# Consumer Belief Formation in Uncertain Times*

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**Abstract**

What can we learn from consumer belief data in the uncertain post-pandemic economy? First, we document that the effect of uncertainty on consumers' belief rigidity is qualitatively in line with Bayesian learning. Second, we show that in this framework belief rigidity can help distinguish between aggregate sources of uncertainty, which we apply to the post-pandemic economy. At the pandemic's onset, we document a decline in belief rigidity alongside an increase in belief uncertainty, attributed to a regime shift in fundamental and economic policy uncertainty. In contrast, in the following high inflation period, we document an increase in belief rigidity, attributed to a deterioration in the accuracy of new information. Our results contribute to understanding how uncertainty affects consumers' beliefs and the macroeconomy.

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Uncertainty has become a hallmark of today's economy. A striking example is the COVID-19 pandemic, which drove a surge in various uncertainty indicators, but especially in consumer expectations data. For instance, the New York Fed's Survey of Consumer Expectations recorded an unprecedented rise in belief uncertainty since the survey began a decade earlier (Armantier et al., 2021). Research has shown that the dynamics of belief formation significantly impact the macroeconomy (Afrouzi and Yang, 2021; Angeletos et al., 2021). While recent literature has increasingly focused on the effects of uncertainty on the macroeconomy, asset prices, and household consumption and saving decisions (Bloom et al., 2012; Jurado et al., 2015; Bloom et al., 2018), there is comparably less evidence on the mechanisms through which uncertainty shapes consumer beliefs about the economy.

This paper investigates how uncertainty affects consumers' belief formation process and, consequently, what we can learn about uncertainty from belief data. Specifically, we study the impact of different sources of uncertainty on belief updating rigidity, which reflect the extent to which consumers rely on prior versus new information when forming their expectations, *i.e.* the degree of information frictions (Coibion and Gorodnichenko, 2012, 2015). We use 3-years ahead inflation expectations data from the Survey of Consumer Expectations (SCE), which gathers monthly data from a rotating panel of households between June 2013 and May 2023, with approximately 1300 monthly observations. This survey is particularly well-suited to address our research question for two reasons. First, it includes density forecasts that enable us to measure belief uncertainty at the individual consumer level.[1] Second, it provides a large panel dimension that allow us to precisely estimate belief rigidity in each month of the survey and for different groups of consumers. We measure belief rigidity as the cross-sectional covariance between current and lagged point forecasts, controlling for common factors (Gemmi and Valchev, 2023; Goldstein, 2023).[2]

First, we show that the way consumers incorporate uncertainty in their beliefs is qualitatively in line with Bayesian learning. This framework implies that belief rigidity is higher when new information is noisier, and lower when prior information is more

[1] Manski (2004, 2018), among others, and others have advocated for the use of probabilistic questions to capture subjective uncertainty in economic surveys, as opposed to relying on point forecast dispersion.

[2] We follow the new methodology proposed by Gemmi and Valchev (2023) and Goldstein (2023), which improves on the benchmark strategy of Coibion and Gorodnichenko (2015). This new methodology allows us to overcome the typical challenges arising in these exercises, such as identifying correct actual data realizations, allowing for common signal noise, or the necessity of long time-series. The latter is especially relevant when considering household surveys like the SCE.

uncertain. We proxy prior uncertainty with the self-reported inflation forecast uncertainty provided in the previous month of the surveys. We extract new information noise from the self-reported inflation forecast uncertainty in the current month (i.e. posterior uncertainty). Our findings confirm the Bayesian learning model's predictions: less accurate signals induce agents to update less, while higher prior uncertainty induces them to update more. However, we find that the estimated belief rigidity is, on average, lower than the rational expectations counterfactual, indicating that agents, while updating in the correct direction, tend to overweight new information—even when it is noisy. Together, this evidence provides an empirically supported framework for belief formation that links belief rigidity with uncertainty.

Second, we leverage on this empirically supported framework to shed light on the aggregate sources of uncertainty in the post-pandemic economy. We begin by documenting a reversal in the correlation between belief uncertainty and rigidity during the COVID-19 period. At the onset of the pandemic, we observe a sharp decline in belief rigidity alongside an increase in belief uncertainty: consumers incorporate more new information into their beliefs 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 rigidity and uncertainty: they incorporate less information into their beliefs while becoming even more uncertain.

The correlation between belief rigidity and uncertainty provides insight into the underlying sources of uncertainty. We show that the negative correlation observed during the pandemic outbreak reflects an increase in prior uncertainty, possibly due to a regime shift in fundamental inflation volatility or uncertainty about economic policies. This structural change in the economic landscape rendered existing information obsolete, prompting households to seek out and incorporate new information into their beliefs. In contrast, in the post-Covid period, belief rigidity 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 heavily on their prior information.

Finally, we show that lockdown policies implemented at the onset of the pandemic contributed to lower belief rigidity, yet do not explain the simultaneous increase in uncertainty. Using variation in the intensity of state-level lockdown policies, measured by the Oxford Covid-19 Government Response Tracker (OxCGRT), we identify a significant and robust negative effect on households' belief rigidity. This finding suggests that restrictions on mobility and the widespread shift to remote work reduced the marginal cost of information acquisition, enabling households to gather more new information. However, lockdown policies alone cannot account for the concurrent rise in belief uncertainty observed during this period. In fact, we find that the impact of lockdown policies on belief uncertainty is negative. This aligns with standard belief formation models, where lower information-gathering costs lead to the collection of more accurate data, thus placing greater relative weight on new information when forming beliefs. Therefore, while reduced information costs help explain the decline in belief rigidity during the pandemic, they do not account for the increase in uncertainty.

Our work offers two key contributions. First, we demonstrate that belief rigidity is a useful statistic to distinguish between different types of macroeconomic uncertainty shocks: fundamental volatility and information noise have opposite effects on belief rigidity, allowing it to serve as a tool for differentiating between these two sources of uncertainty. While the existing literature has traditionally conflated different uncertainty sources, we show that distinguishing them is necessary to understand the dynamic of information frictions in highly uncertain periods such as COVID-19, as they could have significant macroeconomic implications for inflation and the slope of the Phillips Curve. Second, we show that the effect of uncertainty on consumers' belief formation qualitatively aligns with Bayesian framework predictions. This finding corroborates the conclusions of a growing literature on information provision through randomized control trials (RCTs) (Armantier et al., 2016; Coibion et al., 2018, 2024; Kumar et al., 2023; Weber et al., 2024). However, instead of presenting consumers with an ad-hoc piece of information, we rely on *naturally occurring* variation in beliefs to study how consumers incorporate real-world information, irrespective of its source. While our approach sidesteps concerns of external validity concerns, our results remain consistent with those from RCT experiments.

**Contribution 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, 2015; Benhima and Bolliger, 2022; Gemmi and Valchev, 2023). Relative to these studies, we measure information rigidity on household surveys instead of relying on professional forecasters. We build on the empirical strategy developed by Goldstein (2023), who also document a decrease in belief rigidity in the first quarter of the COVID-19 pandemic in professional forecaster surveys, but do not find such a decline in the Michigan Survey of Consumers. Compared to their work, we exploit the higher frequency of the SCE to improve our identification strategy, and, more importantly, we estimate the relationship between different uncertainty sources and household belief rigidity.

Second, we 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), especially the ones measuring uncertainty with survey data (Manski, 2018; Kumar et al., 2023; Fermand et al., 2024; Wang, 2024; Coibion et al., 2024).[3] We show that belief rigidity in survey data is a useful statistic to distinguish between different macroeconomic uncertainty shocks - fundamental volatility and information noise - as they have the opposite effect on belief rigidity. De Bruin et al. (2011) also study subjective uncertainty in the Survey of Consumer Expectations and document that consumers exhibiting higher uncertainty tend to revise their beliefs more. Compared to them, we consider both posterior and prior uncertainty and estimate their impact on belief rigidity. Gambetti et al. (2023) uses forecast disagreement to differentiate between fundamental volatility and information noise as sources of uncertainty. The underlying assumption is that fundamental volatility decreases disagreement, whereas information noise increases it. We show that belief uncertainty is a better statistic to distinguish the two sources, as their effects on it are unambiguous and do not depend on parameter assumptions.[4]

Finally, a growing body of work applying randomized control trials (RCTS) to study how new information shapes expectations by inducing exogenous change in beliefs through an information treatment (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 seem to update beliefs in accordance with the qualitative prediction of a rational Bayesian framework, meaning that they update their belief more the less accurate their prior and the more informative the signal provided.[5] We document a similar result without relying on RCTs

[3]See Cascaldi-Garcia et al. (2023) for a review of different measure of macroeconomic uncertainty.
[4]We further elaborate on this in Appendix I.
[5]While this is true for RCTs with information provision about inflation, the evidence is more mixed when the information provided is about other economic indicators. In particular, Fuster et al. (2022) document the opposite effect of prior uncertainty on housing price expectation rigidity. Armona et al. (2019) and Conlon et al. (2018) do not find any effect of uncertainty on the housing market and labor market expectations.

and exogenous information provision, but instead exploiting the naturally occurring variation of beliefs.[6] As our findings are not subject to external validity concerns, the similarity between our results and the RCT literature is encouraging for the external validity of the results in that literature. More closely related to us, Weber et al. (2024) compare a large sample of RCTs conducted in different countries over time and document that agents adjust belief less in response to the information treatment in high inflation environments. They conclude that high inflation leads agents to collect more information, and therefore have a more accurate prior. In contrast, we directly measure subjective prior and posterior uncertainty and related them with belief updating at the individual level.[7]

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 rigidity. Section 5 investigates the impact of lockdowns on belief rigidity. Section 3 studies the relation between belief rigidity and uncertainty sources. Section 6 discusses our findings and their macro-finance 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 belief about variable realization at horizon $t+h$ after observing a private signal 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 $\sigma^2_{\eta,t}$ and i.i.d. across time and households,

[6] Chahrour et al. (2024) also investigate household belief formation using survey data, but focus instead on the asymmetric response of beliefs to positive and negative news about inflation in the Michigan Survey of Consumers.

[7] A related literature tests the implication of the endogenous information model, meaning the attention allocation of consumers and firms (Roth et al., 2022; Mikosch et al., 2024; Link et al., 2024). Instead of investigating the drivers of agents' attention choice, we measure the final quantity of information, i.e. uncertainty, regardless of its determinant. As we show in Section 3, in the Bayesian framework belief rigidity only depends on this quantity.

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

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

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

where $G_t$ is the weight households assign to new information and $E_t^i[x_{t+h}]$ is a potentially non-optimal 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 "rigidity".

Notice that we have not made any assumption about what determines the weight on new information $G_t$. In other words, we have not assumed any particular belief-updating model, except for 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[8]. 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, which equals

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

where $\Sigma_{t+h,t} \equiv var(x_{t+h} - E_t^i[x_{t+h}])$ is the posterior belief uncertainty, which depends on prior uncertainty $\Sigma_{t+h,t-1} \equiv var(x_{t+h} - E_{t-1}^i[x_{t+h}])$ and new information uncertainty $\sigma^2_{e,t}$.

Before proceeding, let us clarify some of the terminology used in this paper. We refer to $1 - G_t$ as belief rigidity, information rigidity, or belief stickiness (Coibion and Gorodnichenko, 2012, 2015). A related term is belief *anchoring*, which refers to long-run inflation expectations being stable and closely aligned with a central bank's

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

inflation target. The literature uses very long-term horizons to identify beliefs about central banks' target or 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 finding, as we discuss in section 3. Another widely used term is *attention*, which is related to the rational inattention literature (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 $\sigma^2_{e,t}$ . Empirical works on consumers' and firms' attention allocation refer to this measure rather than belief rigidity (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 more in detail in section 3.

# 2 Households' belief rigidity

## 2.1 Data

Our data come 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.[9] 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 0.5 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

[9]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.

12 months (which we define as "1 year"), expected inflation/deflation over the 12 months starting from 24 months in the future (which we define as "3 years") and expected average home price nationwide change over the next 12 months. The SCE asks respondents to indicate both their point forecast for future expected inflation and their subjective distribution over all possible inflation realization. We focus on the 3-year horizon and use the shorter horizon forecasts for robustness.

First, to measure expected mean inflation we use the point forecast provided by respondents.[10] We use this measure to construct (i) expected mean inflation ($For_{i,t}$) as the point forecast about inflation at horizon 3-year provided in month $t$, and (ii) prior mean expectation as the point forecast about horizon 3-year provided in month $t-1$ by the same forecaster ($Prior_{i,t}$). Even if the horizons of the two forecasts differ by one month, this difference is small compared to the length of the overall horizon forecasted, allowing us to assume the horizon is approximately the same.

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).[11] We indicate as posterior uncertainty the standard deviation from the variance of the subjective distribution provided in the current month($Post\ Uncertainty_{i,t}$). 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 1 presents summary statistics for forecasts and uncertainty.

**Socioeconomic characteristics** For each respondents we observe gender ($Female_i$), age ($Age_{it}$) and race ($White_i$). Moreover, we construct an indicator variable with value one if the respondent attended college and zero otherwise ($College_{it}$). We also have

[10] While we could alternatively use the mean forecast computed from the subjective distribution, we think that using the answers to two different survey questions lowers the concern of possible measurement error correlation between expected mean and uncertainty when we test their relation in the data.

[11] 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 instead based on the rounding of point forecasts, as in Binder (2017).

Table 1: Descriptive Statistics

| | Mean | SD | Min | Max | N |
|---|---|---|---|---|---|
| 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 |
| $Income\ Over100k_{it}$ | 0.30 | 0.46 | 0 | 1 | 134293 |
| $Income\ Under50k_{it}$ | 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 |

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.

respondent income, but only as a categorical variable. We construct an indicator with value 1 if the respondent has an income lower than 50k ($Income\ Under50k_{it}$), between 50k and 100k ($Income\ 50kto100k_{it}$), and above 100k ($Income\ Unrder100k_{it}$). 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 ($HighNumeracy_{i,t}$).

## 2.2 Empirical strategy

We estimate belief rigidity by comparing individual posterior with prior forecasts across households, similarly to Goldstein (2023) and Gemmi and Valchev (2023). Previous studies often relied on the approach pioneered by Coibion and Gorodnichenko (2015) to estimate belief rigidity in expectation surveys, which involves regressing consensus forecast errors against forecast revisions. However, this method has significant limitations: first, it is biased in the presence of common errors in the structure of the signal ($\sigma_\omega > 0$

in our theoretical framework);[12] second, it requires a long time series dimension, rarely available in household surveys. Instead, the methodology we adopt overcomes both challenges by exploiting instead the cross-sectional variation of individual forecasts.

Demeaning (2) using consensus forecasts, one obtains[13]

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

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

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

where $i$ indicates the household and $t$ the year-month. We include the year-month fixed effect $\gamma_t$ to demean the individual forecasts. Moreover, $X_{i,t}$ contains age, gender, race, tenure, numeracy, income, and education fixed effects. The coefficient $\beta$ is an unbiased estimator of the belief rigidity $1-G$. Intuitively, higher belief rigidity implies a higher correlation between posterior beliefs and prior beliefs (higher $\beta$), while lower belief rigidity implies a lower correlation between posterior beliefs and prior beliefs (lower $\beta$).

Table 2 reports the estimates of belief rigidity $\beta$ from regression (5). Column (1) reports the belief rigidity in the whole sample, which implies a gain of $G = 0.485$. This 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 (2015), which suffer from the biases 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 rigidity, as this would require knowing the distribution of their signals.

We perform robustness tests addressing two possible concerns with the methodology adopted. First, the estimated belief rigidity reflects a combination of extensive and intensive margin of information adjustment, meaning consumers not updating their

[12]The bias in the presence of common error in the signals was already recognized in Coibion and Gorodnichenko (2015) appendix.

[13]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.

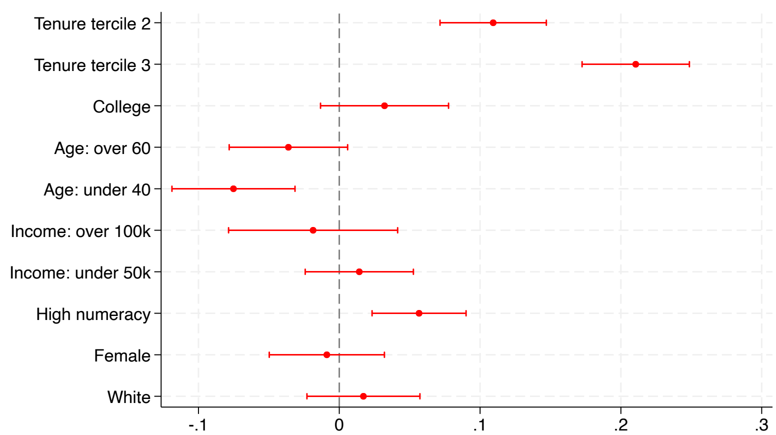
Table 2: Belief rigidity

| | (1) $Forecast$ | (2) $Forecast$ | (3) $Forecast$ |
|---|---|---|---|
| $Prior$ | 0.509*** | 0.494*** | 0.312*** |
| | (0.011) | (0.011) | (0.021) |
| $Prior \times Tenure_{it}$ | | | 0.029*** |
| | | | (0.002) |
| $High\ Numeracy_{it}$=1 $\times$ $Prior$ | | | 0.064*** |
| | | | (0.016) |
| Constant | 2.276*** | 2.354*** | 2.141*** |
| | (0.053) | (0.052) | (0.047) |
| Year-Month FEs | Y | Y | Y |
| Socio-democraphic FEs | Y | Y | Y |
| Adjusted R-squared | 0.34 | 0.32 | 0.35 |
| Observations | 94082 | 90862 | 94082 |

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 horizon 3 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 for socioeconomic characteristics, such as education, income, age, gender, race, and tenure. 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 $p < 0.01$.

beliefs from one month to the other and consumers updating only partially. One possible concern about this measure is the bias introduced by respondents who do change their belief from one month to the other, but do not make the effort to change their answer to the survey. To address this concern, we estimate the belief rigidity 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 rigidity 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 rigidity is not driven by inexperienced respondents. Similar results are documented for 1 year ahead and housing inflation, Tables A.6 and A.7.

Figure 1: Heterogeneity in belief rigidity




Legend: the figure shows the impact of socioeconomic characteristics on our estimate of belief rigidity, $\mathbf{B}_3$ in (6), i.e. column (7) of Table A.1. Sample period: 2020M3-2023M5.

### 2.3 Heterogeneity in belief updating

We explore how socioeconomic characteristics affect households' belief formation. To study how these characteristics affect belief rigidity, we interact them with the prior in our regression. That is, we run

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

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 in belief rigidity. The characteristics we consider are the following: tercile of tenure (i.e. number of months in the survey), whether hold a college degree, whether 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.1 reports all the estimated coefficients. We find that households with higher tenure, a college degree, and higher numeracy exhibit larger belief rigidity. On the other hand, young respondents exhibit lower belief rigidity. Suppose these characteristics reflected information quality: then, a standard Bayesian updating model would imply that more educated and more experienced individuals accessing more accurate information would exhibit lower rigidity. However, we find that the opposite is true. There are two possible explanations for this finding: first, less educated and less experienced are more confident about their information, regardless of whether this is true or not. Second, there may be determinants for belief rigidity other than information quality. For instance, some scarring effects due to past inflation experience, as in Malmendier and Nagel (2016).

# 3 Belief rigidity 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 rigidity $1 - G_t$. Rather, our framework embeds the noisy information rational expectation model as a particular case. Thus, we can compare the empirical properties of our belief rigidity estimates with the implications of the rational expectation framework.

Assume consumers update their beliefs according to the Bayes rule. Suppose the signal is given by equation (1). Then, posterior mean is given by equation (2) and posterior uncertainty by equation (21), where the belief rigidity is given by

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

We test two implications from the rational expectations model (7).

First, higher new information noise $\sigma_{e,t}^2$ is associated with higher belief rigidity. 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 rigidity. 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 rigidity is higher.

**Discussion** We make three related obsverations. 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 rigidity 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 but build on the baseline Bayesian updating in (7). For example, diagnostic expectations (Bordalo et al., 2018, 2020), overconfidence (Broer and Kohlhas, 2024), and over and under-extrapolation (Angeletos et al., 2021) all share the same qualitative impact of prior and new information uncertainty on belief rigidity.[14] Lastly, while the impact of new information noise on belief rigidity 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.

## 3.1 Empirical test

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

We proceed in two steps. First, we divide our sample into groups based on socioeconomic similarities and estimate a time series of belief rigidity for each group. Second, we investigate the relationship between the estimated belief rigidity with prior uncertainty and new information noise.

### 3.1.1 First step: estimate belief rigidity

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

$$s_t^{i,j} = x_{t+h} + e_t^{i,j} \tag{8}$$

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

[14] 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 (Eusepi and Preston, 2011), natural expectations (Fuster et al., 2010) and behavioral inattention (Gabaix, 2017) do not share these implications (at least in their benchmark version).

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

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

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

First, we divide consumers into $j = 1, \ldots, J$ groups based on sociodemographic characteristics, assumed to identify individuals with similar new information quality. We consider the 4 indicators that we show have the most significant effect on belief rigidity 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.[15]

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 $\hat{\beta}_{j,t} = 1 - G_{j,t}$. We can use this estimate of group-specific gain $G_{j,t}$ to extract the group-specific new information noise from the posterior uncertainty.

### 3.1.2 Second step: impact of uncertainty on belief rigidity

Next, we investigate the relationship between our estimates of belief rigidity and measures of prior uncertainty and new information noise.

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 are the same. This assumption is justified by the small difference of one month compared to the total forecast horizon of 36 months. Second, we also need to

[15]There is 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.

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 run robustness checks by limiting our sample to the pre-COVID period.

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

**Posterior uncertainty** We first proxy for new information noise using posterior uncertainty controlling for prior uncertainty. From (21), the posterior variance of group $j$ at time $t$ equal

$$\Sigma^j_{t+h,t} = (1 - G^j_t)^2 \Sigma^j_{t+h,t-1} + (G^j_t)^2 (\sigma^j_{e,t})^2 \tag{11}$$

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

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

where $\hat{\beta}_{j,t} = 1 - G_{j,t}$ is the group-month belief rigidity estimated in the first step, $PosteriorUncert_{j,t}$ 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 rigidity: $\delta_1 < 0$. Second, for a given prior uncertainty, higher new information noise leads to lower belief rigidity: $\delta_2 > 0$.

Our empirical estimates confirm both hypotheses. The first three columns of Table 3 report the estimation result. Column (1) shows that, considered individually, prior uncertainty is not significantly related to belief rigidity, while column (2) shows that posterior uncertainty is significantly positively related. However, both these regressions

Table 3: Belief rigidity and uncertainty

| | (1) Rigidity | (2) Rigidity | (3) Rigidity | (4) Rigidity | (5) Rigidity | (6) Rigidity |
|---|---|---|---|---|---|---|
| $ln(PriorUncert)$ | -0.009 | | -0.292** | | -0.192*** | -0.202*** |
| | (0.076) | | (0.118) | | (0.049) | (0.063) |
| $ln(PostUncert)$ | | 0.161** | 0.378*** | | | |
| | | (0.068) | (0.107) | | | |
| $ln(NewInfoNoise)$ | | | | 0.339*** | 0.358*** | 0.354*** |
| | | | | (0.020) | (0.025) | (0.032) |
| Year-Month FEs | Y | Y | Y | Y | Y | Y |
| Group FE | Y | Y | Y | Y | Y | Y |
| Sample | Jun13-May23 | Jun13-May23 | Jun13-May23 | Jun13-May23 | Jun13-May23 | Jun13-Feb20 |
| Adjusted R-squared | 0.13 | 0.13 | 0.14 | 0.60 | 0.62 | 0.62 |
| Observations | 1076 | 1076 | 1076 | 1028 | 1028 | 687 |

Legend: this table reports the estimated coefficient from regression (12). $PostUncert$ 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. We control for year-month and group fixed effects. $NewInfoNoise$ 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 $p < 0.01$.

suffer from an omitted variable bias. Including both of them in column (3) confirms our hypothesis: belief rigidity decreases in prior uncertainty and increases in 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 rigidity, equation (11) shows that the opposite is also true, as posterior uncertainty depends on belief rigidity. Therefore regression (12) might suffer from an endogeneity bias.[16] To address this issue, we propose an alternative measure for new information uncertainty.

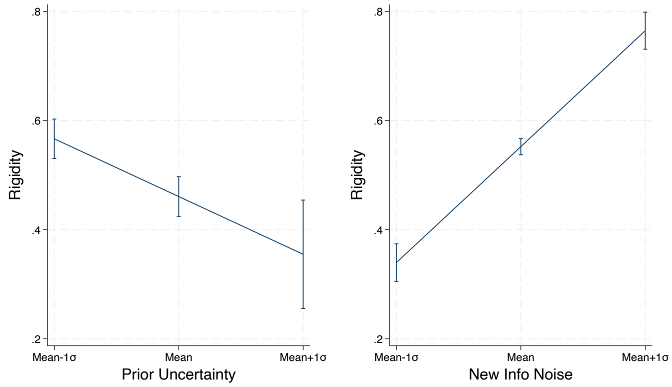
**Extract new information noise** We use our estimate of belief rigidity, together with our measures of prior and posterior uncertainty, to compute the new information noise from (21).[17]

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

[16] 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)).

[17] We notice that equation (21) is part of our general framework and it does not impose any model of belief rigidity, meaning it does not make any assumption on $G_t^j$.

Figure 2: Belief rigidity and uncertainty




Legend: The figure represents graphically the estimated coefficients from column (6) of Table 3. It shows the relationship between belief rigidity and prior uncertainty (on the left-hand side) and new information noise (on the right-hand side).

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

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

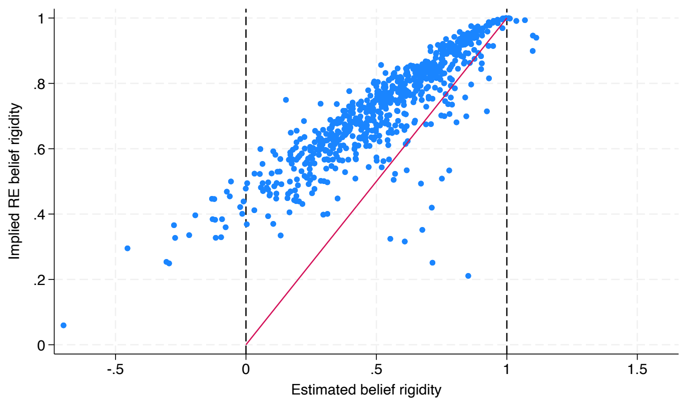
$$Rigidity_{j,t} = \alpha + \delta_1 ln(PriorUncert)_{j,t} + \delta_2 ln(NewInfoNoise)_{j,t} + \gamma_t + \gamma_j + \epsilon_{j,t} \quad (14)$$

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

The empirical estimates confirm both hypotheses. The last three columns of Table 3 report the estimation result. Column (4) shows that our measure of new information noise impact positively belief rigidity, while column (5) shows that the effect of prior uncertainty is negative while controlling for new information noise. Finally, column (6) confirms the results considering only the pre-COVID sample.

Figure 2 plots the estimated effect of prior uncertainty and new information noise on belief rigidity in the main specification of Column (5) in Table 3. The effect of uncertainty on belief rigidity is sizable. A one standard deviation increase in the prior uncertainty reduces belief rigidity by around 0.1, i.e. around 20%. Similarly, a one standard deviation increase in the new information noise increases belief rigidity by around 0.07, i.e. 15%.

Figure 3: Belief rigidity and uncertainty




Legend: The figure plot on the x-axis the estimated belief rigidity $\hat{\beta}_{j,t}$ from regression (10) and on the y-axis the implied rational expectation belief rigidity from equation (7).

In conclusion, we document a robust positive relationship between belief rigidity and prior uncertainty and a negative one with new information uncertainty, in line with the prediction of the Bayesian belief formation model. A recent body of works documents a similar finding on randomized control trials (RCTS), i.e. by inducing an exogenous change in beliefs through an information treatment (Armantier et al., 2016; Cavallo et al., 2017; Armona et al., 2019; Roth and Wohlfart, 2020; Coibion et al., 2022; Link et al., 2023). Rather than relying on exogenous information provision, we utilize the naturally occurring variation in beliefs. This approach alleviates concerns about external validity. Our findings' consistency with RCT literature outcomes is encouraging and hints at potential robustness in such studies.

**Estimated and optimal stickiness** We use our proxies for prior uncertainty and new information noise to construct the counterfactual belief rigidity in the Rational Expectation framework, (7). We notice that, while we used our empirical estimates of belief rigidity to recover a measure for new information noise, we have not made any assumption on belief rigidity so far. As a result, we can compare the belief rigidity measured in the data with the one a consumer would display if he updated rationally given the prior uncertainty and new information noise. Figure 3 report this comparison for each group-month observation in the pre-COVID sample.

We highlight two results. First, a consumer facing the same prior uncertainty and new information noise but updating rationally would have displayed on average a higher belief rigidity. In other words, consumers seem overweight new information compared to the rational counterfactual. This is consistent with the evidence reported in Table 2, which shows that consumers with higher tenure and numeracy scores display higher belief rigidity 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 rigidity lay outside the RE interval, around 3% of them below zero and 4% above one. This could be due to measurement error or non-rational behavior. A negative belief rigidity could imply an overweighting of new information, while a belief rigidity above one could imply overweigthing of prior information.[18]

# 4 Belief rigidity and the pandemic

In this section, we investigate the dynamic of belief rigidity around the COVID-19 outbreak, to shed light on the relation between belief rigidity and uncertainty. We leverage on the sharp increase in belief uncertainty observed during the pandemic. Figure 4a plots the average posterior belief uncertainty for each month, and it shows that uncertainty spiked up after the COVID-19 outbreak and kept increasing in the following months. We use this highly uncertain period as a laboratory to study how uncertainty relates to belief rigidity.

We compute belief rigidity month-by-month by exploiting the large cross-sectional dimension of the SCE data. For each month $t$, we run the following regression

$$For_{i,t} = \alpha_t + \beta_t Prior_{i,t} + X_{i,t} + err_t^i \tag{15}$$

We highlight two results. First, we document a stark decrease in belief rigidity during the COVID outbreak. Figure 4c reports an estimate of belief rigidity is around 0.5 for the pre-COVID sample, followed by a sudden drop to around 0.3 during the COVID period. After the end of the pandemic, the rigidity reverts to the pre-pandemic level, but ends at a slightly higher value during the high inflation period. Figure 4d shows the estimate of belief rigidity in three different subsamples: pre-COVID period

[18] Consider for example the diagnostic expectation belief formal model of Bordalo et al. (2020). In this case, $G_t^j = (1+\theta)G_t^{RE^j}$, where $\theta > 0$ is a parameter governing the overreaction to new information. In this framework, our estimates belief rigidity would equal $\hat{\beta_t^j} = 1-(1+\theta)G_t^{RE^j}$, which may be negative for higher enough $\theta$ and $G_t^{RE^j}$. Conversely, a negative $\theta$, meaning underreaction, and low enough $G_t^{RE^j}$ could lead to estimated belief rigidity above one.

(up to March 2020), COVID period (between March 2020 and January 2021), and high inflation period (after January 2021). Table A.3 reports the estimates.[19] The results are robust to different empirical strategies. First, Figure A.6 reports the same exercise for shorter horizon forecasts with similar results. Second, instead of estimating belief rigidity using the whole cross section in each month, we can divide the sample is subgroups as in Section 3.1 and average the estimated belief rigidity in each month across subgroups. Figure A.2a and A.2b report the results, which display the same empirical patterns highlighted in figures 4c and 4d.[20]

We notice that large shifts in belief rigidity, such as the one we documented during the pandemic, can have important macroeconomic consequences. For example, recent theoretical works have shown how information frictions affect the Philips Curve (Afrouzi and Yang, 2021; Angeletos et al., 2021). In appendix G, we present a stylized analytical general equilibrium model and show that the Phillips curve slope is a function of agents' belief rigidity. Specifically, lower belief rigidity results in economic agents' behavior and prices being more responsive to economic shocks, thereby steepening the Phillips curve. Conversely, higher belief rigidity leads to a diminished response of economic agents' behavior and prices to economic shocks, flattening the Phillips curve. While these findings are illustrative, they highlight the macroeconomic impact of belief rigidity and its policy relevance in recent discussion about the slope of the Philips curve (Negro et al., 2020; Cerrato and Gitti, 2022; Gudmundsson et al., 2024).

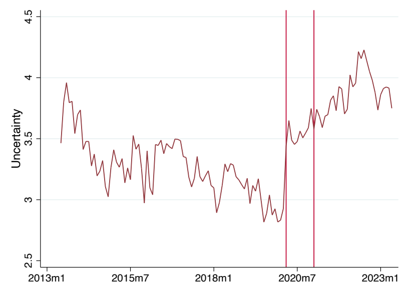
Second, we document a reversal in the correlation between posterior uncertainty and belief rigidity after COVID-19. This can be seen by comparing figures 4a and 4c. Initially, at the onset of the pandemic, uncertainty spikes up and belief rigidity goes in the opposite direction. Intuitively, consumers abandon their priors in favor of new

[19] Our evidence is partially consistent with the findings of Goldstein (2023), which documents a decrease in inattention in the first quarters of COVID in the Surveys of Professional Forecasters. However, the author doesn't find any change in inattention on the Michigan survey of consumers. The difference between our and Goldstein (2023)'s results on consumers might be due to the different structure between the two consumer surveys: while the Michigan survey interviews the same individual only after 6 months, the SCE does it every month, which allows us to measure the forecast revision at higher frequencies. Another difference is that we consider a 3-year forecast horizon, Goldstein (2023) considers a short 1-year horizon. Figure A.6 replicates our analysis for the 1-year horizon and shows that the decrease in inattention is less visible for inflation at this short horizon, but it is for house price forecasts.

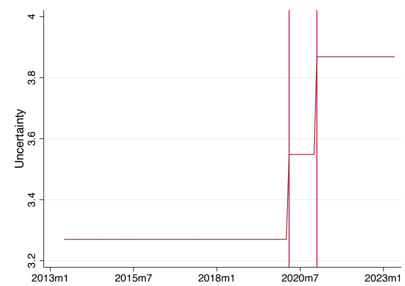
[20] Figure A.4 reports the monthly share of respondents in the Michigan Survey of Consumers declaring to not have heard any news about business conditions, also documenting a sharp decline at the COVID outbreak.

Figure 4: Belief rigidity pre- and post-pandemic

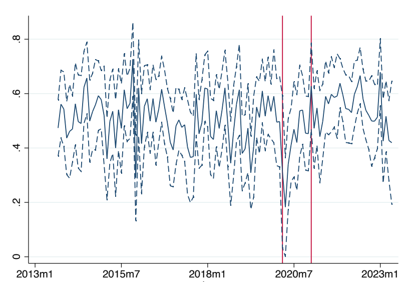
(a) Average uncertainty month-by-month



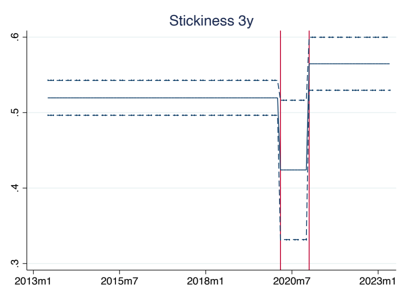

(b) Average uncertainty by periods




(c) Belief rigidity $\beta$ month-by-month




(d) Belief rigidity $\beta$ by periods




Legend: The blue solid line represents our estimates of belief rigidity, while the dashed blue lines represent the 95% confidence interval. In the left plot, belief rigidity $\beta$ is estimated separately in each month of the sample. In the right plot, it is estimated in each sub-sample: pre-Covid, during Covid, and after Covid (during the Biden term). 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 (or the start of the Biden term). Sample period: 2013M1 - 2023M5.

information but are more uncertain about their new beliefs. Then, during the high inflation period after COVID-19, belief rigidity increases together with uncertainty. Intuitively, consumers rely more on their prior beliefs. while being increasingly more uncertain. Importantly, the correlation between belief rigidity and posterior uncertainty is informative about the underlying source of uncertainty. We explore this in more detail in the next section.

## 4.1 The sources of uncertainty

In this section, we use the empirical correlation between belief rigidity and uncertainty to shed light on the underlying sources behind the rise in uncertainty in the post-pandemic economy.

Posterior uncertainty depends positively on two sources, as illustrated by equation (21): the uncertainty of new information, i.e. new information noise, and the one of existing information, i.e., and prior uncertainty. However, as we argued and empirically documented in section 3, these two sources impact belief rigidity in the opposite direction. As a result, the correlation between posterior uncertainty and belief rigidity is informative about the relative importance of these two sources of uncertainty.

**New information noise** Consider an increase in uncertainty, or noise, of new information, i.e. an increase in $\sigma^2_{e,t}$. For a given prior uncertainty, agents receive less accurate signals and therefore update less, meaning higher belief rigidity $1 - G_t$ (equation (7)). For example, households may face a higher cost of collecting information or a lower supply of information from newspapers, television, or social networks.

An increase in new information noise is consistent with our evidence in the post-COVID period, where we observe a positive correlation between belief uncertainty and rigidity. This period, beginning in February 2021, is also marked by a rise in inflation, accompanied by increased coverage in newspapers and other media outlets. At first glance, this may seem inconsistent with the observed increase in noise in new information about inflation. However, upon closer examination, this is not the case. The increase in media coverage does not necessarily indicate a more accurate dissemination of information. Instead, it could reflect efforts to mitigate heightened uncertainty stemming from the increased difficulty in predicting inflation.

This implication holds similarly in models with endogenous information or rational inattention (Sims, 2003, 2006; Mackowiak and Wiederholt, 2009; Maćkowiak et al., 2023). These models allow agents to allocate attention to new information, making the information noise $\sigma^2_{e,t}$ a choice variable. However, equation (7) shows that the only determinant for belief rigidity is the total equilibrium new information noise, regardless of whether it is driven by demand or supply.

**Prior uncertainty** Consider an increase in prior uncertainty. As existing information becomes more uncertain, new information becomes *relatively* more accurate, and therefore consumers update more, meaning belief rigidity $1 - G_t$ decreases (equation (7)).

An increase in prior uncertainty is consistent with our evidence in the COVID outbreak period, where we observe a negative correlation between belief uncertainty and rigidity. 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 case where the fundamental follows an AR(1) process:

$$x_{t+h} = (1-\rho)\mu_x + \rho x_{t+h-1} + u_{t+h} \tag{16}$$

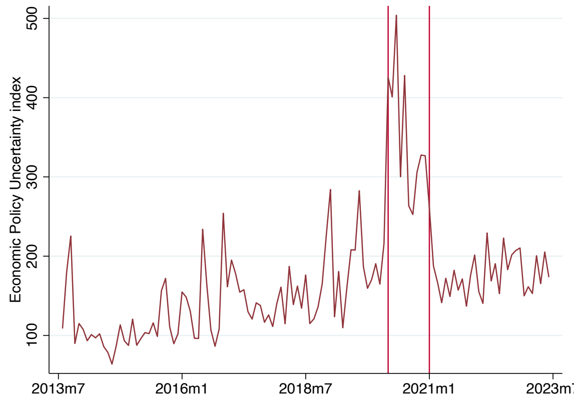
with $u_{t+h} \sim N(0, \sigma^2_u)$ being the fundamental shock and $\mu_x$ the unconditional long-run mean. In this case, prior mean equals $E^i_{t-1}[x_{t+h}] = (1-\rho)\mu_x + \rho E^i_{t-1}[x_{t+h-1}]$, and prior variance

$$\Sigma_{t+h,t-1} = \rho^2 \Sigma_{t+h-1,t-1} + \sigma^2_u \tag{17}$$

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 for example Baker et al., 2020).

Second, consider a loss of trust in the central bank to maintain its inflation target. In this stylized setting, one can think of the belief about the long-run mean of inflation

Figure 5: Economic Policy Uncertainty index




Legend: The figure plot the "news coverage component" from the Economic Uncertainty Index, which is based on the share of articles in US online newspapers that mention economic policy uncertainty (Baker et al., 2016).

becoming uncertain, $\mu_x \sim N(\bar{\pi}, \sigma_\mu^2)$. Prior uncertainty then becomes

$$\Sigma_{t+h,t-1} = (1-\rho)^2\sigma_\mu^2 + \rho^2\Sigma_{t+h-1,t-1} + \sigma_u^2 \tag{18}$$

Similar to a structural increase in fundamental uncertainty, an increase in uncertainty about long-run mean inflation $\sigma_{\mu,t}^2$ would increase prior uncertainty and therefore lower belief rigidity. This could be possibly due to lower trust in the central bank's ability to achieve its price stability objective, or more generally due to uncertainty about economic policy implementation.

Figure 5 plots the Economic Uncertainty Index, constructed by Baker et al. (2016) and offers further validation for this implication. We plot the "news coverage component", which measures the share of articles in US online newspapers that mention economic policy uncertainty.[21] 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.[22]

[21]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).

[22]In theory, a regime shift in the autoregressive parameter $\rho$ might have also played a role. While

Another possible force driving the change in belief rigidity during Covid could be 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 rigidity. We investigate this in the next section.

# 5 Lockdowns and belief formation

## 5.1 Impact of lockdowns on belief rigidity

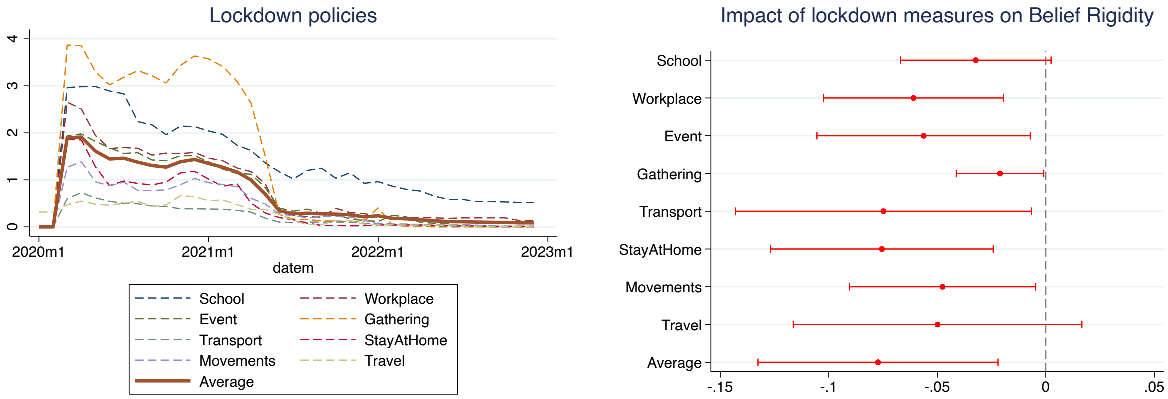
In this section, we investigate the role played by lockdown policies in the decline in belief rigidity we documented during the pandemic. After the burst of COVID, policymakers implemented a series of restrictions on movements, both in terms of leisure and working time, to stop the spread of the virus. This caused many consumers to turn to the Internet for work, education, social interaction, and entertainment. In turn, this more frequent interaction with the Internet might have lowered the marginal cost of searching for news and new information.

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.[23] Figure 6 reports the time series of the country-level average of each indi-

it is hard to detect a structural change in such a short sample, in the appendix ... we plot different rolling-windows AR(1) regression of monthly inflation and show that we don't find any evidence for a shift in the autoregressive parameter $\rho$ around Covid.

[23]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

Figure 6: Belief rigidity and uncertainty




Legend: The left figure represents the average state-level lockdown policies 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 rigidity, $\beta_2$ in (19). Sample period: 2020M3-2023M5.

cator. 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.2 reports the summary statistics.

To estimate the impact of lockdown measures on belief rigidity, we interact the prior forecast in regression (5) with each lockdown indicator and the COVID cases and death measures. Intuitively, controlling for the impact of COVID in each state in terms of cases and deaths allows us to isolate the impact of lockdown policies, which one can think of as a proxy for information acquisition cost. We run the following regression

$$\begin{aligned} For_{i,t} =& \alpha + \beta_1 Prior_{i,t} + \beta_2 Prior_{i,t} \times LockdownIndex_{j,t} + \beta_3 LockdownIndex_{j,t} \\ &+ Prior_{i,t} \times CovidImpact'_{j,t}\Pi + CovidImpact'_{j,t}\Gamma + \lambda X_{i,t} + \gamma_t + err^i_t \end{aligned} \tag{19}$$

where $LockdownIndex_{j,t}$ contains the lockdown indexes, while $CovidImpact_{j,t}$ contains the COVID cases and death in state $j$ at date $t$. We run the regression in the post-pandemic sample, from March 2020.

Figure 6 reports the estimated impact of lockdown indexes on belief rigidity, $\beta_2$, while Table A.4 reports the detailed result. While all the indicators have a robust and negative effect on belief rigidity, 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

on *restrictions on international travel*, as not related to state-level measures, and *public information campaign*, as not related to lockdown measures.

indicators. Once again the impact on belief rigidity 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 4 presents additional evidence. The first column replicates the last column of Table A.4, using the average index *Lockdown* to summarize the stringency of state-level lockdown policies. As shown in Figure 6, 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 rigidity is still negative and robust. In the next three columns, we compare the effect of lockdown policies with measures of state-level economic 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.[24] Even controlling for state-level uncertainty, the estimated impact of lockdown policies on belief rigidity is significant and negative.[25]

Lower information-gathering costs due to lockdown policies can explain the decrease in belief rigidity 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.

## 5.2 The impact of lockdowns on uncertainty

Consider the general framework in Section 1. From (2), one can write

$$x_{t+h} - E_t^i[x_{t+h}] = (1 - G_t)(x_{t+h} - E_{t-1}^i[x_{t+h}]) - G_t e_t^i \tag{20}$$

Equation (20) describes how forecast error relate to belief rigidity $1 - G_t$ and prior information $E_{t-1}^i[x_{t+h}]$. Taking the squared of belief updating equation 20 one can derive the posterior belief uncertainty, which equals

$$\Sigma_{t+h,t} = (1 - G_t)^2 \Sigma_{t+h,t-1} + G_t^2 \sigma_{e,t}^2 \tag{21}$$

[24] We take the percentage change in the measure to isolate the surprise component. The results are robust to using simple differences and levels.

[25] Tables A.8 and A.9 report the results respectively at one year CPI and housing price inflation. While the results do not seem robust for the former, they are for the latter.

Table 4: Belief rigidity and lockdown measures

| | (1) *Forecast* | (2) *Forecast* | (3) *Forecast* | (4) *Forecast* |
|---|---|---|---|---|
| *Prior* | 0.568*** | 0.537*** | 0.605*** | 0.577*** |
| | (0.107) | (0.137) | (0.135) | (0.166) |
| *Prior* × *Lockdown* | -0.077*** | -0.084** | -0.071** | -0.076** |
| | (0.028) | (0.035) | (0.033) | (0.035) |
| *Prior* × *ln(DeathsCOVID)* | -0.016 | -0.016 | -0.016 | -0.016 |
| | (0.015) | (0.015) | (0.015) | (0.015) |
| *Prior* × *ln(CasesCOVID)* | 0.030* | 0.030* | 0.030* | 0.030* |
| | (0.016) | (0.015) | (0.016) | (0.015) |
| *Prior* × *ln(EPUState)* | | 0.007 | | |
| | | (0.021) | | |
| *Prior* × *ln(EPUNational)* | | | -0.009 | |
| | | | (0.023) | |
| *Prior* × *ln(EPUComposite)* | | | | -0.002 |
| | | | | (0.028) |
| Constant | 2.518*** | 2.519*** | 2.519*** | 2.518*** |
| | (0.083) | (0.083) | (0.082) | (0.082) |
| Year-Month FEs | Y | Y | Y | Y |
| Socio-democraphic FEs | Y | Y | Y | Y |
| Non-interacted variables | Y | Y | Y | Y |
| Sample | Mar20-May23 | Mar20-May23 | Mar20-May23 | Mar20-May23 |
| Adjusted R-squared | 0.35 | 0.35 | 0.35 | 0.35 |
| Observations | 25398 | 25397 | 25390 | 25398 |

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 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 for socioeconomic characteristics, such as education, income, age, gender, race, and tenure. Standard errors (in parentheses) are clustered at individual and time levels. $*$ represents $p < 0.10$, $**$ represents $p < 0.05$ , and $***$ represents $p < 0.01$.

where $\Sigma_{t+h,t} \equiv var(x_{t+h} - E_t^i[x_{t+h}])$ is the posterior belief uncertainty, which depends on prior uncertainty $\Sigma_{t+h,t-1} \equiv var(x_{t+h} - E_{t-1}^i[x_{t+h}])$ and new information uncertainty $\sigma_{e,t}^2$.[26] A lower marginal cost of information collection, proxied by lockdown policies, can be thought of as a decrease in new information uncertainty $\sigma_{e,t}^2$ (Maćkowiak et al., 2023; Pomatto et al., 2023). Even with a constant gain $G_t$, this would lead to a decrease in posterior belief uncertainty $\Sigma_{t+h,t} \equiv var(x_{t+h} - E_t^i[x_{t+h}])$. An increase in gain $G_t$ (i.e. a decline in belief rigidity $1 - G_t$), would strengthen further this effect and lead to even lower belief uncertainty. However, in the COVID period, we observe a sharp

[26] While it may seem tempting to estimate equation 21 through a linear OLS using data on posterior and prior uncertainty, we notice that it is not possible as $G_t$ itself may be a function of prior and new information uncertainty, respectively $\Sigma_{t+h,t-1}$ and $\sigma_{e,t}^2$ (for example, in the rational expectation case in equation (7)).

increase in belief uncertainty, as shown in Figure **??**. Therefore, a lower information cost would not be consistent by itself with both a decline in belief rigidity and an increase in belief uncertainty.

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 rigidity and the higher belief uncertainty.

We investigate empirically whether lower information cost, proxied by lockdown policies, increases or decreases belief uncertainty. We run the following state-level regression

$$\begin{aligned} PostUncert_{j,t} =& \alpha + \beta Lockdown_{j,t} + \gamma PriorUncert_{j,t} \\ & + CovidImpact'_{j,t}\Gamma + \delta \Delta ln(EPU)_{j,t} + \gamma_j + err_{j,t} \end{aligned} \tag{22}$$

where $PostUncert_{j,t} = \int_{i\in j} PostUncert_{i,t} di$ is the average posterior uncertainty of consumers in state $j$ at time $t$, and $PriorUncert_{j,t} = \int_{i\in j} PriorUncert_{i,t} di$ is the average prior uncertainty of consumers in state $j$ at time $t$; $Lockdown_{j,t}$ is the average index of lockdown intensity measures, as a proxy for information cost, and $EPU_{j,t}$ is the state-level economic policy uncertainty. Table 5 reports the estimated coefficients, which show a robust and negative effect of lockdown policies on posterior belief uncertainty. This finding is consistent with standard models of information choice, where lower information cost leads to more precise information.[27] Moreover, the impact of innovations in newspaper-reported economic policy uncertainty increases posterior uncertainty as expected. Tables A.10 and A.11 show similar results for shorter horizon forecasts.

Our results show that, while lockdown policies have lowered belief rigidity during the COVID period, they can't account for the sharp increase in belief uncertainty in the same period. In the next section, we consider another possible shock that could

[27] Our uncertainty measure does not reflect the actual precision of consumers' information, but their perceived precision. We do not take a stand on whether they are correct in perceiving their information as uncertain or accurate but only point out that during the COVID pandemic, they perceive their information as more uncertain, while lockdown policies make them perceive their information as less uncertain.

Table 5: Belief rigidity and lockdown measures

| | (1) *PostUncert* | (2) *PostUncert* | (3) *PostUncert* | (4) *PostUncertIQR* |
|---|---|---|---|---|
| *Lockdown* | -0.379*** | -0.362*** | -0.203*** | -0.235*** |
| | (0.084) | (0.084) | (0.061) | (0.072) |
| *PriorUncert* | | | 0.481*** | |
| | | | (0.025) | |
| *PriorUncertIQR* | | | | 0.459*** |
| | | | | (0.024) |
| *ln(DeathsCOVID)* | | | 0.013 | 0.023 |
| | | | (0.035) | (0.042) |
| *ln(CasesCOVID)* | | | -0.025 | -0.031 |
| | | | (0.035) | (0.042) |
| *ln(EPUNational)* | | | 0.052* | 0.053* |
| | | | (0.026) | (0.031) |
| Constant | 3.569*** | 3.557*** | 1.581*** | 1.961*** |
| | (0.103) | (0.052) | (0.273) | (0.325) |
| State FEs | N | Y | Y | Y |
| Sample | Mar20-May23 | Mar20-May23 | Mar20-May23 | Mar20-May23 |
| Adjusted R-squared | 0.05 | 0.28 | 0.51 | 0.48 |
| Observations | 1717 | 1717 | 1684 | 1684 |

Legend: *PostUncert* 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). *PriorUncert* denotes the same variable from the previous issue of the survey in the previous month. *DeathsCOVID* and *CasesCOVID* are respectively the state-level COVID-related deaths and cases per capita. The *EPUComposite* is the state-level economic policy uncertainty indicator from Baker et al. (2022). We control for state FEs. Standard errors (in parentheses) are clustered at state and time levels. $*$ represents $p < 0.10$, $**$ represents $p < 0.05$ , and $***$ represents $p < 0.01$.

be responsible for both a decline in belief rigidity and an increase in belief uncertainty, which is an increase in fundamental volatility.

# 6 Discussion and Policy Implications

Our findings highlight that large shifts in belief rigidity, or information frictions, have significant macroeconomic consequences, particularly in shaping the Phillips curve. In Appendix G, we build a stylized general equilibrium macro model in which the slope of the Phillips curve is endogenous to the belief rigidity of economic agents. The model builds on Afrouzi and Yang (2021) and is illustrative: its purpose is not a careful measurement of the impact of information frictions on the slope of the Phillips curve, but rather to demonstrate that the slope of the Phillips curve diminishes in the degree of information frictions. Specifically, lower belief rigidity makes agents' behavior and prices more responsive to economic shocks, steepening the Phillips curve. Conversely, higher belief rigidity diminishes this responsiveness, flattening the Phillips curve. These results align with the theoretical literature on information frictions (Angeletos et al., 2021; Afrouzi and Yang, 2021).

Our model implies that the dynamics of belief rigidity we documented during COVID-19 caused a steepening of the Philips Curve at the onset of the pandemic and a flattening in the following months. Recent empirical evidence, e.g. Cerrato and Gitti (2022); Gudmundsson et al. (2024), documents instead the opposite, meaning that the Phillips curve became flatter in the early months of the pandemic and then steeper again afterward during the high inflation period. While these facts seem to be at odds with the implications of our belief rigidity estimates on the Phillips curve, the model in this section is purposely kept stylized and does not capture the entirety of macroeconomic events that characterize the pandemic period. We instead argue that, as the variation in belief rigidity steepened the Phillips curve in the pandemic period and flattened it afterward, it had a dampening effect on the other possible driving forces suggested in the literature, such as non-linearities (Boehm and Pandalai-Nayar, 2022; Harding et al., 2023).

Recent works document instead a flattening of the Phillips curve over the last few decades (Coibion and Gorodnichenko, 2015; Negro et al., 2020), and the literature proposes several explanations. According to Stock and Watson (2020), the decrease in the Phillips curve's slope is due to more competition in the import market, higher market concentration, and changes to the network structure of the US production sector. McLeay and Tenreyro (2020) instead ascribe it to the Federal Reserve becoming more assertive in its efforts to fulfill its duty of maintaining price stability over time. Lastly, Hobijn (2020) posits that the makeup of shocks may have altered over time and, specifically, supply shocks might have become more concentrated or comparatively more apparent in the last decades, which would have led to a flattening of the Phillips curve. Bergholt et al. (2023) test these three different hypotheses for the flattening of the Phillips curve over the last few decades and find support for the second and third hypotheses, but not the first.

Our findings highlight the policy relevance of belief rigidity in these discussions, showing that shifts in belief rigidity can significantly alter the Phillips curve's slope above and beyond an aggressive Fed response to inflation fluctuations over time. Moreover, ignoring the degree of belief rigidity can cause misleading estimates of the slope (Coibion et al., 2018). Furthermore, our analysis emphasizes the importance of differentiating between sources of uncertainty, as they variably impact belief rigidity and thus have distinct policy implications.

The analysis of household belief rigidity and its relationship with economic and information uncertainties provides crucial insights for monetary policy. Our findings suggest that policy measures aimed at reducing information frictions and enhancing the quality of information available to households could play a vital role in stabilizing the economy and maintaining the effectiveness of monetary policy.

Furthermore, the differentiation between sources of uncertainty has significant implications for policy design and implementation. When fundamental economic uncertainty is high, as seen during the pandemic, policies facilitating information acquisition and dissemination can help lower belief rigidity and enhance the economy's responsiveness to policy interventions. On the other hand, during periods when the quality of information is compromised, efforts should focus on improving the clarity and reliability of economic data to mitigate the adverse effects of increased belief rigidity. Understanding these dynamics is essential for central banks and policymakers to tailor their communication strategies and policy tools effectively, ensuring that they can manage inflation expectations and economic stability more efficiently in varying economic environments.

# 7 Conclusion

Theories based on new information shocks, fundamental uncertainty shocks, higher-order uncertainty shocks, and belief shocks have significantly influenced macroeconomics. However, they often leave a critical question unanswered: Why do households' beliefs fluctuate in this way? Just as in standard macro models, inputs are turned into output through some micro-founded production function, information sets such as priors and new information signals are turned into household beliefs through a belief-formation mechanism. A thorough theory should elucidate the reasons behind changes in both inputs and outputs, as well as the fluctuations in beliefs both in the cross-section and the time-series.

In this paper, we examined the relationship between fundamental uncertainty, news uncertainty, and the household belief updating process using the NY Fed Survey of Consumer Expectations and a broad belief updating framework, encompassing various Bayesian and behavioral models. Our findings highlight that different sources of uncertainty distinctly affect household belief rigidity: fundamental volatility increases prior uncertainty, prompting households to seek more information and update their beliefs, resulting in lower rigidity, while increased noise in new information discourages updating, resulting in higher rigidity.

By empirically testing these theoretical mechanisms using naturally occurring variations in information provision, we confirmed that the relationship between uncertainty and belief rigidity aligns with a broad class of behavioral models, including the Bayesian framework. This investigation underscores the significant policy implications of belief rigidity. High belief rigidity weakens the relationship between employment and inflation, diminishes the effectiveness of forward guidance, and raises the risk of encountering a liquidity trap. These insights are crucial for monetary policy decisions, emphasizing the importance of understanding how belief rigidity varies across different economic environments.

Our findings suggest a shift in the approach to considering economic uncertainty. Traditional methods often ignore the heterogeneity of uncertainty sources, assuming agents have precise knowledge of the economic model and conflating all sources of uncertainty into a single one. By acknowledging the need for economic agents to consider different uncertainty sources jointly with their impact on agents' belief updating rigidity, we reveal that the impact of information frictions stemming from different origins has opposite effects on agents' belief updating process. This highlights the importance of separating the sources of uncertainty and considering their separate impact on belief formation and household belief rigidity.

This paper has focused on the belief formation process and uncovered the mechanisms driving fluctuations in uncertainty over time, providing a foundation for future research. Our framework can be applied to various economic models, including those examining other types of uncertainty risks and belief updating rigidity estimates for other economic agents, such as professional forecasters, firms, or sovereign institutions. Understanding the dynamics of household belief rigidity can offer deeper insights into fundamental uncertainty, news uncertainty, and macro and asset return puzzles, further enhancing the theoretical and practical applications of our findings.

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# 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, $\tau_t \rightarrow \infty$, 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).

- Misspecified 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.

# B Point estimates and subjective distribution of inflation 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 ...**

*Instruction H4.*

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

## 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).

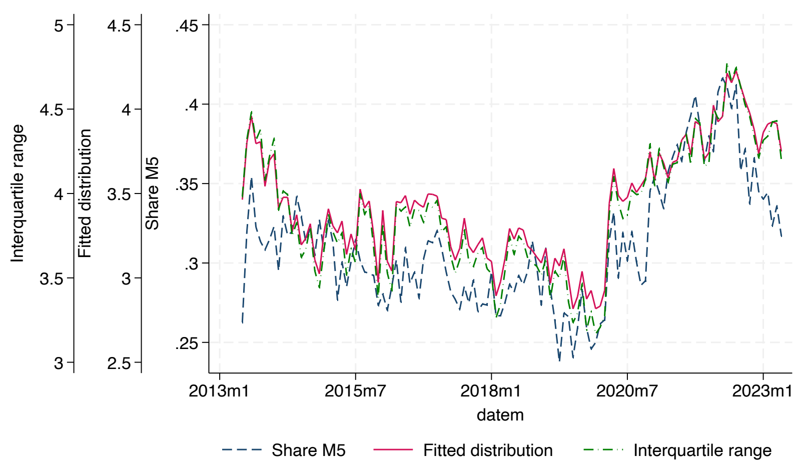



Figure A.1: Uncertainty measures

Figure A.1 plots the measure based on rounding ('Share M5') 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 Additional tables

Table A.1: Heterogeneity in Belief Updating

| | (1) *Forecast* | (2) *Forecast* | (3) *Forecast* | (4) *Forecast* | (5) *Forecast* | (6) *Forecast* | (7) *Forecast* |
|---|---|---|---|---|---|---|---|
| *Prior* | 0.405*** | 0.482*** | 0.539*** | 0.510*** | 0.485*** | 0.505*** | 0.375*** |
| | (0.016) | (0.022) | (0.015) | (0.018) | (0.015) | (0.023) | (0.039) |
| *Tenure Tercile*=2 × *Prior* | 0.107*** | | | | | | 0.109*** |
| | (0.019) | | | | | | (0.019) |
| *Tenure Tercile*=3 × *Prior* | 0.212*** | | | | | | 0.211*** |
| | (0.019) | | | | | | (0.019) |
| $College_{it}$ =1 × *Prior* | | 0.036 | | | | | 0.032 |
| | | (0.024) | | | | | (0.023) |
| *Age Over*60=1 × *Prior* | | | -0.023 | | | | -0.036* |
| | | | (0.021) | | | | (0.021) |
| *Age Under*40=1 × *Prior* | | | -0.079*** | | | | -0.075*** |
| | | | (0.024) | | | | (0.022) |
| *Income Over*100*k*=1 × *Prior* | | | | -0.007 | | | -0.019 |
| | | | | (0.031) | | | (0.031) |
| *Income Under*50*k*=1 × *Prior* | | | | -0.000 | | | 0.014 |
| | | | | (0.020) | | | (0.020) |
| *High Numeracy*=1 × *Prior* | | | | | 0.059*** | | 0.057*** |
| | | | | | (0.017) | | (0.017) |
| *Female*=1 × *Prior* | | | | | | -0.017 | -0.009 |
| | | | | | | (0.021) | (0.021) |
| *White*=1 × *Prior* | | | | | | 0.023 | 0.017 |
| | | | | | | (0.021) | (0.020) |
| Constant | 2.209*** | 2.257*** | 2.267*** | 2.276*** | 2.206*** | 2.244*** | 2.140*** |
| | (0.051) | (0.054) | (0.053) | (0.056) | (0.050) | (0.054) | (0.050) |
| Year-Month FEs | Y | Y | Y | Y | Y | Y | Y |
| Non-interacted variables | Y | Y | Y | Y | Y | Y | Y |
| Sociodemographic controls | Y | Y | Y | Y | Y | Y | Y |
| Sample | Jun13-May23 | Jun13-May23 | Jun13-May23 | Jun13-May23 | Jun13-May23 | Jun13-May23 | Jun13-May23 |
| Adjusted R-squared | 0.35 | 0.34 | 0.34 | 0.34 | 0.34 | 0.34 | 0.35 |
| Observations | 94101 | 94101 | 94101 | 94101 | 94101 | 94101 | 94101 |

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. We control for year-month fixed effects and for socioeconomic characteristics, such as education, income, age, gender, race, and tenure. 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.2: Descriptive Statistics

| | Mean | SD | Min | Max | N |
|---|---|---|---|---|---|
| Lockdown policies | | | | | |
| *School* | 1.45 | 0.96 | 0 | 3 | 35859 |
| *Workplace* | 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 |
| *DeathsCOVID* | 0.00 | 0.00 | 0 | 0.00108 | 35859 |
| Economic Polic 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 |

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.

Table A.3: Belief rigidity

| | (1) $Forecast$ | (2) $Forecast$ | (3) $Forecast$ |
|---|---|---|---|
| $Prior$ | 0.509*** | 0.498*** | 0.488*** |
| | (0.011) | (0.012) | (0.012) |
| $Covid$=1 × $Prior$ | | -0.082* | -0.079* |
| | | (0.043) | (0.043) |
| $Post-Covid$=1 × $Prior$ | | 0.049** | 0.036* |
| | | (0.020) | (0.020) |
| Constant | 2.276*** | 2.295*** | 2.365*** |
| | (0.053) | (0.047) | (0.047) |
| Year-Month FEs | Y | Y | Y |
| Age, Gender, Race FEs | Y | Y | Y |
| Tenure FEs | Y | Y | Y |
| Adjusted R-squared | 0.34 | 0.34 | 0.33 |
| Observations | 94082 | 94082 | 90862 |

Legend: $For3y_{i,t}$ denotes the 3-year ahead forecast of inflation expectations from the NY FED Survey of Consumer Expectations (SCE). $Prior\ 3y_{i,t}$ is the point forecast about horizon 3 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 for socioeconomic characteristics, such as education, income, age, gender, race, and tenure. The estimation period is 2013M6-2023M5. Column (3) 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 $p < 0.01$.

Table A.4: Belief rigidity and lockdown measures

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | *Forecast* | *Forecast* | *Forecast* | *Forecast* | *Forecast* | *Forecast* | *Forecast* | *Forecast* | *Forecast* | *Forecast* |
| *Prior* | 0.497*** | 0.530*** | 0.546*** | 0.529*** | 0.483*** | 0.545*** | 0.486*** | 0.471*** | 0.521*** | 0.568*** |
| | (0.123) | (0.106) | (0.112) | (0.109) | (0.113) | (0.103) | (0.112) | (0.116) | (0.102) | (0.107) |
| *Prior* × *ln(DeathsCOVID)* | -0.029* | -0.019 | -0.019 | -0.023 | -0.030* | -0.019 | -0.030* | -0.034* | -0.019 | -0.016 |
| | (0.015) | (0.015) | (0.016) | (0.016) | (0.016) | (0.014) | (0.017) | (0.017) | (0.014) | (0.015) |
| *Prior* × *ln(CasesCOVID)* | 0.041** | 0.030* | 0.034** | 0.041** | 0.047** | 0.034** | 0.046** | 0.052** | 0.028* | 0.030* |
| | (0.017) | (0.015) | (0.017) | (0.017) | (0.018) | (0.014) | (0.019) | (0.019) | (0.014) | (0.016) |
| *Prior* × *School* | -0.032* | | | | | | | | 0.007 | |
| | (0.018) | | | | | | | | (0.024) | |
| *Prior* × *Workplace* | | -0.061*** | | | | | | | -0.056* | |
| | | (0.021) | | | | | | | (0.031) | |
| *Prior* × *Event* | | | -0.056** | | | | | | 0.002 | |
| | | | (0.025) | | | | | | (0.037) | |
| *Prior* × *Gathering* | | | | -0.021** | | | | | 0.015 | |
| | | | | (0.010) | | | | | (0.014) | |
| *Prior* × *Transport* | | | | | -0.075** | | | | -0.033 | |
| | | | | | (0.035) | | | | (0.036) | |
| *Prior* × *StayAtHome* | | | | | | -0.076*** | | | -0.050 | |
| | | | | | | (0.026) | | | (0.038) | |
| *Prior* × *Movements* | | | | | | | -0.048** | | 0.006 | |
| | | | | | | | (0.022) | | (0.035) | |
| *Prior* × *Travel* | | | | | | | | -0.050 | -0.018 | |
| | | | | | | | | (0.034) | (0.039) | |
| *Prior* × *Lockdown* | | | | | | | | | | -0.077*** |
| | | | | | | | | | | (0.028) |
| Constant | 2.506*** | 2.513*** | 2.517*** | 2.513*** | 2.516*** | 2.511*** | 2.514*** | 2.507*** | 2.509*** | 2.518*** |
| | (0.088) | (0.081) | (0.084) | (0.086) | (0.088) | (0.081) | (0.088) | (0.091) | (0.079) | (0.083) |
| Year-Month FEs | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Socio-demographic FEs | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Non-interacted variables | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Adjusted R-squared | 0.36 | 0.35 | 0.35 | 0.35 | 0.35 | 0.35 | 0.35 | 0.35 | 0.35 | 0.35 |
| Observations | 24626 | 25398 | 25398 | 25398 | 25398 | 25398 | 25398 | 25398 | 25398 | 25398 |

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. $DeathsCOVID$ and $CasesCOVID$ are respectively the state-level COVID-related deaths and cases per capita. 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. Standard errors (in parentheses) are clustered at individual and time levels. $*$ represents $p < 0.10$, $**$ represents $p < 0.05$ , and $***$ represents $p < 0.01$.

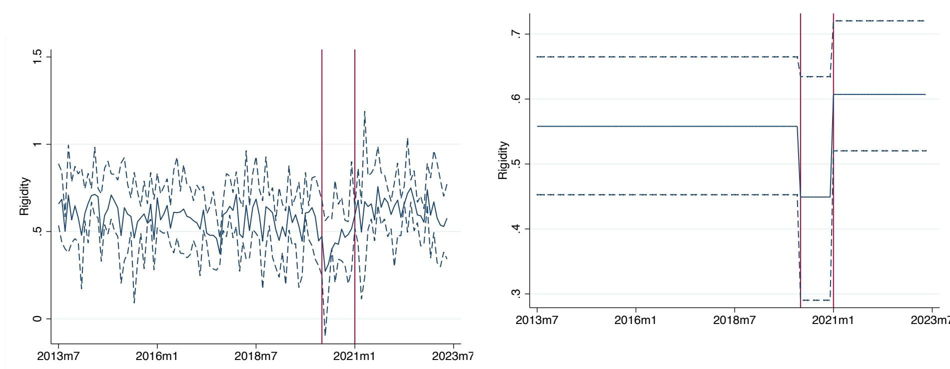
Table A.5: Belief rigidity and uncertainty for different numeracy skill

| | (1)<br>*For 3y* | (2)<br>*For 3y* | (3)<br>*For 3y* | (4)<br>*For 3y* |
|---|---|---|---|---|
| *Prior 3y* | 0.529*** | 0.497*** | 0.526*** | 0.563*** |
| | (0.012) | (0.017) | (0.023) | (0.036) |
| $High\ Numeracy_{it}$=1 × *Prior 3y* | | 0.052*** | 0.050*** | -0.013 |
| | | (0.017) | (0.017) | (0.039) |
| *Prior 3y* × *ln*(*Prior Uncert3y*) | | | -0.138*** | -0.113*** |
| | | | (0.018) | (0.028) |
| *Prior 3y* × *ln*(*Post Uncert3y*) | | | 0.122*** | 0.073*** |
| | | | (0.015) | (0.023) |
| $High\ Numeracy_{it}$=1 × *Prior 3y* × *ln*(*Prior Uncert3y*) | | | | -0.046 |
| | | | | (0.031) |
| $High\ Numeracy_{it}$=1 × *Prior 3y* × *ln*(*Post Uncert3y*) | | | | 0.093*** |
| | | | | (0.027) |
| Constant | 1.896*** | 2.657*** | 1.660*** | 1.262*** |
| | (0.051) | (0.101) | (0.107) | (0.182) |
| Year-Month FEs | Y | Y | Y | Y |
| Socio-demographic FEs | Y | Y | Y | Y |
| Non-interacted variables | Y | Y | Y | Y |
| Adjusted R-squared | 0.33 | 0.33 | 0.36 | 0.36 |
| Observations | 91841 | 91824 | 74838 | 74838 |

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. $PostUncert3y$ 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). $PriorUncert3y$ is the same variable but from the previous month. $HighNumeracy$ equals one if the respondent is assigned a high score on numeracy skill tests in the SCE. We control for year-month fixed effects, and for socioeconomic characteristics, such as education, income, age, gender, race, and tenure. 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.2: Belief rigidity pre- and post-pandemic

(a) Belief rigidity $\beta$ month-by-month (b) Belief rigidity $\beta$ by periods

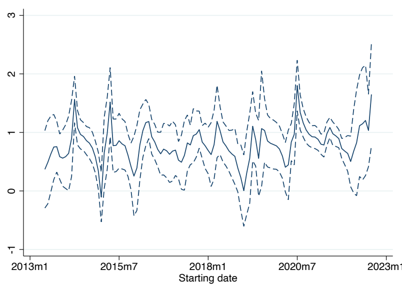



Legend: The blue solid line represents the average estimate of belief rigidity (estimated in regression (10)) across subgroup. The dashed blue lines represent the top 80% percentile and bottom 20% percentile in the distribution across subgroups. In the left plot, belief rigidity is estimated separately in each month of the sample. In the right plot, it is estimated in each sub-sample: pre-Covid, during Covid, and after Covid (during the Biden term). 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 (or the start of the Biden term). Data sources: Our estimates. Sample period: 2013M1 - 2023M5.

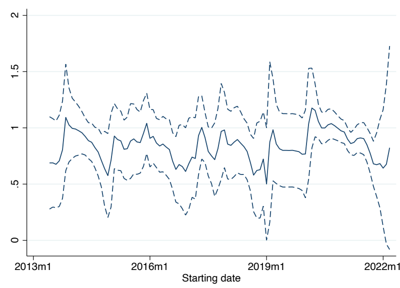
# E Estimation of inflation autoregressive structure

Figure A.3: Rolling window autoregressive estimation of monthly inflation

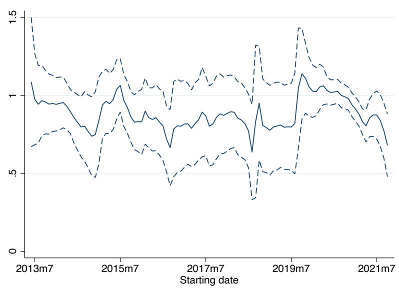
(a) 10-months window




(b) 15-month window



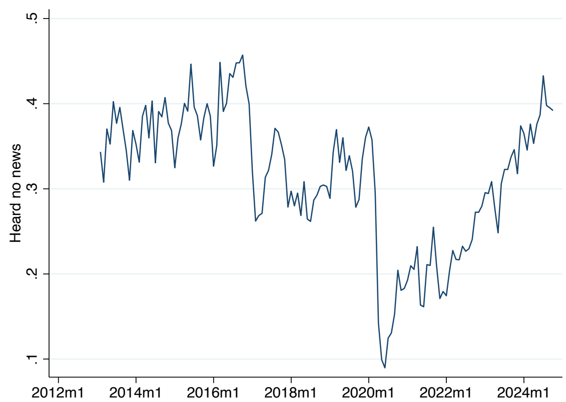

(c) 20-month window




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

# F Michigan Survey of Consumers

Figure A.4: 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.4 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.

# G Implications for the Phillips Curve

Information frictions contribute to flattening the Phillips Curve, as documented by a recent body of theoretical works (Angeletos and Huo, 2021; Afrouzi and Yang, 2021). We present here a stylized analytical general equilibrium model to highlight how our estimates of belief rigidity $1 - K_t$ affect the slope of the Phillips Curve, i.e. the relation between aggregate demand and inflation.

## G.1 Environment

The model is a simplified version of the framework proposed in Afrouzi and Yang (2021).[28] We make two important assumptions. First, we assume firms to be imperfectly informed and use our estimates of belief rigidity to inform their belief updating. While we do not have access to a survey of firm's beliefs comparable to the SCE, previous work on expectations surveys showed that consumer expectations are a better proxy for firm managers' beliefs compared to professional forecasters (Coibion et al., 2021). Second, we follow Afrouzi and Yang (2021) and assume that agents are instead fully informed. We make this assumption to maintain the model tractable and to derive closed-form solution.

**Household** Consider a representative household who supplies labor $L_t$ in a competitive labor market at nominal wage $W_t$, trades nominal bonds with a net interest rate of $R_t$ and demands a varieties of goods indexed by $i \in [0, 1]$.

$$\max_{\{(C_{i,t})_{i\in[0,1]}, B_t, L_t\}_{t=0}^{\infty}} \mathbb{E}_0^f \left[ \sum_{t=0}^{\infty} \beta^t (\log(C_t) - L_t) \right] \tag{A.1}$$

$$\text{s.t.} \quad \int_0^1 P_{i,t} C_{i,t} di + B_t \leq W_t L_t + R_{t-1} B_{t-1} + \Pi_t + T_t, \quad C_t = \left[ \int_0^1 C_{i,t}^{\left(\frac{\theta-1}{\theta}\right)} di \right]^{\left(\frac{\theta}{\theta-1}\right)},$$

where $\mathbb{E}_t^f[\cdot]$ denotes the full information rational expectation operator at time t, $C_{i,t}$ is the demand for variety $i$ at price $P_{i,t}$, $B_t$ is the demand for nominal bonds at $t$ that yield a nominal return of $R_t$ at $t + 1$, $\Pi_t$ is the aggregated profits of firms, and $T_t$ is

[28] While Afrouzi and Yang (2021) use this framework to investigate how dynamic information choice affects belief rigidity, we instead assume exogenous information and use our empirical estimates to inform belief rigidity in the model.

the net lump-sum transfers. Finally, $C_t$ is the final consumption good aggregated with a constant elasticity of substitution $\theta > 1$ across varieties.

Let $P_t \equiv \left[\int_0^1 P_{i,t}^{1-\theta} di\right]^{-\frac{1}{\theta-1}}$ denote the aggregate price index and $Q_t \equiv P_t C_t$ the nominal aggregate demand in this economy. The solution to the household's problem is then summarized by:

$$C_{i,t} = C_t \left(\frac{P_{i,t}}{P_t}\right)^{-\theta} \qquad \forall i \in [0,1], \forall t \geq 0, \tag{A.2}$$

$$1 = \beta R_t \mathbb{E}_t^f \left[\frac{Q_t}{Q_{t+1}}\right] \qquad \forall t \geq 0, \tag{A.3}$$

$$W_t = Q_t, \qquad \forall t \geq 0 \tag{A.4}$$

Equation (A.2) is the demand for variety $i$ at time $t$, Equation (A.3) is the consumption Euler Equation and Equation is the intratemporal optimality condition that relates nominal wage and nominal aggregate demand.[29]

**Monetary Policy** For analytical tractability, we assume that the monetary authority targets the growth of the nominal aggregate demand, specifically to make it follow a random walk

$$\log(Q_t) = \log(Q_{t-1}) + u_t, \quad u_t \sim \mathcal{N}(0, \sigma_u^2) \tag{A.5}$$

where $u_t$ is an exogenous shock to monetary policy that affects the nominal rates with a standard deviation of $\sigma_u$.[30]

**Firms** We assume prices are perfectly flexible, but firms have imperfect information about the shocks affecting the economy. Every variety $i \in [0,1]$ is produced by a price-setting firm that hires labor $L_{i,t}$ from a competitive labor market at a subsidized wage $W_t = (1-\theta^{-1})Q_t$ where the subsidy $\theta^{-1}$ is paid per unit of worker to eliminate steady-state distortions introduced by monopolistic competition (Galí, 2015). Firms produce their product with a linear technology in labor, $Y_{i,t} = L_{i,t}$. Firms commit to a price level before producing and observing their marginal cost. As a result, in each

[29] We follow Afrouzi and Yang (2021) and assume an infinite Frisch elasticity of labor supply, which results in this labor supply condition.

[30] Assuming that the monetary authority targets the nominal aggregate demand is common in the literature[CIT]

period $t$ they decides their price $P_{i,t}$ to maximize expected profit

$$\max_{\{P_{i,t}\}} E_t^i \left[ \frac{1}{P_t C_t} \left( P_{i,t} C_{i,t} - (1-\theta^{-1}) Q_t L_{i,t} \right) \right] \tag{A.6}$$

where $E_t^i[\cdot]$ is the expectation operator of an imperfectly informed, and potentially not rational, firm $i$ at time $t$. Substituting for the household optimality and the market equilibrium conditions, the log-linearization of the first order condition of the firm $i$ is

$$p_{i,t} = E_t^i[q_t] \tag{A.7}$$

with small letters denoting the logs of corresponding variables. Equation (A.7) implies that firms set prices equal to perceived marginal cost, which is exogenous and given by Equation (A.5).

**Information structure** We assume each firm receives a private signal $s_t^i$ about the realization of the shock $q_t$

$$s_t^i = q_t + e_t^i \tag{A.8}$$

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 $\sigma_{\eta,t}^2$ which is i.i.d. across time and across households, and (ii) a common component $\omega_t$ normally distributed mean-zero noise with variance $\omega_{\omega,t}^2$ 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.

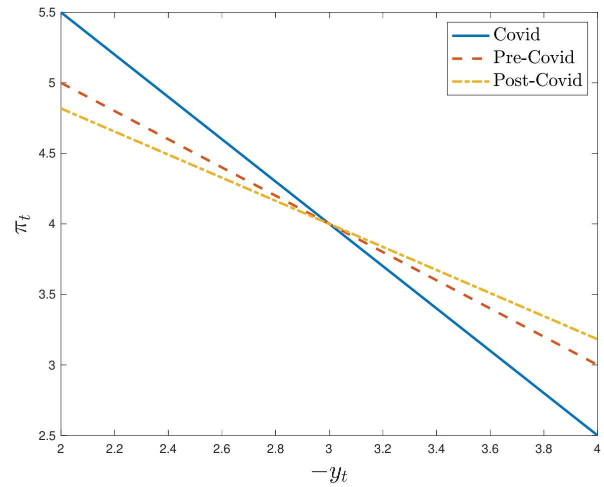
We assume firms update their beliefs similarly to the rule in Section 1:

$$E_t^i[q_t] = (1 - G_t) E_{t-1}^i[q_t] + G_t s_t^i \tag{A.9}$$

where $G_t$ is the weight attributed to new information when forming new beliefs, and $(1 - G_t)$ is the weight on prior information. This model encompasses the rational Bayesian model when $G_t = \frac{\Sigma_{t,t-1}}{\Sigma_{t,t-1} + \sigma_{e,t}^2}$ is the Kalman gain and $\Sigma_{t,t-1} \equiv var_t(q_t - E_{t-1}^i[q_t])$ is the prior uncertainty. However, the model embeds different possible belief updating models, discussed in Appendix A.

Since the individual firm price equals the perceived marginal cost $p_{i,t} = E_t^i[q_t]$, Equation (A.9) describes also the evolution of firm's $i$ price.

Figure A.5: Phillips Curve with estimated rigidity




## G.2 The Phillips curve with information frictions

Let $\pi_t \equiv p_t - p_{t-1}$ denote the aggregate inflation rate and $y_t \equiv q_t - p_t$ denote the aggregate output. The Phillips Curve then equals

$$\pi_t = \frac{G_t}{1 - G_t}(y_t + \omega_t) \tag{A.10}$$

The slope of the Phillips Curve is time-varying and depends on the firms' belief rigidity. Intuitively, the more informed firms are about the economy, the more they adjust their prices in response to economic shocks, i.e. the Phillips Curve is steeper. Conversely, the less informed firms are about the economy, the less they adjust their prices in response to economic shocks, i.e. the Phillips Curve is flatter. This result is in line with the prediction of the recent theoretical literature, such as Angeletos and Huo (2021) and Afrouzi and Yang (2021).

Figure A.5 shows the slope of the Phillips curve in Equation (A.10) with the belief rigidity in the pre-pandemic, pandemic, and post-pandemic period estimated in section 2.2. The decrease in belief rigidity in the pandemic period implies a steeper Phillips curve, while the subsequent increase in belief rigidity in the post-pandemic period implies a flatter Phillips curve. While these results are illustrative and not quantitative, they clarify that how changes in belief rigidity affect the Phillips curve and therefore their policy relevance.

**Discussion** Recent empirical evidence, e.g. Cerrato and Gitti (2022); Gudmundsson et al. (2024), documents that the Phillips curve became flatter in the early months of the pandemic and then steeper again afterward during the high inflation period. While these facts seem to be at odds with the implications of our belief rigidity estimates on the Phillips curve, the model in this section is purposely kept stylized and does not capture the entirety of macroeconomic events that characterize the pandemic period. We instead argue that, as the variation in belief rigidity steepened the Phillips curve in the pandemic period and flattened it afterward, it had a dampening effect on the other possible driving forces suggested in the literature, such as non-linearities (Boehm and Pandalai-Nayar, 2022; Harding et al., 2023).

The Phillips curve in equation (A.10) does not depend on inflation expectations as we abstract from nominal frictions, which makes the firm's problem static. However, in a more general model with nominal frictions, not only the slope of the Phillips Curve in Equation (A.10) would include measures of price rigidity, but it would also feature an "expected inflation" term. While some studies proxy this expectation terms with realized inflation or assume it to be the same across agents, our evidence suggests this is misleading for two reasons. First, there is a large heterogeneity in inflation expectations even for a medium-term horizon of three years. Second, because the degree of belief rigidity changes considerably during this period, which means that proxying expectations with the full information counterparts could lead to significantly biased results. For example, another strand of the literature argues that estimated changes in the Phillips Curve might be instead traced to an omitted variable bias, and in particular inflation expectations (Coibion et al., 2021; Hazell et al., 2022).

# H Shorter forecast horizon

Table A.6: Belief rigidity

| | (1) *For 1y* | (2) *For 1y* | (3) *For 1y* |
|---|---|---|---|
| *Prior 1y* | 0.514*** | 0.501*** | 0.322*** |
| | (0.012) | (0.012) | (0.018) |
| *Prior 1y* × $Tenure_{it}$ | | | 0.032*** |
| | | | (0.002) |
| $High\ Numeracy_{it}$=1 × *Prior 1y* | | | 0.013 |
| | | | (0.016) |
| Constant | 2.455*** | 2.539*** | 2.357*** |
| | (0.065) | (0.064) | (0.067) |
| Year-Month FEs | Y | Y | Y |
| Socio-democraphic FEs | Y | Y | Y |
| Adjusted R-squared | 0.39 | 0.38 | 0.40 |
| Observations | 93500 | 90033 | 93500 |

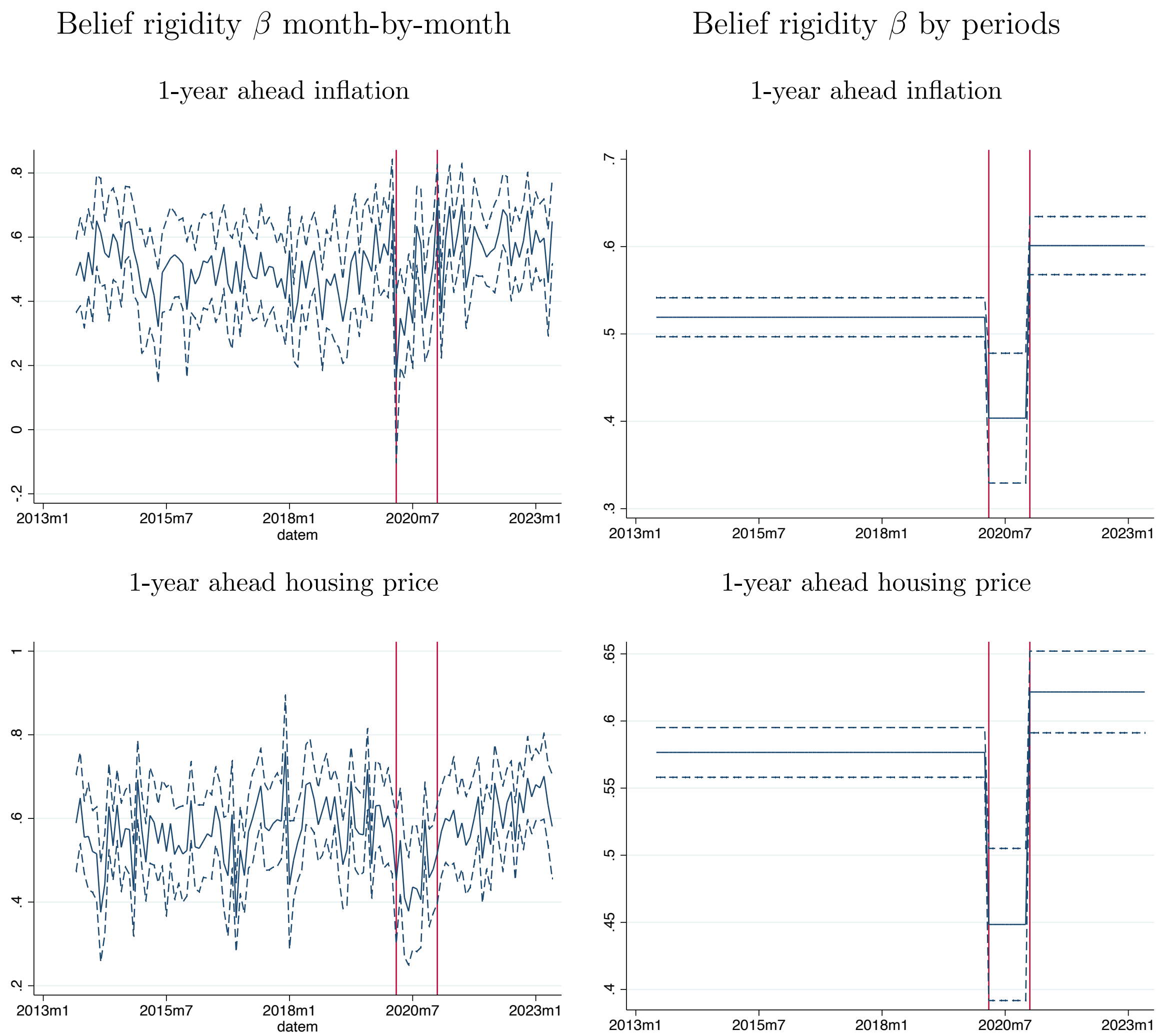
Legend: $For1y_{i,t}$ denotes the 1-year ahead forecast of inflation expectations from the NY FED Survey of Consumer Expectations (SCE). $Prior\ 1y_{i,t}$ is the point forecast about horizon 1 years provided in the previous month, while $Tenure_{i,t}$ is a continuous variable of a household's tenure in the survey, and $High\ Numeracy_{i,t} = 1$ is a dummy for high-numeracy individuals. We control for year-month fixed effects, and for socioeconomic characteristics, such as education, income, age, gender, race, and tenure. 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 $p < 0.01$.

# I 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

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




Legend: The blue solid line represents our estimates of belief rigidity, while the dashed blue lines represent the 95% confidence interval. The orange line is a Kernel-weighted local polynomial smoothing of the estimated coefficient. In the left plot, belief rigidity $\beta$ is estimated separately in each month of the sample. In the right plot, it is estimated in each sub-sample: pre-Covid, during Covid, and after Covid (during the Biden term). The first green vertical line corresponds to the start of Covid-19 in March 2020. The second green vertical line corresponds to the start of the high-inflation period in February 2021 (or the start of the Biden term). Data sources: Our estimates. Sample period: 2013M1 - 2023M5.

Table A.7: Belief rigidity

| | (1) *For H* | (2) *For H* | (3) *For H* |
|---|---|---|---|
| *Prior H* | 0.580*** | 0.562*** | 0.433*** |
| | (0.010) | (0.010) | (0.026) |
| *Prior H* $\times$ $Tenure_{it}$ | | | 0.019*** |
| | | | (0.002) |
| $High\ Numeracy_{it}$=1 $\times$ *Prior H* | | | 0.027 |
| | | | (0.018) |
| Constant | 2.127*** | 2.211*** | 2.100*** |
| | (0.054) | (0.052) | (0.047) |
| Year-Month FEs | Y | Y | Y |
| Socio-democraphic FEs | Y | Y | Y |
| Adjusted R-squared | 0.42 | 0.40 | 0.42 |
| Observations | 83038 | 80876 | 83038 |

Legend: $Forh_{i,t}$ denotes the 1-year ahead forecast of housing inflation expectations from the NY FED Survey of Consumer Expectations (SCE). $Prior\ h_{i,t}$ is the point forecast 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 for socioeconomic characteristics, such as education, income, age, gender, race, and tenure. 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 $p < 0.01$.

variance. Agents can not observe $x$ directly, but receive a private noisy signal about it, similarly to equation (1)

$$s^i = x + e^i \tag{A.11}$$

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

$$E^i[x|s^i] = (1 - G)\mu_x + Gs^i \tag{A.12}$$

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

Table A.8: Belief rigidity and lockdown measures: 1 year inflation

| | (1)<br>*For 1y* | (2)<br>*For 1y* | (3)<br>*For 1y* | (4)<br>*For 1y* |
|---|---|---|---|---|
| *Prior 1y* | 0.745*** | 0.780*** | 0.688*** | 0.778*** |
| | (0.201) | (0.224) | (0.234) | (0.248) |
| *Prior 1y* × *Lockdown* | -0.103*** | -0.096*** | -0.111*** | -0.099*** |
| | (0.026) | (0.035) | (0.031) | (0.034) |
| *Prior 1y* × $ln(DeathsCOVID)$ | 0.008 | 0.009 | 0.008 | 0.009 |
| | (0.020) | (0.020) | (0.020) | (0.020) |
| *Prior 1y* × $ln(CasesCOVID)$ | 0.016 | 0.015 | 0.016 | 0.015 |
| | (0.015) | (0.016) | (0.016) | (0.015) |
| *Prior 1y* × $ln(EPUState)$ | | -0.007 | | |
| | | (0.022) | | |
| *Prior 1y* × $ln(EPUNational)$ | | | 0.013 | |
| | | | (0.021) | |
| *Prior 1y* × $ln(EPUComposite)$ | | | | -0.006 |
| | | | | (0.027) |
| Constant | 3.167*** | 3.166*** | 3.169*** | 3.166*** |
| | (0.119) | (0.119) | (0.120) | (0.119) |
| Year-Month FEs | Y | Y | Y | Y |
| Socio-demographic FEs | Y | Y | Y | Y |
| Non-interacted variables | Y | Y | Y | Y |
| Sample | Mar20-May23 | Mar20-May23 | Mar20-May23 | Mar20-May23 |
| Adjusted R-squared | 0.40 | 0.41 | 0.41 | 0.41 |
| Observations | 25263 | 25262 | 25256 | 25263 |

Legend: $For3y$ 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. We control for year-month fixed effects and for socioeconomic characteristics.

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

$$Var^i[x|s^i] = \sigma_e^2 G = \frac{\sigma_x^2 \sigma_e^2}{\sigma_e^2 + \sigma_x^2} \tag{A.13}$$

Therefore

$$\frac{\partial Var^i[x|s^i]}{\partial \sigma_e^2} = \left( \frac{\sigma_x^2}{\sigma_e^2 + \sigma_x^2} \right)^2 > 0 \tag{A.14}$$

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.

Table A.9: Belief rigidity and lockdown measures: 1 year house prices

| | (1) *For H* | (2) *For H* | (3) *For H* | (4) *For H* |
|---|---|---|---|---|
| *Prior H* | 0.486*** | 0.613*** | 0.442*** | 0.537*** |
| | (0.097) | (0.128) | (0.126) | (0.146) |
| *Prior H* × *Lockdown* | -0.100*** | -0.071*** | -0.106*** | -0.092*** |
| | (0.021) | (0.026) | (0.023) | (0.026) |
| *Prior H* × $ln(DeathsCOVID)$ | -0.005 | -0.005 | -0.004 | -0.005 |
| | (0.013) | (0.013) | (0.013) | (0.013) |
| *Prior H* × $ln(CasesCOVID)$ | -0.017 | -0.018 | -0.017 | -0.017 |
| | (0.014) | (0.014) | (0.014) | (0.014) |
| *Prior H* × $ln(EPUState)$ | | -0.032* | | |
| | | (0.018) | | |
| *Prior H* × $ln(EPUNational)$ | | | 0.010 | |
| | | | (0.014) | |
| *Prior H* × $ln(EPUComposite)$ | | | | -0.011 |
| | | | | (0.020) |
| Constant | 2.306*** | 2.293*** | 2.315*** | 2.302*** |
| | (0.081) | (0.080) | (0.080) | (0.080) |
| Year-Month FEs | Y | Y | Y | Y |
| Socio-democraphic FEs | Y | Y | Y | Y |
| Non-interacted variables | Y | Y | Y | Y |
| Sample | Mar20-May23 | Mar20-May23 | Mar20-May23 | Mar20-May23 |
| Adjusted R-squared | 0.44 | 0.44 | 0.44 | 0.44 |
| Observations | 22524 | 22523 | 22516 | 22524 |

Legend: $Forh_{i,t}$ denotes the 1-year ahead forecast of housing prices from the NY FED Survey of Consumer Expectations (SCE). $Prior\ h_{i,t}$ is the same forecast in the previous month. $DeathsCOVID$ and $CasesCOVID$ are respectively the state-level COVID-related death 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 for socioeconomic characteristics, such as education, income, age, gender, race, and tenure.

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

$$Disp(E^i[x|s^i]) = G^2\sigma_\eta^2 \tag{A.15}$$

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,

Table A.10: Belief rigidity and lockdown measures

| | (1) *PostUncert* | (2) *PostUncert* | (3) *PostUncert* | (4) *PostUncertIQR* |
|---|---|---|---|---|
| *Lockdown* | -0.468*** | -0.459*** | -0.271*** | -0.312*** |
| | (0.085) | (0.083) | (0.060) | (0.073) |
| *PriorUncert* | | | 0.451*** | |
| | | | (0.027) | |
| *PriorUncertIQR* | | | | 0.433*** |
| | | | | (0.027) |
| *ln(DeathsCOVID)* | | | -0.001 | 0.003 |
| | | | (0.042) | (0.050) |
| *ln(CasesCOVID)* | | | -0.050 | -0.053 |
| | | | (0.033) | (0.040) |
| *ln(EPUNational)* | | | 0.044 | 0.047 |
| | | | (0.033) | (0.039) |
| Constant | 3.754*** | 3.748*** | 1.579*** | 1.927*** |
| | (0.099) | (0.053) | (0.313) | (0.383) |
| State FEs | N | Y | Y | Y |
| Sample | Mar20-May23 | Mar20-May23 | Mar20-May23 | Mar20-May23 |
| Adjusted R-squared | 0.07 | 0.29 | 0.51 | 0.49 |
| Observations | 1718 | 1718 | 1684 | 1684 |

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). *DeathsCOVID* and *CasesCOVID* are respectively the state-level COVID-related deaths and cases per capita. The *EPUComposite* is the state-level economic policy uncertainty indicator from Baker et al. (2022). We control for state FEs. Standard errors (in parentheses) are clustered at individual and time levels. $*$ represents $p < 0.10$, $**$ represents $p < 0.05$ , and $***$ represents $p < 0.01$.

leading to a decrease in disagreement:

$$\frac{\partial Disp(E^i[x|s^i])}{\partial \sigma_\omega^2} = \sigma_\eta^2 \frac{\partial G^2}{\partial \sigma_\omega^2} = -2\frac{\sigma_x^2 \sigma_\eta^2}{(\sigma_\eta^2 + \sigma_\omega^2 + \sigma_x^2)^2} < 0 \tag{A.16}$$

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.17). 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.17)

$$\frac{\partial Disp(E^i[x|s^i])}{\partial \sigma_\eta^2} = G^2 + \sigma_\eta^2 \frac{\partial G^2}{\partial \sigma_\eta^2} \tag{A.17}$$

Table A.11: Belief rigidity and lockdown measures

| | (1) *PostUncert* | (2) *PostUncert* | (3) *PostUncert* | (4) *PostUncertIQR* |
|---|---|---|---|---|
| *Lockdown* | -0.538*** | -0.531*** | -0.252*** | -0.327*** |
| | (0.089) | (0.091) | (0.056) | (0.066) |
| *PriorUncert* | | | 0.516*** | |
| | | | (0.037) | |
| *PriorUncertIQR* | | | | 0.474*** |
| | | | | (0.036) |
| $ln(DeathsCOVID)$ | | | 0.040 | 0.058** |
| | | | (0.024) | (0.027) |
| $ln(CasesCOVID)$ | | | -0.026 | -0.039* |
| | | | (0.019) | (0.021) |
| $ln(EPUNational)$ | | | 0.014 | 0.019 |
| | | | (0.039) | (0.049) |
| Constant | 3.987*** | 3.983*** | 2.068*** | 2.619*** |
| | (0.093) | (0.057) | (0.287) | (0.365) |
| State FEs | N | Y | Y | Y |
| Sample | Mar20-May23 | Mar20-May23 | Mar20-May23 | Mar20-May23 |
| Adjusted R-squared | 0.08 | 0.22 | 0.52 | 0.48 |
| Observations | 1705 | 1705 | 1670 | 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). *DeathsCOVID* and *CasesCOVID* are respectively the state-level COVID-related deaths and cases per capita. The *EPUComposite* is the state-level economic policy uncertainty indicator from Baker et al. (2022). We control for state FEs. Standard errors (in parentheses) are clustered at individual and time levels. $*$ represents $p < 0.10$, $**$ represents $p < 0.05$ , and $***$ represents $p < 0.01$.

Therefore,

$$\frac{\partial Disp(E^i[x|s^i])}{\partial \sigma_\eta^2} > 0 \iff \sigma_\eta^2 < \frac{\sigma_x^2}{2} \tag{A.18}$$

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.