Lumpy Forecasts*

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Abstract

We document that professional forecasters adjust inflation forecasts in a lumpy way—forecasts are changed infrequently, and when adjusted, they are revised by a large amount. As the forecasting horizon shrinks, the frequency of revisions, the variance of revisions, and forecast errors decrease. Using a fixed-event forecasting framework, we assess the role of the consensus forecast and private information in shaping forecast revisions, both at the extensive and the intensive margins. A model of Bayesian belief formation with fixed revision costs and strategic concerns (i) delivers lumpy forecasts consistent with the survey evidence, (ii) rationalizes forecast efficiency tests without introducing behavioral biases, and (iii) generates the observed response to increases in inflation volatility.

JEL: D80, D81, D83, D84, E20, E30

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1 Introduction

Expectations and belief formation are central to macroeconomics. Both theoretical and empirical work has questioned the Full Information Rational Expectations (FIRE) paradigm in favor of other rigidities.[1] For instance, Coibion and Gorodnichenko (2015) argues that professional forecasters deviate from the traditional rational expectations full-information hypothesis as they form expectations facing limitations on the rate by which they observe and acquire information. Relying on surveys of expectations for firms, Coibion, Gorodnichenko and Kumar (2018) and Coibion, Gorodnichenko and Ropele (2020), confirm that, similar to professional forecasters, firms are also prone to suffer from information rigidities.

A common assumption at the core of the literature is that forecasts accurately reflect agents' beliefs. We challenge this assumption and ask to what extent and why forecasts may differ from agents' beliefs. First, using a relatively understudied survey of professional forecasters, we document that inflation forecasts are *lumpy*: Forecasts are characterized by periods of inaction followed by significant revisions. Forecast lumpiness is present despite relevant information becoming available during the forecasting period, which should, in principle, change agents' beliefs. Thus, forecasts are a rather *imperfect measure* of agents' information sets. This evidence casts doubts on the extent to which forecasts are a useful proxy for individual beliefs and has important implications for monetary and other policy tools that rely on these forecasts. Second, to rationalize the evidence, we build a new model of Bayesian belief formation with fixed revision costs and strategic concerns. The model (i) delivers lumpy forecasts consistent with the survey evidence, (ii) rationalizes forecast efficiency tests without introducing behavioral biases, and (iii) generates the observed response to increases in inflation volatility. Next, we explain in more detail the empirical and theoretical contributions.

Facts on lumpy revisions The first part of the paper documents new facts on lumpy forecast revisions. Using the Economic Forecasts ECFC survey conducted by Bloomberg for the US for the period 2010-2020, we document the evolution of monthly inflation forecasts about end-of-year inflation. We show that the frequency of revisions, the variance of revisions, and forecast errors *fall* as the date when the forecasted variable is released approaches. Since we focus on predictions for the same variable (annual inflation) at different horizons, these patterns are puzzling as it is precisely at shorter horizons when the most significant amount of relevant information is available, and we should, in principle, expect more revisions. We also study agents' learning rates, adjustment hazards, and other revision patterns along the forecasting horizon, which we label the "term structure" of forecast revisions and errors.

[1]For instance, sticky information model (Mankiw and Reis, 2002), rational inattention (Sims, 2003) and (Mackowiak and Wiederholt, 2009), higher-order uncertainty (Morris and Shin, 2002) and (Woodford, 2003), level-k thinking (García-Schmidt and Woodford, 2019), over- and under-reaction to private information (Bordalo, Gennaioli, Ma and Shleifer, 2018), to name a few.

Related to the triggers of revisions, we show that the distance to the average forecast (the consensus forecaster) and the distance to a statistical AR(1) prediction significantly drive revisions, both at the extensive and the intensive margin. The probability of revision increases with these two distances, and conditional on a revision, new forecasts are closer to the consensus and the AR(1) prediction. The results suggest that strategic complementarities are at play, in which forecasts depend on the forecasts of others, reflecting, on the one hand, correlated information and, on the other hand, reputational costs.

Forecasting model with fixed revisions costs In the second part of the paper, we build a novel forecasting model with fixed revision and strategic concerns. Since revision costs reduce the frequency and size of revisions, we interpret them as forecaster preference for forecast stability. We calibrate the model parameters to match average cross-sectional statistics. The model delivers horizon-dependent frequency and variance of revisions and forecast errors that match the empirical term structure of these moments. Alternative calibration that shut down either motive cannot jointly explain the term structure of revisions and forecast errors.

With the calibrated model at hand, we conduct three exercises that shed light on the relevance of lumpy forecasts in different dimensions. First, we assess forecast efficiency regression tests in the spirit of Bordalo, Gennaioli, Ma and Shleifer (2020). By regressing forecast errors on forecast revisions, the test investigates the predictability of forecast errors at the individual level, and thus, it is a test for rational expectations. Following Broer and Kohlhas (2022) and Valchev and Gemmi (2023), we extend the baseline test to incorporate the consensus forecast as a source of public information. Consistent with the empirical regressions, we find a non-significant bias, a negative and significant coefficient on forecast revisions (interpreted as over-reaction to private information), and a positive and significant coefficient on the distance to the consensus (interpreted as an under-reaction to public information). Importantly, our results are generated in a model with Bayesian agents, without the need of behavioral biases (e.g., extrapolating expectations) as in Bordalo, Gennaioli, Ma and Shleifer (2020).

Second, we use the model to investigate the strength of strategic concerns and the preference for forecast stability across the four types of forecasters in our data: (i) banks, (ii) financial institutions, (iii) consulting companies, and (iv) universities and research centers. For this purpose, we recalibrate the model to match type-specific moments. The most significant differences in these moments occur between consulting companies and universities. For instance, relative to universities, consulting companies adjust 1.4 times more frequently more than universities and do revisions that are 1.3 times more dispersed. Through the lens of the model, these moments imply that universities face larger revisions costs and stronger concerns for forecast stability. Thus, our results suggest that forecast heterogeneity is an important dimension to consider when working with this type of surveys.

Third, we investigate the forecasts response to increases in underlying inflation volatility. We motivate this exercise by the observation that during the years of the Great Recessions (2008-2009) and the Covid-19 pandemic (2020-2021), what we label turbulent years, monthly inflation volatility spiked. In the same period, forecast revision became more frequent and dispersed, and forecast errors sharply increased. In the model, we implement this change by increasing the volatility of the underlying state in the same amount as in the data and simulate the economy under two scenarios. In the first scenario, we give forecasters the information that volatility has changed (disclosed volatility shock). In the second scenario, we do not give this information and thus keep the policy functions as in the benchmark calibration (undisclosed volatility shock). In both cases, the cross-sectional moments of forecast revisions and errors increase as in the data. However, the forecasts' response under the undisclosed volatility shock better matches the large increase in the empirical moments, especially the forecast errors.

Contributions to the literature We highlight three main contributions. First, we contribute to the literature that uses survey data to elicit expectations. Our work complements studies focusing on model heterogeneity as a driver behind professional forecasters reports being different predictions for the same macroeconomic outcome (Giacomini, Skreta and Turen, 2020). Focusing on the micro-level, agent forecasts' characteristics have also captured researchers' attention. Mankiw and Reis (2002) build a model where agents update their expectations in a lumpy way. They claim that a model that allows agents to collect and update information relatively infrequently can reconcile different macro facts. Building on the "sticky information" theory of Mankiw and Reis (2002), Andrade and Le Bihan (2013) provides further empirical evidence that expectations from professional forecasters are indeed sticky. Interestingly, they notice that there is still disagreement in their predictions for agents who are forecasting the same variable *and* choose to update at the same time. Recently, using the well-known Ifo Survey of firms in Germany, Born, Enders, Müller and Niemann (2022) confirms that firms' expectations are also sticky as they are adjusted only infrequently.

2 The Anatomy of Inflation Forecasts

This section discusses the data. First, we describe the data sources and the fixed-event forecasting framework. Then we describe how forecast revisions and forecast errors evolve over the forecasting horizon.

2.1 Inflation

We construct annual inflation in the United States using the Consumer Price Index (CPI) index. For any year τ, we let cpi_j be the CPI measured j months before the end of year and we let $\overline{cpi}_\tau = \frac{1}{12}\sum_{j=0}^{11} cpi_j$ be the average CPI in year τ. Then, the annual inflation rate π_τ in any year τ is calculated as

$$\pi_\tau = \frac{\overline{cpi}_\tau - \overline{cpi}_{\tau-1}}{\overline{cpi}_{\tau-1}} \tag{1}$$

Following Giacomini, Skreta and Turen (2020), we alternatively express the annual inflation rate using the CPI in month h, cpi_h, as follows:

$$\pi_\tau \cong \sum_{h=0}^{11} x_h, \quad \text{with} \quad x_h = \frac{1}{12}\left(\frac{cpi_h - cpi_{h+12}}{cpi_{h+12}}\right), \quad \forall h = 11, \ldots, 0. \tag{2}$$

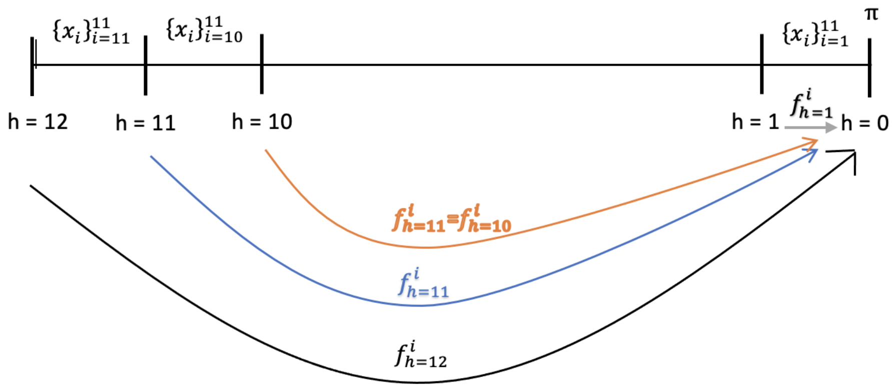
2.2 Inflation Forecasts

We analyze revisions of US annual (year-on-year) CPI inflation forecasts from the "Economic Forecasts ECFC" survey of professional forecasters conducted by Bloomberg. This survey is comparable to other surveys of professional forecasters regarding the number of participants and the background of forecasters, i.e., financial institutions and banks, consulting firms, universities, and research centers.[2] Besides its similarities, one of the most appealing features of this particular dataset is that the most recent forecasts of any other forecaster, the date when each prediction was last updated, and the consensus forecast (the mean forecast) are visible to users of the Bloomberg terminal in *real-time*.

Sample We examine monthly fixed-event forecasts of annual US inflation. Our sample covers the years 2008 to 2022. In the main analysis, we focus on low-volatility years 2010-2019. Section 8 analyses the turbulent years of the Great Recession, 2008-09, and the COVID-19 pandemic, 2020-21, in which the inflation process is more volatile. For each year, we consider survey participants who forecast inflation for all 12 months before the final figure (end-of-year inflation) is officially published. We remove forecasters who fail to provide at least one annual inflation revision. This

[2] See Giacomini, Skreta and Turen (2020) for further details related to the comparison between the Bloomberg survey and other existing surveys.

Figure I – Fixed-event forecasting



Notes: The figure illustrates how fixed-event forecasts work. The fixed event is the end-of-year inflation π. All forecasts f_h^i refer to the fixed event.

leaves approximately 100 forecasters per year. The panel dataset contains the history of forecast updates for all forecasters over the 12-month horizon (h) before the end of each year.[3]

Inflation forecasts Within each year, we denote with f_h^i the inflation forecast of forecaster i at horizon h (to save on notation, we do not explicitly use the year):

$$f_h^i, \quad i = 1...N, \quad h = 12, ...1. \tag{3}$$

We count the horizon backward so that the index $h = 12, ..., 1$ indicates that the forecast was produced h months before the end of each corresponding year (the fixed event). Figure I illustrates the workings of a fixed-event forecast. The fixed event is the end-of-year inflation π. All forecasts f_h^i refer to the fixed event. Monthly inflation rates x_h are published at the end of the month.

Consensus forecast At each horizon, the consensus forecast is the average forecast:

$$F_h \equiv \frac{1}{N} \sum_{i=1}^{N} f_h^i \, \mathrm{d}i. \tag{4}$$

Bloomberg reports the consensus in real-time.

[3]Although we have information on the precise dates when a forecast was revised, we analyze a monthly frequency as there are only very few weekly updates. In particular, we use the forecast available on the terminal on the last day of the month to construct our monthly panel data.

2.3 Forecasts revisions

We define the forecast revision at horizon h, Δf_h^i, as the one-period difference between the forecast in two consecutive horizons:

$$\Delta f_h^i \equiv f_h^i - f_{h+1}^i. \tag{5}$$

Table I reports summary statistics of forecast revisions averaged across years, forecasters, and horizons. The average revision is close to zero, $\mathbb{E}[\Delta f] = -0.013$, which suggests a symmetric environment in which positive and negative revisions, on average, cancel out. The average revision size (in absolute value and excluding zeros) equals $\mathbb{E}[abs(\Delta f)|\Delta f \neq 0] = 0.247$. There are, on average, 5 forecast revisions in a given year, which means that forecasts are inactive for 1.6 months. The adjustment frequency is 0.427, and downward revisions (0.231) are slightly more likely than upward revisions (0.196). The spike rate, which counts the proportion of large adjustments (above 20%), is close to 3%. Next, we examine the "term structure" of forecast revisions—that is, how the frequency and the variance of forecast revisions evolve along the forecasting horizon h.

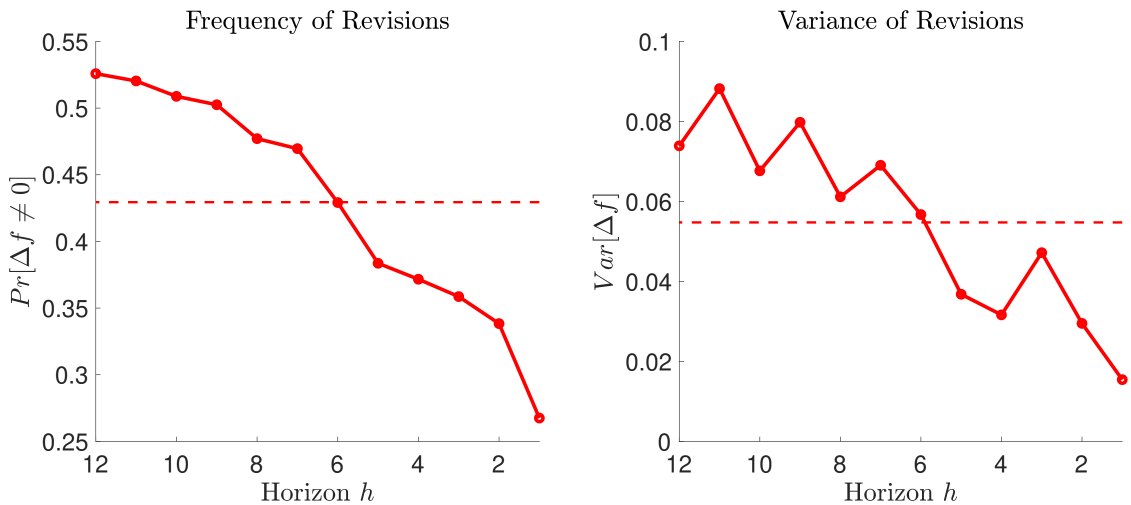
Table I – Summary Statistics of Forecast Revisions

Average	$\mathbb{E}[\Delta f]$	−0.013
Size	$\mathbb{E}[abs(\Delta f)\|\Delta f \neq 0]$	0.247
Variance	$\mathbb{V}ar[\Delta f]$	0.055
Number of revisions in a year	$count[\Delta f \neq 0]$	5.059
Months of inaction	$\mathbb{E}[\tau]$	1.594
Adjustment frequency	$\Pr[\Delta f \neq 0]$	0.427
Upward	$\Pr[\Delta f > 0]$	0.196
Downward	$\Pr[\Delta f < 0]$	0.231
Spike rate	$\Pr[abs(\Delta f) > 0.2]$	0.028
Serial correlation (all Δf)	$corr[\Delta f, \Delta f_{-1}]$	−0.043
Serial correlation (non-zero Δf)	$corr[\Delta f, \Delta f_{-1}]$	−0.107
Observations	N	9,256

Sources: Bloomberg data for years 2010-2019. Averages across sample years and 12 horizons.

Figure II shows the unconditional probability of updating a forecast across the horizon (left panel) and the variance of revisions (right panel). Regarding the extensive margin of adjustment, the left panel in Figure II shows that forecasts are updated infrequently. On average, around 38% of forecasters choose to update their predictions throughout the year. Interestingly, the share of updaters also drops as the date when the final inflation figure is published $h = 0$ approaches. The increasing lumpiness is puzzling as every month, a new piece of relevant information (the monthly release of inflation, x_h) is published, which could be used to improve the accuracy of the prediction further. Turning to the intensive margin, the right panel of Figure II shows that the magnitude of revisions becomes smaller as the horizon h shrinks.

Figure II – Term Structure of Forecast Revisions



Notes: Left panel shows the frequency of non-zero revisions $\Pr[\Delta f \neq 0]$. The right panel shows the variance of revisions $\mathbb{V}ar[\Delta f]$. Bloomberg data for normal years = 2010-2019.

2.4 Forecast errors

At any given year, we let e^i_h be the forecast error of individual i at horizon h, defined as the difference between the actual end-of-year inflation π and the reported forecast f^i_h. Because errors require knowledge about the actual realization of inflation, they are an ex-post measure.

$$e^i_h \equiv \pi - f^i_h. \tag{6}$$

Table II provides summary statistics on forecast errors averaged across years, forecasters, and horizons. The average error is small $\mathbb{E}[e] = -0.055$. Typically, agents tend to overpredict inflation and thus a negative error e^i_h.

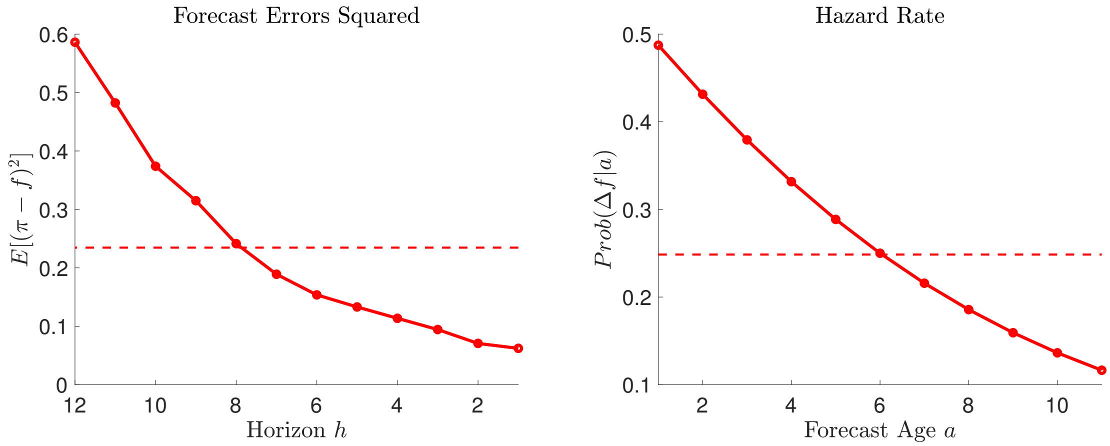
Table II – Summary Statistics of Forecast Errors

Average	$\mathbb{E}[e]$	−0.055
Average of squares	$\mathbb{E}[e^2]$	0.255
Serial correlation	$corr[e, e_{-1}]$	0.877
Observations	N	9,256

Sources: Bloomberg data for 2010-2019. Between-year averages of within-year statistics.

The term structure of forecast errors across horizons is shown in the left panel in Figure III. The average squared forecast errors decrease with the horizon. As expected, as the fixed event (end of the year) approaches, more information is accumulated, making the prediction more precise. Nonetheless, despite the monotonic decrease, the forecast error does not converge to zero, even at $h = 1$. This is a tell-tale sign that forecast accuracy is not the only driving force behind forecasters'

Figure III – Term Structure of Forecast Errors and Hazard Rate



Notes: Bloomberg data for years 2010-2019.

activities.

2.5 Hazard rate

The hazard rate of forecast adjustment is a dynamic moment useful to assess learning speed. We assess how forecast revisions depend on the time elapsed since the last revision (the forecast's age). The right panel in Figure III plots the adjustment hazard against the forecast age. The hazard is downward slopping: The probability of adjusting a newly set forecast ($age = 0$) is 0.5. As the forecast age increases, the probabilities drop gradually and monotonically. Revision probabilities drop below 0.3 after six months ($age = 6$).[4]

Taking stock To summarize, forecasts are lumpy: they exhibit significant periods of inaction that are followed by large adjustments. The frequency and dispersion of revisions fall with the forecasting horizon. Forecast errors also decrease with the horizon but do not converge to zero.

3 Forecasting with fixed revision costs

This section builds a fixed-event Bayesian forecasting model with frequent information revelation, strategic concerns, and fixed forecast revision costs.

3.1 Forecasting problem

A large number of forecasters, indexed by $i \in N$, produce forecasts about end-of-year inflation π. End-of-year inflation inflation π equals the sum of within-year monthly inflations x_h, namely

[4]Appendix F shows the adjustment hazard conditional on the number of revisions. The age dependence of forecast updating changes as a function of the number of revisions the agent has done in the past.

$\pi \equiv \sum_{h=1}^{12} x_h$. Forecasters believe monthly inflation follows an AR(1) process:

$$x_h \;=\; c_x \;+\; \phi_x x_{h+1} \;+\; \varepsilon_h^x, \qquad \varepsilon_h^x \sim \mathcal{N}(0,\sigma_x^2), \tag{7}$$

where c is a constant, ϕ is the persistence parameter, and ε_h^x is an *iid* normally distributed noise with volatility σ_x^2. The parameters c_x, ϕ_x and σ_x^2 are common knowledge.

Payoffs At each horizon h, forecaster i chooses a forecast f_h^i based on their information set $\mathcal{I}_h^i$. Changing a forecast entails paying a fixed revision cost $\kappa > 0$ measured in utility units. For a given initial forecast f_{13}^i, forecasts minimize the yearly sum of monthly losses:

$$\min_{\{f_h^i\}_{h=12}^1} \mathbb{E}\left[\sum_{h=12}^{1} \underbrace{(f_h^i - \pi)^2}_{\text{accuracy}} + r\,\underbrace{(f_h^i - \;F_h)^2}_{\text{strategic}} \;+\; \underbrace{\kappa \mathbb{1}_{\{f_h^i \neq f_{h+1}^i\}}}_{\text{stability}} \middle| \mathcal{I}_0^i\right]. \tag{8}$$

The first term in the payoff function is the distance between the forecast and the actual end-of-year inflation, reflecting losses from the lack of *accuracy*. The second term is the distance between the forecast and the consensus (the average) $F_h = N^{-1}\sum_{i=1}^N f_h^i$, multiplied by the parameter r that measures the strength of *strategic concerns*. If $r > 0$, there is strategic complementarity, as the payoff increases when the forecast is close to the consensus. If $r < 0$, there is strategic substitutability, as the payoff increases when the forecast is far from the consensus. The third term is the fixed cost $\kappa > 0$ paid for any forecast revision, capturing preference for *forecast stability*.

Public signal Let $\mathcal{I}_h$ denote the publicly available information at each horizon, corresponding to the lagged values of x_h and F_h:

$$\mathcal{I}_h = \{(x_j, F_j) : j \geq h+1\}. \tag{9}$$

Under $\mathcal{I}_h$, the inflation process implies a monthly public signal z_h about yearly inflation:

$$z_h \;=\; h\left(\frac{c_x}{1-\phi_x}\right) \;+\; \frac{\phi_x(1-\phi_x^h)}{1-\phi_x}\left(x_{h+1} - \frac{c_x}{1-\phi_x}\right) \;+\; \sum_{j=h+1}^{12} x_j, \qquad h = 12,\ldots,1. \tag{10}$$

Private signal Following Patton and Timmermann (2010), at the beginning of the month, each forecaster receives an unbiased private signal $\widetilde{x}_h^i$ about what inflation in that month will be (the true monthly inflation is only released at the end of the period):

$$\widetilde{x}_h^i \;=\; x_h \;+\; \zeta_h^i. \tag{11}$$

Idiosyncratic noise $\zeta_h^i \overset{\text{iid}}{\sim} \mathcal{N}(0,\sigma_\zeta^2)$ reflects the heterogeneity in beliefs or models across agents.

Information dynamics At the end of the period, and after f_h^i is decided, monthly inflation x_h is revealed (a stand for the official release from a statistical agency), removing all the uncertainty about its lagged values. Similarly, the consensus forecast F_h is observed at the end of the period. These timing assumptions eliminate a fixed point between individual choices and the consensus, as in a beauty contest (Morris and Shin, 2002), greatly simplifying the model solution with revision costs.

Therefore, individual information sets $\mathcal{I}_h^i$ at the time of choosing the forecast equal

$$\mathcal{I}_h^i \;=\; \widetilde{x}_h^i \,\cup\, \mathcal{I}_h \;=\; \widetilde{x}_h^i \cup \, \{x_{h+1}, x_{h+2}, \ldots, F_{h+1}, F_{h+2}, \ldots\}, \tag{12}$$

where $\mathcal{I}_h$ stands for the public information set, including past releases and consensus.

3.2 Belief formation

Proposition 1 writes the sequential problem in (8) as a function of inflation and consensus beliefs, using the law of iterated expectations and conditioning payoffs on horizon-specific information sets. All proofs are in the Appendix.

Proposition 1. *Let $\hat{\pi}_h^i \equiv \mathbb{E}[\pi|\mathcal{I}_h^i]$ and $\Sigma_h^\pi \equiv \mathbb{E}[(\hat{\pi}_h^i - \pi)^2|\mathcal{I}_h^i]$ be the conditional mean and variance of end-of-year inflation beliefs. Let $\hat{F}_h \equiv \mathbb{E}[F_h|\mathcal{I}_h^i]$ and $\Sigma^F \equiv \mathbb{E}[(\hat{F}_h - F_h)^2|\mathcal{I}_h^i]$ be the conditional mean and variance of consensus beliefs. Then forecasters solve the following problem:*

$$\min_{\{f_h^i\}_{h=12}^1} \sum_{h=12}^{1} \mathbb{E}\left[\Sigma_h \;+\; \mathbb{E}[(f_h^i - \hat{\pi}_h^i)^2|\mathcal{I}_h^i] \;+\; r\mathbb{E}[(f_h^i - \hat{F}_h)^2|\mathcal{I}_h^i] \;+\; \kappa \mathbb{1}_{\{f_h^i \neq f_{h+1}^i\}} \Big| \mathcal{I}_0^i\right]. \tag{13}$$

where $\Sigma_h \;\equiv\; \Sigma_h^\pi \;+\; r\Sigma^F$ and f_{13}^i given.

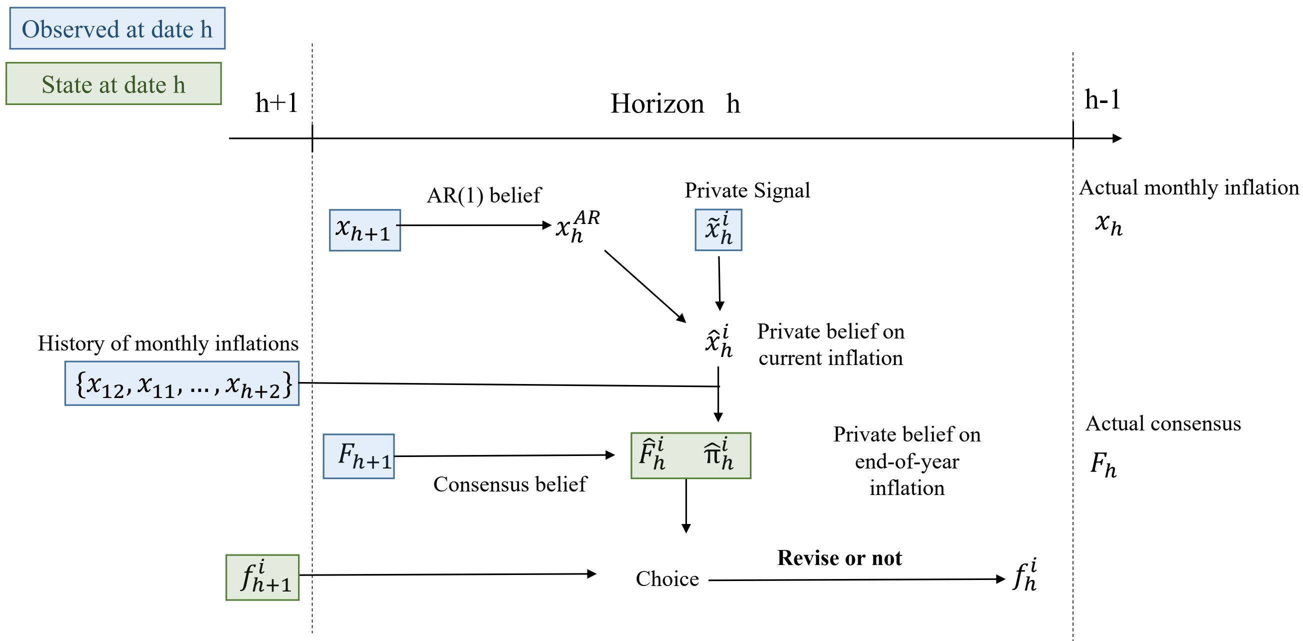
Next, we characterize forecasters' beliefs about the consensus and end-of-year inflation. To guide the characteriztion, Figure IV shows the timeline of how information becomes available and how it is used to form beliefs.

Consensus Beliefs Since the consensus is observed with a one-period delay (e.g., at horizon h, F_{h+1} is observed), forecasters must form expectations about the contemporaneous consensus when choosing their forecasts. All forecasters entertain the following beliefs about the consensus:

$$F_h \;=\; c_F \;+\; \phi_F F_{h+1} \;+\; \varepsilon_h^F, \qquad \varepsilon_h^F \sim \mathcal{N}(0, \sigma_F^2). \tag{14}$$

The parameters c_F, ϕ_F and σ_F^2 are common knowledge. Given this assumption, they generate common horizon-specific consensus beliefs $F_h|\mathcal{I}_h^i \sim \mathcal{N}(\hat{F}_h, \Sigma_F)$, where the conditional mean $\hat{F}_h$

Figure IV – Timeline of events



Notes: The figure illustrates the timeline of information revelation, belief formation, and forecast revisions for three contiguous horizons $h+1, h, h-1$.

and variance Σ_F are given by

$$\hat{F}_h = c_F + \phi_F F_{h+1}, \tag{15}$$

$$\Sigma_F = \sigma_F^2. \tag{16}$$

Inflation beliefs To form end-of-year inflation beliefs, forecasters construct monthly beliefs, which are then projected into end-of-year beliefs. In the first step, forecasters combine two sources of information at the monthly frequency. The AR(1) assumption of the inflation process implies a "statistical" common expectation about next month's inflation:

$$x_h^{AR} \equiv \mathbb{E}[x_h | x_{h+1}] = c_x + \phi_x x_{h+1}, \tag{17}$$

with variance σ_x^2. Forecasters combine this statistical expectation x_h^{AR} with their private signal $\tilde{x}_h^i$ in (11) to construct an individual monthly inflation belief $\hat{x}_h^i$:

$$\hat{x}_h^i \equiv \mathbb{E}[x_h | \mathcal{I}_h^i] = \frac{\sigma_x^{-2} x_h^{AR} + \sigma_\zeta^{-2} \tilde{x}_h^i}{\sigma_x^{-2} + \sigma_\zeta^{-2}} = (1-\alpha) x_h^{AR} + \alpha \tilde{x}_h^i, \tag{18}$$

where we define the weight on the private signal as $\alpha \equiv \frac{\sigma_\zeta^{-2}}{\sigma_x^{-2} + \sigma_\zeta^{-2}}$. The weight increases in the precision of the private signal.

In the second step, forecasters form end-of-year inflation beliefs at each horizon $\pi | \mathcal{I}_h^i \sim$

$\mathcal{N}(\hat{\pi}_h^i, \Sigma_h^\pi)$. To obtain the conditional mean $\hat{\pi}_h^i$, forecasters combine past "official" releases $\{x_j\}_{j>h}$ with their individual monthly beliefs $\hat{x}_h^i$:

$$(19) \qquad \hat{\pi}_h^i = \underbrace{h\left(\frac{c_x}{1-\phi_x}\right) + \frac{1-\phi_x^h}{1-\phi_x}\left(\hat{x}_h^i - \frac{c_x}{1-\phi_x}\right)}_{\text{AR(1) projection using } h \text{ info}} + \underbrace{\sum_{j=h+1}^{12} x_j}_{\text{realized, } j>h}, \quad h = 12, \ldots, 1.$$

The first part of the expression (19) uses the AR(1) statistical model to project the monthly belief $\hat{x}_h^i$ into the future. The second part equals the sum of the true monthly inflation values released to date.

The conditional variance Σ_h^π is a function of the AR(1) parameters $\{\phi_x, \sigma_x^2\}$ and noise σ_ζ^2; it decreases with the horizon and is independent of i.[5]

$$(20) \quad \Sigma_h^\pi = (\sigma_\eta^2 + \sigma_\zeta^2)\left(\frac{1-\phi_x^h}{1-\phi_x}\right)^2 + \frac{\sigma_x^2}{(1-\phi_x)^2}\left[(h-1) - \frac{2\phi_x(1-\phi_x^{h-1})}{1-\phi_x} + \frac{\phi_x^2(1-\phi_x^{2(h-1)})}{1-\phi_x^2}\right].$$

Finally, it is useful to establish a relationship between individual beliefs under $\mathcal{I}_h^i$ in (**??**) and public beliefs z_h under $\mathcal{I}_h$ in (10)

$$(21) \qquad \hat{\pi}_h^i = z_h + \nu_h^i, \quad \text{with} \quad \nu_h^i \sim \mathcal{N}\left(0, \left[\frac{1-\phi_x^h}{1-\phi_x}\right]^2 \alpha^2(\sigma_x^2 + \sigma_\zeta^2)\right).$$

where α is the updating weight defined in (18).

Discussion of assumptions Although participants interpret public information differently, we argue that the prediction that builds on an AR(1) process is a tractable and accurate proxy for a fixed-event forecast. We provide further discussion about the features and accuracy of the proxy in Section E.1. See Giacomini, Skreta and Turen (2020).

3.3 Optimal forecast revision policy

Proposition 2 writes the problem in recursive form as a stopping-time problem using the principle of optimality. The individual state includes the past forecast, the mean and variance of inflation beliefs, and the mean and variance of consensus beliefs. It is equivalent to working with posterior beliefs instead of the signals. The aggregate state includes past realizations of monthly inflation and consensus. Because total uncertainty evolves deterministically and is common across agents, we include it in the aggregate state. We thus index value function with the horizon h to account for the aggregate state.

[5] Appendix B.1 presents a detailed derivation of z_h^i and Σ_h^z.

Proposition 2. *The value of a forecaster i at horizon h with state $(\hat{\pi}_h^i, \hat{F}_h, f_{h+1}^i)$ equals*

$$\mathcal{V}_h(\hat{\pi}_h^i, \hat{F}_h, f_{h+1}^i) \;=\; \min\{\, \underbrace{\mathcal{V}_h^I(\hat{\pi}_h^i, \hat{F}_h, f_{h+1}^i)}_{inaction},\;\; \underbrace{\mathcal{V}_h^A(\hat{\pi}_h^i, \hat{F}_h)}_{action} \,\} \tag{22}$$

where the value of inaction $\mathcal{V}_h^I$ and the value of action $\mathcal{V}_h^A$ are, respectively,

$$\begin{aligned}
\mathcal{V}_h^I(\hat{\pi}_h^i, \hat{F}_h, f_{h+1}^i) &= \Sigma_h \;+\; (f_{h+1}^i - \hat{\pi}_h^i)^2 + r(f_{h+1}^i - \hat{F}_h)^2 \;+\; \mathbb{E}[\mathcal{V}_{h-1}(\hat{\pi}_{h-1}^i, \hat{F}_{h-1}, f_{h+1}^i)|\mathcal{I}_h^i] \\
\mathcal{V}_h^A(\hat{\pi}_h^i, \hat{F}_h) &= \kappa \;+\; \Sigma_h \;+\; \min_{f_h^i} \Big\{ (f_h^i - \hat{\pi}_h^i)^2 \;+ r(f_h^i - \hat{F}_h)^2 \;+\; \mathbb{E}[\mathcal{V}_{h-1}(\hat{\pi}_{h-1}^i, \hat{F}_{h-1}, f_h^i)|\mathcal{I}_h^i] \Big\}
\end{aligned}$$

subject to the evolution of inflation beliefs in (19) and (20), and consensus beliefs in (14).

Optimal policy The solution entails an *horizon-specific* inaction region

$$\mathcal{R}_h \equiv \{(\hat{\pi}_h^i, \hat{F}_h, f_{h+1}^i) : \mathcal{V}_h^I(\hat{\pi}_h^i, \hat{F}_h, f_{h+1}^i) \geq \mathcal{V}_h^A(\hat{\pi}_h^i, \hat{F}_h)\} \tag{23}$$

and a reset forecast $f_h^{i*}(\hat{\pi}_h^i, \hat{F}_h)$, such that, for given the beliefs, the forecast remains unchanged $f_h^i = f_{h+1}^i$, i.e., a zero revision $\Delta f_h = f_h^i - f_{h+1}^i$, whenever $f_{h+1}^i \in \mathcal{R}_h$. The forecast changes to f_h^{i*}, i.e., a revision of size $\Delta f_h = f_h^{i*} - f_{h+1}^i$, whenever $f_{h+1}^i \notin \mathcal{R}_h$.

For a given past forecast f_{h+1}^i, we can express the inaction region as a function of beliefs $\mathcal{R}_h(\hat{\pi}_h^i, \hat{F}_h | f_{h+1}^i)$. It includes the set of beliefs such that it is optimal not to reset the forecast.

Idiosyncratic uncertainty and forecasting Discuss here the option and volatility effects. Show inaction region for various horizons h.

3.4 Calibration

Given parameters, we compute the decision rules of forecasters using backward induction. Appendix C.1 derives expressions to compute the distributions of expected beliefs needed to compute the value functions.

Initial forecast At the beginning of each year, we assume initial forecasts equal the 13-months ahead belief, which is optimal without frictions ($\kappa = r = 0$):[6]

$$f_{13}^i \;=\; \hat{\pi}_{13}^i \;=\; z_{13} + \nu_{13}^i \tag{24}$$

[6] We initialize forecasts in the first year at the unconditional mean plus some noise: $f_{13}^i = c_x/1-\phi_x + \epsilon_{13}^i, \quad \epsilon_{13}^i \sim \mathcal{N}(0, \sigma_{13}^2)$. Then we burn P periods to eliminate its dependence on the initial condition.

where z_{13} is constructed using the projection formula in (10)

$$z_{13} = 12\left(\frac{c_x}{1-\phi_x}\right) + \phi_x \frac{1-\phi_x^{12}}{1-\phi_x}\left(\hat{x}_{13} - \frac{c_x}{1-\phi_x}\right) \quad (25)$$

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

Externally set parameters We feed the AR(1) parameters estimated directly from the data. By relying on the available information to forecasters in real time, we estimate the AR(1) process parameters using a rolling window over the sample years. For the monthly inflation process x_t, we estimate $(c_x, \phi_x, \sigma_x) = (0.013, 0.932, 0.036)$. For the consensus process F_t, we estimate $(c_F, \phi_F, \sigma_F) = (0.153, 0.913, 0.26)$. More details are in Appendix D.

Internally calibrated parameters Using the simulated method of moments, we estimate values for the six remaining parameters by matching the cross-sectional moments in normal years. We calibrate three parameters: the strength of strategic concerns r, the fixed revision cost κ, and the private noise σ_ζ. We target three moments: the frequency of adjustment $\Pr[\Delta f \neq 0] = 0.43$, $\mathbb{V}ar_i[\Delta f] = 0.05$ and the average forecast error squared $\mathbb{E}[(\pi - f^i_h)^2] = 0.23$. Table III shows the baseline parameterization, the moments in the data, and the model fit.

Table III – Internally calibrated parameters, Baseline

Parameter		Value	Moment	Data	Model
κ	adjustment cost	0.083	$\Pr[\Delta f \neq 0]$	0.43	0.43
r	strategic concerns	0.263	$\mathbb{V}ar[\Delta f]$	0.05	0.05
σ_ζ	private noise	0.098	$\mathbb{E}[e^2]$	0.23	0.21

The calibrated parameters are as follows. First, the fixed adjustment cost of $\kappa = 0.083$ implies a preference for forecast stability. Second, the positive value for $r = 0.263$ signals strategic complementarities. Lastly, the private noise $\sigma_\zeta = 0.098$ is 2.5 larger than the volatility of the inflation process, $\sigma_x = 0.036$.

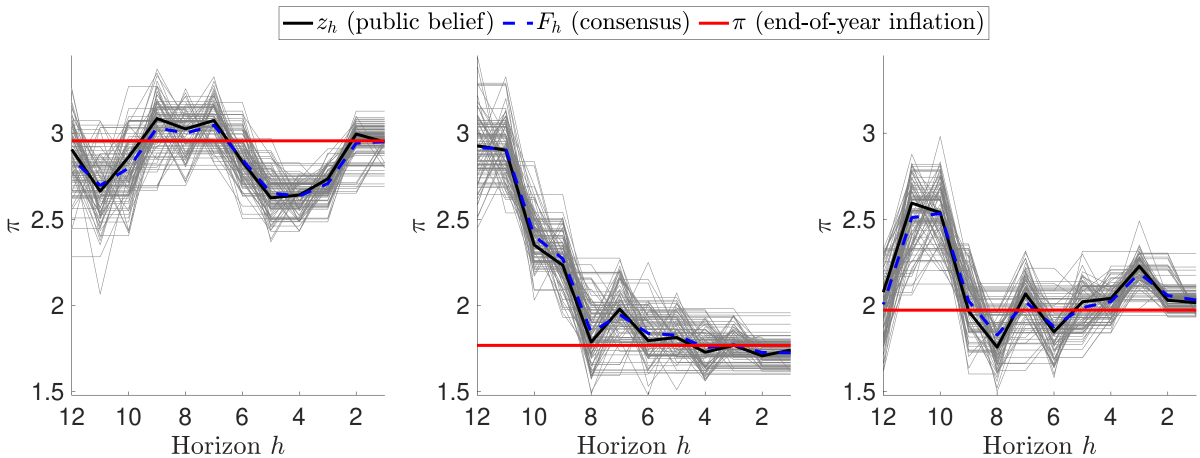
4 The model in action

This section explores various dimensions of the forecasting model.

4.1 Evolution of individual forecasts and consensus

Figure V shows individual forecasts, the consensus, and the public signal for three different years. The first year inflation was 3%, the second year 1.8% and the third year 2%.

Figure V – Simulation for ten years



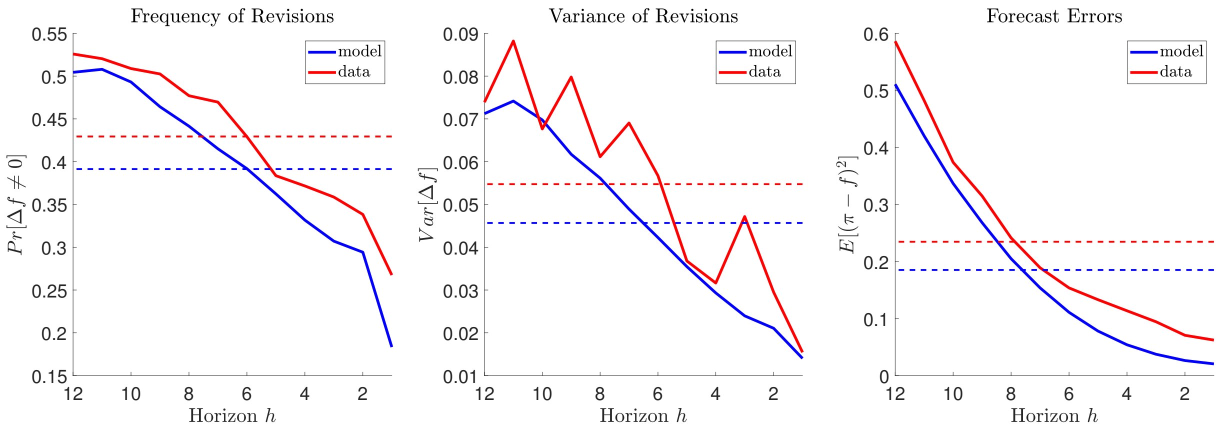
4.2 Cross-sectional statistics

With the calibration, we now assess the model's capacity to replicate some of the studied features of forecasters across the horizons. Figure VI shows the term structures of frequency/variance of revisions and forecast errors. While we only targeted average values of these moments across all horizons, the model does a very good job in tracking their patterns along the forecasting period.

Both the frequency of revisions (extensive margin, first panel) and the variance of revisions conditioning on adjustment (intensive margin, second panel). The model predicts these two margins would decrease over the horizon in both cases. Hence, although the inaction region is horizon-dependent, it seems that at longer horizons, the volatility effect dominates (when there is higher uncertainty about π) relative to the option value effect. At shorter horizons, the option value effects dominate, leading to less updating frequency. Moreover, it is precisely at shorter horizons when the contribution of each extra piece of information (monthly release) will only marginally affect the inflation belief, making it less likely to hit out of the bands, leading to fewer revisions as predicted by the data. The contribution of each extra bit of information only marginally affects the inflation beliefs, which is also reflected in the decreasing magnitude of forecast revisions.

Forecast errors (third panel) also decrease with the horizon; this is unsurprising, as more information gets accumulated as the end-of-year event approached.

Figure VI – Cross-sectional statistics across horizons



Notes: Model, benchmark calibration.

Untargeted moments We present additional suggestive evidence of lumpy forecast revisions. To this end, we assess how the model performs in delivering untargeted moments from the data. Table IV presents autocorrelations of forecast errors and revisions (for all and non-zero revisions). The model values are very close to those in the data.

Table IV – Autocorrelations: Model vs. Data

		Data	**Model**
Forecast errors	$corr[e, e_{-1}]$	0.877	0.626
All revisions	$corr[\Delta f, \Delta f_{-1}]$	−0.043	-0.161
Non-zero revisions	$corr[\Delta f, \Delta f_{-1} \vert \Delta f \neq 0]$	−0.107	-0.296

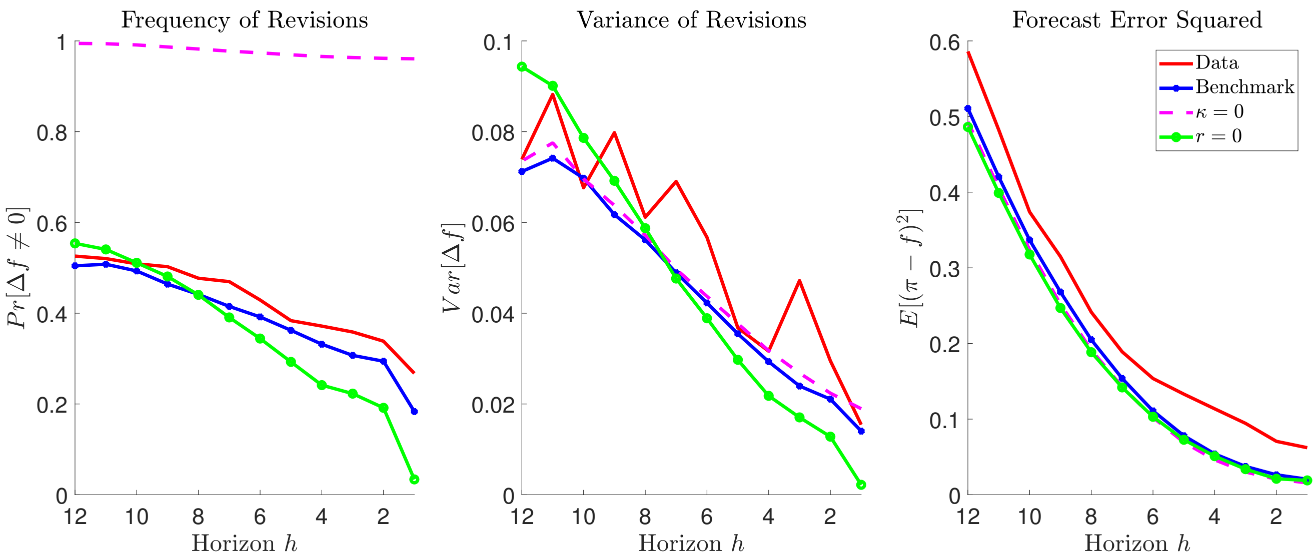
Sources: Data for 2010-2019. Model with benchmark calibration

4.3 On the role of fixed revision costs and strategic concerns

We explore two alternative model versions of the model to assess the role of fixed costs κ and strategic concerns r. In each panel of Figure VII, we plot four lines: data (red), benchmark calibration (blue), zero fixed costs $\kappa = 0$ (dashed pink), and zero strategic concerns $r = 0$ (dotted blue).

As expected, the model with zero fixed costs implies a frequency of revisions close to one for all horizons, and thus fails dramatically in replicating the observed empirical patterns. The model with zero strategic concerns delivers steeper profiles in frequency and variance. Notably, all model configurations delivers very similar patterns for the square of forecast errors.

Figure VII – Cross-sectional moments across model configurations



5 Extensive and Intensive Margins of Revisions

This section explores the determinants of forecast revisions' extensive and intensive margins, both in data and model. First, we construct two gaps: (i) the distance between the past forecast and the current AR(1) projection and (ii) the distance between the past forecast and the current consensus.

Given individual forecasts and public information, we define the following variables at the individual level. Let b_h^i be the gap between individual i's forecast at horizon $h+1$ and an AR(1) estimate z_h defined in (10) at horizon h:

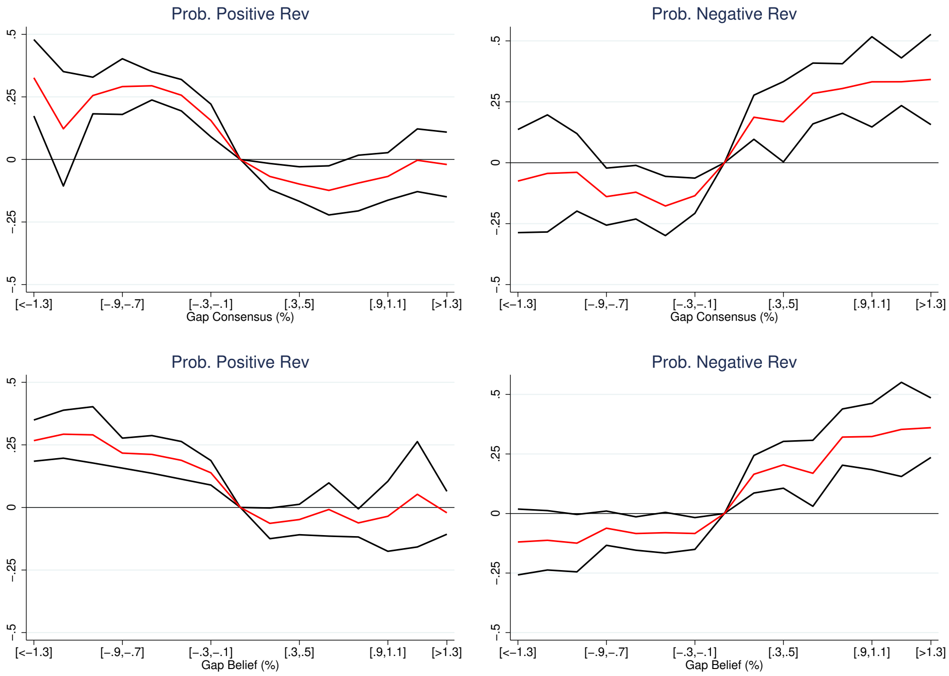
$$b_h^i \equiv f_{h+1}^i - z_h. \tag{26}$$

Also, let c_h^i be the gap between individual i's forecast at horizon $h+1$ and the consensus forecast at horizon h:

$$c_h^i \equiv f_{h+1}^i - F_h. \tag{27}$$

In the model, these gaps arise because of revision costs, private information, and strategic concerns. In the data, they may also arise because of other forces not considered in the model, such as higher-order beliefs, heterogeneous parameters, model misspecification, and heterogeneity in revision costs or strategic concerns.

Figure VIII – Extensive Margin: Data



Notes: Bloomberg data.

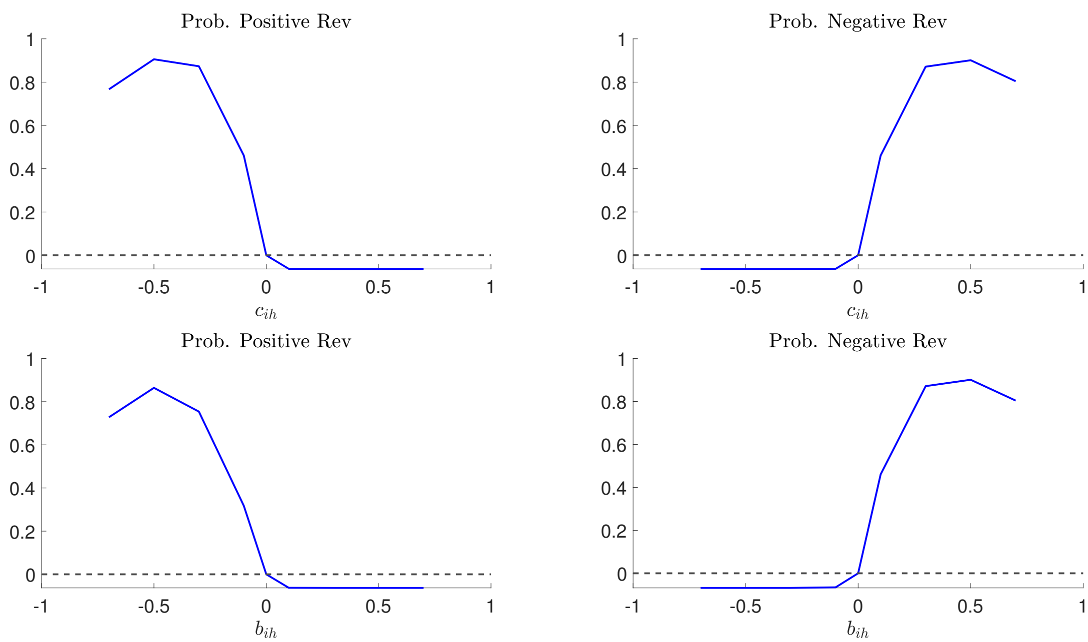
5.1 The extensive margin and its determinants

First, we examine how the consensus gap c_h^i and the AR gap b_h^i shape the probability of updating a prediction, that is, the extensive margin. Figure VIII plots the average frequency of upward revisions (left column) and the average frequency of downward revisions (right column) with respect to the consensus gap (top row) and the AR(1) gap (bottom row). These probabilities are residuals that control for forecaster-fixed effects.[7] Figure IX plots the same variables in the model.

Two interesting features arise. First, as the relative distance between the forecasts and either gap increases, the probability of a revision increases as well; however, the likelihood of revising upward or downward depends on the sign of the gap. When gaps are above zero, the probability of doing a positive revision ($f_h^i > f_{h+1}^i$) drops while the probability of revising downwards ($f_h^i < f_{h+1}^i$) significantly increases. Likewise, when gaps are negative, the probability of revising upward significantly increases, and the probability of revising downward decreases. Second, the extensive margin reaction appears to be asymmetric; that is, the updating probability reacts differently depending on whether the forecast is below or above the focal point (consensus or belief). Overall, these two gaps have a significant effect on the extensive margin of revisions.

[7]See the Appendix for details on constructing residual adjustment probabilities.

Figure IX – Extensive Margin: Model

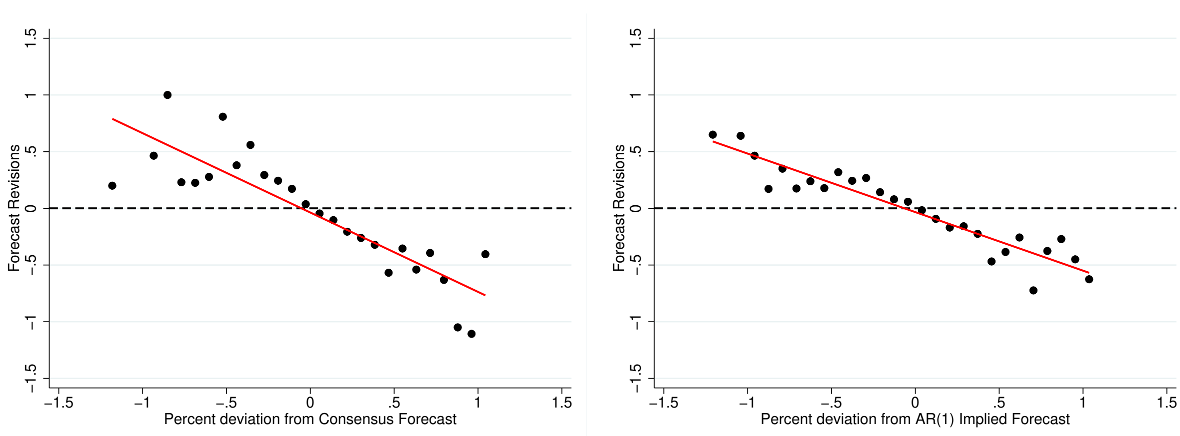


Notes: Model, benchmark calibration.

5.2 The intensive margin and its determinants

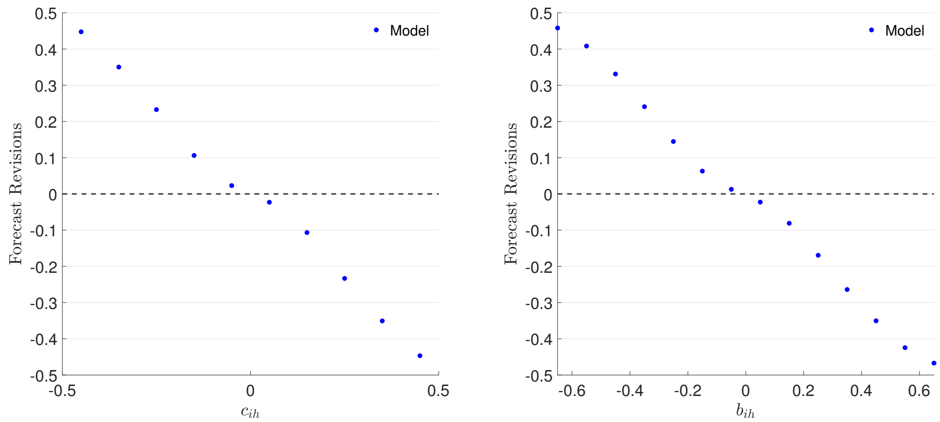
Conditioning on agent revisions, we now study the determinants behind the magnitude of revisions as a function of the two gaps. Figure X plots the average revision as a function of both c_h^i and b_h^i. As with the extensive margin, we plot residual revisions that control for a battery of fixed effects. Figure XI shows the intensive margin for the model. All figures show that positive deviations call for negative revisions and the contrary for negative deviations. The strong negative correlation implies that larger deviations call for larger revisions. When either gap is positive (negative), the agent partially revises downwards (upwards) to close this gap.

Figure X – Intensive Margin: Data



Notes: Bloomberg data.

Figure XI – Intensive Margin: Model



Notes: Model generated, benchmark calibration.

6 Forecast efficiency tests

In our first exercise, we analyze forecast error predictability at the individual level using the following empirical strategy. The tests build on the work by Bordalo, Gennaioli, Ma and Shleifer (2020), extended by Broer and Kohlhas (2022) and Valchev and Gemmi (2023) to incorporate the consensus forecast as a source of public information.

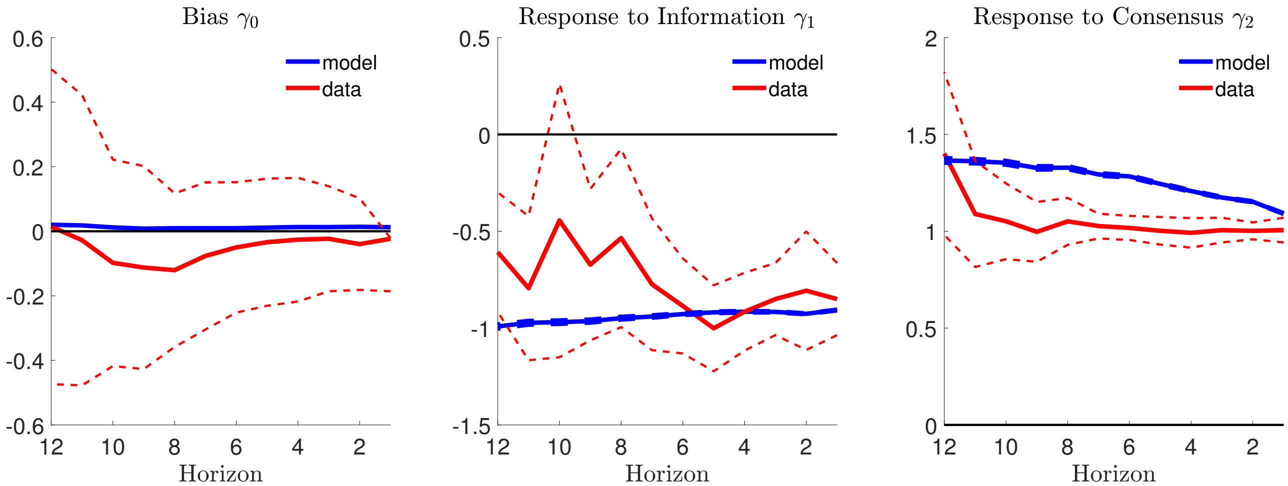
Let $\pi_t - f^h_{t-h}$ be the individual forecast error at horizon h about annual inflation (known at time t), $f^i_{t-h} - f^i_{t-h+1}$ be the forecast revision between consecutive months for the same variable, and $F_{t,h} - f^i_{t,h+1}$ be the surprise contained in public information. Relying on the panel structure, we run the following OLS regression.

$$\underbrace{\pi_t - f^i_{t,h}}_{\text{error}} = \underbrace{\gamma^h_0}_{\text{bias}} + \gamma^h_1 \underbrace{(f^i_{t,h} - f^i_{t,h+1})}_{\text{revision}} + \gamma^h_2 \underbrace{(F_{t,h} - f^i_{t,h+1})}_{\text{public info}} + \epsilon^i_h. \tag{28}$$

Relative to the literature, which considers a fixed horizon h, we run the regression for different horizons. As a useful benchmark, note that rational expectations imply that $\gamma^h_0 = \gamma^h_1 = 0$, even under the presence of information frictions. Moreover, if $\gamma^h_1 > 0$, a positive revision predicts a higher realization of inflation relative to the forecast, meaning that the average forecaster underreacts to his own information. In contrast, if $\gamma^h_1 < 0$ indicates that the average forecasters overreact to his information. Analogously, the sign of γ^h_2 reflects how information contained in public surprises affects forecast errors.

With our simulated data, we also run regression (28). Interestingly, and although we did not target any of these results, the model can predict, across all horizons, three features of the data: (i) the zero bias (left panel), (ii) the over-reaction to private information (middle panel), and (iii) the under-reaction to the consensus (right panel).

Figure XII – Efficiency tests in model and data



Notes: Data for normal years. Model with benchmark calibration.

Consistent with the empirical regressions, we find a non-significant bias, a negative and significant coefficient on forecast revisions (interpreted as over-reaction to private information), and a positive and significant coefficient on the distance to the consensus (interpreted as an under-reaction to public information). Importantly, our results are generated in a model with Bayesian agents, without the need of behavioral biases (e.g., extrapolating expectations) as in Bordalo, Gennaioli, Ma and Shleifer (2020).

7 Forecaster Heterogeneity

In our second exercise, we explore heterogeneity across forecaster types. The survey contains four types of forecasters: (i) banks, (ii) financial and investment institutions, (iii) economic consulting companies, and (iv) universities and research centers. Table V shows substantial heterogeneity in average cross-sectional moments in normal years. The most significant differences occur between consulting firms and universities. For instance, relative to universities, consulting firms adjust 30% more than universities.

Table V – Cross-sectional moments by forecaster type

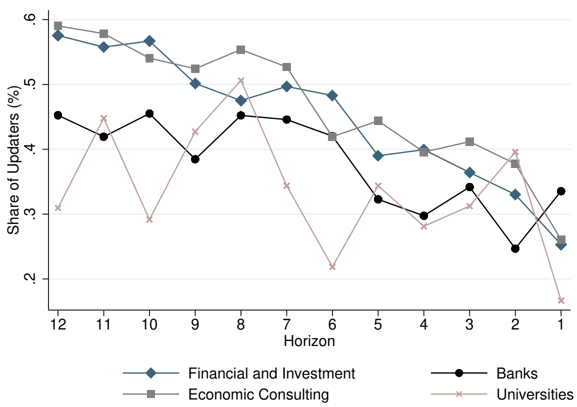
	All		**Financial Inst.**		**Banks**		**Consulting**		**Universities**	
Moment	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model
$\Pr[\Delta f \neq 0]$	0.43	0.43	0.45	0.46	0.38	0.37	0.47	0.45	0.34	0.34
$\mathbb{V}ar[\Delta f]$	0.05	0.05	0.06	0.06	0.06	0.07	0.08	0.07	0.06	0.07
$\mathbb{E}[(\pi - f)^2]$	0.23	0.21	0.28	0.21	0.22	0.23	0.25	0.23	0.24	0.24
Observations	12,355		5,366		2,567		2,982		1,440	

Notes: Bloomberg data. Data for normal years 2010-2019.

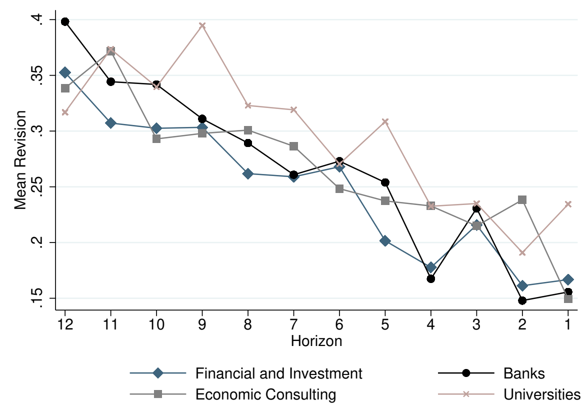
For each of the four groups, Figure XIII shows the term structure of adjustment frequency, size, and forecast errors. These term structures are broadly consistent with the general patterns observed for the average moments, with universities being the group that adjusts less often but for larger amounts across horizons, while consulting firms do the opposite.

Figure XIII – Term Structure of Revisions and Errors: By Forecaster Type

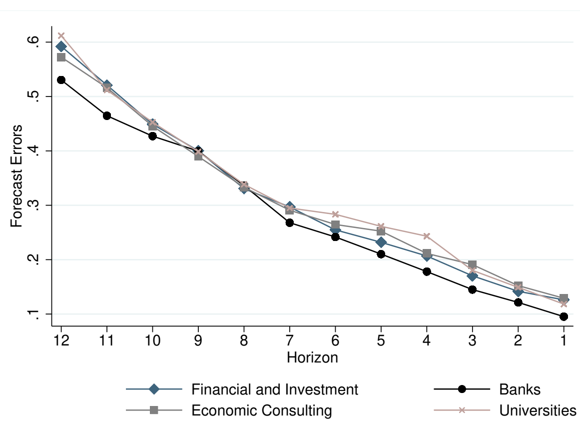
(a) Frequency



(b) Size



(c) Accuracy by Group



Notes: Bloomberg data.

Calibration by forecaster type The differences in the cross-sectional moments of forecast revisions and forecast errors reflect potential differences in strategic concerns (r) and preference for forecast stability (κ). Given the observed heterogeneity, we recalibrate four versions of the model, each matching type-specific moments. We consider heterogeneity in two parameters: fixed costs κ_G and strategic concerns r_G. Results are reported in Table VI. Through the lens of the model, these moments imply that universities face higher revision costs and stronger concerns for forecast stability. Thus, our results suggest that forecast heterogeneity is an important dimension to consider when working with this type of survey.

Table VI – Calibration by forecaster type

Parameter	All	Financial Inst.	Banks	Consulting	Universities
κ	0.083	0.087	0.143	0.116	0.190
r	0.263	0.193	0.520	0.528	0.604
σ_ζ^2	0.098	0.045	0.067	0.050	0.054

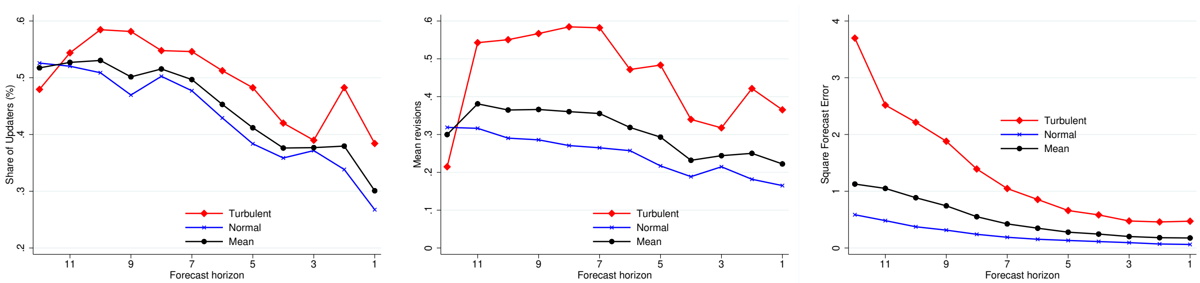
Notes: Calibration that targets the group-specific moments reported in Table V.

8 Changes in inflation volatility

In our third and last exercise, we investigate the forecasts' response to changes in underlying inflation volatility. In four years in our sample, economic conditions were far from ordinary. In particular, at the two ends of the sample, we have the Great Recession between 2008 and 2009 and the COVID-19 pandemic between 2020 and 2021. The volatility of monthly inflation was different over these two episodes: in turbulent years, inflation volatility is 36% higher than in normal years. We split the sample between normal years, 2010-2019, and turbulent years, 2008-2009 and 2020-21. Tables VII and VIII in the Appendix show summary statistics of forecast revisions and errors for normal and turbulent years. Figure XIV shows the term structure of (a) frequency of revisions, (b) variance of revisions, and (c) forecast errors squared. In turbulent years, forecast revisions are more frequent and dispersed, and forecast errors sharply increase.

Figure XIV – Term Structure of Forecast Revisions: Normal vs. Turbulent Tears

(a) Frequency **(b)** Size **(c)** Accuracy

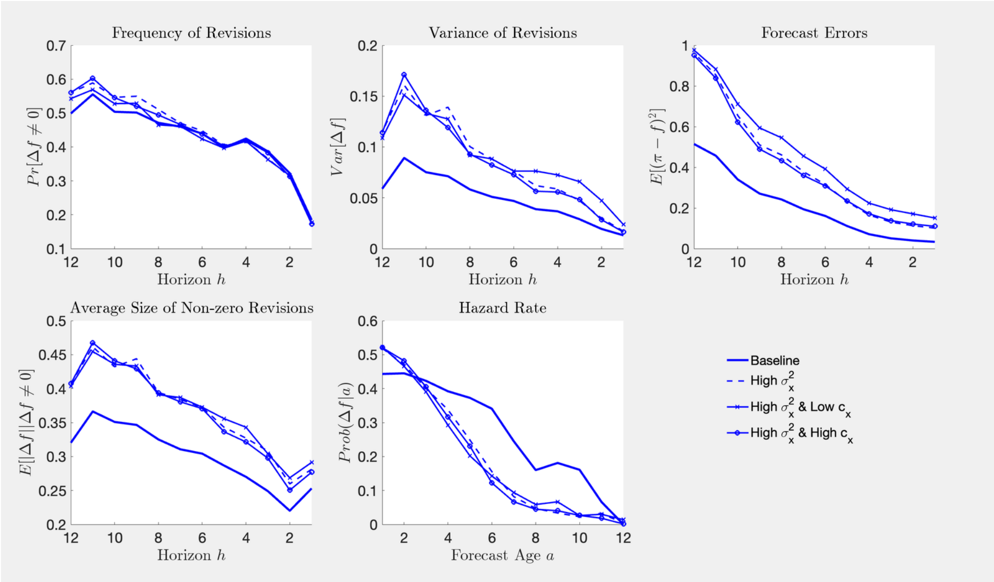


Notes: Bloomberg data. Notes: Normal years = 2010-2019. Turbulent years = 2008-2009 and 2020-21.

We explore if the model is able to deliver these changes in cross-sectional moments. We implement increasing monthly inflation volatility as in the data, $1.36 \times \sigma_x^2$. We also consider two different unconditional means. Low c_x for 2008-2009 and high c_x for 2020-2021. Then we simulate the economy under two scenarios: disclosed and undisclosed regime changes in the underlying parameters.

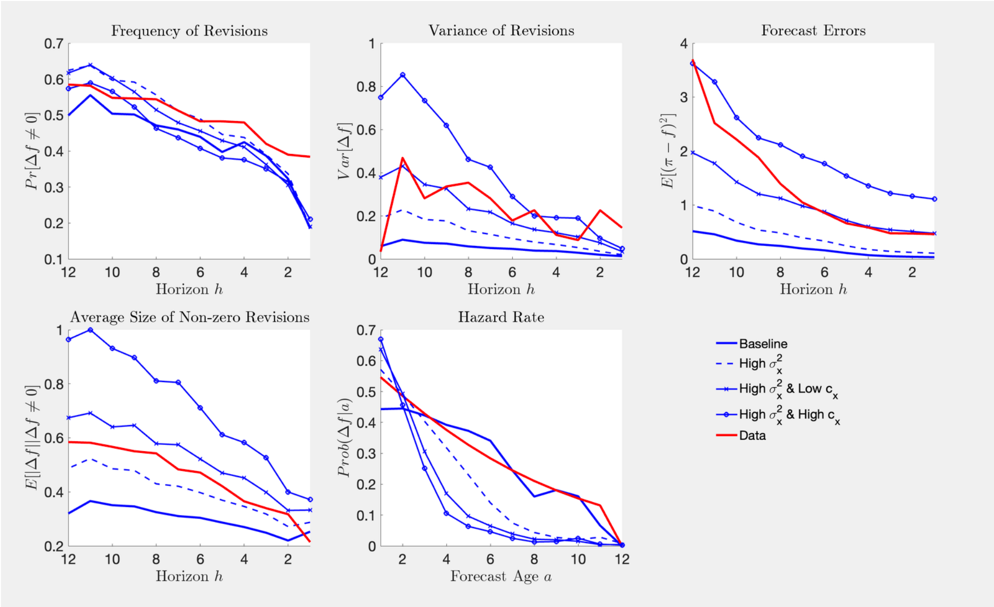
Disclosed regime change In the first scenario, we give forecasters the information that volatility and mean have changed. Figure XV shows the results. Relative to the baseline calibration (solid line, that matches moments in normal years) higher volatility increases all moments, regardless of the change in the mean.

Figure XV – Changes in underlying process: Disclosed shock



Undisclosed regime change In the second scenario, agents ignore that parameters have changed and thus keep the policy functions as in the benchmark calibration. Figure XVI shows the results. We also superimpose the data for turbulent years. The cross-sectional moments increase much more, especially forecast errors.

Figure XVI – Changes in underlying process: Undisclosed shock



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Lumpy Forecasts

Isaac Baley and Javier Turén

Online Appendix

A Summary statistics

Table VII – Summary Statistics of Forecast Revisions

		All	**Turbulent**	**Normal**
Average	$\mathbb{E}(\Delta f)$	-0.002	0.028	-0.013
Size	$\mathbb{E}(abs(\Delta f)\|\Delta f \neq 0)$	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
Positive spikes	$\Delta f/f > 0.2$	0.076	0.227	0.023
Negative spikes	$\Delta f/f < -0.2$	0.005	0.004	0.005
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
Annual Inflation	π	1.896	2.175	1.795
Observations	N	12,619	3,363	9,256

Sources: Bloomberg data. Notes: Normal years = 2010-2019. Turbulent years = 2008-2009 and 2020-21. Numbers are averages across sample years and 12 horizons.

Table VIII – Summary Statistics of Forecast Errors

		All	**Turbulent**	**Normal**
Average	$\mathbb{E}(e)$	0.023	0.237	-0.055
Size	$\mathbb{E}(abs(e))$	0.434	0.789	0.305
Positive	$\Pr(e > 0)$	0.414	0.606	0.345
Negative	$\Pr(e < 0)$	0.510	0.340	0.572
Dispersion	$\sigma(e)$	0.663	1.105	0.502
Serial correlation	$corr(e, e_{-1})$	0.882	0.878	0.877
Observations	N	12,619	3,363	9,256

Sources: Bloomberg data. Notes: Normal years = 2010-2019. Turbulent years = 2008-2009 and 2020-21. Numbers are between-year averages of within-year statistics.

B Proofs

B.1 Forecasters' Beliefs

In this section we derive expressions for the mean $z_h^i \equiv \mathbb{E}[\pi|\mathcal{I}_h^i]$ and the variance $\Sigma_h^z \equiv \mathbb{E}[(\pi - z_h^i)^2|\mathcal{I}_h^i]$ of annual inflation beliefs.

Demeaned monthly inflation We begin from the assumption of an AR(1) process for monthly inflation:

$$x_h = c_x + \phi_x x_{h+1} + \varepsilon_h^x. \tag{B.1}$$

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

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

Annual inflation Annual inflation π is approximately equal to the sum of the twelve realizations of monthly inflation x_h within each target year $\pi = \sum_{h=1}^{12} x_h$. Add proof.

Without loss of generality, we can derive π as a function of the initial value of monthly inflation x_{12}:

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

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

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

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 while 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 $h = 12, 11, \ldots, 1$ can be written as follows:

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

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 end-of-year inflation are:

$$\mathbb{E}[\pi] = \tag{B.5}$$

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

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

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

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

$$\pi \;=\; 12 \left(\frac{c_x}{1-\phi_x} \right) \;+\; \phi_x \frac{1-\phi_x^{12}}{1-\phi_x} \left(x_{13} - \frac{c_x}{1-\phi_x} \right) \;+\; \sum_{j=1}^{11} \frac{1-\phi_x^j}{1-\phi_x} \varepsilon^x_j. \tag{B.8}$$

B.1.1 Private Signals

As each horizon h, forecasters observed a noisy signal $\widetilde{x}_h$ about monthly inflation, given by $\widetilde{x}^i_h = x_h + \eta_h + \zeta_{ih}$. Agents update their beliefs at the beginning of each month before the actual value of monthly inflation is released. Hence, we interpret the signal $\widetilde{x}_{ih}$ as news. In addition, the historical values of lagged monthly inflation are observed without noise. Thus, the forecasters information set at each horizon $\mathcal{I}^i_h = \{\widetilde{x}^i_h, x_{h+1}, x_{h+2}, \ldots\}$.

Taking the conditional expectation of equation (B.4), given information up to horizon h, delivers the signal z^i_h:

$$z^i_h \;=\; h \left(\frac{c_x}{1-\phi_x} \right) \;+\; \frac{1-\phi_x^h}{1-\phi_x} \left(\widetilde{x}^i_h - \frac{c_x}{1-\phi_x} \right) \;+\; \sum_{i=h+1}^{12} x_j \qquad \text{for } h = 12, \ldots, 1 \tag{B.9}$$

which corresponds to equation (19) in the main text.

B.1.2 Signal Precision

Forecasters evaluate their signals' precision through the AR(1) model. We define forecast errors as the difference between end-of-year inflation and the signal: $\varepsilon^i_h \equiv \pi - z^i_h$. Given the expressions for π in (B.4) and z_h in (B.9), forecast errors are expressed as:

$$\varepsilon^i_h \;=\; \pi - z^i_h \;=\; \frac{1-\phi_x^h}{1-\phi_x}(\zeta_{ih} + \eta_h) \;+\; \sum_{j=1}^{h-1} \frac{1-\phi_x^j}{1-\phi_x} \varepsilon^x_j \qquad \forall h \tag{B.10}$$

Squaring and taking expectations, we obtain the variance of the forecast error $\Sigma^z_h \equiv \mathbb{E}[(\varepsilon^i_h)^2]$ at each horizon h:

$$\Sigma^z_h \;=\; \left(\frac{1-\phi_x^h}{1-\phi_x} \right)^2 (\sigma^2_\zeta + \sigma^2_\eta) \;+\; \frac{\sigma^2_x}{(1-\phi_x)^2} \sum_{j=1}^{h-1} (1-\phi_x^j)^2 \qquad \forall h \tag{B.11}$$

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

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

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

$$\Sigma_h^z \;=\; (\sigma_\eta^2+\sigma_\zeta^2)\left(\frac{1-\phi^h}{1-\phi}\right)^2 + \frac{\sigma_v^2}{(1-\phi)^2}\left[(h-1)-\frac{2\phi(1-\phi^{h-1})}{1-\phi}+\frac{\phi^2(1-\phi^{2(h-1)})}{1-\phi^2}\right]. \tag{B.12}$$

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

B.1.3 Relationship between individual vs. public signals

The public signal z_h in (10) projects the past release x_{h+1} to obtain the yearly forecast:

$$z_h \;=\; h\left(\frac{c_x}{1-\phi_x}\right) \;+\; \frac{\phi_x(1-\phi_x^h)}{1-\phi_x}\left(x_{h+1}-\frac{c_x}{1-\phi_x}\right) \;+\; \sum_{j=h+1}^{12} x_j. \tag{B.13}$$

In contrast, the private signal z_h^i in (**??**) projects the noisy observation $\widetilde{x}_h^i$ to obtain the yearly forecast (note the extra ϕ in the second term of the expression above, reflecting the timing of the information):

$$z_h^i \;=\; h\left(\frac{c_x}{1-\phi_x}\right) \;+\; \frac{1-\phi_x^h}{1-\phi_x}\left(\hat{x}_h^i-\frac{c_x}{1-\phi_x}\right) \;+\; \sum_{j=h+1}^{12} x_j. \tag{B.14}$$

Next, in the first line, we substitute the expression for the noisy signal $\widetilde{x}_h^i = x_h + \zeta_h^i + \eta_h$. In the second line, we substitute the expression for the (demeaned) true monthly inflation $x_h - c_x/(1-\phi_x) = \phi_x(x_{h+1} - c_x/(1-\phi_x)) + \varepsilon_h^x$. Lastly, in the third line we define the noise term $\nu_h^i \equiv \frac{1-\phi_x^h}{1-\phi_x}(\varepsilon_h^x \;+\; \eta_h)$ and compute its noise.

B.1.4 Relationship between z_h and z_h^i

Next, we establish a relationship between the public and the private signals about yearly inflation.

$$\begin{aligned} z_h^i \;&=\; h\left(\frac{c_x}{1-\phi_x}\right) \;+\; \frac{1-\phi_x^h}{1-\phi_x}\left(x_h-\frac{c_x}{1-\phi_x}\;+\;\zeta_h^i\right) \;+\; \sum_{j=h+1}^{12} x_j \\ &=\; h\left(\frac{c_x}{1-\phi_x}\right) \;+\; \frac{1-\phi_x^h}{1-\phi_x}\left(\phi_x\left(x_{h+1}-\frac{c_x}{1-\phi_x}\right)\;+\;\varepsilon_h^x\;+\;\zeta_h^i\right) \;+\; \sum_{j=h+1}^{12} x_j \\ &=\; z_h \;+\; \nu_h^i, \qquad \nu_\eta^i \sim \mathcal{N}\left(0, \left[\frac{1-\phi_x^h}{1-\phi_x}\right]^2 \alpha^2(\sigma_v^2+\sigma_\zeta^2)\right). \end{aligned} \tag{B.15}$$

B.1.5 Martingale property of beliefs

Beliefs follow a martingale: expected of future belief equal current beliefs, i.e, $\mathbb{E}[z_{h-1}^i|\mathcal{I}_h^i] = z_h^i$. First, we use the relationship between public and private beliefs in (B.15) to set the expectation of individual noise ν to zero.

$$\mathbb{E}[z_{h-1}^i|\mathcal{I}_h^i] \;=\; \mathbb{E}[z_{h-1}+\nu_{h-1}^i|\mathcal{I}_h^i] \;=\; \mathbb{E}[z_{h-1}|\mathcal{I}_h^i]. \tag{B.16}$$

Next, we show that the expected public belief equals current public belief. Substituting in the expression for z_{h-1} in (10) and applying the expectation conditional on $\mathcal{I}_h^i$, we get:

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

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

$$\mathbb{E}[z_{h-1}|\mathcal{I}_h^i] \quad = \quad \underbrace{h\frac{c_x}{1-\phi_x} + \frac{1-\phi_x^h}{1-\phi_x}\left(\widehat{x}_h^i - \frac{c_x}{1-\phi_x}\right) + \sum_{j=h+1}^{12} x_j}_{=\, z_h^i} \quad \underbrace{-\frac{c_x}{1-\phi_x} - \frac{1-\phi_x}{1-\phi_x}\left(\widehat{x}_h^i - \frac{c_x}{1-\phi_x}\right) + \widehat{x}_h^i}_{=\,0}.$$

We conclude that $\mathbb{E}[z_{h-1}|\mathcal{I}_h^i] = z_h^i$. 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.2 Proof of Proposition 1

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

$$\mathbb{E}\left[\sum_{h=12}^{1} \mathbb{E}[(f_h^i - \pi)^2|\mathcal{I}_h^i] \;+ r\; \mathbb{E}[(f_h^i - F_h)^2|\mathcal{I}_h^i] \;+\; \kappa \mathbb{1}_{\{f_h^i \neq f_{h+1}^i\}} \Big| \mathcal{I}_0^i\right]$$

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:

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

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 $\mathbb{E}[(\hat{\pi}_h^i - \pi)|\mathcal{I}_h^i] = \mathbb{E}[(\hat{F}_h^i - F_h)|\mathcal{I}_h^i] = 0$:

$$\sum_{h=12}^{1} \mathbb{E}\left[\Sigma_h^\pi \;+\; r\Sigma_h^F \;+\; \mathbb{E}[(f_h^i - \hat{\pi}_h^i)^2|\mathcal{I}_h^i] \;+\; r\mathbb{E}[(f_h^i - \hat{F}_h^i)^2|\mathcal{I}_h^i] \;+\; \kappa \mathbb{1}_{\{f_h^i \neq f_{h+1}^i\}} \Big| \mathcal{I}_0^i\right].$$

B.3 Proof of Proposition 2

Given the stationarity of the problem and the stochastic processes, we apply the Principle of Optimality to the sequential problem and express it as a sequence of stopping-time problems Let τ be the stopping data associated with the optimal decision given the state $(\hat{\pi}_h^i, \hat{F}_h^i)$. The stopping time problem is given by:

B.4 Frictionless benchmark

As a benchmark, we assume away the adjustment cost and set $\kappa = 0$. In this case, the problem becomes static, and the optimal forecast at horizon h minimizes per-period losses:

$$\min_{\{f_h^i\}} \ (f_h^i - \hat{\pi}_h^i)^2 \ + \ r(f_h^i - \hat{F}_h)^2 \tag{B.17}$$

The FOC yields:

$$f_h^i \ = \ \frac{1}{1+r}\left(\hat{\pi}_h^i + r\hat{F}_h\right). \tag{B.18}$$

Substituting the Bayesian beliefs yields:

$$f_h^i \ = \ z_h \ + \ r\,(c_F + \phi_F F_{h+1}) \ + \ \nu_h^i, \quad \text{with} \quad \nu_h^i \sim \mathcal{N}\left(0, \left[\frac{1-\phi_x^h}{1-\phi_x}\right]^2 \alpha^2(\sigma_x^2 + \sigma_\zeta^2)\right). \tag{B.19}$$

where α is the weight on private signals: $\alpha \equiv \frac{(\sigma_\zeta^2+\sigma_\eta^2)^{-1}}{(\sigma_x^2)^{-1}+(\sigma_\zeta^2+\sigma_\eta^2)^{-1}}$.

Rationality tests The rationality test is

$$\pi - f_h^i \ = \ \gamma_0 \ + \ \gamma_1(f_h^i - f_{h+1}^i) \ + \ \gamma_2(F_h - f_{h+1}^i) \ + \ \eta_h^i, \qquad \mathbb{E}[\eta_h^i] = 0. \tag{B.20}$$

It can be written as:

$$\pi - f_h^i \ = \ \gamma_0 \ + \ (\gamma_1 + \gamma_2)(f_h^i - f_{h+1}^i) \ + \ \gamma_2(F_h - f_h^i) \ + \ \eta_h^i, \qquad \mathbb{E}[\eta_h^i] = 0. \tag{B.21}$$

or

$$\pi - f_h^i \ = \ \gamma_0 \ + \ (\gamma_1 + \gamma_2)(f_h^i - f_{h+1}^i) \ + \ \gamma_2(F_h - \hat{F}_h) + \gamma_2(\hat{F}_h - f_h^i) \ + \ \eta_h^i. \tag{B.22}$$

Let us first compute the forecast revision $(f_h^i - f_{h+1}^i)$. From the FOC in the frictionless case:

$$f_h^i \ = \ z_h \ + \ r\hat{F}_h \ + \ \nu_h^i, \quad \text{with} \quad \nu_h^i \sim \mathcal{N}\left(0, \left[\frac{1-\phi_x^h}{1-\phi_x}\right]^2 \alpha^2(\sigma_x^2 + \sigma_\zeta^2)\right). \tag{B.23}$$

we have that revisions are driven by two surprises in beliefs and an *iid* term:

$$f_h^i - f_{t+1}^i \quad = \quad \frac{1}{1+r}\left[\underbrace{(z_h - z_{h+1})}_{\text{surprise I: } \frac{1-\phi_x^{h+1}}{1-\phi_x}\epsilon_{h+1}^x} \quad + r\underbrace{\left(\hat{F}_h - \hat{F}_{h+1}\right)}_{\text{surprise II}} + (\nu_h^i - \nu_{h+1}^i)\right] \tag{B.24}$$

Now we compute the two surprise or news terms.

- Surprise I—difference in the z_h's—is computed as

$$
\begin{aligned}
z_h - z_{h+1} &= (h-(h+1))\left(\frac{c_x}{1-\phi_x}\right) + \frac{\phi_x(1-\phi_x^h)}{1-\phi_x}\left(x_{h+1} - \frac{c_x}{1-\phi_x}\right) - \frac{\phi_x(1-\phi_x^{h+1})}{1-\phi_x}\left(x_{h+2} - \frac{c_x}{1-\phi_x}\right) + \sum_{j=h+1}^{12} x_j - \sum_{j=h+2}^{12} x_j \\
&= -\left(\frac{c_x}{1-\phi_x}\right) + \frac{\phi_x(1-\phi_x^h)}{1-\phi_x}\left(x_{h+1} - \frac{c_x}{1-\phi_x}\right) - \frac{\phi_x(1-\phi_x^{h+1})}{1-\phi_x}\left(x_{h+2} - \frac{c_x}{1-\phi_x}\right) + \frac{1-\phi_x}{1-\phi_x}x_{h+1} \\
&= -(1-\phi^{h+1})\left(\frac{c_x}{1-\phi_x}\right) \;+\; \frac{(1-\phi_x^{h+1})}{1-\phi_x}\left(x_{h+1} - \phi_x x_{h+2}\right) \\
&= -\frac{1-\phi^{h+1}}{1-\phi_x}c_x \;+\; \frac{1-\phi_x^{h+1}}{1-\phi_x}(c_x + \epsilon_{h+1}^x) \\
&= \frac{1-\phi_x^{h+1}}{1-\phi_x}\epsilon_{h+1}^x
\end{aligned}
$$

- Surprise II—difference in the $\hat{F}_h$'s—is computed as

$$
\begin{aligned}
\hat{F}_h - \hat{F}_{h+1} &= c_F \;-\; (1-\phi_F)F_{h+1} \;+\; \epsilon_h^F \;+\; (F_{h+1} - \hat{F}_{h+1}) \\
&= c_F \;-\; (1-\phi_F)F_{h+1} \;+\; \epsilon_h^F \;+\; \epsilon_{h+1}^F
\end{aligned}
$$

Next, we compute the consensus gap $F_h - f_h^i$. From the AR(1) assumption on the consensus process:

$$\hat{F}_h - f_h^i \;=\; \hat{F}_h - \; z_h \;-\; r\hat{F}_h \;+\; \nu_h^i \;=\; (1-r)\hat{F}_h - \; z_h \;+\; \nu_h^i \tag{B.25}$$

Putting everything together, we have:

$$
\begin{aligned}
\pi - f_h^i &= \gamma_0 + (\gamma_1+\gamma_2)(f_h^i - f_{h+1}^i) + \gamma_2(F_h - f_h^i) + \eta_h^i \\
&= \gamma_0 + \frac{(\gamma_1+\gamma_2)}{1+r}\left[\frac{1-\phi_x^{h+1}}{1-\phi_x}\epsilon_{h+1}^x + r(c_F - (1-\phi_F)F_{h+1}) + r(\epsilon_h^F + \epsilon_{h+1}^F) + \nu_h^i - \nu_{h+1}^i\right] + \gamma_2\left[\epsilon_h^F + (1-r)\hat{F}_h - z_h + \nu_h^i\right. \\
&= \gamma_0 + \frac{(\gamma_1+\gamma_2)}{1+r}\left[\frac{1-\phi_x^{h+1}}{1-\phi_x}\epsilon_{h+1}^x + r(\epsilon_h^F + \epsilon_{h+1}^F) + \nu_h^i - \nu_{h+1}^i\right] + \gamma_2\left[\epsilon_h^F + \nu_h^i\right] + \eta_h^i \\
&+ \frac{(\gamma_1+\gamma_2)}{1+r}r(c_F - (1-\phi_F)F_{h+1}) + \gamma_2[(1-r)\hat{F}_h - z_h] \\
&= \gamma_0 + \frac{(\gamma_1+\gamma_2)}{1+r}\left[\frac{1-\phi_x^{h+1}}{1-\phi_x}\epsilon_{h+1}^x + r(\epsilon_h^F + \epsilon_{h+1}^F) + \nu_h^i - \nu_{h+1}^i\right] + \gamma_2\left[\epsilon_h^F + \nu_h^i\right] + \eta_h^i \\
&+ \frac{(\gamma_1+\gamma_2)}{1+r}r(c_F - (1-\phi_F)F_{h+1}) + \gamma_2[(1-r)\hat{F}_h - z_h]
\end{aligned}
$$

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$$\pi - f_h^i \;=\; \gamma_0 \;+\; \gamma_1(f_h^i - f_{h+1}^i) \;+\; \eta_h^i, \qquad \mathbb{E}[\eta_h^i] = 0. \tag{B.26}$$

Since we have

$$f_h^i - f_{t+1}^i \;=\; \frac{1}{1+r}(z_h - z_{h+1}) \;=\; \frac{1}{1+r}\frac{1-\phi_x^{h+1}}{1-\phi_x}\epsilon_{h+1}^x \tag{B.27}$$

then

$$\pi - f_h^i \;=\; \gamma_0 \;+\; \gamma_1\left[\frac{1}{1+r}\frac{1-\phi_x^{h+1}}{1-\phi_x}\epsilon_{h+1}^x\right] \;+\; \eta_h^i \tag{B.28}$$

Average forecast errors in frictionless benchmark Alternatively, it can be written as:

$$\pi - f_h^i \;=\; \gamma_0 \;+\; \gamma_1 f_h^i - (\gamma_1 + \gamma_2) f_{h+1}^i \;+\; \gamma_2 F_h \;+\; \eta_h^i, \qquad \mathbb{E}[\eta_h^i] = 0. \tag{B.29}$$

$$e_h \;=\; \pi - \int f_h^i \, \mathrm{d}i \;=\; \pi - \; z_h \;-\; r\left(c_F + \phi_F F_{h+1}\right) \tag{B.30}$$

$$h\left(\frac{c_x}{1-\phi_x}\right) \;+\; \frac{\phi_x(1-\phi_x^h)}{1-\phi_x}\left(x_{h+1} - \frac{c_x}{1-\phi_x}\right) \;+\; \sum_{j=h+1}^{12} x_j \tag{B.31}$$

C 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.

C.1 Distributions of expected beliefs

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

$$\hat{\pi}^i_{h-1} = \left(\frac{\Sigma_{z,h-1}}{\sigma_o^2 + \Sigma_{z,h-1}}\right)\mu_o + \left(1 - \frac{\Sigma_{z,h-1}}{\sigma_o^2 + \Sigma_{z,h-1}}\right) z^i_{h-1} \tag{C.32}$$

$$\hat{F}_{h-1} = c_F + \phi_F F_h \tag{C.33}$$

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:

$$\mathbb{E}[\hat{F}_{h-1}|\mathcal{I}^i_h] = c_F + \phi_F \mathbb{E}[F_h|\mathcal{I}^i_h] = c_F(1+\phi_F) + \phi_F^2 F_{h+1} \tag{C.34}$$

$$\mathbb{V}ar[\hat{F}^i_{h-1}|\mathcal{I}^i_h] = \phi_F^2 \mathbb{V}ar[F_h|\mathcal{I}^i_h] = \phi_F^2 \sigma_F^2 \tag{C.35}$$

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

$$\mathbb{E}[\hat{\pi}^i_{h-1}|\mathcal{I}^i_h] = \left(\frac{\Sigma_{z,h-1}}{\sigma_o^2 + \Sigma_{z,h-1}}\right)\mu_o + \left(1 - \frac{\Sigma_{z,h-1}}{\sigma_o^2 + \Sigma_{z,h-1}}\right)\mathbb{E}[z^i_{h-1}|\mathcal{I}^i_h] \tag{C.36}$$

$$\mathbb{V}ar[\hat{\pi}^i_{h-1}|\mathcal{I}^i_h] = \left(\frac{\sigma_o^2\Sigma_{z,h-1}}{\sigma_o^2 + \Sigma_{z,h-1}}\right)^2 \mathbb{V}ar[z^i_{h-1}|\mathcal{I}^i_h] \tag{C.37}$$

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

Expected signals We evaluate the formula for z^i_h in (**??**) at $h-1$, and separate the observation x_h from the sum yields:

$$z^i_{h-1} = (h-1)\left(\frac{c_x}{1-\phi_x}\right) + \frac{1-\phi_x^{h-1}}{1-\phi_x}\left(\widetilde{x}^i_{h-1} - \frac{c_x}{1-\phi_x}\right) + x_h + \sum_{j=h+1}^{12} x_j. \tag{C.38}$$

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

$$\mathbb{E}[z^i_{h-1}|\mathcal{I}^i_h] = (h-1)\left(\frac{c_x}{1-\phi_x}\right) + \frac{1-\phi_x^{h-1}}{1-\phi_x}\left(\mathbb{E}[\widetilde{x}^i_{h-1}|\mathcal{I}^i_h] - \frac{c_x}{1-\phi_x}\right) + \mathbb{E}[x_h|\mathcal{I}^i_h] + \sum_{j=h+1}^{12} x_j \tag{C.39}$$

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

$$\mathbb{E}[z^i_{h-1}|\mathcal{I}^i_h] = (h-1)\left(\frac{c_x}{1-\phi_x}\right) + \frac{1-\phi_x^{h-1}}{1-\phi_x}\left(c_x + \phi_x\mathbb{E}[x_h|\mathcal{I}^i_h] - \frac{c_x}{1-\phi_x}\right) + \mathbb{E}[x_h|\mathcal{I}^i_h] + \sum_{j=h+1}^{12} x_j$$

Rearranging, we obtain:

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

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

$$\text{(C.40)} \qquad \mathbb{E}[z^i_{h-1}|\mathcal{I}^i_h] \;=\; h\left(\frac{c_x}{1-\phi_x}\right) \;+\; \phi_x^2\frac{1-\phi_x^{h-1}}{(1-\phi_x)^2}x_{h+1} \;+\; \phi_x\left(x_{h+1} - \frac{c_x}{1-\phi_x}\right) + \sum_{j=h+1}^{12} x_j.$$

For the variance, we apply the variance operator to (C.38) and note that the terms in the sum disappear because they are known at h. Thus we are left with two terms.

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

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

$$\text{(C.41)} \qquad \widetilde{x}^i_{h-1} \;=\; x^i_{h-1} + \zeta^i_{h-1} + \eta_{h-1} \;=\; c_x + \phi_x x_h + \varepsilon^x_{h-1} + \zeta^i_{h-1} + \eta_{h-1}.$$

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

$$\text{(C.42)} \qquad \mathbb{E}[\mathcal{V}_{h-1}(\hat{\pi}^i_{h-1}, \hat{F}_{h-1}, f^i_{h+1})|\mathcal{I}^i_h] = \sum_{\hat{\pi}^i_{h-1}}\sum_{\hat{F}_{h-1}} \mathcal{V}_{h-1}(\hat{\pi}^i_{h-1}, \hat{F}_{h-1}, f^i_{h+1})\omega(\hat{\pi}^i)\omega(\hat{F})$$

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 $\hat{F}_{h-1}|\mathcal{I}^i_h \sim \mathcal{N}(\mathbb{E}[\hat{F}_{h-1}|\mathcal{I}^i_h], \mathbb{V}ar[\hat{F}^i_{h-1}|\mathcal{I}^i_h])$ with

$$\begin{aligned}
\mathbb{E}[\hat{F}_{h-1}|\mathcal{I}^i_h] &= c_F(1+\phi_F) + \phi_F^2 F_{h+1} \\
\mathbb{V}ar[\hat{F}^i_{h-1}|\mathcal{I}^i_h] &= \phi_F^2\sigma_F^2
\end{aligned}$$

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

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

D Rolling Estimates

Inflation estimates Let the monthly inflation rate x_h follow an AR(1) process:

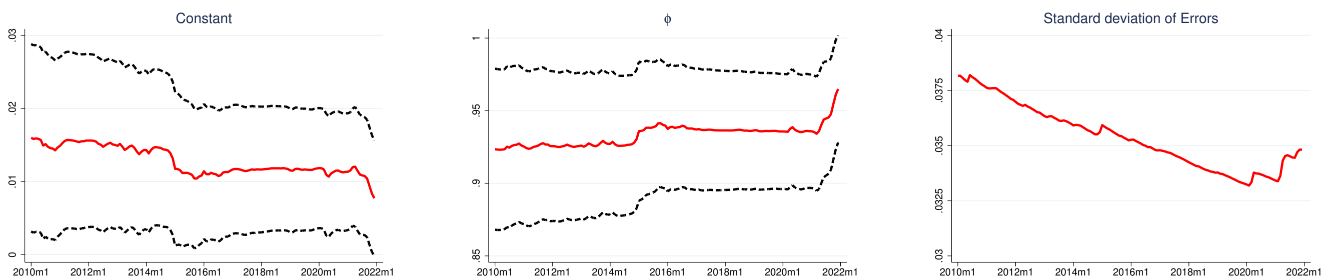
$$x_h \;=\; c_x + \phi_x x_{h+1} + \varepsilon_h^x, \qquad \varepsilon_h^x \sim \mathcal{N}(0, \sigma_x^2), \tag{D.43}$$

where c_x is a constant, ϕ_x is the persistence parameter, and ε_h^x is an *iid* normally distributed noise with volatility σ_x^2. We estimate the three parameters $(c_x, \phi_x, \sigma_x^2) = (0.013, 0.932, 0.036)$ using the monthly inflation rate from the CPI.

Figure XVII plots the resulting estimates and 95% confidence intervals.

Figure XVII – Rolling Estimates for Inflation Parameters

(a) (b) (c)



Notes: Bloomberg data.

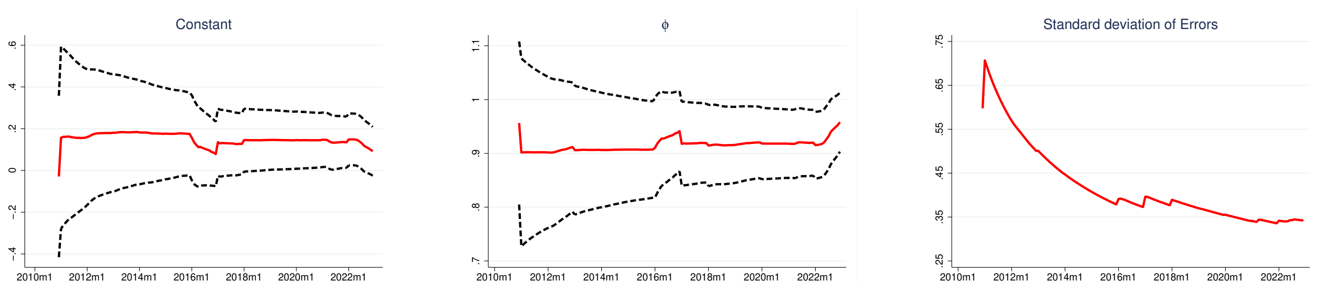
Consensus estimates Let the consensus F_h follow an AR(1) process:

$$F_h \;=\; c_F + \phi_F F_{h+1} + \varepsilon_h^F, \qquad \varepsilon_h^F \sim \mathcal{N}(0, \sigma_F^2), \tag{D.44}$$

where c_F is a constant, ϕ_F is the persistence parameter, and ε_h^F is an *iid* normally distributed noise with volatility σ_F^2. We estimate the three parameters $(c_F, \phi_F, \sigma_F^2) = (0.153, 0.913, 0.26)$ using the monthly consensus from the survey. Figure XVIII plots the resulting estimates and 95% confidence intervals.

Figure XVIII – Rolling Estimates for Consensus Parameters

(a) (b) (c)

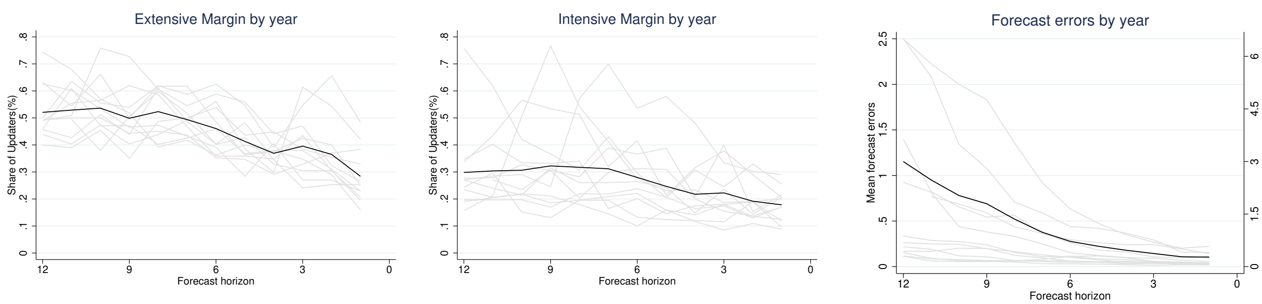


Notes: Bloomberg data.

E Cross-sectional statistics by year

Figure XIX – Adjustment Frequency and Size by Horizon and Year

(a) Frequency **(b)** Size **(c)** Forecast errors



Notes: Bloomberg data.

E.1 Accuracy of AR(1) forecast vs. consensus

Since yearly inflation π equals to the sum of year-on-year monthly inflation x_h: $\pi = \sum_{h=1}^{12} x_h$, then monthly inflation releases x_h are relevant information strictly related to the forecasted variable. We assume forecasters believe monthly inflation follows an AR(1) process:[8] As noticed by $\mathcal{I}_h$, the public belief is formed using the available information at each horizon, corresponding to the lagged values of x_h. By relying on the available information for forecasters in real time, we estimate the AR(1) process parameters using a rolling window over the sample years. The parameters are $(c_x, \phi_x, \sigma_x^2) = (0.013, 0.932, 0.036)$. The estimates are presented in Appendix D. Given these estimates, we compute our proxy for public beliefs each month.

Given the estimates, we compare the forecast errors from the AR(1) project and the average prediction of forecasters (consensus). We compute the evolution of forecast errors over the horizon using these two forecasts, where

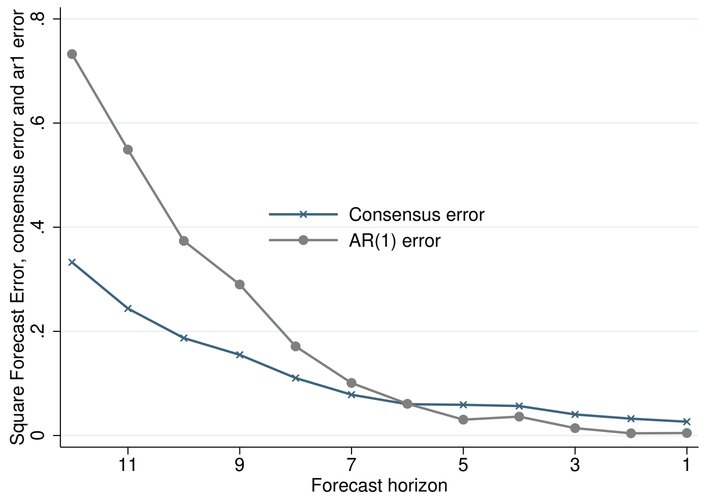
$$e_h = \pi - f_h, \qquad \text{where} \quad f_h \in \{z_h, F_h\}. \tag{E.45}$$

The results are presented in Figure XX.

As expected, the accuracy of the AR(1) process increases monotonically as the release date of inflation approaches. This feature is particularly salient for normal years. As more relevant information is accumulated, the accuracy improvements are notorious. If we focus on normal years at longer and medium horizons, the forecast error of the consensus forecast is relatively better than the AR(1). This could be caused by the possible combination of public and private information from forecasters that makes predictions more accurate. However, at shorter horizons, the accuracy of the public belief is slightly better than the average prediction. Interestingly, the consensus is consistently more accurate during turbulent years.

[8]Although participants interpret public information differently, we argue that the prediction that builds on the AR(1) is a tractable and accurate proxy for a fixed-event forecast. We provide further discussion about the features and accuracy of the proxy in Appendix YY. See Giacomini, Skreta and Turen (2020).

Figure XX – Accuracy of AR(1) proxy and Consensus Forecasts



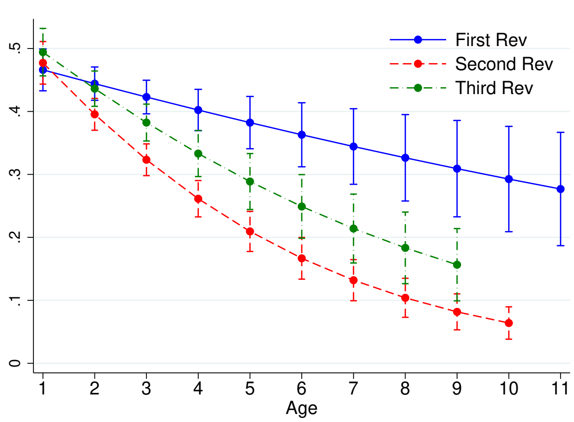
F Hazard Rates

F.1 By number of Revisions

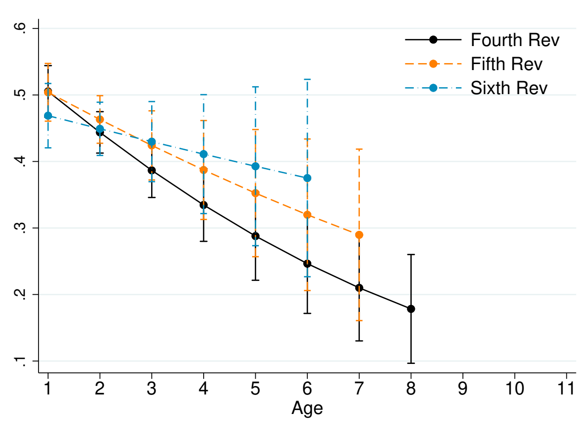
Building on the discussion in Section 2.5, we compute the hazard rates conditioning on the number of revisions the forecasters have done in the past. In this sense, we explore whether the age-dependence of updating probabilities changes as a function of the revision being the first, second, third, and so forth. This is shown in Figure XXI.

Figure XXI – Hazard Rates by revisions

(a) Hazard Rate: 1st, 2nd and 3rd Rev.



(b) Hazard Rate: 4th, 5th and 6th Rev.



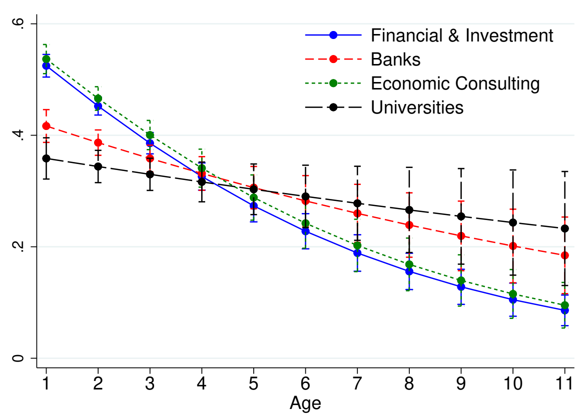
Notes: Bloomberg data.

Independently of the revision, the decaying pattern of the hazard rates remains across specifications. While the chance of an immediate revision right at age one is roughly the same across the number of revisions (between 45% and 50%), the likelihood drops as more revisions accumulate throughout the year. Although the relations are not monotonic, in most cases, the age probabilities are not statistically different across groups. We interpret the decaying probability as a function of revisions as an implication of both the fixed-event scheme, whereas age growths, we get closer to the final release date, and the fact that, as time passes, we accumulate more relevant information to predict the annual inflation.

F.2 By forecasters' type

As in the previous section, we can also compute the hazard rate conditioning on the four types of forecasters. This is shown in Figure XXII. The hazard rates for forecasters belonging to either "Financial & Investment" or "Economic Consulting" are the steepest relative to the other two groups. Hence, although they decrease, the updating probability is less sensible to the age of both Banks and Universities.

Figure XXII – Hazard Rates by Groups



Notes: Bloomberg data. Notes: Normal years = 2010-2019. Turbulent years = 2008-2009 and 2020-21.

G Gap to "Top Forecasters"

Although forecasters participating in the Bloomberg survey can observe the consensus forecast in real-time, the average prediction of participants is not necessarily the statistic they aim to be close to. While the consensus acts as a focal point for participants, they could have incentives for being close to a different subset of forecasters, for instance, the group of the most accurate ones. Thus, we revisit the estimation for the extensive and intensive margin of Sections 5.1 and 5.2, but now rely on an alternative measure of the consensus gap.

Let $F_{T,h}$ be the average forecast at each h for the group of ten forecasters that provide the most accurate predictions (i.e., the lowest forecast error) the year before[9]. Then we define gaps to the top $c^i_{T,h}$ as

$$c^i_{T,h} \equiv f^i_{h+1} - F_{T,h}. \tag{G.46}$$

The idea of $c^i_{T,h}$ is to assess whether the relevant focal point is somehow related to past (or historical) accuracy rather than the average of others. With this new measure, we repeat the extensive and intensive margin estimations, shown in Table IX and X, respectively.

Consistent with the baseline results, the gap to the average predictions of the "top-ten" forecasters constitutes a relevant adjustment predictor. A positive gap not only reduces the probability of positive revisions but also significantly increases the probability of downward revisions, closing the gap. The effect of downward revisions was only mildly significant in the baseline specification, while in this case, it becomes highly significant. Concerning the intensive margin, the results remain with respect to the baseline specification, in particular for the persistence of revisions and the willingness to close the two gaps once a revision is decided.

The results thus support the presence of strategic considerations to understand the behavior of forecast revisions. In this sense, the motivation is not to take a stance on the specific object forecasters are following but rather to stress that forecasters have incentives to report their forecasts close to some (observed) focal point.

[9] We compute the group of the best ten forecasters by ranking their forecast error, during the previous year, at $h = 1$

Table IX – Extensive Margin Determinants

	$Update > 0$	$Update < 0$	$Update > 0$	$Update < 0$	$Update > 0$	$Update < 0$	$Update > 0$	$Update < 0$
$c^i_{T,h}$	-0.067**	0.070**			-0.067**	0.071**		
	(0.022)	(0.023)			(0.021)	(0.022)		
b^i_h	-0.012	0.041**			-0.011	0.036**		
	(0.018)	(0.017)			(0.017)	(0.015)		
${c^i_{T,h}}^+$			-0.033***	0.044***			-0.034***	0.046***
			(0.004)	(0.010)			(0.004)	(0.011)
${c^i_{T,h}}^-$			-0.186	0.242*			-0.178	0.223**
			(0.134)	(0.109)			(0.128)	(0.098)
${b^i_h}^+$			-0.001	0.036**			0.000	0.031**
			(0.007)	(0.011)			(0.006)	(0.010)
${b^i_h}^-$			0.195	-0.070			0.197	-0.080
			(0.110)	(0.107)			(0.111)	(0.112)
Age^i_h	0.024***	0.025***	0.022***	0.026***	0.025***	0.025***	0.022***	0.027***
	(0.005)	(0.007)	(0.005)	(0.008)	(0.006)	(0.007)	(0.005)	(0.008)
${s_h}^{MP}$					-0.143	0.386	-0.096	0.338
					(0.453)	(0.610)	(0.442)	(0.651)
π_{h+1}	0.002	-0.004	0.003	-0.003	0.003	-0.014	0.004	-0.013
	(0.007)	(0.018)	(0.009)	(0.020)	(0.007)	(0.021)	(0.008)	(0.021)
π_{h+2}	0.017	0.035*	0.014	0.040**	0.016	0.030**	0.013	0.034**
	(0.018)	(0.017)	(0.013)	(0.016)	(0.017)	(0.013)	(0.011)	(0.012)
Constant	0.116**	0.101	0.082*	0.116*	0.115**	0.137*	0.082**	0.151**
	(0.043)	(0.063)	(0.040)	(0.060)	(0.040)	(0.063)	(0.034)	(0.060)
Observations	7,619	7,619	7,619	7,619	7,207	7,207	7,207	7,207
Forecaster FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Macro Controls	✓	✓	✓	✓	✓	✓	✓	✓

Standard errors (in parenthesis) are robust to heteroskedasticity and clustered at both forecaster and time level.
Macro controls include lagged vales of the growth of industrial production and the 3-month Treasury rate in the US.
*** p<0.01, ** p<0.05, * p<0.1

H Forecast Rationality Test

Table X – Intensive Margin Determinants

	Without Zero Revisions				With Zero Revisions			
	Rev_{ih}	Rev_{ih}	Rev_{ih}	Rev_{ih}	Rev_{ih}	Rev_{ih}	Rev_{ih}	Rev_{ih}
Rev_{ih+1}	-0.248***	-0.198***	-0.254***	-0.203***	-0.069**	-0.051**	-0.073**	-0.054**
	(0.068)	(0.046)	(0.070)	(0.043)	(0.027)	(0.017)	(0.028)	(0.017)
$c^i_{T,h}$	-0.177***		-0.178***		-0.112**		-0.119**	
	(0.045)		(0.046)		(0.042)		(0.046)	
b^i_h	-0.038**		-0.033**		-0.022*		-0.015	
	(0.016)		(0.014)		(0.011)		(0.013)	
${c^i_{T,h}}^+$		-0.118***		-0.121***		-0.075***		-0.081***
		(0.011)		(0.011)		(0.018)		(0.022)
${c^i_{T,h}}^-$		-0.260		-0.248		0.359**		0.351**
		(0.228)		(0.213)		(0.145)		(0.138)
${b^i_h}^+$		-0.036***		-0.033***		-0.025**		-0.020
		(0.010)		(0.009)		(0.009)		(0.012)
${b^i_h}^-$		0.369*		0.369*		-0.020		-0.019
		(0.194)		(0.200)		(0.055)		(0.055)
Age^i_h	0.002	0.002	0.002	0.002	0.001	-0.001	0.001	-0.001
	(0.011)	(0.011)	(0.011)	(0.011)	(0.006)	(0.006)	(0.007)	(0.006)
${s_h}^{MP}$			-0.333	-0.099			-0.578	-0.389
			(1.085)	(1.079)			(0.403)	(0.397)
π_{h+1}	-0.008	-0.014	-0.001	-0.008	-0.004	-0.006	-0.002	-0.004
	(0.024)	(0.027)	(0.028)	(0.030)	(0.009)	(0.012)	(0.011)	(0.013)
π_{h+2}	0.017	0.010	0.020	0.013	-0.008	-0.011	-0.008	-0.011
	(0.037)	(0.042)	(0.036)	(0.041)	(0.015)	(0.015)	(0.013)	(0.015)
Constant	-0.010	-0.045	-0.031	-0.065	0.024	0.010	0.018	0.003
	(0.107)	(0.128)	(0.109)	(0.131)	(0.044)	(0.058)	(0.045)	(0.062)
Observations	3,031	3,031	2,882	2,882	7,619	7,619	7,207	7,207
Forecaster FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Macro Controls	✓	✓	✓	✓	✓	✓	✓	✓

Standard errors (in parenthesis) are robust to heteroskedasticity and clustered at both forecaster and time level.
Macro controls include lagged vales of the growth of industrial production and the 3-month Treasury rate in the US.
*** p<0.01, ** p<0.05, * p<0.1

I Correlation between the gaps

As expected, both the belief and the consensus gap are highly correlated in the data. This is shown in Figure XXIII below. In fact, in the sample, 88% of the time, the gaps share the same sign.

Table XI – Efficiency Tests in the Literature

	Coibion-Gorodnichencko (2015)			Bordalo et.al (2020)			Broer and Kohlhas (2022)			
Horizon	Constant	Revision	F-test	Constant	Revision	F-test	Constant	Revision	Consensus	F-test
1	-0.0341	5.7198	0.0720	-0.0657	-0.5379	0.0008	-0.0651	-0.2359	0.0026	0.0008
	(.0418)	(2.7197)		(.0003)	(.1092)		(.0220)	(.1101)	(.0133)	
2	-0.1001	7.1433	0.0004	-0.0665	-0.3284	0.0080	-0.0648	-0.1006	0.0011	0.0184
	(.0233)	(1.0654)		(.0008)	(.0969)		(.0227)	(.2296)	(.0136)	
3	-0.0318	5.9955	0.0007	-0.0657	-0.5048	0.0001	-0.0555	-0.2895	0.0001	0.0078
	(.0426)	(1.0723)		(.0002)	(.0729)		(.0236)	(.1396)	(.01415)	
4	-0.0172	7.9209	0.2830	-0.0707	-0.3527	0.0022	-0.0678	-0.1225	0.0076	0.0112
	(.0775)	(5.3897)		(.00001)	(.0833)		(.02543)	(.1012)	(.0153)	
5	-0.1020	-0.5235	0.3723	-0.0820	-0.3501	0.0030	-0.1044	-0.2546	0.0221	0.0000
	(.1352)	(2.1798)		(.0001)	(.0867)		(.0286)	(.0674)	(.0169)	
6	-0.0812	1.4816	0.0458	-0.1054	-0.4286	0.0012	-0.1676	-0.2687	0.0440	0.0000
	(.1394)	(2.2645)		(.00112)	(.0916)		(.0285)	(.1175)	(.01667)	
7	-0.0441	2.9080	0.0023	-0.1363	-0.5388	0.0013	-0.2014	-0.3205	0.0476	0.0000
	(.1261)	(1.2488)		(.0037)	(.1172)		(.0273)	(.1273)	(.0159)	
8	-0.1902	3.4327	0.0050	-0.1471	-0.5098	0.0020	-0.2788	0.0075	0.0783	0.0000
	(.0622)	(1.2121)		(.0006)	(.1186)		(.0282	(.0912)	(.0161)	
9	-0.2616	5.8216	0.0019	-0.1326	-0.3888	0.0396	-0.3447	0.0146	0.1217	0.0000
	(.0736)	(1.0557)		(.0042)	(.1616)		(.0328)	(.12729	(.01879)	
10	-0.2470	4.3845	0.0059	-0.1031	-0.4776	0.0011	-0.4016	0.2655	0.1671	0.0000
	(.0695)	(1.0055)		(.0034)	(.1016)		(.0433)	(.0805)	(.0247)	
11	-0.0247	2.2792	0.0236	-0.1018	-0.5368	0.0000	-0.5377	-0.1216	0.2778	0.0000
	(.1140)	(1.0906)		(.00007)	(.0619)		(.0507)	(.1007)	(.0293)	
12	0.1126	2.5178	0.0010	-0.1590	-0.8157	0.0016	-0.4858	0.1883	0.2381	0.0000
	(.2179)	(.9034)		(.0142)	(.1737)		(.0717)	(.1163)	(.0363)	

Notes: The first columns of the table reports the estimates of running Coibion and Gorodnichenko (2015)'s aggregate Rationality Test. Standard are estimated using a HAC matrix. The middle columns present the results of Bordalo *et al.* (2020)'s individual test. Finally, the last columns shows the estimates of Broer and Kohlhas (2022). The panel estimations include individual fixed-effects. Standard errors are robust and clustered by forecaster and time. All the tests are estimated using the "Normal years" sample (2010-2019).

Figure XXIII – Correlation between the gaps