligned, exhibiting an almost perfect correlation. This strong correlation provides additional validation for our cleansing procedure and further validates our decision to disregard the influence of continuation values from forecasts, thereby capturing the dynamics of agents' underlying beliefs successfully.



(a) Time series

(b) Beliefs vs. Cleansed Forecast

Figure F.12 – Consensus belief consistency. The figure shows the evolution of the consensus cleansed forecasts $\widetilde{F}_{h,t}$ and beliefs $\mathbb{E}[\hat{\pi}^i_{h,t}]$ over time. The time series is constructed using our proposed model using the benchmark calibration.

F.2 Backing out r through Survey data

Table F.3 presents the estimates from equation (25) to back out the data-implied parameter r. The first column includes all observations, while the second and third columns condition on non-zero revisions. We include forecasters, horizon, and year-fixed effects. Standard errors are clustered at the forecaster and horizon-year levels to account for the potential serial correlation within individuals and for common shocks or forecast-specific information for within each horizon - year time period.

The strategic concern parameter $\widehat{r}$ was backed-out through $\widehat{\beta}_2$ using the Delta-Method. Conditioning on updaters (column 2), we obtain an estimate of $\hat{r} = 0.79$, in line with the structural estimate of $r = 0.73$. The estimate remains relatively stable when additional macro controls, such as the lagged inflation rate, industrial production, and the 3-month T-bill rate, are included.

Table F.3 – Individual forecast determinants

	All	Updaters	
β_1	0.1998	0.2807	0.2668
	(.0444)	(.0646)	(.0566)
β_2	0.5791	0.4411	0.4846
	(.1070)	(.1113)	(.0888)
Constant	0.4033	0.4798	0.5215
	(.2036)	(.2765)	(.2868)
Macro Controls	×	×	✓
Horizon, Year FE	✓	✓	✓
Forecasters FE	✓	✓	✓
N	9,562	3,898	3,898
R^2	0.7674	0.8398	0.8501
$\widehat{r} = \widehat{\beta}_2/(1-\widehat{\beta}_2)$	1.3760	0.7891	0.9401
	(.5278)	(.4187)	(.4096)

Notes: Own estimations of equation (25) using Bloomberg data. In all specifications, we include horizon, years, and forecasters FE. Standard errors are clustered at the individual and the horizon-year levels

F.3 Rationality Tests with Survey of Professional Forecasters

As a robustness, we also apply our two-stage cleansing procedure to the SPF. We first use expression (25) to recover the data-implied r, while controlling for both the lagged consensus and the AR(1) projection forecasts.[22] Building on the estimated r, we construct the cleansed series and re-estimate the rationality tests. This is shown in Figure F.13. As noted, our main takeaway remains after we rely on this alternative survey. In particular, once we are able to recover a more accurate reflection of the agent's beliefs, the estimated level of overreaction to information is reduced by almost half, approaching zero.

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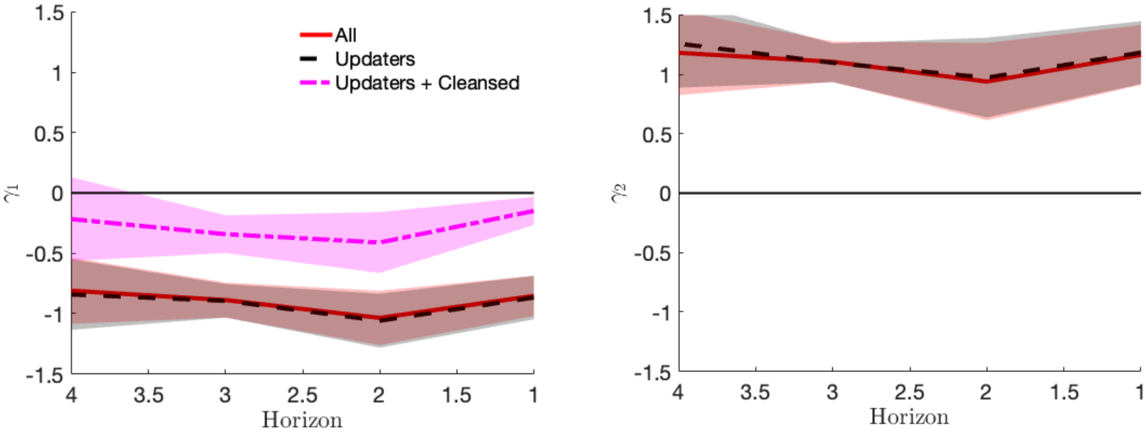
[22] In this case, we adjust the AR(1) forecast formula as SPF participants are asked to predict the annual percentage change of the CPI between the last quarter of the present year, relative to the last quarter of the previous year.



(a) Coefficient on Revisions (γ_1^h)

(b) Coefficient on Consensus (γ_2^h)

Figure F.13 – Rationality Tests with SPF