# Unpacking Uncertainty in Household Expectations<sup>\*</sup>

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#### Abstract

We study how different sources of uncertainty shape household expectations about inflation. Using the Survey of Consumer Expectations, we show that belief stickiness declines when prior information is uncertain, but rises when new information is uncertain. While broadly consistent with Bayesian updating, households overreact relative to the Rational Expectations benchmark. We use this framework to decompose the recent rise in inflation expectation uncertainty: during the pandemic, macroeconomic volatility rendered priors more uncertain; during the high-inflation period, uncertainty stemmed from noisier signals. Belief stickiness offers a valuable statistic to distinguish sources of uncertainty in expectations data.

**Keywords**: Expectations, inflation, household surveys, consumer beliefs, information frictions, uncertainty.

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Uncertainty is a defining feature of the modern economy. Its recent surges have spurred a growing literature examining the implications for macroeconomic aggregates, asset prices, and household consumption and saving decisions (Jurado et al., 2015; Bloom et al., 2018; Coibion et al., 2024; Georgarakos et al., 2024). The COVID-19 pandemic stands out as a particularly significant episode, marked by sharp increases across multiple uncertainty measures. Notably, the New York Fed's Survey of Consumer Expectations recorded the most pronounced and persistent rise in uncertainty since its inception over a decade ago (Armantier et al., 2021). While expectations are widely recognized as a key channel through which uncertainty influences household behavior, much less is known about how uncertainty itself shapes the formation of those expectations. Recent work has pointed to attention dynamics and belief updating as central mechanisms in macroeconomic behavior (Afrouzi and Yang, 2021; Angeletos et al., 2021; Maćkowiak and Wiederholt, 2025), yet empirical evidence on how different forms of uncertainty affect these processes remains limited.

In this paper, we address this gap by analyzing how subjective uncertainty influences the formation of expectations using household survey data. We report three main findings. First, we show that the responsiveness of expectations to new information, i.e., *belief stickiness*, depends critically on the source of subjective uncertainty, i.e., individual confidence about own expectations. When subjective uncertainty stems from prior beliefs, households update more; when it arises from noisy information, they update less. Second, we compare this behavior to the Rational Expectations (RE) benchmark and document a systematic overreaction relative to RE, driven by households' underweighting of information noise. Third, we demonstrate that belief stickiness is an informative statistic for identifying the sources of subjective uncertainty.

Because prior uncertainty and information noise have opposing effects on belief updating, our estimates of aggregate belief stickiness allow us to disentangle the underlying sources of the post-pandemic surge in subjective uncertainty. We find that the initial phase of the COVID-19 shock was dominated by increased uncertainty about prior information reflecting heightened fundamental macroeconomic volatility - while the period of elevated inflation that followed was shaped more by declining signal precision. These distinct sources of macroeconomic uncertainty have different implications for belief formation and attention allocation, and consequently for shock propagation and monetary policy effectiveness.

We use inflation forecasts from the Survey of Consumer Expectations (SCE) collected by the Federal Reserve Bank of New York, capturing a monthly rotating panel of US households between June 2013 and May 2023. We focus on inflation expectations because they play a central role in households' consumption and saving decisions (Georgarakos et al., 2024).<sup>1</sup> The SCE survey is particularly well-suited to estimate two key moments for our analysis. The first is subjective belief uncertainty, measured as the standard deviation of the conditional subjective distribution of future outcomes (in our case, future inflation) given the individual's information set, estimated from probabilistic expectation questions (Manski, 2004, 2018). The second is belief rigidity, measured as the extent to which consumers rely on prior versus new information when forming their expectations (Coibion and Gorodnichenko, 2012, 2015a).<sup>2</sup> The large panel structure of the SCE allows us to precisely estimate belief stickiness each month and across consumer groups using a novel methodology based on the cross-sectional covariance between current and lagged point forecasts while controlling for common factors (Goldstein, 2023).<sup>3</sup>

Our analysis proceeds in three steps. First, we estimate how households' updating of inflation expectations depends on different sources of uncertainty. We distinguish between two sources: uncertainty regarding existing (or prior) information and uncertainty about new information. We proxy prior uncertainty using the self-reported inflation forecast uncertainty from the previous month's surveys. We extract the noisiness, i.e. inaccuracy, of new information from the self-reported inflation forecast uncertainty in the current month. We find that less accurate new information lead agents to update their expectations less, while higher prior uncertainty induces them to update more. While these findings align with the theoretical implications of the Bayesian updating framework, we find that the estimated belief stickiness is, on average, lower than the rational expectations counterfactual, meaning that households overreact to new information. Finally, we estimate a functional form for household belief adjustment and its relationship with prior and new information noise using moment matching.

Second, we use our empirically estimated belief formation framework to decompose the aggregate sources of uncertainty in the post-pandemic economy. We document a reversal in the correlation between belief uncertainty and stickiness during the COVID-19 period. At the onset of the pandemic, we observe a sharp decline in belief stickiness alongside an increase in belief uncertainty: consumers incorporate more new information into their beliefs,

<sup>&</sup>lt;sup>1</sup>Beyond its economic significance, Binder (2024) documents how inflation expectations also carry deep social and political resonance, influencing public trust and democratic accountability in the U.S.

<sup>&</sup>lt;sup>2</sup>Formally, we define belief stickiness, or information rigidity, as 1 - G, where G is the weight on new information in posterior expectations, or the "Kalman gain" in the Rational Expectation framework.

<sup>&</sup>lt;sup>3</sup>The strategy of Coibion and Gorodnichenko (2015a) uses time-series variation in consensus beliefs to estimate stickiness, but requires long time spans rarely available in consumer surveys. We instead use cross-sectional variation in individual beliefs, enabling estimation with short-duration surveys.

while becoming more uncertain. This correlation, however, turns positive during the high inflation period beginning in February 2021, when consumers display increased levels of both belief stickiness and uncertainty: they incorporate less information into their beliefs while becoming even more uncertain.

The correlation between belief stickiness and uncertainty allows us to decompose the surge in uncertainty into its different sources. We show that the negative correlation observed during the pandemic outbreak reflects an increase in prior uncertainty, possibly due to a regime shift in macroeconomic volatility or uncertainty about economic policies. This structural change in the economy rendered existing information obsolete, prompting house-holds to seek out and incorporate new information into their beliefs. In contrast, in the following high-inflation period, belief stickiness increased along with rising inflation uncertainty, suggesting a relative increase in the noise of new information: reduced accuracy of news discouraged consumers from updating their beliefs and instead led them to rely more on their prior information. This may reflect the increased difficulty in predicting future inflation in this period, with economists disagreeing on how long the high-inflation period would last (Markovitz, 2021).

Finally, we show that lockdown policies implemented at the onset of the pandemic contributed to lower belief stickiness, yet alone cannot explain the simultaneous increase in uncertainty. We exploit variation in the intensity of state-level lockdown policies, measured by the Oxford Covid-19 Government Response Tracker (OxCGRT), and identify two effects: we document a significant and robust negative effect on both consumers belief stickiness and belief uncertainty. This finding suggests that restrictions on mobility and the widespread shift to remote work might have reduced the marginal cost of information acquisition, enabling households to gather more accurate new information, which would explain the negative effect on uncertainty. Therefore, lockdown policies alone cannot account for the concurrent rise in belief uncertainty observed during this period.

Our work makes two key contributions. First, we demonstrate that belief stickiness is a valuable statistic for distinguishing between sources of uncertainty: macroeconomic fundamental volatility and information noise both increase uncertainty, but have opposing effects on belief stickiness. With the growing availability and frequency of large-scale expectation surveys, our approach provides policymakers with a valuable resource for tracking different sources of uncertainty across contexts and designing optimal monetary policies and central bank communication.

Second, we contribute to the understanding of household belief formation, particularly

in relation to uncertainty. We show that while the relationship between uncertainty and belief stickiness is qualitatively consistent with Bayesian updating, the survey respondents underweight the noise of new information and therefore overreact relative to the RE benchmark. As uncertainty becomes an increasingly prominent feature of the economic landscape, and could continue to rise, understanding how beliefs respond to it is essential for effective policymaking going forward.

**Relation to the literature** This paper contributes to several strands of the literature, which we detail below. First, our work contributes to the empirical literature measuring information frictions in expectation surveys (Mankiw and Reis, 2002; Coibion and Gorodnichenko, 2015a; Kohlhas and Walther, 2021; Benhima and Bolliger, 2022; Gemmi and Valchev, 2023). Relative to these studies, we measure belief stickiness on household surveys instead of relying on professional forecasters. We build on the empirical strategy developed by Goldstein (2023), which also documents a decrease in belief stickiness in the first quarter of the COVID-19 pandemic in professional forecaster surveys, but not in the Michigan Survey of Consumers. Pfäuti (2023) also measures belief stickiness in the Michigan Survey of Consumers, but using the consensus forecast, and relates it to the level of realized inflation. Compared to their work, we exploit the higher frequency and panel dimension of the SCE to improve our identification strategy, and, more importantly, we estimate the relationship between belief stickiness and subjective uncertainty.<sup>4</sup>

We also contribute to a large literature on the measurement and consequences of macroeconomic uncertainty (Bloom, 2009; Jurado et al., 2015; Baker et al., 2016; Bloom et al., 2018; Baley and Blanco, 2019), especially the ones measuring uncertainty with survey data (Manski, 2018; Binder et al., 2022; Kumar et al., 2023; Fermand et al., 2024; Wang, 2024; Coibion et al., 2024; Georgarakos et al., 2024).<sup>5</sup> The definitions of uncertainty adopted in the literature often conflate different sources of uncertainty, namely macroeconomic volatility and information noise, which are structurally and statistically different from each other (Kozeniauskas et al., 2018). We show that belief stickiness in survey data is a useful statistic to distinguish between these different macroeconomic uncertainty sources, as they have the

<sup>&</sup>lt;sup>4</sup>De Bruin et al. (2011) also examines subjective uncertainty in the SCE and documents that more uncertain consumers revise their beliefs more. Instead, we consider both posterior and prior uncertainty and estimate their impact on information rigidities. Baker et al. (2020) proxies uncertainty shocks with natural disasters and finds that they decrease both belief stickiness and forecast errors in the Consensus Economics Surveys. Instead, we directly measure individual subjective uncertainty and show that the relation with belief stickiness depends on the source of uncertainty.

<sup>&</sup>lt;sup>5</sup>See Cascaldi-Garcia et al. (2023) for a review of different measures of macroeconomic uncertainty.

opposite effect on belief stickiness. Gambetti et al. (2023) uses forecast disagreement to differentiate between fundamental volatility and information noise as sources of uncertainty, with the underlying assumption that the former lowers disagreement, whereas the latter increases it. In contrast, we propose belief stickiness as a valuable statistic for distinguishing these two sources, as their effects are unambiguous and do not depend on parameter assumptions.

Third, we contribute to the literature on testing the rational expectation (RE) hypothesis (Bordalo et al., 2020; Broer and Kohlhas, 2024; Baley and Turén, 2023; Adam et al., 2025). This literature provides evidence for overreaction to new information by documenting a systematic predictability of individual forecast errors. Such a test requires observing the same forecasters for long periods, forcing this literature to focus mainly on professional forecaster surveys. Instead, we test RE by investigating the relationship between belief stickiness and uncertainty implied by the Bayesian updating framework. This allows us to test rationality on surveys with a shorter time sample, but a larger panel, such as consumer surveys. Similar to this literature, we document overreaction to new information.

A growing body of research applies randomized controlled trials (RCTs) to study how new information shapes expectations by inducing exogenous changes in beliefs through information treatments (Armantier et al., 2016; Cavallo et al., 2017; Armona et al., 2019; Roth and Wohlfart, 2020; Coibion et al., 2022; Link et al., 2023). A common finding in this literature is that firms and households update their beliefs in line with the qualitative predictions of a rational Bayesian framework—updating more when their prior beliefs are more uncertain and when the provided signal is more informative.<sup>6</sup> Instead, we exploit *naturally occurring* variations in beliefs, allowing us to bypass the external validity concerns of the RCT settings and study the time-variation of belief stickiness. More recently, Weber et al. (2024) finds that information treatments in RCTs are less effective during periods of high inflation, which can be attributed to households paying greater pre-treatment attention to inflation, thereby reducing prior uncertainty (Mackowiak and Wiederholt, 2024). We directly test the relationship between prior uncertainty and belief adjustment, showing that households adjust their beliefs less when they perceive prior information as more accurate.<sup>7</sup>

 $<sup>^{6}</sup>$ While this holds for RCTs that provide information about inflation, the evidence is more mixed for other economic indicators. In particular, Fuster et al. (2022) documents the opposite effect of prior uncertainty on housing price expectation stickiness. Similarly, Armona et al. (2019) and Conlon et al. (2018) find no significant effect of uncertainty on expectations in the housing and labor markets.

<sup>&</sup>lt;sup>7</sup>A related literature examines the implications of endogenous information acquisition, focusing on how consumers and firms allocate attention (Roth et al., 2022; Mikosch et al., 2024; Link et al., 2024). Rather than analyzing the determinants of attention choices, we measure the resulting quantity of information—i.e.,

The paper proceeds as follows: Section 1 illustrates the general framework we use to guide and interpret our empirical strategy. Section 2 presents our empirical estimates of belief stickiness. Section 3 studies the relation between belief stickiness and uncertainty sources. Section 4 investigates the dynamic of belief stickiness around the COVID-19 outbreak. Section 5 investigates the impact of lockdowns on belief stickiness. Section 6 discusses our findings and their broader implications. Lastly, Section 7 concludes.

## 1 A general framework of belief updating

We present a general theoretical framework embedding different models of belief updating, which will guide our empirical strategy. In particular, consider a random variable  $x_t$  with some arbitrary autoregressive process. Households in time t form beliefs about the variable realization at horizon t + h after observing a private signal,  $s_t^i$ , with some private and public noise.

$$s_t^i = x_{t+h} + e_t^i \tag{1}$$

where the signal noise  $e_t^i = \eta_t^i + \omega_t$  contains (i) an idiosyncratic component  $\eta_t^i$  normally distributed mean-zero noise with variance  $\sigma_{\eta,t}^2$  and i.i.d. across time and households, i.e.  $\int^i e_t^i di = 0$ , and (ii) a common component  $\omega_t$  normally distributed mean-zero noise with variance  $\sigma_{\omega,t}^2$  which is i.i.d. only across time, but not across agents. Let  $\sigma_{e,t}^2 \equiv \sigma_{\eta,t}^2 + \sigma_{\omega,t}^2$ define the overall variance of the signal noise. We follow the existing literature and assume normality of the error term (Coibion and Gorodnichenko, 2015b; Bordalo et al., 2020; Broer and Kohlhas, 2024).

Each household *i* forms beliefs  $E_t^i[x_{t+h}]$  at time *t* about the variable at *h* periods ahead according to

$$E_t^i[x_{t+h}] = (1 - G_t)E_{t-1}^i[x_{t+h}] + G_t s_t^i,$$
(2)

where  $G_t$  is the weight households assign to new information and  $E_t^i[x_{t+h}]$  is a potentially non-rational expectation operator, conditional on the information set of agents *i* at time *t* about  $x_{t+h}$ . We follow the literature in referring to  $G_t$  as "gain" and  $1 - G_t$  as "stickiness".

We don't make any assumption about what determines the weight on new information

uncertainty—regardless of its source. As we demonstrate in Section 3, in the Bayesian framework, belief stickiness depends solely on this quantity.

 $G_t$ . In other words, we have not assumed any particular belief-updating model, except for the linearity of posterior belief in prior and signal. This general framework embeds a large set of belief-updating models, including but not limited to the rational Bayesian model, in which case  $G_t$  would equal the Kalman gain.<sup>8</sup> Other models embedded in the general framework include, among others, the behavioral Diagnostic Expectations and the overconfidence model, as described in Appendix A.

From (2), one can construct forecast errors by taking the difference between realization  $x_{t+h}$  and forecast  $E_t^i[x_{t+h}]$ . Taking the variance of forecast errors conditional on information available in time t, one can derive the posterior belief uncertainty  $\Sigma_{t+h,t} \equiv var(x_{t+h} - E_t^i[x_{t+h}])$ , as

$$\Sigma_{t+h,t} = (1 - G_t)^2 \Sigma_{t+h,t-1} + G_t^2 \sigma_{e,t}^2$$
(3)

where  $\Sigma_{t+h,t-1} \equiv var(x_{t+h} - E_{t-1}^i[x_{t+h}])$  is the prior uncertainty and  $\sigma_{e,t}^2$  the new information uncertainty.

Before proceeding, let us clarify some of the terminology used throughout this paper. We refer to  $1 - G_t$  as belief stickiness, belief updating rigidity, or information rigidity (Coibion and Gorodnichenko, 2012, 2015a). A related term is belief *anchoring*, which refers to long-run inflation expectations being stable and closely aligned with a central bank's inflation target. The literature requires very long-term horizons to identify beliefs about the central banks' target or the steady state inflation level, typically 5 to 10 years, (for example, Kumar et al., 2015; Carvalho et al., 2023). Instead, the 3-year horizon we consider is too short to relate to the inflation target directly. However, anchoring may play a role in our findings, as we discuss in Section 3. Another widely used term is *attention*, which is related to the literature on rational inattention (for a review, see Maćkowiak et al., 2023). It indicates the amount of information collected by agents, who can pay some attention cost to decrease the noise on new information  $\sigma_{e,t}^2$ . Empirical works on consumers' and firms' attention allocation refer to this measure rather than belief stickiness (Mikosch et al., 2024; Link et al., 2024). While the weight on new information  $G_t$  may depend on attention, the two are different concepts, as explained in more detail in Section 3.

<sup>&</sup>lt;sup>8</sup>The weight on new information in the Bayesian rational expectation case is the Kalman gain, which equals  $G_t^{RE} = \frac{\Sigma_{t+h,t-1}}{\sigma_{e,t}^2 + \Sigma_{t+h,t-1}}$  where  $\Sigma_{t+h,t-1} = var_t(E_{t-1}^i[x_{t+h}] - x_{t+h})$  is the prior variance.

## 2 Households' belief stickiness

#### 2.1 Data

The data comes from the Survey of Consumer Expectations (SCE), a monthly survey of a rotating panel of approximately 1,200 household heads collected by the Federal Reserve Bank of New York (FRBNY) since late 2012.<sup>9</sup> The SCE uses a rotating panel structure where respondents participate for up to 12 months, with a roughly equal number rotating in and out of the panel each month. We consider here the core survey sample, which contains monthly observations from June 2013 to May 2023, and it includes point and density expectations about future inflation as well as socioeconomic characteristics and other background questions. We have a total of 108 months with around 1,300 observations per month, with a total of 130,000 month-respondent observations from around 20,000 unique respondents. We consider point forecasts only if respondents provide a meaningful density forecast (i.e. the survey provides the variance) and if the point forecast is contained in the support of the density forecast. Moreover, in each month we drop the observations at the top and bottom 1 percentiles to avoid outliers.

Inflation expectations The SCE asks respondents to provide expectations about future inflation at two different horizons: expected inflation/deflation over the next 12 months (which we define as "1 year") and expected inflation/deflation over the 12 months starting from 24 months in the future (which we define as "3 years"). The SCE asks respondents to indicate both their point forecast for future expected inflation and their subjective distribution over all possible inflation realizations.

First, to measure expected mean inflation we use the point forecast provided by respondents.<sup>10</sup> We use this measure to construct (i) expected mean inflation  $(For_{i,t})$  as the point forecast provided in month t, and (ii) prior mean expectation as the point forecast provided in month t - 1 by the same forecaster  $(Prior_{i,t})$ . We consider point forecasts of inflation at 1- and 3-year horizons. Due to the monthly frequency of data, forecasts from adjacent

<sup>&</sup>lt;sup>9</sup>The respondents are household heads, defined as "the person in the household who owns, is buying, or rents the home". See Armantier et al. (2017) for additional details.

<sup>&</sup>lt;sup>10</sup>While we could alternatively use the mean forecast computed from the subjective distribution, we use the answers to two different survey questions to measure the first and second moments of subjective beliefs to lower the concern of possible measurement error correlation between the two measures. However, in Appendix P we replicate our main results using the mean of the subjective density forecast to measure the expected mean, with the same results.

months refer to outcomes with slightly different horizons. This mismatch is negligible at the 3-year horizon, which we therefore treat as approximately constant over time. Accordingly, our main analysis focuses on 3-year forecasts, with 1-year forecasts used for robustness.

Second, we use the subjective distribution to measure posterior uncertainty. Respondents provide probabilities over a support of 10 symmetrical beans of possible values, ranging from -12% to 12% in steps of 2 to 4 percentage points (see Appendix B). The FRNBY also provides a measure of individual forecast variance by estimating parametric subjective densities using a method developed by Engelberg et al. (2009) and explained in detail in Armantier et al. (2017).<sup>11</sup> We indicate as posterior uncertainty the standard deviation from the variance of the subjective distribution provided in the current month(*Post Uncertainty<sub>i,t</sub>*). For robustness, we also consider the interquartile range as a measure of uncertainty, as it is less sensible to small variations in the tails of subjective distributions. The top panel of Table A.3 presents summary statistics for forecasts and uncertainty.

**Socioeconomic characteristics** For each respondents, the survey reports gender (*Female<sub>i</sub>*), age ( $Age_{it}$ ) and race (*White<sub>i</sub>*). Moreover, we construct an indicator variable with value one if the respondent attended college and zero otherwise (*College<sub>it</sub>*). The survey provides respondent income, but only as a categorical variable. We construct an indicator with value 1 if the respondent has an income lower than 50k (*Income Under50k<sub>it</sub>*), between 50k and 100k (*Income 50kto100k<sub>it</sub>*), and above 100k (*Income Under50k<sub>it</sub>*). The SCE also reports respondents' numeracy, based on their ability to answer questions about probabilities and compound interest (Lusardi, 2008). Respondents who answer at least four out of the five questions correctly are assigned a high numeracy indicator (*HighNumeracy<sub>i,t</sub>*). Finally, the variable *Tenure<sub>i,t</sub>* indicates the number of months each respondent has been present in the survey, from 1 to 12. Kim and Binder (2023) shows that tenure in the survey has crucial effects on inflation expectations and uncertainty, by prompting information acquisition between survey waves, i.e. "learning-through-survey". Therefore, we include tenure as a determinant of belief stickiness.

<sup>&</sup>lt;sup>11</sup>A possible concern with this method is that the maximum interval bins proposed in the survey question might be too low in periods of high inflation. This could cause respondents to cluster in the upper-bound bin in those periods, leading to a measurement error for our uncertainty measure. To address this concern, in Appendix C we show that our bins-based uncertainty measure closely tracks an alternative one which is instead based on the rounding of point forecasts, as in Binder (2017).

#### 2.2 Empirical strategy

Building on the recent methodology developed in Goldstein (2023) and Gemmi and Valchev (2023), we estimate belief stickiness by comparing individual posterior with prior forecasts across households. Previous studies often rely on the approach pioneered by Coibion and Gorodnichenko (2015a) to estimate belief stickiness in expectation surveys, which involves regressing consensus forecast errors against forecast revisions. However, this approach is not suitable for our exercise due to two key reasons: first, it is biased in the presence of common errors in the structure of the signal ( $\sigma_{\omega} > 0$  in our theoretical framework);<sup>12</sup> second, it requires a long time series dimension, unavailable in the SCE. Instead, the methodology we adopt overcomes both challenges by exploiting the cross-sectional variation of individual forecasts.

Demeaning (2) using consensus forecasts, one obtains<sup>13</sup>

$$E_t^i[x_{t+h}] - \bar{E}_t[x_{t+h}] = (1 - G)(E_{t-1}^i[x_{t+h}] - \bar{E}_{t-1}[x_{t+h}]) - G\eta_t^i$$
(4)

Equation (4) provides an unbiased strategy to measure information rigidity. We run the following panel regression

$$For_{i,t} = \alpha + \beta Prior_{i,t} + \gamma_t + err_t^i \tag{5}$$

where *i* indicates the household and *t* the year-month. We include the year-month fixed effect  $\gamma_t$  to demean the individual forecasts. The coefficient  $\beta$  is an unbiased estimator of the belief stickiness 1 - G. Intuitively, higher belief stickiness implies a higher correlation between posterior beliefs and prior beliefs (higher  $\beta$ ), while lower belief stickiness implies a lower correlation between posterior beliefs and prior beliefs (lower  $\beta$ ). Our belief stickiness measure,  $\beta$ , captures the average responsiveness of household expectations to new information, incorporating both the extensive margin (whether consumers update at all) and the intensive margin (how much they update, conditional on updating).

Table 1 reports the estimates of belief stickiness  $\beta$  from regression (5). Column (1) reports the belief stickiness in the whole sample, which implies a gain of G = 0.478. This

<sup>&</sup>lt;sup>12</sup>The bias in the presence of common error in the signals was already recognized in Coibion and Gorodnichenko (2015a), Online Appendix A.

<sup>&</sup>lt;sup>13</sup>Demeaning the belief updating equation eliminates the actual realization of the underlying process, which could represent only part of the actual variable realization observable by the econometrician. In other words, the econometrician does not need to observe  $x_t$  to run the regression.

	(1) Forecast	(2) Forecast	(3) Forecast	(4) Forecast
Prior	$\begin{array}{c} 0.542^{***} \\ (0.011) \end{array}$	$\begin{array}{c} 0.528^{***} \\ (0.010) \end{array}$	$\begin{array}{c} 0.331^{***} \\ (0.020) \end{array}$	$\begin{array}{c} 0.318^{***} \\ (0.021) \end{array}$
$Prior \times Tenure_{it}$			$\begin{array}{c} 0.028^{***} \\ (0.002) \end{array}$	$0.030^{***}$ (0.002)
$High \ Numeracy_{it} = 1 \times Prior$			$\begin{array}{c} 0.071^{***} \\ (0.016) \end{array}$	$\begin{array}{c} 0.075^{***} \\ (0.016) \end{array}$
$Tenure_{it}$			$-0.147^{***}$ (0.012)	
$High \ Numeracy_{it}$			$-1.936^{***}$ (0.129)	
Constant	$2.109^{***} \\ (0.052)$	$2.182^{***} \\ (0.050)$	$\begin{array}{c} 4.495^{***} \\ (0.151) \end{array}$	$2.046^{***} \\ (0.046)$
Year-Month FEs	Y	Y	Y	Y
Tenure $\times$ Year-Month FEs	Ν	Ν	Ν	Y
Numeracy $\times$ Year-Month FEs	Ν	Ν	Ν	Υ
Adjusted R-squared	0.33	0.31	0.34	0.35
Observations	95098	91848	95070	95070

Table 1: Belief stickiness

Legend: Forecast denotes the point expectation about the 12-month inflation starting 24 months into the future from the current month issue of the SCE. Prior denotes the expectation about the same variable but in the previous month issue of the SCE. Tenure<sub>i,t</sub> is a continuous variable of a household's tenure in the survey, and High Numeracy<sub>i,t</sub> = 1 is a dummy for high-numeracy individuals. We control for year-month fixed effects and their interaction with Tenure<sub>i,t</sub> and High Numeracy<sub>i,t</sub> = 1. The estimation period is 2013M6-2023M5. Column (2) excludes respondents who never revised their forecasts. Standard errors (in parentheses) are clustered at individual and time levels. \*, \*\*, and \*\*\* represent p < 0.10, p < 0.05, and p < 0.01, respectively.

estimate translates roughly to equal weight on prior and new information when forming new beliefs in equation (2). This estimate is higher than the ones in Coibion and Gorodnichenko (2015a), possibly because of the public information bias mentioned before, but in line with Goldstein (2023) and Gemmi and Valchev (2023), who use a similar empirical strategy on the Survey of Professional Forecasters. Notice that the empirical strategy adopted here is not informative about the optimality of consumers' belief stickiness, i.e. whether the weight on new information G equals the Bayesian Kalman gain. We discuss this in the next section.

We perform robustness tests addressing two possible concerns with the methodology adopted. First, some respondents may change their expectations from one month to the other, but without changing their answer to the survey. This would bias our result toward higher stickiness. To address this concern, we estimate the belief stickiness excluding consumers who never changed their reported forecasts. Column (2) reports this estimate, which is lower but comparable to column (1). Second, we investigate whether the estimate is driven by inexperienced consumers who might not pay attention or understand the survey questions. To do this, we interact the prior and the time-fixed effect with variables measuring tenure (how long the respondent has been in the survey) and numeracy skills. Column (3) shows that belief stickiness is higher for consumers with higher tenure in the survey and for consumers with a high level of numeracy. This result suggests that the large estimated belief stickiness is not driven by inexperienced respondents. Similar results are documented for 1-year ahead inflation expectations, presented in Table A.12.

While the positive effect of tenure on belief stickiness may appear at odds with the "learning-through-survey" finding of Kim and Binder (2023), this is not the case. Using the same SCE data, Kim and Binder (2023) documents a negative effect of tenure on the level of inflation expectations—a result we also find, as shown in column (3) of Table 1. However, while tenure lowers the level of expected inflation, it increases the stickiness of belief adjustments. Kim and Binder (2023) also finds that tenure has a negative effect on inflation uncertainty, which may help explain our result: as high-tenure consumers become better informed, they tend to adjust their beliefs less in response to new information. We further explore the relationship between uncertainty and belief adjustment in the following sections.

#### 2.3 Heterogeneity in belief updating

To better understand the mechanics of belief formation, we investigate how socioeconomic characteristics such as income, education, gender, age, numeracy, and tenure affect house-holds' belief updating. To this scope, we interact them with the prior in the previous regression (5):

$$For_{i,t} = \alpha + \beta_1 Prior_{i,t} + \mathbf{X}_{i,t}\mathbf{B}_2 + Prior_{i,t} \times \mathbf{X}_{i,t}\mathbf{B}_3 + \gamma_t + \beta_4(\gamma_t \times \mathbf{X}_{i,t}) + \epsilon_t^i$$
(6)

where  $\mathbf{X}_{i,t}$  is a vector containing a set of socioeconomic characteristics binary indicators, and  $\mathbf{B}_3$  is a vector of coefficients capturing their impact on belief stickiness. The characteristics we consider are the following: tercile of tenure (i.e. number of months in the survey), whether they hold a college degree, whether their age is over 60 or under 40, income over 100k or below 50k, high numeracy, gender, and race.

Figure 1 reports the estimated coefficients  $\mathbf{B}_3$ , while Table A.4 reports all the estimated



Figure 1: Heterogeneity in belief stickiness

Legend: The figure shows belief stickiness ( $\mathbf{B}_3$  in (6), i.e. column (7) of Table A.4) for different socioeconomic categories. Sample: 2013M6-2023M5. Bars represent the 95% confidence interval.

coefficients. We find that households with higher tenure, a college degree, and higher numeracy exhibit larger belief stickiness. On the other hand, young respondents exhibit lower belief stickiness.<sup>14</sup>

According to the standard Bayesian updating model, belief stickiness depends on the perceived quality of information. This would imply that less skilled, less experienced, and younger individuals have access to more accurate information. Another possible explanation is that these individuals are more confident about their information, meaning they perceive it as more accurate, regardless of whether this is true or not. Alternatively, households might form beliefs in a non-Bayesian fashion, and these differences between socioeconomic groups might depend on behavioral biases. In the next section, we investigate these questions by formally testing the Bayesian framework using perceived information accuracy.<sup>15</sup>

<sup>&</sup>lt;sup>14</sup>In Appendix D, we explore heterogeneity in belief adjustment on the intensive and extensive margins by the same demographic characteristics as above. We document similar results, but with generally higher significance. In particular, less educated and less numerate respondents are more responsive to new information - reflecting greater updating frequency, and have stronger revisions, while experienced and high-numeracy individuals exhibit more persistent expectations - consistent with fewer updates, and more conservative revisions. Although our stickiness measure captures the average adjustment, these patterns indicate that the underlying behavioral intensive and extensive margins differ across groups in similar ways. For a deeper analysis of attention heterogeneity in consumer and professional forecasters surveys, see Boccanfuso and Neri (2024).

 $<sup>^{15}</sup>$ In Appendix N we document that lower belief stickiness is associated with lower forecast errors, suggesting that better-informed households are adjusting their beliefs more. In Section 3, we derive and formally

### **3** Belief stickiness and uncertainty

In this section, we investigate the relationship between information rigidity and uncertainty. As discussed in Section 1, our empirical strategy does not require us to make any assumption on the belief formation model determining belief stickiness  $1 - G_t$ . Rather, our framework embeds the noisy information rational expectation model as a particular case. Thus, we can compare the empirical properties of our belief stickiness estimates with the implications of the rational expectation framework.

#### 3.1 The Bayesian framework

Assume consumers update their beliefs according to the Bayes rule. Suppose the signal is given by equation (1). Then, the posterior mean is given by equation (2) and the posterior uncertainty by equation (3), where the belief stickiness is given by

$$1 - G_t^{RE} = \frac{\sigma_{e,t}^2}{\sigma_{e,t}^2 + \Sigma_{t+h,t-1}}$$
(7)

The RE model (7) provides two testable implications. First, higher new information noise  $\sigma_{e,t}^2$  is associated with higher belief stickiness. For example, households may face a higher cost of collecting information or a lower supply of information from newspapers, television, or social networks. Second, higher prior uncertainty is associated with higher belief stickiness. The noisier the history of signals the agents received in the past, the more accurate the new signal will be *relative* to this stock of existing information. As a result, the agent allocates more weight to the new signal in forming posterior beliefs, i.e. belief stickiness is higher.

**Discussion** We make three related observations. First, these implication holds similarly in models with endogenous information or rational inattention (Sims, 2003, 2006; Mackowiak and Wiederholt, 2009; Maćkowiak et al., 2023). These frameworks allow agents to allocate attention to new information, making the information noise  $\sigma_{e,t}^2$  a choice variable. However, equation (7) shows that the only determinant for belief stickiness is the total equilibrium new information noise, regardless of whether it is driven by demand or supply. Second, although we derived under the rational expectation assumption, these qualitative implications hold in many models that depart from but build on the baseline Bayesian updating in (7). For example, diagnostic expectations (Bordalo et al., 2018, 2020), overconfidence (Broer and Kohlhas,

test the implications of Bayesian updating.

2024), and over- and under-extrapolation (Angeletos et al., 2021) all share the same qualitative impact of prior and new information uncertainty on belief stickiness. On the other hand, these results do not hold in models where the gain  $G_t$  does not depend on the uncertainty of the economy, but only on some fixed parameter. For example, the baseline case of sticky information (Mankiw and Reis, 2002), adaptive learning with a constant gain (Orphanides and Williams, 2007; Eusepi and Preston, 2011), natural expectations (Fuster et al., 2010), and behavioral inattention (Gabaix, 2019) do not share these implications (at least in their benchmark version). Lastly, while the impact of new information noise on belief stickiness is unambiguous, its impact on belief disagreement is not. Belief disagreement, defined as the variance of posterior mean forecast across agents, could either increase or decrease with noisier information, depending on whether the signals are correlated (i.e. common noise) or not.

#### **3.2** Belief stickiness and sources of uncertainty

We empirically test the two implications of the Bayesian belief updating framework in equation (7). First, higher prior uncertainty implies lower belief stickiness. Second, higher new information noise implies higher belief stickiness.

A main limitation of using variation in survey expectations is that we do not directly observe the new information noise. Instead, we leverage our general framework to estimate it from the survey data. To do this, we proceed in two steps. First, we divide our sample into groups based on socioeconomic similarities and estimate belief stickiness in each month for each group. Second, use belief stickiness and posterior uncertainty to estimate new information noise. Once we have obtained these measures, we investigate the relationship between belief stickiness, prior uncertainty, and new information noise.

#### 3.2.1 First step: estimate belief stickiness

We estimate belief stickiness for each month in each consumer group. The assumption behind this procedure is that different groups receive similar new information noise, and therefore have similar belief stickiness. Formally, we consider a group-specific version of the signal structure in (1), which is now

$$s_t^{i,j} = x_{t+h} + e_t^{i,j} (8)$$

where  $e_t^{i,j} = \eta_t^{i,j} + \omega_t$ . Similar to before, we allow the signal noise to have an idiosyncratic and a common component. However, signals now are specific to an individual *i* in group *j*. We assume the variance of the idiosyncratic component  $\eta_t^{i,j}$  is the same for individuals in a specific group,  $\eta_t^{i,j} \sim N(0, (\sigma_{\eta,t}^j)^2)$ , while the common component is the same for all groups,  $\omega_t \sim N(0, (\sigma_{\omega,t})^2)$ . Therefore, a "group" refers to a set of individuals with similar quality of information.

This gives the structural equation

$$E_t^{i,j}[x_{t+h}] - \bar{E}_t^j[x_{t+h}] = (1 - G_t^j)(E_{t-1}^{i,j}[x_{t+h}] - \bar{E}_{t-1}^j[x_{t+h}]) - G_t^j\eta_t^{i,j}$$
(9)

where  $\bar{E}^{j}[x] = \int^{i} E^{i,j}[x] di$  is the average forecast in group j.

First, we divide consumers into j = 1, ..., J groups based on sociodemographic categories, assumed to identify individuals with similar new information quality. We consider the 4 indicators that we show have the most impact on belief stickiness in Figure 1: tercile of tenure, high numeracy, college education, and under 40 years old. Each combination of these indicators is a group, which gives a total of 24 groups.<sup>16</sup>

We estimate regression (5) for each group and in each month. In other words, for each group j, and month t we run

$$For_{i,j,t} = \alpha_{j,t} + \beta_{j,t}Prior_{i,t} + err_{i,j,t}$$

$$\tag{10}$$

We obtain a series of estimates  $\hat{\beta}_{j,t} = 1 - G_{j,t}$ . Figure A.3 plots the distribution of the estimated belief rigidities.

#### 3.2.2 Second step: impact of uncertainty on belief stickiness

Next, we examine whether the relationship between our estimates of belief stickiness and measures of prior uncertainty and new information noise aligns with the Bayesian RE framework (7).

We proxy for *current* prior uncertainty using *lagged* posterior uncertainty, meaning the uncertainty derived from density forecasts provided by the same individual in the previous month. This proxy is valid under two assumptions. First, similarly to our proxy for prior belief means, we assume that the horizon of current and lagged density forecasts is the same.

<sup>&</sup>lt;sup>16</sup>There is a trade-off between the granularity of the group definition and the sample size required to run period-by-period regression in each group. While we keep the number of groups low to allow period-by-period estimation, we exclude group-month combinations with less than 20 observations.

This assumption is justified by the small difference of one month compared to the total forecast horizon of 36 months. Second, we assume no structural change in the volatility of the underlying process for inflation. Intuitively, our proxy for current prior uncertainty uses lagged information, namely the history of accumulated signal accuracy up to t - 1, and therefore would not include any structural change occurring in t. We discuss this in more detail in Section 4, where we provide evidence for such a structural change during COVID. While the time fixed effect should lower common measurement concerns in some of our regressions, we limit our sample to the pre-COVID period in this section.

Second, we use two different proxies for new information noise, which is otherwise not directly observable in the data. First, we use variation in group-average posterior uncertainty controlling for prior uncertainty, which would therefore reflect variation in new information noise. Second, we use our estimates of belief stickiness, together with our measure of prior uncertainty, to directly extract new information noise from posterior uncertainty.

**Proxy 1: posterior uncertainty** We first proxy for new information noise using posterior uncertainty controlling for prior uncertainty. From (3), the posterior variance of group j at time t equal

$$\Sigma_{t+h,t}^{j} = (1 - G_{t}^{j})^{2} \Sigma_{t+h,t-1}^{j} + (G_{t}^{j})^{2} (\sigma_{e,t}^{j})^{2}$$
(11)

Posterior variance is a function of prior variance and new information noise. By controlling for the first, we aim to isolate the latter. In other words, we run the regression

$$(1-G)_{j,t} = \alpha + \delta_1 ln(PriorUncert_{j,t}) + \delta_2 ln(PosteriorUncert_{j,t}) + \gamma_t + \gamma_j + \epsilon_{j,t}$$
(12)

where  $1 - G_{j,t} = \hat{\beta}_{j,t}$  is the group-month belief stickiness estimated in the first step in regression (10),  $PosteriorUncert_{j,t}$  is the mean of individual posterior uncertainty (the squared root for the variance) in group j, and similarly for  $PriorUncert_{j,t}$ . We include time and group-level fixed effects. We test two hypotheses. First, for a given new information noise, higher prior uncertainty leads to lower belief stickiness:  $\delta_1 < 0$ . Second, for a given prior uncertainty, higher new information noise leads to lower belief stickiness:  $\delta_2 > 0$ .

Our empirical estimates confirm both hypotheses. Table 2 reports the estimation result. Column (1) shows that belief stickiness decreases in prior uncertainty and increases in posterior uncertainty. Column (2) shows the same result using the interquartile range of the density forecast to measure uncertainty. Column (3) shows the same result using absolute

	(1) Stickiness	(2) Stickiness	(3) Stickiness	(4) Stickiness	(5) Stickiness
ln(PriorUncert)	$-0.393^{***}$ (0.134)		$-0.260^{***}$ (0.091)		$-0.202^{***}$ (0.065)
ln(PostUncert)	$\begin{array}{c} 0.422^{***} \\ (0.136) \end{array}$				
ln(PriorUncertIQR)		$-0.378^{***}$ (0.128)			
ln(PostUncertIQR)		$\begin{array}{c} 0.419^{***} \\ (0.129) \end{array}$			
ln(absoluteFE)			$0.356^{***}$ (0.049)		
ln(NewInfoNoise)				$\begin{array}{c} 0.345^{***} \\ (0.027) \end{array}$	$\begin{array}{c} 0.354^{***} \\ (0.029) \end{array}$
Year-Month FEs	Y	Y	Y	Y	Y
Group FE	Y	Υ	Υ	Υ	Υ
Sample	Jun13-Feb20	Jun13-Feb20	Jun13-Feb20	Jun13-Feb20	Jun13-Feb20
Adjusted R-squared	0.12	0.12	0.18	0.62	0.62
Observations	722	722	695	687	687

Table 2: Belief stickiness and uncertainty

Legend: This table reports the estimated coefficient from regression (12). PostUncert denotes the group-month average of 1-year ahead forecast of inflation expectations uncertainty starting 24 months into the future from the NY Fed Survey of Consumer Expectations (SCE). PriorUncert is the same variable, but from the previous month. We control for year-month and group fixed effects. PriorUncertIQR and PostUncertIQR are the interquartile ranges of the same forecasts. absoluteFE is the group-month average absolute forecast error. NewInfoNoise is described in the main text. Standard errors (in parentheses) are bootstrapped at the group-month level. \* represents p < 0.10, \*\* represents p < 0.05, and \* \* \* represents p < 0.01.

forecast errors to measure the quality of new information.

Measuring new information noise using posterior uncertainty does not require the twostep procedure presented here. Instead, we can directly test the impact of prior and posterior uncertainty on belief stickiness by including interactions in a single regression. We conduct this analysis in Appendix G and obtain qualitatively the same result: belief stickiness decreases with prior uncertainty and increases with posterior uncertainty.

Using posterior uncertainty as a proxy for new information uncertainty has the advantage of being easily observable in the survey, but it presents a potential drawback. While regression (12) tests the impact of posterior uncertainty on belief stickiness, equation (11) shows that the opposite is also true, as posterior uncertainty depends on belief stickiness. Therefore regression (12) might suffer from an endogeneity bias.<sup>17</sup> To address this issue, we propose an alternative measure for new information noise.

<sup>&</sup>lt;sup>17</sup>While one might want to estimate equation 11 through a linear OLS using data on posterior and prior uncertainty, we notice that it is not possible as  $G_t^j$  itself may be a function of prior and new information uncertainty, respectively  $\Sigma_{t+h,t-1}^j$  and  $(\sigma_{e,t}^j)^2$  (for example, in the rational expectation case in equation (7)).

Figure 2: Belief stickiness and uncertainty



Legend: The figure represents graphically the estimated coefficients from column (6) of Table 2. It shows the relationship between belief stickiness and prior uncertainty (on the left-hand side) and new information noise (on the right-hand side).

**Proxy 2: new information noise** The benefit of the two-step procedure is that it allows us to estimate new information noise from our model equations. Specifically, we use our estimate of belief stickiness, together with our measures of prior and posterior uncertainty, to compute the new information noise from (3).<sup>18</sup>

$$\widehat{\sigma}_{e,t}^{j,2} = \frac{PosteriorUncert_{j,t}^2 - \widehat{\beta}_{j,t}^2 PriorUncert_{j,t}^2}{(1 - \widehat{\beta}_{j,t})^2}$$
(13)

where  $PosteriorUncert_{j,t}$  is the mean of individual posterior uncertainty in group j, and similarly for  $PriorUncert_{j,t}$ . We drop the observations  $\hat{\sigma}_{e,t}^{j,2}$  lower than zero, around 5% of the sample.

We regress belief stickiness on this new measure of new information noise. That is, we run the regression

$$Stickiness_{j,t} = \alpha + \delta_1 ln(PriorUncert)_{j,t} + \delta_2 ln(NewInfoNoise)_{j,t} + \gamma_t + \gamma_j + \epsilon_{j,t}$$
(14)

where  $NewInfoNoise_{j,t} = \hat{\sigma}_{e,t}^{j}$  and  $stickiness_{j,t} = \hat{\beta}_{j,t}$ . We test the same hypotheses as in the previous regression, meaning  $\delta_1 < 0$  and  $\delta_2 > 0$ .

The empirical estimates using this second proxy confirm both hypotheses. The last two columns of Table 2 report the estimation result. Column (4) shows that our measure of new

<sup>&</sup>lt;sup>18</sup>We notice that equation (3) is part of our general framework and it does not impose any model of belief stickiness, meaning it does not make any assumption on  $G_t^j$ .

information noise impacts positively belief stickiness, while column (5) shows that the effect of prior uncertainty is negative while controlling for new information noise. Figure 2 plots the estimated effect of prior uncertainty and new information noise on belief stickiness in the main specification of Column (5) in Table 2. The effect of uncertainty on belief stickiness is sizable. A one standard deviation increase in the prior uncertainty reduces belief stickiness by around 0.1, i.e. around 20%. Similarly, a one standard deviation increase in the new information noise increases belief stickiness by around 0.07, i.e. 15%. In conclusion, we document a robust positive relationship between belief stickiness and prior uncertainty and a negative one with new information uncertainty, in line with the prediction of the Bayesian belief formation model. However, we note that aggregate inflation variation in our pre-COVID sample is limited.

**Discussion** Recent studies suggest that households' belief adjustment depends on the level of inflation. Empirically, Weber et al. (2024) compares various RCT experiments and finds that the impact of the exogenously provided information on households is weaker (i.e., belief stickiness is higher) during periods of high inflation. Theoretically, Mackowiak and Wiederholt (2024) shows that when inflation is high, consumers pay more attention to it, making them better informed and reducing the effectiveness of additional information provision in RCTs. In other words, the impact of high inflation on belief stickiness in an RCT operates through lower prior uncertainty. However, prior uncertainty is influenced by factors beyond inflation. Using naturally occurring variation instead of RCT data, we directly examine the relationship between prior uncertainty and belief stickiness and confirm a negative relationship.<sup>19</sup>

#### **3.3** Are consumers rational?

We documented that consumers are *qualitatively* Bayesian, but are they also quantitatively Bayesian? We use our proxies for prior uncertainty and new information noise to construct the counterfactual belief stickiness in the Rational Expectation framework, (7). We notice that, while we used our empirical estimates of belief stickiness to recover a measure for new information noise, we have not made any assumptions on what determines belief stickiness. As a result, we can compare the belief stickiness measured in the data with the one a

<sup>&</sup>lt;sup>19</sup>In Table A.9, we replicate our analysis while controlling for annual, monthly, and lagged monthly inflation and find no significant impact on belief stickiness. However, we note that inflation variation in our pre-COVID sample is limited.



Figure 3: Counterfactual RE and estimated belief stickiness

Legend: The left panel plots on the x-axis the estimated belief stickiness  $\hat{\beta}_{j,t}$  from regression (10) and on the y-axis the implied rational expectation belief stickiness from equation (7). If the observation lies above the 45-degree red line, then the implied RE belief stickiness is larger than the estimated one. The right panel plots the two distributions, showing that the distribution of the implied RE belief rigidities is to the right of the estimated ones. Sample Jun13-Feb20.

consumer would display if he updated rationally given the observed prior uncertainty and new information noise. From equation (7),

$$1 - \tilde{G}_{j,t}^{RE} = \frac{\widehat{\sigma}_{e,t}^{j,2}}{\widehat{\sigma}_{e,t}^{j,2} + PriorUncert_{j,t}^2}$$
(15)

Figure 3 reports the results for each group-month in the pre-COVID sample.<sup>20</sup>

We highlight two takeaways. First, a consumer facing the same prior uncertainty and new information noise, but updating rationally, would display on average a higher belief stickiness than the estimated one. This can be seen in Figure 3a, as the estimates of belief stickiness lie above the 45-degree line. Figure 3b plots the distributions of estimated and counterfactual RE belief stickiness, with means of respectively around 0.5 and 0.7. In other words, the households in the SCE seem to overreact by placing around a 60% higher weight on new information compared to the rational counterfactual. This is consistent with the evidence reported in Table 1, which shows that consumers with higher tenure and numeracy

 $<sup>^{20}</sup>$ As we extract new information noise from individual subjective uncertainty, it measures *perceived* new information noise, and it might not be equal to the *actual* new information noise. Therefore, a belief stickiness equal to (15) is a necessary condition for Rationality, but not sufficient, as one would also need to assume that the subjective accuracy of information equals the perceived one. However, we show that even this necessary condition is rejected by the data.

scores display higher belief stickiness than the average. Moreover, this is also consistent with the evidence of overreaction to new information documented in laboratory experiments (Afrouzi et al., 2023) and surveys (Bordalo et al., 2020; Broer and Kohlhas, 2024). Second, some estimates of belief stickiness lay outside the RE interval, around 3% of them below zero and 4% above one. While this could be due to measurement error, it can also be due to non-rational behavior. A negative belief stickiness could imply an overweighting of new information, while a belief stickiness above one could imply overweighting of prior information.<sup>21</sup>

To sum up, consumers seem to overreact to new information, displaying too little belief stickiness compared to the Rational Expectation framework.<sup>22</sup> We quantify this overreaction below.

**Estimating a belief formation model** Next, we investigate possible belief formation biases on consumer expectations. We test the following functional form for the estimated belief stickiness

$$1 - \tilde{G}_{j,t} = 1 - \left(\bar{g} + (1+\delta)\frac{PriorUncert_{j,t}^2}{(1-\alpha)\widehat{\sigma}_{e,t}^{j,2} + PriorUncert_{j,t}^2}\right)$$
(16)

We consider three parameters introducing a wedge between the estimated belief stickiness and the RE counterfactual, namely  $\bar{g}, \delta, \alpha$ , encompassing different behavioral models. If they are all equal to zero, then we get the rational expectation belief stickiness (15). First,  $\alpha \neq 0$ indicates an over- or under-weighting of new information compared to the RE Kalman gain  $G^{RE}$ . In case of  $0 < \alpha < 1$ , this is similar to an overconfidence bias (Broer and Kohlhas, 2024; Adam et al., 2025).<sup>23</sup> Second,  $\delta \neq 0, \alpha = 0$  indicates an over- or under-reaction to the Kalman gain  $G^{RE}$ . In case of  $\delta > 0$ , this is similar to the diagnostic expectation framework

<sup>&</sup>lt;sup>21</sup>Consider for example the diagnostic expectation belief formal model of Bordalo et al. (2020). In this case,  $G_t^j = (1+\theta)G_t^{REj}$ , where  $\theta > 0$  is a parameter governing the overreaction to new information. In this framework, our estimates belief stickiness would equal  $\hat{\beta}_t^j = 1 - (1+\theta)G_t^{REj}$ , which may be negative for higher enough  $\theta$  and  $G_t^{REj}$ . Conversely, a negative  $\theta$ , meaning underreaction, and low enough  $G_t^{REj}$  could lead to estimated belief stickiness above one.

<sup>&</sup>lt;sup>22</sup>Figure A.4 reports the same comparison excluding observations in the first quartile of tenure, i.e., considering only consumers who participate in the survey for longer periods. The result is virtually the same.

 $<sup>^{23}</sup>$ An important difference between the bias we test here and overconfidence is that in the latter framework agents overweight new information because they underestimate its noise. Instead, we extract the new information noise from consumers' subjective beliefs. Therefore, we estimate how much they overweigh their subjective new information noise.

	(1)	(2)	(3)	(4)	(5)
δ	$0.672^{***}$ (0.018)			-0.093 (0.095)	-0.094 (0.081)
α		$0.625^{***}$ (0.008)		$0.792^{***}$ (0.094)	$\begin{array}{c} 0.817^{***} \\ (0.089) \end{array}$
$ar{g}$			$0.194^{***}$ (0.005)	$-0.067^{***}$ (0.026)	$-0.086^{***}$ (0.031)
Sample N	Jun13-Feb20 687	Jun13-Feb20 687	Jun13-Feb20 687	Jun13-Feb20 687	Jun13-May23 1028

Table 3: GMM estimation

Legend: This table reports the estimated coefficients  $\delta, \alpha$  and  $\bar{g}$  from objective function (16) with GMM.  $\alpha \neq 0$  and  $\delta \neq 0$  capture different forms of overreaction documented in the literature, and  $\bar{g}$  allow for a constant component of belief stickiness. Standard errors (in parentheses) are bootstrapped at the group-month level. \* represents p < 0.10, \*\* represents p < 0.05, and \* \* \* represents p < 0.01.

(Bordalo et al., 2018, 2020).<sup>24</sup> Finally, we allow for a constant component of belief stickiness  $\bar{g}$  that does not depend on the information accuracy. We estimate the three parameters by generalized moment matching, minimizing the distance between (16) and our estimates of belief stickiness, i.e.  $min_{\bar{g},\delta,\alpha} \left( \widehat{(1-G_{j,t})} - (1-\tilde{G}_{j,t}) \right)^2$ . Table 3 reports the results.

We find  $\alpha > 0$ , while the other parameters  $\bar{g}$  and  $\delta$  are not significant. In other words, consumers' belief stickiness relatively overweighs new information compared to the prior, leading consumers to overreact to new information. Figure 4a shows that the fitted value from model (2) of Table 3 aligns well with the estimates of belief stickiness. While this behavior is inconsistent with rational expectations—which assumes accurate model knowledge—it remains qualitatively Bayesian in that revisions respond to relative uncertainty. However, while households are qualitatively Bayesian — adjusting more when prior beliefs are uncertain and less when signals are noisy — they are not quantitatively Bayesian. They over-react, implying that they systematically place too much weight on new information relative to what a fully Bayesian agent would do, even given their own perceived uncertainty.

Next, we investigate how the overreaction parameter  $\alpha$  depends on sociodemographic characteristics:

$$1 - \hat{G}_{j,t} = 1 - \left(\bar{g} + \frac{PriorUncert_{j,t}^2}{(1 - \alpha_0 - \sum_{k=1}^5 \alpha_k D_k)\widehat{\sigma}_{e,t}^{j,2} + PriorUncert_{j,t}^2}\right)$$
(17)

 $<sup>^{24}</sup>$ An important difference between the bias we test here and diagnostic expectation is that in the latter framework the bias only applies to the first moment of belief and not to the second moment. In our framework, the same belief stickiness is applied to first and second moments of beliefs, equation (2) and (3) (Bordalo et al., 2020). Bianchi et al. (2024) proposes a "smooth" DE setting where the bias also affects the second moment of beliefs.

#### Figure 4: Overreaction bias



Legend: The left panel plot the estimated belief stickiness from (9) and the fitted values from model (2) of Table 3. The right panel plots the estimated  $\alpha_k$  of model (16). Confidence intervals are at the 90% level and standard errors are bootstrapped at the group and month level. Sample Jun13-Feb20. Table A.7 reports the detailed results.

where  $D_k = 1$  is the group belong to the socioeconomic characteristics k and  $\alpha_k$  measure the impact of this characteristic on the overreaction parameter  $\alpha$ . We estimate the parameters with GMM,  $\min_{\{\alpha_k\}_{k=0}^5} \left( \widehat{(1-G_{j,t})} - (1-\widehat{G}_{j,t}) \right)^2$ . Table A.7 reports the results and Figure (4b) plots the estimated coefficients. We find that younger consumers display a higher overreaction bias, while consumers with high numeracy skills display a lower overreaction bias. This is consistent with the intuition that this bias derives from suboptimal behavior.

### 4 Belief stickiness and the pandemic

In this section, we use our estimates of belief stickiness to examine the economic factors contributing to the surge in uncertainty in the post-pandemic economy. Figure 5a presents the monthly average posterior belief uncertainty, which spiked following the COVID-19 outbreak and continued to rise in the subsequent months. We have shown that the relationship between uncertainty and belief stickiness varies depending on its source—whether it stems from prior uncertainty or new information. Therefore, our estimates of belief stickiness allow us to identify the underlying sources of uncertainty in the post-pandemic economy.

We document a sharp decrease in belief stickiness during the COVID-19 outbreak. Figure 5b reports the average belief stickiness across subgroups for each month in the sample. Before the pandemic, belief stickiness averaged around 0.5, but it dropped abruptly to approximately 0.3 during the COVID period. After the first month of the pandemic, belief stickiness reverted to pre-pandemic levels, eventually stabilizing at a similar value during the high inflation period. These findings are robust to different empirical strategies. First, Figure A.10 shows that the same pattern holds for the shorter one-year forecast horizon. Second, in A.6, we estimate belief stickiness for each month using the entire sample instead of subgroups, yielding similar results with narrower confidence intervals.





Legend: The left panel plots the average posterior belief uncertainty (standard deviation) across all consumers. The right panel plots the average belief stickiness across subsamples estimates of regression 10, while the dashed blue lines represent the average 90% confidence interval. The first red vertical line corresponds to the start of Covid-19 in March 2020. The second red vertical line corresponds to the start of the high-inflation period in January 2021. Sample period: 2013M1 - 2023M5.

Large shifts in belief stickiness, such as the ones during the pandemic, can have significant macroeconomic implications. Increased belief stickiness may, for example, weaken the impact of monetary policy and forward guidance (Angeletos and Huo, 2021; Afrouzi and Yang, 2021), reduce the effectiveness of central bank communication (Angeletos and Lian, 2018; Blinder et al., 2024), influence the frequency of portfolio adjustments (Giglio et al., 2021), and more broadly, alter the transmission of economic shocks. While the macroeconomic consequences of the shift in belief stickiness observed during the pandemic warrant further investigation, our focus here is on using these shifts to shed light on the factors driving the rise in uncertainty during this period.

We document a reversal in the correlation between posterior uncertainty and belief stickiness after COVID-19, as illustrated in Figures 5a and 5b. At the onset of the pandemic, uncertainty surged while belief stickiness declined. Intuitively, consumers abandoned their priors in favor of new information, but became more uncertain about their new beliefs. Then, during the high inflation period following COVID-19, both belief stickiness and uncertainty increased. Intuitively, consumers relied more on their prior beliefs while becoming increasingly uncertain. Importantly, the correlation between belief stickiness and posterior uncertainty is informative about the underlying source of uncertainty. We explore this in more detail in the next section.

**Discussion** Our findings align with Goldstein (2023), which documents a decrease in belief stickiness in the early quarters of COVID-19 in the Surveys of Professional Forecasters.<sup>25</sup> Pfäuti (2023), on the other hand, estimates a regime-switching model using consensus forecasts from the Michigan Survey of Consumer Expectations over a longer sample period. It finds a decrease in belief stickiness when inflation exceeds the 4% threshold, which in our sample occurred only after 2021. In contrast, the large panel structure of the SCE allows us to estimate belief stickiness on a month-by-month basis, revealing a decline as early as the onset of the COVID-19 outbreak. While the Michigan Survey lacks the panel structure required for our empirical strategy, in Figure A.9 we plot the monthly share of respondents in this survey who report not having heard any news about business conditions. We observe a sharp decline in the share of consumers unaware of economic news during the COVID-19 outbreak, which is consistent with our findings from the SCE.

#### 4.1 The sources of uncertainty

Next, we use our estimates of belief stickiness to decompose the underlying sources contributing to the rise in uncertainty in the post-pandemic economy.

The correlation between posterior uncertainty and belief stickiness is informative about the relative importance of these two sources of uncertainty. As illustrated by equation (3), posterior uncertainty depends positively on two factors: the volatility (or noise) of new information  $\sigma_{e,t}$ , and the uncertainty of prior information  $\Sigma_{t+h,t-1}$ . However, in Section 3 we show that these two factors impact belief stickiness in opposite directions. Specifically, for a given prior uncertainty, an increase in new information noise  $\sigma_{e,t}$  reduces the accuracy of signals, leading consumers to update less. Conversely, for a given new information noise, higher prior uncertainty  $\Sigma_{t+h,t-1}$  makes new information *relatively* more accurate than prior

<sup>&</sup>lt;sup>25</sup>While we employ a similar empirical strategy to Goldstein (2023), they do not find any change in belief stickiness during COVID-19 in the Michigan Survey of Consumers. This discrepancy may stem from structural differences between the two consumer surveys: whereas the Michigan survey interviews the same individual only once every six months, the SCE does so monthly, allowing us to measure forecast revisions at higher frequencies.

Figure 6: Decomposing uncertainty: prior and new information noise



Legend: The figure plots the moving average around a window of 3 months for the estimates of new information noise (left y-axis) and prior uncertainty (right y-axis) from equations (3) and (18), as described in Appendix O.

information, leading consumers to update more.

Building on this qualitative insight, we leverage our estimated belief formation model to quantitatively decompose posterior belief uncertainty into new information noise and prior uncertainty.<sup>26</sup> Specifically, in Section 3.3 we estimate consumers' belief stickiness to follow

$$1 - G_t = 1 - \left(\bar{g} + \frac{\Sigma_{t+h,t-1}}{(1-\alpha)\sigma_{e,t}^2 + \Sigma_{t+h,t-1}}\right)$$
(18)

where  $\hat{\alpha} = 0.792$  and  $\hat{g} = -0.067$ . We use equations (3) and (18), together with the estimates of belief stickiness and uncertainty reported in Figure 5, to construct a time series for new information noise and prior uncertainty. Appendix O provides further details and analytical solutions. Figure 6 presents the three-month moving average of each series to smooth out estimation noise. Figure A.12 shows the same decomposition under the Rational Expectations assumption ( $\alpha = 0, \bar{g} = 0$ ), yielding qualitatively similar results.<sup>27</sup>

<sup>&</sup>lt;sup>26</sup>In Section 3, we proxy for prior uncertainty in the pre-COVID period using lagged posterior uncertainty. While this approach is valid under the assumption of no structural breaks in the economy, the COVID pandemic might violate this assumption. Instead of relying on this proxy for prior uncertainty, in this section we use the belief formation model estimated on the pre-COVID sample to extract prior uncertainty from the estimated belief stickiness.

<sup>&</sup>lt;sup>27</sup>Figures A.14 and A.13 display the original estimated series under the estimated belief model and the RE assumption, and exhibit the same pattern.

**Post-COVID** After the initial months of COVID-19, i.e., from the second half of 2020 onward, we document an increase in new information noise, as shown in Figure 6. The initial rise in new information noise *relative* to prior uncertainty explains the positive correlation between belief uncertainty and stickiness observed during the same period in Figure 5. Subsequently, while new information noise remains elevated, its relative magnitude compared to prior uncertainty returns to pre-COVID levels. This, in turn, explains both the similarity in belief stickiness between the pre- and post-COVID periods and the higher belief uncertainty in the latter.

Higher information noise may result from consumers facing greater costs in gathering information or a reduced supply of information from newspapers, television, and social networks. This period, beginning in February 2021, is also marked by rising inflation and increased media coverage. At first glance, this may seem inconsistent with the observed increase in noise in new information about inflation. However, greater media coverage does not necessarily imply more accurate information dissemination. Instead, it may reflect efforts to manage heightened uncertainty driven by the increasing difficulty of predicting inflation.

**COVID outbreak** Interestingly, we find a sharp increase in prior uncertainty at the COVID-19 outbreak, in March 2020. This follows from the contemporaneous spike in belief uncertainty and decline in belief stickiness displayed in Figure 5.

We highlight two possible causes behind this increase in prior uncertainty. In Section 3, we proxied prior uncertainty using lagged posterior uncertainty, which is driven only by shocks dated in t - 1. On the other hand, changes in prior uncertainty in month t could be due to a regime change in the fundamental process for inflation. For example, consider the simple case where the fundamental follows an AR(1) process:

$$x_{t+h} = (1-\rho)\mu_x + \rho x_{t+h-1} + u_{t+h} \tag{19}$$

with  $u_{t+h} \sim N(0, \sigma_u^2)$  being the fundamental shock and  $\mu_x$  the unconditional long-run mean. In this case, prior mean equals  $E_{t-1}^i[x_{t+h}] = (1-\rho)\mu_x + \rho E_{t-1}^i[x_{t+h-1}]$ , and prior variance

$$\Sigma_{t+h,t-1} = \rho^2 \Sigma_{t+h-1,t-1} + \sigma_u^2$$
(20)

First, consider an increase in fundamental volatility  ${\sigma'_u}^2 > {\sigma_u}^2$ . Such higher volatility implies that prior information becomes obsolete, and therefore more uncertain, when forecasting the future, as the stochastic process of the fundamental becomes more unpredictable. We do not take a stand on what could have driven such an increase in fundamental volatility, as some determinants might have been specific to the COVID-19 case: the lethality of the virus, the capacity of healthcare systems to meet an extraordinary challenge, its economic consequences, the waiting time to develop a safe vaccine, et cetera (see Baker et al. (2020)).

Second, consider a loss of trust in the central bank's ability to maintain its inflation target. In this stylized setting, one can think of the belief about the long-run mean of inflation becoming uncertain,  $\mu_x \sim N(\bar{\pi}, \sigma_{\mu}^2)$ . Prior uncertainty then becomes

$$\Sigma_{t+h,t-1} = (1-\rho)^2 \sigma_{\mu}^2 + \rho^2 \Sigma_{t+h-1,t-1} + \sigma_u^2$$
(21)

A larger uncertainty about long-run mean inflation  $\sigma_{\mu}^2$  would increase prior uncertainty and, as a result, lower belief stickiness. This could be possibly due to lower trust in the central bank's ability to achieve its price stability objective. Aikman et al. (2024) measures the trust in the Federal Reserve from Twitter data and finds the lowest point at the COVID outbreak. Alternatively, it could be more generally due to uncertainty about economic policy implementation.<sup>28</sup>

A regime shift in the autoregressive parameter  $\rho$  could also have played a role. However, detecting a structural change within such a short sample is challenging. In Appendix I, we present rolling-window AR(1) regressions of monthly inflation and show that there is no evidence of a stronger shift in the autoregressive parameter  $\rho$  around the COVID-19 period compared to previous periods.

Another possible force driving the change in belief stickiness during COVID-19 is the lockdown policy restrictions on movements implemented by policymakers to stop the spread of the virus. These restrictions might have lowered the cost of browsing for news and therefore contributed to this decrease in belief stickiness. We investigate this in the next section.

<sup>&</sup>lt;sup>28</sup>Figure A.5 plots the Economic Uncertainty Index, constructed by Baker et al. (2016) and offers additional evidence for this implication. We plot the "news coverage component", which measures the share of articles in US online newspapers that mention economic policy uncertainty. This index spikes up during the Covid outbreaks and decreases to the pre-Covid level in the following period, corroborating our results that the increase in belief uncertainty observed during Covid might be due to this policy uncertainty.



Figure 7: Belief stickiness and uncertainty

Legend: The left figure represents the average state-level lockdown policy intensity for different social activities, weighted by state population. The data source for lockdowns is the Oxford Covid-19 Government Response Tracker (OxCGRT). The right plot shows the impact of lockdown measures on our estimate of belief stickiness,  $\beta_2$  in (22). Sample period: 2020M3-2022M12.

# 5 Lockdowns and belief formation

#### 5.1 Impact of lockdowns on belief stickiness

In this section, we investigate the role played by lockdown policies in driving the decline in belief stickiness we documented during the pandemic. The restrictions on movement and activity implemented to stop the spread of the virus might have led many consumers to shift to the internet for work, education, and entertainment. This transition might have lowered the marginal cost of acquiring new information, contributing to changes in how consumers form beliefs.

To analyze the impact of lockdown policies on belief stickiness, we utilize state-level lockdown stringency measures from the Oxford COVID-19 Government Response Tracker (Ox-CGRT) (Hallas et al., 2021). This tracker compiles data on the severity of closure and containment policies, such as school and workplace closings, restrictions on public events, gathering sizes, public transportation, stay-at-home mandates, and internal movement. These indicators are averaged into a summary lockdown measure, weighted by the share of vaccinated and non-vaccinated individuals in each state.<sup>29</sup> Figure 7 reports the time series of the country-level average of each indicator. We also track local COVID-19 impact using per capita state-level COVID-19 cases and deaths.

 $<sup>^{29}</sup>$ We provide more details on the index construction in the Appendix K.

To estimate the effect of lockdown measures on belief stickiness, we interact prior inflation forecasts with the lockdown index and COVID-19 case and death measures. This approach allows us to isolate the impact of lockdown policies from the effects of COVID-19's direct health impact. We run the following regression:

$$For_{i,t} = \alpha + \beta_1 Prior_{i,t} + \beta_2 Prior_{i,t} \times Lockdown_{k,t} + \beta_3 Lockdown_{k,t} + Prior_{i,t} \times CovidSeverity'_{k,t}\Pi + CovidSeverity'_{k,t}\Gamma + \lambda X_{i,t} + [CovidSeverity'_{k,t} \quad Lockdown_{k,t}] \times \gamma_t + err_t^i$$

$$(22)$$

where  $Lockdown_{k,t}$  contains the lockdown indexes, while  $CovidSeverity_{k,t}$  contains the COVID cases and death in state k at date t. The key coefficient of interest,  $\beta_2$ , captures how lockdown policies influence belief stickiness. We run the regression in the post-pandemic sample, from March 2020. Figure 7 reports the estimates of  $\beta_2$ , while Table A.6 reports the detailed result.

We document that all lockdown indicators have a robust negative effect on belief stickiness. This result suggests that lockdown policies might have lowered the cost of collecting information for consumers, leading them to adjust their beliefs more than before. The results are robust to controlling for economic policy uncertainty (i.e., the newspaper-based Economic Policy Uncertainty, EPU), as reported in table A.11.

#### 5.2 Impact of lockdowns on uncertainty

We showed that lockdown restrictions lowered belief stickiness, consistent with a decline in the cost of collecting information. From the lens of our general framework in Section 1, a lower marginal cost of information collection can be thought of as a decrease in new information noise  $\sigma_{e,t}^2$  (Maćkowiak et al., 2023; Pomatto et al., 2023). Such higher new information accuracy would then not only lead to a decrease in belief stickiness, but also a decline in posterior uncertainty.<sup>30</sup> To test this empirically, we estimate the following regression at the US state level:

$$PostUncert_{k,t} = \alpha + \beta Lockdown_{k,t} + \gamma PriorUncert_{k,t} + + CovidImpact'_{k,t}\Gamma + \delta ln(EPU)_{k,t} + \gamma_j + err_{k,t}$$
(23)

<sup>&</sup>lt;sup>30</sup>An alternative possibility is that lower information costs led to higher, instead of lower belief uncertainty. This could be the case, for example, if consumers could learn about signals' accuracy only by acquiring more signals. In this case, a lower information cost would allow consumers to acquire more signals and learn about the increase in the signal's noise, which could explain both the lowering belief stickiness and the higher belief uncertainty.

Where  $PostUncert_{k,t} = \int_{i \in k} PostUncert_{i,t} di$  denotes the average posterior uncertainty for consumers in state k at time t, and  $PriorUncert_{k,t}$  is the prior month's uncertainty for the same group. The key variable of interest is  $Lockdown_{k,t}$ , the average index of lockdown intensity. Table 4 reports the estimated coefficients. Results show a robust and negative effect of lockdown policies on posterior belief uncertainty, consistent with the idea that lower information costs allow for better information gathering. Economic policy uncertainty  $(EPU_{k,t})$  increases posterior uncertainty, as expected.

	$(1) \\ PostUncert$	$\begin{array}{c} (2)\\ PostUncert \end{array}$	$(3) \\ PostUncert$	$(4) \\ PostUncertIQR$
Lockdown	$-0.379^{***}$ (0.084)	$-0.362^{***}$ (0.084)	$-0.203^{***}$ (0.061)	$-0.235^{***}$ (0.072)
PriorUncert			$\begin{array}{c} 0.481^{***} \\ (0.025) \end{array}$	
PriorUncertIQR				$0.459^{***}$ (0.024)
ln(EPUNational)			$0.052^{*}$ (0.026)	$0.053^{*}$ (0.031)
Constant	$3.569^{***}$ (0.103)	$3.557^{***}$ (0.052)	$\begin{array}{c} 1.581^{***} \\ (0.273) \end{array}$	$\begin{array}{c} 1.961^{***} \\ (0.325) \end{array}$
State FEs Covid Controls	N N	Y N	Y Y	Y Y
Sample Adjusted R-squared Observations	Mar20-May23 0.05 1717	Mar20-May23 0.28 1717	Mar20-May23 0.51 1684	Mar20-May23 0.48 1684

Table 4: Belief stickiness and lockdown measures

Our findings show that lockdowns significantly reduced belief stickiness, as stricter policies lowered the cost of acquiring information. However, lockdown policies also lowered posterior uncertainty, suggesting that consumers perceived the information they collected as more precise. This finding aligns with theoretical predictions about the effects of lower information costs on belief formation. However, at the aggregate level, lower information costs can explain the decline in belief stickiness during the pandemic, but they do not account for the simultaneous rise in uncertainty. As illustrated in Section 4, an increase in fundamental uncertainty can instead simultaneously match both empirical facts.

Legend: PostUncert denotes the state-level average 1-year ahead forecast of inflation expectations uncertainty starting 24 months into the future from the SCE. PriorUncert denotes the same variable from the previous issue of the survey in the previous month. The *EPUComposite* is the state-level economic policy uncertainty indicator from Baker et al. (2022). We control for state FEs. Covid controls are logged *DeathsCOVID* and *CasesCOVID*, which are the state-level COVID-related deaths and cases per capita. Standard errors (in parentheses) are clustered at state and time levels.  $\star, \star\star$ , and  $\star\star\star$  are 10%, 5%, and 1% confidence levels.

## 6 Policy Implications

One of the most important insights in macroeconomics and behavioral finance is how expectations shape economic outcomes. Our paper makes a significant contribution by empirically demonstrating that belief stickiness varies systematically with different types of uncertainty: prior versus new information noise, consistent with Bayesian learning, but also displaying systematic deviations from Rational Expectations. Unlike prior work, which often assumes a static or one-dimensional relationship between uncertainty and expectation stickiness, our study disentangles different sources of uncertainty (prior vs. information noise) and shows that they have opposite effects on belief stickiness. This is not trivial. The fact that consumers increase stickiness when faced with noisy new information, but decrease it when prior uncertainty is high is not just confirmation of Bayesian principles – it is an important insight into how households process economic uncertainty in real-world settings.

The persistence of belief stickiness has significant implications for macroeconomic dynamics, financial markets, and policy design. By shaping the way agents incorporate information into their expectations, belief stickiness influences inflation dynamics, asset price movements, and the formation of risk premia. Below, we outline key areas where shifts in belief stickiness play a fundamental role in economic and financial outcomes.

Belief stickiness shapes inflation expectations, central bank communication, and monetary policy effectiveness. When expectations adjust slowly, inflation becomes less responsive to economic shocks, flattening the Phillips curve (Angeletos and Huo, 2021; Afrouzi and Yang, 2021). This issue has intensified post-COVID, as uncertainty and sluggish expectation updating complicate monetary interventions. Effective policy depends on distinguishing uncertainty types: during periods of high fundamental uncertainty, transparency amplifies the reduction in belief stickiness and leads to faster learning, but if the state of the economy changes when learning is fast, asset prices adjust quickly and a sudden crash occurs (Veldkamp, 2005). In contrast, high information noise requires clearer economic signals to prevent further stickiness. These insights align with research on the role of central bank communication in anchoring expectations (Hansen et al., 2019; Cieslak and McMahon, 2024).

Belief stickiness, shaped by different types of uncertainty, plays a critical role in asset prices and macro-finance dynamics. In rational expectations (RE) asset pricing models, investors efficiently process new information, ensuring that prices reflect fundamentals. However, belief stickiness introduces systematic deviations, leading to predictable mispricing. Fundamental uncertainty (e.g., uncertainty about long-term macroeconomic conditions) decreases belief stickiness as investors place more weight on new information, making them more responsive to shocks. This leads to overreaction, excess volatility, price overshooting, and return reversals. Information noise uncertainty (e.g., unreliable or conflicting signals) increases belief stickiness as investors discount new information, causing underreaction to earnings announcements and macroeconomic news. This inertia drives momentum effects, where past winners continue to outperform past losers, and dampens responses to gradual changes while exacerbating sensitivity to rare shocks—a pattern consistent with disaster risk models (Barro (2006); Kozlowski et al. (2020)). These mechanisms provide a unified framework for explaining market anomalies, including short-term momentum and long-term mean reversion in equity returns, highlighting how different sources of uncertainty shape belief dynamics and asset pricing inefficiencies.

These insights suggest that belief stickiness is a key determinant of macro-financial dynamics. Whether in inflation expectations, central bank communication, monetary policy, asset price movements, or risk premia, the extent to which agents update their beliefs in uncertain times influences asset prices, macroeconomic stability, and the effectiveness of policy interventions.

## 7 Conclusion

Our study investigates the relationship between uncertainty and belief formation, particularly how consumers incorporate new information when forming expectations. Using inflation forecasts from the Survey of Consumer Expectations (SCE), we measure how belief stickiness—the extent to which individuals rely on prior versus new information—relates to individual subjective belief uncertainty. Our findings show that belief stickiness responds to uncertainty in a manner qualitatively consistent with Bayesian learning: when prior uncertainty is higher, consumers update their beliefs more, whereas noisier new information leads to lower updates.

Furthermore, our study reveals that the relationship between uncertainty and belief stickiness is not straightforward, but depends on the specific source of uncertainty—whether it arises from macroeconomic volatility or information noise. This distinction has important policy implications: while uncertainty driven by fundamental volatility reduces information frictions and enhances shock propagation, uncertainty stemming from information noise may require policies aimed at improving information dissemination and market transparency. By identifying the conditions under which uncertainty amplifies or dampens economic responses, our findings contribute to a deeper understanding of macroeconomic policy effectiveness.

Our work also suggests several directions for future research. While this paper focuses on household expectations, understanding the determinants of information frictions on the production side of the economy is equally important to improve macroeconomic models, allowing for a more precise study of macroprudential policy and its dependence on different sources of uncertainty. In addition, while this paper studies the total adjustment of beliefs, future work can use this methodology to distinguish between intensive and extensive margins of belief adjustment. Finally, belief stickiness could be used empirically to examine the macroeconomic effects of different types of uncertainty.

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# Online Appendix

### A Belief formation models

The theoretical framework in equation 2 embeds different models of belief formation in the literature. The first set of models comprises the rational Bayesian updating and departures from it.

- Rational expectations:  $G_t^{RE} = \frac{\tau_t}{\tau_t + \Sigma_{t+h,t-1}^{-1}}$ , where  $\Sigma_{t+h,t-1} \equiv var(x_{t+h} E_{t-1}^i[x_{t+h}])$  is the prior variance (Sims, 2003; Woodford, 2001; Mackowiak and Wiederholt, 2009). In the case of full-information, the signal is perfectly informative,  $\tau_t \to \infty$ , and therefore  $G_t = 1$ .
- Diagnostic expectation: households overreact to new information according to  $\theta > 0$ , therefore  $G_t = (1 + \theta)G_t^{RE}$  (Bordalo et al., 2018, 2020).
- Overconfidence: households perceived signal accuracy as more accurate,  $\tilde{\tau}_t > \tau_t$ , and therefore  $G_t = \frac{\tilde{\tau}_t}{\tilde{\tau}_t + \Sigma_{t-h,t-1}^{-1}} > G_t^{RE}$  (Broer and Kohlhas, 2024).
- Over-extrapolation and under-extrapolation: agents perceive the fundamental as more or less persistent, which leads respectively to over or under-weight the signal accuracy,  $G_t > G_t^{RE}$  with over-extrapolation and  $G_t < G_t^{RE}$  with under-extrapolation (Angeletos et al., 2021)

The second set of models differs completely from the Bayesian updating, as the weight is not related to signal and prior accuracy.

- Sticky information: household has a probability  $1 \lambda$  of fully updating her beliefs  $G_t = 1$ , and  $\lambda$  of not updating their belief at all,  $G_t = 0$  (Mankiw and Reis, 2002).
- Learning with constant gain: households learn about the model's parameters in each period using a constant gain, so that they never learn completely (Eusepi and Preston, 2011).
- Mis-specified model: households are fully informed, but form expectations using a mental model which differs from the actual model, e.g. natural expectations (Fuster et al., 2010).

while the baseline version of this second set of models presents a constant gain that does not depend on signal or fundamental accuracy, each of these models can be micro-founded to endogenize the information rigidity to the economic environment, including uncertainty.

#### Point estimates and subjective distribution of infla-Β tion in the SCE

#### Q9c

And in your view, what would you say is the percent chance that, over the 12-month period between August 2015 and August 2016 ....

Total 100	)
the rate of deflation (opposite of inflation) will be 12% or higher	percent chance
the rate of deflation (opposite of inflation) will be between $8\%$ and $12\%$	percent chance
the rate of deflation (opposite of inflation) will be between $4\%$ and $8\%$	percent chance
the rate of deflation (opposite of inflation) will be between 2% and 4% $$	percent chance
the rate of deflation (opposite of inflation) will be between 0% and 2% $$	percent chance
the rate of inflation will be between 0% and 2%	percent chance
the rate of inflation will be between 2% and 4%	percent chance
the rate of inflation will be between $4\%$ and $8\%$	percent chance
the rate of inflation will be between 8% and 12%	percent chance
the rate of inflation will be 12% or higher	percent chance

### C Alternative measure of belief uncertainty

A drawback of using bins questions to measure the individual density forecast is that the intervals considered in the bins might too wide or too narrow to capture the whole belief distribution fully. The bins of the Survey of Consumer Expectations range from -12% to 12% in steps of 2 to 4 percentage points. During high inflation periods, such as the post-Covid months, consumers might attribute a large probability on inflation realization above this upper bound, which could lead to inaccuracies in measuring their true belief distribution from bins question.

To address this concern, we compare our benchmark measure with an alternative measure of belief uncertainty based on the rounding of point forecasts, as in Binder (2017). In each month we compute the share of respondents that provide a forecast multiple of 5. This uncertainty measure is based on the Round Numbers Suggest Round Interpretation (RNRI) principle, which suggests that round numbers are frequently used to convey that a quantitative expression should be interpreted as imprecise (Krifka, 2007).



Figure A.1: Uncertainty measures

Legend: This plot shows different measures of subjective uncertainty over time. The blue dashed line is the share of respondents that provide a forecast multiple of 5 from Binder (2017), the red solid line is the average subjective standard deviation provided by the SCE, and the green dotted line is the average subjective interquartile range provided by the SCE. Sample period: 2013M6-2023M5. Bars represent the 95% confidence interval.

Figure A.1 plots the measure based on rounding ('Share M5', from Binder (2017)) together with the average uncertainty measures from the bins survey question: the standard deviation of the fitted distribution and the interquartile range. The rounding uncertainty measure closely tracks the other two and exhibits the same pattern during and after the COVID period.

# D Heterogeneity on the intensive and extensive margins

We differentiate the impact of socioeconomic characteristics on the extensive and intensive margins of belief adjustment separately.

First, consider the impact on the intensive margin, meaning studying the belief adjustment of only households with a non-zero belief revision from previous to current month. We run regression (6) only considering cases when the posterior forecast differs from the prior forecast. Figure A.2a and Table A.2 report the result.

Second, consider the impact on the extensive margin, meaning whether households revise their expectation or not at all, independently of the magnitude of revision. We run the following regression:

$$NoAdj_{i,t} = \alpha + \mathbf{X}_{i,t}\mathbf{B}_2 + \gamma_t + \epsilon_t^i \tag{A.1}$$

where  $NoAdj_{i,t}$  is a dummy variable with value 1 if the difference in forecast of the household between period t and t-1 is zero, and 0 otherwise. In other words, it measures the belief stickiness at the extensive margin. Figure A.2b and Table A.1 report the result. Column (1) uses a linear probability model and column (2) a Probit model.



(a) Heterogeneity on the Intensive Margin

Legend: The figure shows the relationship between socioeconomic characteristics and belief stickiness. The left panel consider the intensive margin of adjustment, column (1) in Table A.2, while the right panel consider the extensive margin of adjustment, i.e. column (1) of Table A.1. Sample period: 2013M6-2023M5. Bars represent the 95% confidence interval.

#### (b) Heterogeneity on the Extensive Margin

	(1)	(2)
	NoAuj	NoAuj
$Tenure \ Tercile=2$	$0.088^{***}$	$0.250^{***}$
	(0.004)	(0.012)
Tenure Tercile=3	0.141***	0.392***
	(0.005)	(0.012)
<i>C</i> -11	0.000***	0.000***
$College_{it} = 1$	$(0.022^{+++})$	$(0.002^{+++})$
	(0.008)	(0.022)
Age $Over60=1$	$-0.021^{***}$	$-0.057^{***}$
	(0.005)	(0.015)
Age Under40=1	0.023***	0.061***
	(0.006)	(0.015)
L	0.020***	0 10/***
Income Over100k=1	(0.059)	(0.104)
	(0.000)	(0.013)
$Income \ Under 50k{=}1$	-0.026***	-0.073***
	(0.006)	(0.015)
High Numeracy=1	0.079***	0.226***
5	(0.006)	(0.016)
Female-1	0.052***	0 1//***
remaie=1	(0.005)	(0.013)
	(0.005)	(0.013)
White=1	$0.045^{***}$	$0.128^{***}$
	(0.006)	(0.019)
Constant	$0.176^{***}$	-0.953***
	(0.011)	(0.058)
Year-Month FEs	Y	Y
Sample	Jun13-May23	Jun13-May23
Adjusted R-squared	0.03	<b>v</b>
Pseudo R-squared		0.03
Observations	94101	94101

Table A.1: Heterogeneity on the Extensive Margin

Legend: NoAdj is an indicator with value 1 if the forecast revision from month t-1 to t of individual j is zero, and one otherwise. Standard errors (in parentheses) are clustered at individual and time levels. \* represents p < 0.10, \*\* represents p < 0.05, and \*\* \* represents p < 0.01.

	(1) Forecast
Prior	$0.280^{***}$ (0.040)
Tenure Tercile= $2 \times Prior$	$0.085^{***}$ (0.019)
Tenure Tercile= $3 \times Prior$	$\begin{array}{c} 0.181^{***} \\ (0.021) \end{array}$
$College_{it} = 1 \times Prior$	$0.051^{**}$ (0.025)
Age $Over60=1 \times Prior$	$-0.052^{**}$ (0.023)
Age Under40=1 $\times$ Prior	$-0.097^{***}$ (0.024)
Income $Over100k=1 \times Prior$	$-0.052^{*}$ (0.029)
Income Under50 $k=1 \times Prior$	$\begin{array}{c} 0.005 \\ (0.020) \end{array}$
$High Numeracy = 1 \times Prior$	$0.062^{***}$ (0.017)
$Female=1 \times Prior$	-0.024 (0.021)
$White=1 \times Prior$	$\begin{array}{c} 0.027 \\ (0.021) \end{array}$
Constant	$2.936^{***}$ (0.055)
Year-Month FEs Non-interacted variables Year-Month $\times$ variables Sample	Y Y Y Jun13-May23
Observations	0.22 59747

Table A.2: Heterogeneity on the Intensive Margin

Legend: For denotes the 1-year ahead forecast of inflation expectations starting 24 months into the future from the NY Fed Survey of Consumer Expectations (SCE). Prior is the 1-year ahead forecast of inflation expectations starting 24 months into the future provided in the previous month. The regression considers only households with  $For \neq Prior$ . Standard errors (in parentheses) are clustered at individual and time levels. \* represents p < 0.10, \*\* represents p < 0.05, and \*\*\* represents p < 0.01.

	Mean	SD	Min	Max	Ν
Beliefs					
Forecast	5.24	8.68	-50	75	131007
Revision	-0.21	7.27	-100	110	95098
Post Uncert	2.94	3.06	0	22	133362
Post Uncert IQR	3.32	3.52	0	28	133362
Socioeconomic characteristics					
$College_{it}$	0.89	0.31	0	1	135669
$Income \ 50kto100k_{it}$	0.35	0.48	0	1	134293
Income $Over 100k_{it}$	0.30	0.46	0	1	134293
Income $Under 50k_{it}$	0.34	0.47	0	1	134293
$High \ Numeracy_{it}$	0.74	0.44	0	1	135610
$Female_i$	0.47	0.50	0	1	135606
$Age_{it}$	50.57	15.25	17	94	135549
$White_i$	0.85	0.35	0	1	135663
$Tenure_{it}$	5.62	3.39	1	16	135669

Table A.3: Descriptive Statistics

Legend: This table provides descriptive statistics for beliefs and household socioeconomic characteristics derived from the Survey of Consumer Expectations (SCE). The sample period is 2013M6-2023M5.

### E Additional tables

	$(1) \\ Forecast$	(2) Forecast	(3) Forecast	(4) Forecast	(5) Forecast	(6) Forecast	(7) Forecast
Prior	$0.431^{***}$ (0.016)	$\begin{array}{c} 0.497^{***} \\ (0.022) \end{array}$	$0.570^{***}$ (0.015)	$0.530^{***}$ (0.018)	$0.496^{***}$ (0.015)	$0.527^{***}$ (0.023)	$0.375^{***}$ (0.039)
Tenure Tercile= $2 \times Prior$	$\begin{array}{c} 0.113^{***} \\ (0.019) \end{array}$						$0.109^{***}$ (0.019)
Tenure Tercile= $3 \times Prior$	$0.222^{***}$ (0.019)						$\begin{array}{c} 0.211^{***} \\ (0.019) \end{array}$
$College_{it} = 1 \times Prior$		$0.051^{**}$ (0.024)					$0.032 \\ (0.023)$
Age Over60=1 $\times$ Prior			-0.022 (0.021)				$-0.036^{*}$ (0.021)
Age Under40=1 $\times$ Prior			$-0.080^{***}$ (0.024)				$-0.075^{***}$ (0.022)
Income Over100 $k$ =1 × Prior				-0.010 (0.031)			-0.019 (0.031)
Income Under50k=1 $\times$ Prior				-0.003 (0.020)			$0.014 \\ (0.020)$
$\textit{High Numeracy}{=}1 \times \textit{Prior}$					$0.071^{***}$ (0.017)		$0.057^{***}$ (0.017)
$Female=1 \times Prior$						-0.024 (0.021)	-0.009 (0.021)
$White=1 \times Prior$						0.031 (0.021)	$0.017 \\ (0.020)$
Constant	$2.049^{***}$ (0.049)	$2.119^{***} \\ (0.052)$	$2.109^{***}$ (0.052)	$2.184^{***} \\ (0.054)$	$2.114^{***} \\ (0.049)$	$2.121^{***} \\ (0.053)$	$2.140^{***}$ (0.050)
Year-Month FEs Non-interacted variables Year-Month × variables Sample Adjusted R-squared	Y Y Jun13-May23 0.33	Y Y Jun13-May23 0.33	Y Y Jun13-May23 0.33	Y Y Jun13-May23 0.33	Y Y Jun13-May23 0.34	Y Y Jun13-May23 0.33	Y Y Jun13-May23 0.35

Table A.4: Heterogeneity in Belief Updating

Legend: For denotes the 1-year ahead forecast of inflation expectations starting 24 months into the future from the NY Fed Survey of Consumer Expectations (SCE). Prior is the 1-year ahead forecast of inflation expectations starting 24 months into the future provided in the previous month. Standard errors (in parentheses) are clustered at individual and time levels. \* represents p < 0.10, \*\* represents p < 0.05, and \*\*\* represents p < 0.01.

	Mean	SD	Min	Max	Ν
Lockdown policies					
School	1.45	0.96	0	3	35859
Work place	0.82	0.91	0	3	35859
Event	0.72	0.79	0	2	35859
Gathering	1.44	1.78	0	4	35859
Transport	0.25	0.47	0	2	35859
StayAtHome	0.48	0.67	0	2	35859
Movements	0.45	0.66	0	2	35859
Travel	0.24	0.58	0	2	35859
CasesCOVID	0.01	0.01	0	0.103	35859
Deaths COVID	0.00	0.00	0	0.00108	35859
Economic Policy Uncertainty					
EPUState	1.98	1.88	0	14.66	40756
EPUNational	1.97	1.53	0	15.63	40756
EPUComposite	3.23	2.47	0.151	19.64	40756

 Table A.5: Descriptive Statistics

Legend: This table provides descriptive statistics for lockdown policy intensity (from Hale et al. (2020)) and economic policy uncertainty (from Baker et al. (2022)). The sample period is 2020M3-2023M5.

	(1) Forecast	$\begin{array}{c} (2)\\ Forecast \end{array}$	(3) Forecast	(4) Forecast	(5) Forecast	(6) Forecast	(7) Forecast	(8) Forecast	(9) Forecast	(10) Forecast
Prior	$0.554^{***}$ (0.123)	$0.582^{***}$ (0.107)	$0.598^{***}$ (0.113)	$0.577^{***}$ (0.110)	$0.529^{***}$ (0.116)	$0.592^{***}$ (0.106)	$\begin{array}{c} 0.534^{***} \\ (0.114) \end{array}$	$0.519^{***}$ (0.118)	$0.565^{***}$ (0.104)	$0.619^{***}$ (0.108)
$Prior \times ln(DeathsCOVID)$	$-0.028^{*}$ (0.016)	-0.019 (0.015)	-0.018 (0.016)	-0.024 (0.016)	$-0.031^{*}$ (0.017)	-0.019 (0.014)	$-0.030^{*}$ (0.017)	$-0.034^{*}$ (0.018)	-0.019 (0.014)	-0.015 (0.015)
$Prior \times ln(CasesCOVID)$	$0.043^{**}$ (0.018)	$0.031^{*}$ (0.016)	$0.036^{**}$ (0.017)	$0.043^{**}$ (0.018)	$0.050^{**}$ (0.018)	$0.036^{**}$ (0.015)	$0.048^{**}$ (0.019)	$0.054^{**}$ (0.020)	$0.030^{*}$ (0.015)	$0.032^{*}$ (0.016)
$Prior \times School$	$-0.034^{*}$ (0.018)								$0.009 \\ (0.024)$	
$Prior \times Workplace$		$-0.065^{***}$ (0.022)							$-0.065^{**}$ (0.032)	
$Prior \times Event$			$-0.059^{**}$ (0.026)						-0.001 (0.038)	
$Prior \times Gathering$				$-0.021^{**}$ (0.010)					$0.019 \\ (0.014)$	
$Prior \times Transport$					$-0.075^{**}$ (0.036)				-0.030 (0.036)	
$Prior \times StayAtHome$						$-0.077^{***}$ (0.028)			-0.048 (0.040)	
$Prior \times Movements$							$-0.050^{**}$ (0.022)		$0.003 \\ (0.036)$	
$Prior \times Travel$								-0.052 (0.035)	-0.017 (0.040)	
$Prior \times Lockdown$										$-0.080^{***}$ (0.029)
Constant	$\begin{array}{c} 2.313^{***} \\ (0.084) \end{array}$	$\begin{array}{c} 2.324^{***} \\ (0.077) \end{array}$	$2.327^{***}$ (0.080)	$\begin{array}{c} 2.322^{***} \\ (0.082) \end{array}$	$2.324^{***}$ (0.085)	$2.320^{***}$ (0.078)	$2.325^{***}$ (0.084)	$\begin{array}{c} 2.317^{***} \\ (0.087) \end{array}$	$2.320^{***}$ (0.075)	$2.328^{***}$ (0.079)
Year-Month FEs Year-Month × Variables Non-interacted variables Adjusted R-squared Observations	Y Y V 0.35 24845	Y Y V 0.34 25626	Y Y O.34 25626	Y Y V 0.34 25626	Y Y V 0.34 25626	Y Y V 0.34 25626	Y Y V 0.34 25626	Y Y V 0.34 25626	Y Y Y 0.34 25626	Y Y 0.34 25626

Table A.6: Belief stickiness and lockdown measures

Legend:  $For3y_{i,t}$  denotes the 1-year ahead forecast of inflation expectations starting 24 months into the future from the NY Fed Survey of Consumer Expectations (SCE). *Prior*  $3y_{i,t}$  is the point forecast about the horizon 3 years provided in the previous month. Variables *School* to *Travel* measure lockdown policies intensity for different social activities, from the Oxford Covid-19 Government Response Tracker (OxCGRT). *Lockdown* is the average of the other lockdown indicators. We control for year-month fixed effects, and for socioeconomic characteristics, such as education, income, age, gender, race, and tenure. Covid Controls are ln(DeathsCOVID) and ln(CasesCOVID), which are the log state-level COVID-related deaths and cases per capita. Standard errors (in parentheses) are clustered at individual and time levels. \* represents p < 0.10, \*\* represents p < 0.05, and \*\* represents p < 0.01.

	(1)	(2)	(3)	(4)	(5)	(6)
α	$0.605^{***}$ (0.020)	$0.573^{***}$ (0.067)	$0.604^{***}$ (0.048)	$\begin{array}{c} 0.633^{***} \\ (0.017) \end{array}$	$0.568^{***}$ (0.042)	$0.671^{***}$ (0.165)
$\alpha \times$ Tenure tercile=2	$0.030 \\ (0.024)$				$0.029 \\ (0.024)$	$0.019 \\ (0.040)$
$\alpha \times$ Tenure tercile=3	$0.028 \\ (0.024)$				$0.028 \\ (0.025)$	$0.022 \\ (0.040)$
$\alpha \times$ College		$0.053 \\ (0.036)$			0.041 (0.038)	$0.020 \\ (0.055)$
$\alpha \times$ Young			$0.062^{***}$ (0.018)		$0.083^{***}$ (0.020)	$0.071 \\ (0.066)$
$\alpha \times$ High numeracy				-0.012 (0.019)	$-0.047^{**}$ (0.022)	-0.041 (0.054)
$ar{g}$						-0.049 (0.109)
Sample N	Jun13-Feb20 687	Jun13-Feb20 687	Jun13-Feb20 687	Jun13-Feb20 687	Jun13-Feb20 687	Jun13-Feb20 687

Table A.7: Estimated over reaction  $\alpha$ 

Legend: This table reports the results from GMM estimation

	$(1) \\ Forecast$	$(2) \\ Forecast$	(3) Forecast
Prior	$0.535^{***}$ (0.012)	$\begin{array}{c} 0.171^{***} \\ (0.012) \end{array}$	$\begin{array}{c} 0.019^{***} \\ (0.003) \end{array}$
$Prior \times abs(FE)$		$0.007^{***}$ (0.001)	
Quartile $abs(FE)=2 \times Prior$			$0.054^{***}$ (0.007)
Quartile $abs(FE)=3 \times Prior$			$0.182^{***}$ (0.013)
Quartile $abs(FE)=4 \times Prior$			$0.501^{***}$ (0.018)
Constant	$2.051^{***}$ (0.056)	$3.556^{***}$ $(0.085)$	$3.269^{***}$ (0.044)
Year-Month FEs	Υ	Y	Y
Year-Month FEs $\times$ FE	Ν	Y	Υ
Non-interacted FE	Y	Y	Y
Sample	Jun13-Dec19	Jun13-Dec19	Jun13-Dec19
Adjusted R-squared	0.32	0.59	0.43
Observations	63509	63509	63509

Table A.8: Forecast errors and belief stickiness

Legend: Forecast denotes the expectation about the 12-month inflation starting 24 months into the future from the current month issue of NY Fed Survey of Consumer Expectations (SCE). Prior denotes the expectation about the same variable, but in the previous month issue of the SCE. abs(FE) indicates the absolute forecast error of the individual, defined as the absolute difference between the 12-month inflation starting 24 months into the future and Forecast. Quartile abs(FE) equals 1 if abs(FE) lies in the specific quartile of the unconditional distribution of abs(FE). The estimation period is 2013M6-2023M5. Standard errors (in parentheses) are clustered at individual and time levels. \* represents p < 0.10, \*\* represents p < 0.05, and \*\* \* represents p < 0.01.

	(1)	(2)	(3)
	Stickiness	Stickiness	Stickiness
ln(PriorUncert)	$-0.187^{***}$	$-0.194^{***}$	$-0.196^{**}$
	(0.061)	(0.060)	(0.081)
ln(NewInfoNoise)	$0.350^{***}$	$0.350^{***}$	$0.350^{***}$
	(0.028)	(0.028)	(0.044)
$Inflation_{t,t-12}$	0.010 (0.008)		
$Inflation_{t,t-1}$		0.011 (0.035)	
$Inflation_{t-1,t-2}$			$0.023 \\ (0.044)$
Year-Month FEs	N	N	N
Group FE	Y	Y	Y
Sample	Jun13-Feb20	Jun13-Feb20	Jun13-Feb20
Adjusted R-squared	0.63	0.63	0.62
Observations	687	687	679

Table A.9: Belief stickiness, uncertainty and inflation

Legend: This table reports the estimated coefficient from regression (12) while controlling also for inflation. PostUncert denotes the group-month average of 1-year ahead forecast of inflation expectations uncertainty starting 24 months into the future from the NY Fed Survey of Consumer Expectations (SCE). PriorUncert is the same variable, but from the previous month. We control for year-month and group fixed effects. PriorUncertIQR and PostUncertIQR are the interquartile ranges of the same forecasts. absoluteFE is the group-month average absolute forecast error. NewInfoNoise is described in the main text. Standard errors (in parentheses) are bootstrapped at the group-month level. \* represents p < 0.10, \*\* represents p < 0.05, and \*\*\* represents p < 0.01.

## F Additional figures



Figure A.3: Distribution of estimated belief stickiness

Legend: The figure plots the estimate of (10). Sample period: 2013M1 - 2023M5.



Figure A.4: Belief stickiness and uncertainty: consumer with large tenure

Legend: The figure plots on the x-axis the estimated belief stickiness  $\hat{\beta}_{j,t}$  from regression (10) against the implied rational expectation belief stickiness from equation (7) on the y-axis. The sample excludes consumers in the first quartile of the tenure distribution.

Figure A.5: Economic Policy Uncertainty index



Legend: The figure plots the "news coverage component" from the Economic Policy Uncertainty Index, which is based on the share of articles in US online newspapers that mention economic policy uncertainty (Baker et al., 2016). This index is based on the share of articles in 10 large newspapers (USA Today, the Miami Herald, the Chicago Tribune, the Washington Post, the Los Angeles Times, the Boston Globe, the San Francisco Chronicle, the Dallas Morning News, the Houston Chronicle, and the WSJ) containing the terms 'uncertainty' or 'uncertain', the terms 'economic' or 'economy' and one or more of the following terms: 'congress', 'legislation', 'white house', 'regulation', 'federal reserve', or 'deficit'. For additional details, see Baker et al. (2016).

# G Belief stickiness and uncertainty: alternative empirical strategy

We investigate the relationship between uncertainty and belief stickiness with a different empirical strategy compared to section 3.2. Instead of regressing prior and posterior uncertainty on the estimated group-month belief stickiness, we estimate belief stickiness and its relationship with uncertainty in the same regression by using an interaction term. That is, we regress

$$For_{i,t} = \alpha + \beta_1 Prior_{i,t} + \mathbf{X}_{i,t}\mathbf{B}_2 + Prior_{i,t} \times \mathbf{X}_{i,t}\mathbf{B}_3 + \gamma_t + \beta_4(\gamma_t \times \mathbf{X}_{i,t}) + err_t^i$$
(A.2)

where  $\mathbf{X}_{i,t}$  is a vector containing the measure of prior and a proxy for new information noise, namely posterior uncertainty or forecast error. Tale A.10 shows that the results are consistent with the result of 2 and with Bayesian updating: belief stickiness is higher if new information is noisy and lower if the prior uncertainty is higher.

	$(1) \\ Forecast$	(2) Forecast	(3) Forecast	(4) Forecast	(5) Forecast
Prior	$0.508^{***}$ (0.023)	$0.423^{***} \\ (0.021)$	$0.075^{**}$ (0.030)	$\begin{array}{c} 0.441^{***} \\ (0.022) \end{array}$	$0.148^{***} \\ (0.022)$
$Prior \times ln(PostUncert)$	$0.106^{***}$ (0.014)				
$Prior \times ln(PriorUncert)$	$-0.125^{***}$ (0.016)		$-0.130^{***}$ (0.011)		
$Prior \times ln(PostUncertIQR)$		$0.121^{***}$ (0.011)			
$Prior \times ln(PriorUncertIQR)$		$-0.096^{***}$ (0.013)			
$Prior \times ln(absoluteFE)$			$0.237^{***}$ (0.012)		
$HighPriorUncert=1 \times Prior$				$0.228^{***}$ (0.018)	
$HighPriorUncert=1 \times Prior$				$-0.178^{***}$ (0.022)	$-0.119^{***}$ (0.025)
$HighAbsFE=1 \times Prior$					$0.462^{***}$ (0.014)
Constant	$2.633^{***}$ (0.069)	$\begin{array}{c} 2.527^{***} \\ (0.062) \end{array}$	$3.665^{***}$ (0.090)	$2.405^{***} \\ (0.055)$	$2.838^{***}$ (0.051)
Year-Month FEs	Y	Y	Y	Y	Y
Non-interacted variables	Υ	Υ	Y	Υ	Υ
Year-Month $\times$ variables	Y	Υ	Υ	Υ	Υ
Socioeconomic controls	Υ	Υ	Υ	Υ	Υ
Sample	Jun13-Feb20	Jun13-Feb20	Jun13-Feb20	Jun13-Feb20	Jun13-Feb20
Adjusted R-squared	0.39	0.40	0.50	0.37	0.39
Observations	51891	65191	54327	65192	62786

Table A.10: Belief stickiness and uncertainty

Legend: This table reports the estimated coefficient from regression (A.2). PostUncert denotes the individual 1-year ahead forecast of inflation expectations uncertainty starting 24 months into the future from the NY Fed Survey of Consumer Expectations (SCE). PriorUncert is the same variable, but from the previous month. PriorUncertIQR and PostUncertIQR are the interquartile ranges of the same forecasts. absolute FE is the individual absolute forecast error. HighPostUncert is a dummy of value 1 if PostUncert is above the median, and the same for HighPriorUncert and HighAbsFE. We control for time fixed effect and their interaction wit the variables. Standard errors (in parentheses) are bootstrapped at the group-month level. \* represents p < 0.10, \*\* represents p < 0.05, and \*\* \* represents p < 0.01.

### H Aggregate belief stickiness

We compute belief stickiness by running the following panel regression regression in a rolling window of three months

$$For_{i,t} = \alpha + \beta Prior_{i,t} + \gamma_t + X_{i,t} + err_t^i$$
(A.3)

where  $X_{i,t}$  contains sociodemographic controls, such as tenure (i.e. number of months in the survey), whether holding a college degree, age, income over 100k or below 50k, high numeracy, gender, and race. Figure A.6 plots the estimated belief stickiness  $\hat{\beta}$  for each final month of the 3-month rolling window. Figure A.7 reports the same regression, but considering only the intensive margin of belief adjustment, meaning excluding observations where the posterior (forecast in t) equals the prior (forecast in t - 1), with the same result.

Figure A.6: Belief stickiness pre- and post-pandemic



Legend: The figure plots the estimate of A.3 excluding observations where the posterior equals the prior, meaning excluding revisions equal to zero. The dashed blue lines represent the 95% confidence interval. The first red vertical line corresponds to the start of Covid-19 in March 2020. The second red vertical line corresponds to the start of the high-inflation period in January 2021. Sample period: 2013M1 - 2023M5.

Figure A.7: Belief stickiness pre- and post-pandemic (non-zero revisions)



Legend: The figure plots the estimate of A.3, while the dashed blue lines represent the 95% confidence interval. The first red vertical line corresponds to the start of Covid-19 in March 2020. The second red vertical line corresponds to the start of the high-inflation period in January 2021. Sample period: 2013M1 - 2023M5.

### I Estimation of inflation autoregressive structure



Figure A.8: Rolling window autoregressive estimation of monthly inflation

Legend: This figure show the estimates of an AR(1) autoregressive process for monthly inflation in a rolling window.

### J Michigan Survey of Consumers



Figure A.9: Share of respondents who heard no news about Business Conditions

We consider a question in the Michigan Survey of Consumers: "During the last few months, have you heard of any favorable or unfavorable changes in business conditions?". In each month, we compute the share of respondents that answer "No". Figure A.9 reports this share, which declines at the onset of the COVID-19 pandemic, only to increase back in the following periods. While we can distinguish whether this is driven by demand (consumer) or supply (media) factors, it is nevertheless consistent with the evidence that consumers look for new information during the COVID period and less afterwards.

### K Lockdown Impact during Covid

Measuring Lockdown Stringency. We measure the US state-level stringency of lockdown policies from the Oxford COVID-19 Government Response Tracker (OxCGRT) database. The database covers the period between January 2020 and December 2022 and contains information about closure and containment restrictions, which are recorded as ordinal categorical scales measuring the intensity or severity of the policy. Details about the collection process for a variety of countries are in Hale et al. (2020), while Hallas et al. (2021) provides an overview of the policy implemented at the US state level. We consider the following indicators: school closing, workplace closing, cancel public events, restrictions on gathering size, close public transport, stay at home requirements, and restrictions on internal movements. As the severity of these policies differs between vaccinated and non-vaccinated individuals, we consider the state average weighted by the number of vaccinated and non-vaccinated individuals. Finally, we compute a summary measure of the severity of lockdown measures, lockdown, equal to the simple average of these indicators.<sup>31</sup> Figure 7 reports the time series of the country-level average of each indicator. Moreover, to measure the local impact of the pandemic we use the US state-level monthly level of COVID deaths and cases per capita. Table A.5 reports the summary statistics.

Figure 7 reports the estimated impact of lockdown indexes on belief stickiness,  $\beta_2$ , while Table A.6 reports the detailed result. While all the indicators have a robust and negative effect on belief stickiness, including all of them together might create collinearity issues. As a result, we use the average of the indexes as a summary of the individual indicators. Once again the impact on belief stickiness is negative and robust. This result suggests that lockdown policies might have lowered the cost of collecting information for consumers, leading them to adjust their beliefs more than before.

Table A.11 presents additional evidence. The first column replicates the last column of Table A.6, using the average index *Lockdown* to summarize the stringency of state-level lockdown policies. As shown in Figure 7, these policies were mainly in place until June 2021. Therefore, we run the same regression considering only this subsample. The impact of lockdown policies on belief stickiness is still negative and robust. In the next three columns, we compare the effect of lockdown policies with measures of state-level economic

<sup>&</sup>lt;sup>31</sup>This measure is similar to the *stringency index* in Hale et al. (2020), as they also consider a simple average of each indicator. However, differently from them, we exclude from this average the indicators on *restrictions on international travel*, as not related to state-level measures, and *public information campaign*, as not related to lockdown measures.

	$(1) \\ Forecast$	(2) Forecast	(3) Forecast	(4) Forecast
Prior	$0.619^{***}$ (0.108)	$0.573^{***}$ (0.140)	$\begin{array}{c} 0.644^{***} \\ (0.136) \end{array}$	$0.600^{***}$ (0.168)
$Prior \times Lockdown$	$-0.080^{***}$ (0.029)	$-0.090^{**}$ (0.036)	$-0.076^{**}$ (0.034)	$-0.082^{**}$ (0.037)
$Prior \times ln(DeathsCOVID)$	-0.015 (0.015)	-0.015 (0.015)	-0.015 (0.015)	-0.015 (0.015)
$Prior \times ln(CasesCOVID)$	$0.032^{*}$ (0.016)	$0.032^{*}$ (0.016)	$0.031^{*}$ (0.016)	$0.032^{*}$ (0.016)
$Prior \times ln(EPUState)$		$0.010 \\ (0.022)$		
$Prior \times ln(EPUNational)$			-0.006 (0.023)	
$Prior \times ln(EPUComposite)$				$0.004 \\ (0.029)$
Constant	$2.328^{***}$ (0.079)	$2.330^{***}$ (0.080)	$2.329^{***}$ (0.079)	$2.329^{***}$ (0.079)
Year-Month FEs	Y	Y	Y	Y
Year-Month $\times$ Variables	Υ	Y	Y	Y
Non-interacted variables	Y	Y	Y	Y
Sample	Mar20-May23	Mar20-May23	Mar20-May23	Mar20-May23
Adjusted R-squared	0.34	0.34	0.34	0.34
Observations	25626	25625	25618	25626

Table A.11: Belief stickiness and lockdown measures

Legend: For denotes the 1-year ahead forecast of inflation expectations starting 24 months into the future from the NY Fed Survey of Consumer Expectations (SCE). Prior is the point forecast about the 3-year horizon provided in the previous month. DeathsCOVID and CasesCOVID are respectively the state-level COVID-related deaths and cases per capita. The EPUstate, National, and Composite are the state-level economic policy uncertainty indicators from Baker et al. (2022). We control for year-month fixed effects and their interaction with the other variables. Standard errors (in parentheses) are clustered at individual and time levels. \* represents p < 0.10, \*\* represents p < 0.05, and \*\*\* represents p < 0.01.

policy uncertainty, from Baker et al. (2022). The indexes are constructed from articles in local newspapers containing terms such as 'economic' and 'uncertainty', and are divided according to the topic of the economic policy considered: national-level, state-level, and a composite of the two.<sup>32</sup> Even controlling for state-level uncertainty, the estimated impact of lockdown policies on belief stickiness is significant and negative.<sup>33</sup>

Lower information-gathering costs due to lockdown policies can explain the decrease in belief stickiness observed at the pandemic's onset. However, is it also consistent with the sharp increase in belief uncertainty in the same period? We investigate this question in the following Section.

 $<sup>^{32}</sup>$ We take the percentage change in the measure to isolate the surprise component. The results are robust to using simple differences and levels.

<sup>&</sup>lt;sup>33</sup>Tables A.13 reports the results for the one year inflation forecasts, with similar results.

### L Shorter forecast horizon



Figure A.10: Belief stickiness pre- and post-pandemic: 1 year horizon

Legend: the figure plots the average belief stickiness across subsamples estimates of regression 10, while the dashed blue lines represent the average 90% confidence interval. The first red vertical line corresponds to the start of Covid-19 in March 2020. The second red vertical line corresponds to the start of the high-inflation period in January 2021. Sample period: 2013M1 - 2023M5.

Table A.12: Belief stickiness

	$(1) \\ For \ 1y$	$(2) \\ For \ 1y$	$(3) \\ For \ 1y$	(4) For 1y
Prior				
$Prior \times Tenure_{it}$				
$High \ Numeracy_{it} = 1 \times Prior$				
Prior 1y	$\begin{array}{c} 0.553^{***} \\ (0.012) \end{array}$	$0.540^{***}$ (0.012)	$\begin{array}{c} 0.353^{***} \\ (0.018) \end{array}$	$0.330^{***}$ (0.018)
$High \ Numeracy_{it} = 1 \times Prior \ 1y$			$\begin{array}{c} 0.013 \ (0.015) \end{array}$	$0.026 \\ (0.016)$
Prior $1y \times Tenure_{it}$			$\begin{array}{c} 0.031^{***} \\ (0.002) \end{array}$	$\begin{array}{c} 0.033^{***} \\ (0.002) \end{array}$
$Tenure_{it}$			$-0.164^{***}$ (0.011)	
$High \ Numeracy_{it}$			$-1.711^{***}$ (0.114)	
Constant	$2.245^{***}$ (0.063)	$\begin{array}{c} 2.323^{***} \\ (0.063) \end{array}$	$\begin{array}{c} 4.627^{***} \\ (0.135) \end{array}$	$2.239^{***}$ (0.065)
Year-Month FEs	Y	Y	Y	Y
Tenure $\times$ Year-Month FEs	Ν	Ν	Ν	Υ
Numeracy $\times$ Year-Month FEs	Ν	Ν	Ν	Υ
Adjusted R-squared	0.37	0.36	0.39	0.40
Observations	94531	91003	94504	94504

Legend:  $For1y_{i,t}$  denotes the 1-year ahead forecast of inflation expectations from the NY Fed Survey of Consumer Expectations (SCE). *Prior*  $1y_{i,t}$  is the point forecast about horizon 1 years provided in the previous month, while  $Tenure_{i,t}$  is a continuous variable of a household's tenure in the survey, and  $High \ Numeracy_{i,t} = 1$  is a dummy for high-numeracy individuals. We control for year-month fixed effects, and their interaction with  $Tenure_{i,t}$  and  $High \ Numeracy_{i,t} = 1$ . The estimation period is 2013M6-2023M5. Column (2) excludes respondents who never revised their forecasts. Standard errors (in parentheses) are clustered at individual and time levels. \* represents p < 0.10, \*\* represents p < 0.05, and \* \* \* represents p < 0.01.

	$(1) \\ For \ 1y$	$(2) \\ For \ 1y$	$(3) \\ For \ 1y$	$(4) \\ For \ 1y$
Prior 1y	$0.800^{***}$ (0.192)	$0.836^{***}$ (0.218)	$\begin{array}{c} 0.734^{***} \\ (0.228) \end{array}$	$0.819^{***} \\ (0.244)$
$Prior \; 1y \times Lockdown$	$-0.111^{***}$ (0.025)	$-0.104^{***}$ (0.035)	$-0.120^{***}$ (0.031)	$-0.109^{***}$ (0.034)
$Prior \ 1y \times ln(DeathsCOVID)$	$0.008 \\ (0.019)$	$0.009 \\ (0.019)$	$0.008 \\ (0.019)$	$0.009 \\ (0.019)$
$Prior \ 1y \times ln(CasesCOVID)$	$0.016 \\ (0.015)$	$0.016 \\ (0.016)$	$0.017 \\ (0.015)$	$0.016 \\ (0.015)$
$Prior \ 1y \times ln(EPUState)$		-0.007 (0.023)		
Prior $1y \times ln(EPUNational)$			$0.015 \\ (0.022)$	
$Prior \ 1y \times ln(EPUComposite)$				-0.003 (0.028)
Constant	$2.830^{***} \\ (0.115)$	$2.830^{***} \\ (0.115)$	$2.832^{***} \\ (0.116)$	$2.829^{***}$ (0.116)
Year-Month FEs Year-Month × Variables Non-interacted variables Sample Adjusted R-squared Observations	Y Y Y Mar20-May23 0.39 25504	Y Y Y Mar20-May23 0.39 25503	Y Y Y Mar20-May23 0.39 25497	Y Y Y Mar20-May23 0.39 25504

Table A.13: Belief stickiness and lockdown measures: 1 year inflation

Legend: For denotes the 1-year ahead forecast of inflation expectations from the NY Fed Survey of Consumer Expectations (SCE). Prior is the point forecast about the 1-year horizon provided in the previous month. DeathsCOVID and CasesCOVID are respectively the state-level COVID-related deaths and cases per capita. The EPUstate, National, and Composite are the state-level economic policy uncertainty indicators from Baker et al. (2022). We control for year-month fixed effects and their interaction with the other variables. Standard errors (in parentheses) are clustered at individual and time levels. \* represents p < 0.10, \*\* represents p < 0.05, and \*\*\* represents p < 0.01.

	$(1) \\ PostUncert$	(2) PostUncert	(3) PostUncert	$(4) \\ PostUncertIQR$
Lockdown	$-0.468^{***}$ (0.085)	$-0.459^{***}$ (0.083)	$-0.271^{***}$ (0.060)	$-0.312^{***}$ (0.073)
PriorUncert			$0.451^{***}$ (0.027)	
PriorUncertIQR				$0.433^{***}$ (0.027)
ln(EPUNational)			0.044 (0.033)	$0.047 \\ (0.039)$
Constant	$3.754^{***}$ (0.099)	$3.748^{***}$ (0.053)	$\begin{array}{c} 1.579^{***} \\ (0.313) \end{array}$	$1.927^{***}$ (0.383)
State FEs Covid Controls Sample Adjusted R-squared Observations	N N Mar20-May23 0.07 1718	Y N Mar20-May23 0.29 1718	Y Y Mar20-May23 0.51 1684	Y Y Mar20-May23 0.49 1684

Table A.14: Belief stickiness and lockdown measures

Legend: Uncertainty3y denotes the state-level average 1-year ahead forecast of inflation expectations uncertainty starting 24 months into the future from the NY Fed Survey of Consumer Expectations (SCE). The *EPUComposite* is the state-level economic policy uncertainty indicator from Baker et al. (2022). We control for state FEs. Covid Controls are ln(DeathsCOVID) and ln(CasesCOVID), which are the log state-level COVID-related deaths and cases per capita. Standard errors (in parentheses) are clustered at individual and time levels. \* represents p < 0.10, \*\* represents p < 0.05, and \*\* \* represents p < 0.01.

Table A.15: Belief stickiness and lockdown measures

	$(1) \\ PostUncert$	$\begin{array}{c} (2)\\ PostUncert \end{array}$	$(3) \\ PostUncert$	(4) PostUncertIQR
Lockdown	$-0.538^{***}$ (0.089)	$-0.531^{***}$ (0.091)	$-0.252^{***}$ (0.056)	$-0.327^{***}$ (0.066)
PriorUncert			$0.516^{***}$ (0.037)	
PriorUncertIQR				$\begin{array}{c} 0.474^{***} \\ (0.036) \end{array}$
ln(EPUNational)			0.014 (0.039)	$0.019 \\ (0.049)$
Constant	$3.987^{***}$ (0.093)	$3.983^{***}$ (0.057)	$2.068^{***}$ (0.287)	$2.619^{***}$ (0.365)
State FEs Covid Controls Sample Adjusted R-squared Observations	N N Mar20-May23 0.08 1705	Y N Mar20-May23 0.22 1705	Y Y Mar20-May23 0.52 1670	Y Y Mar20-May23 0.48 1670

Legend: Uncertainty3y denotes the state-level average 1-year ahead forecast of inflation expectations uncertainty starting 24 months into the future from the NY Fed Survey of Consumer Expectations (SCE). The *EPUComposite* is the state-level economic policy uncertainty indicator from Baker et al. (2022). We control for state FEs. Covid Controls are ln(DeathsCOVID) and ln(CasesCOVID), which are the log state-level COVID-related deaths and cases per capita. Standard errors (in parentheses) are clustered at individual and time levels. \* represents p < 0.10, \*\* represents p < 0.05, and \*\* \* represents p < 0.01.

#### M Belief uncertainty and disagreement

In this section we clarify the difference between belief uncertainty, namely the variance of posterior beliefs, and disagreement, meaning the cross-sectional dispersion in posterior mean. We show that new information noise unambiguously increases the former, but not the latter.

Simple model Consider a simple version of the belief-updating setting considered in section 3 where the variable forecasted is i.i.d. Suppose agents form beliefs about stochastic variable  $x \sim N(\mu_x, \sigma_x^2)$  where  $\mu_x$  is the prior mean and  $\sigma_x^2$  is the prior variance. Agents can not observe x directly, but receive a private noisy signal about it, similarly to equation (1)

$$s^i = x + e^i \tag{A.4}$$

where the signal noise  $e^i = \eta^i + \omega$  contains (i) an idiosyncratic component  $\eta^i$  normally distributed mean-zero noise with variance  $\sigma_{\eta}^2$  and i.i.d. across time and households, i.e.  $\int^i e_t^i di = 0$ , and (ii) a common component  $\omega$  normally distributed mean-zero noise with variance  $\sigma_{\omega}^2$  which is i.i.d. only across time, but not across agents. Let  $\sigma_e^2 \equiv \sigma_{\eta}^2 + \sigma_{\omega}^2$  define the overall variance of the signal noise.

The Bayesian posterior beliefs is  $x|s^i \sim N(E^i[x|s^i], Var^i[x|s^i])$ . The posterior mean equals

$$E^{i}[x|s^{i}] = (1-G)\mu_{x} + Gs^{i}$$
(A.5)

where the Bayesian weight on new information is  $G = \frac{\sigma_x^2}{\sigma_e^2 + \sigma_x^2} = \frac{\sigma_x^2}{\sigma_\eta^2 + \sigma_\omega^2 + \sigma_x^2}$ .

Belief uncertainty The Bayesian posterior variance, or uncertainty, then equals

$$Var^{i}[x|s^{i}] = \sigma_{e}^{2}G = \frac{\sigma_{x}^{2}\sigma_{e}^{2}}{\sigma_{e}^{2} + \sigma_{x}^{2}}$$
(A.6)

Therefore

$$\frac{\partial Var^{i}[x|s^{i}]}{\partial \sigma_{e}^{2}} = \left(\frac{\sigma_{x}^{2}}{\sigma_{e}^{2} + \sigma_{x}^{2}}\right)^{2} > 0 \tag{A.7}$$

Posterior uncertainty increases in the new information noise, no matter whether the increase is due to new private information noise  $\sigma_{\eta}^2$  or new public information noise  $\sigma_{\omega}^2$ . In section 3, we do not need to take a stand about what drives the increase in new information noise to derive our main implications.

**Belief disagreement** Let's consider now disagreement, meaning cross-sectional dispersion of posterior mean across agents.

$$Disp(E^{i}[x|s^{i}]) = G^{2}\sigma_{\eta}^{2}$$
(A.8)

As we consider the second moment of the cross-sectional distribution, the common error and realization across forecasters drop out.

First, consider an increase in public information noise  $\sigma_{\omega}^2$ . Intuitively, there is no direct effect on disagreement, as new information received by agents becomes equally more uncertain. If all information were public, then there would be no effect at all on disagreement. However, since the new signal also contains private information, an increase in public noise has an indirect effect on belief dispersion: as the new signal is overall noisier, agents allocate less weight G to it, and more to the common prior, leading to a decrease in disagreement:

$$\frac{\partial Disp(E^{i}[x|s^{i}])}{\partial \sigma_{\omega}^{2}} = \sigma_{\eta}^{2} \frac{\partial G^{2}}{\partial \sigma_{\omega}^{2}} = -2 \frac{\sigma_{x}^{2} \sigma_{\eta}^{2}}{(\sigma_{\eta}^{2} + \sigma_{\omega}^{2} + \sigma_{x}^{2})^{2}} < 0$$
(A.9)

Now consider an increase in private information noise  $\sigma_{\eta}^2$ . In this case, there are two effects. First, a direct effect: larger volatility of idiosyncratic shocks makes new information more dispersed across agents. This is represented by the first term on the right-hand side of equation (A.10). Second, an indirect effect: as new information is overall noisier, agents allocate less weight to G to it, and more to the common prior. This is represented by the second term on the right-hand side of equation (A.10)

$$\frac{\partial Disp(E^{i}[x|s^{i}])}{\partial \sigma_{\eta}^{2}} = G^{2} + \sigma_{\eta}^{2} \frac{\partial G^{2}}{\partial \sigma_{\eta}^{2}}$$
(A.10)

Therefore,

$$\frac{\partial Disp(E^{i}[x|s^{i}])}{\partial \sigma_{\eta}^{2}} > 0 \iff \sigma_{\eta}^{2} < \frac{\sigma_{x}^{2}}{2}$$
(A.11)

The first effect prevails for low values of  $\sigma_{\eta}^2$ , while the second prevails for higher values of  $\sigma_{\eta}^2$ . In other words, the effect of new private information noise in belief dispersion is non-monotone.

To sum up, while an increase in new information noise unambiguously increases posterior uncertainty, the effect on belief disagreement is nuanced and can go in either direction.

Figure A.11: Forecast errors



Legend: The figure shows the relationship between forecast errors and belief stickiness,  $\mathbf{B}_3$  from regression A.12 as reported in column (3) of table A.8. Bars represent the 95% confidence interval. Sample period: 2013M6-2019M11.

#### **N** Belief stickiness and forecast errors

We investigate whether higher belief stickiness is associated with higher forecast errors. We define forecast error as the difference between the realization of 12-month inflation starting 24 months from the survey data and the individual forecast. We run the following regression

$$For_{i,t} = \alpha + \beta_1 Prior_{i,t} + \mathbf{F}\mathbf{E}_{i,t}\mathbf{B}_2 + Prior_{i,t} \times \mathbf{F}\mathbf{E}_{i,t}\mathbf{B}_3 + \gamma_t + \beta_4(\gamma_t \times \mathbf{F}\mathbf{E}_{i,t}) + err_t^i \quad (A.12)$$

where  $FE_{i,t}$  contains the dummy indicators with value 1 if the absolute forecast error of individual *i* at time *t* is in the first, second, third, or fourth quartile of the unconditional absolute forecast error distribution. The coefficient **B**<sub>3</sub> identifies belief stickiness at different forecast error quartiles.

Figure A.11 reports the results. We find that the relation between belief stickiness and forecast errors is positive: higher belief stickiness is associated with higher forecast errors. Table A.8 reports alternative specifications. The results are robust to using absolute forecast errors and limiting the sample to pre-Covid period.

Figure A.12: Decomposing uncertainty: prior and new information noise (under RE)



Legend: The figure plots the moving average around a window of 3 months for the estimates of new information noise (left y-axis) and prior uncertainty (right y-axis) from equations (3) and (18), as described in Appendix O.

## O Decomposing uncertainty into prior uncertainty and new information noise

To decompose posterior uncertainty in new information noise and prior uncertainty, consider equations (3) and (18). Together, they form a system of two observables (posterior uncertainty  $\Sigma_{t+h,t}$  and belief stickiness  $1 - G_t$ , which we estimate and report in Figure 5 and two unknowns, in new information noise and prior uncertainty. Solving the system yields

$$\sigma_{e,t}^{2} = \frac{\Sigma_{t+h,t}}{(1 - G_{t})^{2} \frac{(1 - \alpha)(G_{t} - \bar{g})}{1 - (G_{t} - \bar{g})} + G_{t}^{2}}}$$

$$\Sigma_{t+h,t-1} = \frac{(1 - \alpha)(G_{t} - \bar{g})}{1 - (G_{t} - \bar{g})} \sigma_{e,t}^{2}$$
(A.13)

where  $\alpha$  and  $\bar{g}$  are estimated in column 3, Table 3. The RE corresponds to the case  $\alpha = 0$  and  $\bar{g} = 0$ .




Legend: The figure plots the estimates of new information noise (left y-axis) and prior uncertainty (right y-axis) from equations (3) and (18), as described in Appendix O.

Figure A.14: Decomposing uncertainty: prior and new information noise



Legend: The figure plots the estimates of new information noise (left y-axis) and prior uncertainty (right y-axis) from equations (3) and (18), as described in Appendix O.

## P Alternative measure of expected inflation: mean of subjective density forecasts

In the main text we use the point forecasts to measure expected mean inflation, i.e. the first moment of the subjective belief distribution, and the density forecasts uniquely to measure uncertainty, i.e. the second moment. Here, we instead measure the expected mean using the implied mean of the individual density forecasts.

Table A.16 and figure A.15 replicate Table A.4 and figure 1 with this different measure of mean forecasts. The socioeconomic characteristics that affect belief stickiness slightly differ from the main text: in addition to tenure and young age, now old age and race seem to affect stickiness as well, while numeracy skills and college degrees do not. As a result, we replicate the 2-steps procedure of section 3 by dividing the sample based on these characteristics rather than the open used in the main text. Table A.17 replicates Table 2 with this new measure and different grouping, with the same results: belief stickiness is lower when prior uncertainty is higher and new information noise is lower.

Finally, figure A.16b replicates figure 5b by plotting the average belief stickiness across groups for each month. While it also shows a decrease in belief stickiness during COVID, this measure is much noisier than in the main text. Figure A.16a replicates figure ??, by estimating belief stickiness on the whole sample in a rolling window of 3 months. The drop in belief stickiness here is more robust.



## Figure A.15: Heterogeneity in belief stickiness using the mean of density forecasts

Legend: the figure shows the impact of socioeconomic characteristics on our estimate of belief stickiness,  $\mathbf{B}_3$  in (6), i.e. column (7) of Table A.16. Posterior and prior mean forecasts are measured using the mean of subjective density forecasts. Bars represent the 95% confidence interval. Sample period: 2020M3-2023M5.

	$(1) \\ Forecast$	(2) Forecast	(3) Forecast	(4) Forecast	(5) Forecast	(6) Forecast	(7) Forecast
Prior	$0.435^{***}$ (0.014)	$0.588^{***}$ (0.024)	$0.621^{***}$ (0.013)	$\begin{array}{c} 0.572^{***} \\ (0.017) \end{array}$	$0.584^{***}$ (0.015)	$0.536^{***}$ (0.022)	$0.388^{***}$ (0.039)
Tenure Tercile= $2 \times Prior$	$0.166^{***}$ (0.017)						$0.165^{***}$ (0.018)
Tenure Tercile= $3 \times Prior$	$\begin{array}{c} 0.254^{***} \\ (0.018) \end{array}$						$0.254^{***}$ (0.018)
$College_{it} = 1 \times Prior$		$0.000 \\ (0.025)$					$0.007 \\ (0.024)$
Age Over60=1 $\times$ Prior			$-0.065^{***}$ (0.019)				$-0.081^{***}$ (0.018)
Age Under40=1 $\times$ Prior			$-0.055^{**}$ (0.022)				$-0.048^{**}$ (0.021)
Income Over100 $k$ =1 × Prior				$0.013 \\ (0.023)$			$0.013 \\ (0.022)$
Income Under $50k=1 \times Prior$				$0.022 \\ (0.019)$			$0.023 \\ (0.020)$
High Numeracy= $1 \times Prior$					$0.007 \\ (0.017)$		$0.005 \\ (0.017)$
$Female=1 \times Prior$						$0.010 \\ (0.016)$	$0.009 \\ (0.016)$
$White=1 \times Prior$						$0.057^{***}$ (0.020)	$0.062^{***}$ (0.019)
Constant	$\begin{array}{c} 1.455^{***} \\ (0.033) \end{array}$	$\begin{array}{c} 1.482^{***} \\ (0.032) \end{array}$	$1.499^{***}$ (0.033)	$1.499^{***}$ (0.035)	$1.480^{***}$ (0.033)	$\begin{array}{c} 1.477^{***} \\ (0.035) \end{array}$	$1.480^{***}$ (0.034)
Year-Month FEs Non-interacted variables Year-Month × variables Sample Adjusted R-squared Observations	Y Y Jun13-May23 0.37 97362	Y Y Jun13-May23 0.36 97362	Y Y Jun13-May23 0.36 97326	Y Y Jun13-May23 0.36 96410	Y Y Jun13-May23 0.36 97334	Y Y Jun13-May23 0.36 97321	Y Y Jun13-May23 0.37 96345

Table A.16: Heterogeneity in belief Updating using the mean of density forecasts

Legend: For denotes the 1-year ahead forecast of inflation expectations starting 24 months into the future from the NY Fed Survey of Consumer Expectations (SCE). Prior is the 1-year ahead forecast of inflation expectations starting 24 months into the future provided in the previous month. Posterior and prior mean forecasts are measured using the mean of subjective density forecasts. Standard errors (in parentheses) are clustered at individual and time levels. \* represents p < 0.10, \*\* represents p < 0.05, and \*\*\* represents p < 0.01.



Figure A.16: Belief stickiness pre- and post-pandemic using the mean of density forecasts

Legend: The left panel plots the estimate of A.3, while the dashed blue lines represent the 95% confidence interval. The right panel plots the average belief stickiness across subsamples estimates of regression 10, while the dashed blue lines represent the average 90% confidence interval. Posterior and prior mean forecasts are measured using the mean of subjective density forecasts. The first red vertical line corresponds to the start of Covid-19 in March 2020. The second red vertical line corresponds to the start of the high-inflation period in January 2021. Sample period: 2013M1 - 2023M5.

	(1) Stickiness	(2) Stickiness	(3) Stickiness	(4) Stickiness	(5) Stickiness
ln(PriorUncert)	$-0.587^{***}$ (0.153)		$-0.163^{*}$ (0.093)		$-0.207^{***}$ (0.046)
ln(PostUncert)	$0.616^{***}$ (0.139)				
ln(PriorUncertIQR)		$-0.571^{***}$ (0.153)			
ln(PostUncertIQR)		$\begin{array}{c} 0.622^{***} \\ (0.132) \end{array}$			
ln(absoluteFE)			$0.406^{***}$ (0.068)		
ln(NewInfoNoise)				$\begin{array}{c} 0.287^{***} \\ (0.022) \end{array}$	$0.295^{***}$ (0.023)
Year-Month FEs Group FE Sample Adjusted R-squared Observations	Y Y Jun13-Feb20 0.23 812	Y Y Jun13-Feb20 0.23 812	Y Y Jun13-Feb20 0.27 784	Y Y Jun13-Feb20 0.60 785	Y Y Jun13-Feb20 0.61 785

Table A.17: Belief stickiness and uncertainty using the mean of density forecasts

Legend: This table reports the estimated coefficient from regression (12). PostUncert denotes the group-month average of 1-year ahead forecast of inflation expectations uncertainty starting 24 months into the future from the NY Fed Survey of Consumer Expectations (SCE). Posterior and prior mean forecasts are measured using the mean of subjective density forecasts. PriorUncert is the same variable, but from the previous month. We control for year-month and group fixed effects. PriorUncertIQR and PostUncertIQR are the inter-quartile ranges of the same forecasts. absoluteFE is the group-month average absolute forecast error. NewInfoNoise is described in the main text. Standard errors (in parentheses) are bootstrapped at the group-month level. \* represents p < 0.10, \*\* represents p < 0.05, and \*\* \* represents p < 0.01.