Household Belief Formation in Uncertain Times*

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Abstract

How does uncertainty influence how households form beliefs about the economy? We show that the impact of uncertainty on consumers' belief rigidity depends crucially on its sources, i.e. information noise or economic volatility, in line with the predictions of a broad class of belief-updating models. First, we document a decline in households' belief rigidity at the pandemic's onset, which we attribute to households' desire to seek information to navigate a more uncertain economic landscape, and partly by lockdown policies lowering information acquisition costs. Second, we document an increase in households' belief rigidity in the subsequent period of high inflation, driven by a deterioration in the accuracy of information, further increasing uncertainty. Overall, we show that belief rigidity can be used to distinguish between uncertainty sources, with opposite effects on information frictions and macro-finance real outcomes, such as the Phillips Curve.

Keywords: beliefs, expectations, household surveys, information frictions, uncertainty.

JEL Classification: D81, D83, D84, E31.

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1 Introduction

In recent years, uncertainty has become a defining feature of the economic landscape. On January 24, 2020, Kristalina Georgieva, Managing Director of the IMF, stated: "If I had to identify a theme at the outset of the new decade, it would be increasing uncertainty." Her prediction was confirmed just a few months later, with the outbreak of COVID-19 causing a surge in various uncertainty indicators (Altig et al., 2020). Its impact is particularly visible on consumer expectation data: the New York Fed's Survey of Consumer Expectations recorded an unprecedented increase in belief uncertainty since its inception ten years earlier (Armantier et al., 2021). Although there is an extensive body of literature on the impact of uncertainty on the macroeconomy and household decisions, such a large effect on belief calls for a deeper examination of the impact of uncertainty on households' expectations.

This paper investigates how uncertainty affects consumers' belief formation. In particular, we study the impact of uncertainty on belief updating rigidity, which refers to how much prior versus new information consumers internalize when forming beliefs, or, in other words, the degree of information frictions (Coibion and Gorodnichenko, 2012, 2015; Goldstein, 2023). We use 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 especially suited to answer our question for two reasons: first, consumers provide density forecasts from which we can extract belief uncertainty at the individual consumer level;[1] second, the large cross-sectional dimension allows us to estimate belief rigidity and delve into its heterogeneity and dynamics.[2]

We show that the effect on belief rigidity crucially depends on the source of uncertainty. First, we document that the correlation between belief uncertainty and rigidity is negative during the first months of COVID-19, but positive afterward, suggesting that the high uncertainty characterizing the two periods might have different sources. Then, we pinpoint possible uncertainty sources through the lens of a benchmark Bayesian belief updating model. On the one hand, increased economic volatility

[1] Among others, Manski (2004, 2018) have long advocated for measuring subjective uncertainty with probabilistic questions in economics surveys, rather than using point forecast dispersion.

[2] We adopt the novel empirical strategy to estimate belief rigidity developed in Goldstein (2023) and Gemmi and Valchev (2023), which improve on the benchmark strategy of Coibion and Gorodnichenko (2015).

makes prior information obsolete and new information more attractive, lowering belief rigidity. On the other hand, an increase in new information noise has the opposite effect, causing consumers to rely more on prior information and increasing belief rigidity. Third, we test these implications by relating individual prior and new information uncertainty with belief rigidity in our sample and find support for the Bayesian model's prediction, shared by a large class of belief-updating models.

The contribution of this paper is twofold. First, we show that the impact of uncertainty on consumers' belief formation is qualitatively in line with the prediction of the Bayesian framework. This finding confirms the conclusion of a growing literature on information provision with RCTs (Armantier et al., 2016; Coibion et al., 2018, 2024; Kumar et al., 2023; Weber et al., 2024). However, rather than presenting to the consumers an ad-hoc piece of information, we leverage on *naturally occurring* variation in beliefs, studying how they incorporate their real-world information, regardless of its source. While our strategy is therefore unaffected by external validity concerns, our results still align with the RCT experiments. Second, we show that belief rigidity is a useful statistic to distinguish between different macroeconomic uncertainty shocks: fundamental volatility and information noise have the opposite effect on belief rigidity, and therefore the latter can be used to differentiate between the two uncertainty sources.

Post-pandemic beliefs We start by documenting a novel fact about belief formation in the pre- and post-pandemic economy. We uncover a sharp decline in belief rigidity at the onset of the COVID-19 pandemic in March 2020, accompanied by a stark increase in uncertainty about their beliefs. Notably, this negative correlation between belief rigidity and uncertainty shifts to a positive one during the high inflation period starting in February 2021, with households exhibiting increased levels of both belief rigidity and uncertainty. This finding is crucial for two reasons. Firstly, it indicates that different types of uncertainty may affect belief formation in opposite ways. Second, shifts in belief rigidity could have significant macroeconomic implications for the inflation dynamics, by affecting the slope of the Phillips Curve and its estimation, both of which depend on inflation expectations (Coibion et al., 2018; Afrouzi and Yang, 2021). We delve into these aspects further in the subsequent sections of the paper.

We investigate the causes behind these shifts in belief rigidity and their correlation with uncertainty. First, we demonstrate that while lockdown policies implemented to stop the spread of the virus at least partly explain the large decline in belief rigidity during the COVID-19 period, they can not fully account for the simultaneous rise in belief uncertainty. Leveraging on the variation in the intensity of state-level lockdown policies, as measured by the Oxford Covid-19 Government Response Tracker (OxCGRT), we document a sizable and robust negative impact on households' belief rigidity. This finding suggests that the constraints on mobility and the widespread shift to remote work reduced the marginal cost of information acquisition, enabling households to collect more new information. Furthermore, we show that lockdown policies had a negative effect on belief uncertainty. This result is in line with standard models of belief formation, in which lower costs of gathering information allow the collection of more accurate data, and therefore a lower reliance on prior information when forming new beliefs (Maćkowiak et al., 2023; Pomatto et al., 2023). Hence, while reduced information costs contribute to decreased belief rigidity during the pandemic, they fail to explain the increased uncertainty.

Model of belief uncertainty and rigidity Next, we show how the opposite dynamics of belief rigidity at the pandemic's onset and the subsequent period can be ascribed to different uncertainty sources: *fundamental* and *new information* uncertainty. We consider a general framework that encompasses a broad class of belief-updating models, including, but not limited to, the Bayesian model. In this framework, an increase in the volatility of the *fundamental* stochastic process underlying the economy makes existing information obsolete, i.e. prior information more uncertain. Because of that, households seek out new information to navigate an increasingly uncertain world. Thus, a structural change in the economic environment can explain the simultaneous increase in belief uncertainty and decrease in rigidity at the pandemic's onset. Conversely, an increase in *new information* uncertainty, or noise, can explain the simultaneous increase in belief uncertainty and rigidity observed in the most recent period: as households receive less accurate signals about the evolution of the economy, they become more uncertain and more reliant on their prior beliefs.

Testing the theory We test the model predictions on the correlation between belief uncertainty and rigidity in the households' expectation data and document strong support. Specifically, we investigate the correlation between belief rigidity with prior and new information uncertainty. We proxy prior uncertainty with the self-reported inflation forecast uncertainty provided in the previous month of the surveys.[3] We extract new information noise from the self-reported inflation forecast uncertainty in the current month (i.e. posterior uncertainty), with two different methods based on our belief-updating framework. First, we use posterior uncertainty controlling for prior uncertainty, to isolate the component due to new information. Second, we use prior uncertainty and our estimates of belief rigidity to directly extract the new information noise from posterior uncertainty. We find that new information uncertainty is positively correlated with belief rigidity: less accurate signals induce agents to update less and be more uncertain about their forecast. In contrast, prior uncertainty is negatively correlated with belief rigidity: higher uncertainty in existing information leads agents to place greater weight on new information when forming beliefs. Our results are consistent with the Bayesian rational expectations model and a broad class of models that, while deviating from, are grounded in Bayesian updating.[4] Unlike previous studies, which primarily explore the relationship between belief uncertainty and belief through RCTs with information provision, our study leverages naturally occurring variation within a comprehensive dataset of U.S. households and therefore is unaffected by external validity concerns.

Macroeconomic implications Finally, we present a stylized analytical general equilibrium model to highlight the impact of time-varying belief rigidity on the slope of the Phillips curve. Recent literature documents a flattening of the Phillips curve over the last few decades (Coibion and Gorodnichenko, 2015; Negro et al., 2020), while other papers document a steepening in the last post-pandemic years (Cerrato and Gitti, 2022; Gudmundsson et al., 2024). In our stylized general equilibrium model with information frictions, we show that the Phillips curve slope is endogenous to the belief rigidity of economic agents. 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.[5]

[3]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 of 3 years, and therefore we assume the horizon is approximately the same.

[4]For example, diagnostic expectations (Bordalo et al., 2018, 2020), overconfidence (Broer and Kohlhas, 2018), and over and under-extrapolation (Angeletos et al., 2021) all share the same qualitative impact of prior and new information uncertainty on belief rigidity.

[5]These results mirror the ones from the theoretical literature on information frictions (Angeletos et al., 2021; Afrouzi and Yang, 2021).

While these findings are illustrative rather than quantitative, they shed light on how shifts in belief rigidity influence the Phillips curve, highlighting their policy significance. Furthermore, our analysis emphasizes the need to differentiate between sources of uncertainty, as they differentially affect belief rigidity and have therefore different policy implications.

1.1 Contribution to the literature

This paper contributes to several strands of the literature. First, 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.[6] We document a similar result without relying on RCTs and exogenous information provision, but instead exploiting the naturally occurring variation of beliefs. 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 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]

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;

[6] 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) don't find any effect of uncertainty on the housing market and labor market expectations.

[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 4.4, in the Bayesian framework belief rigidity only depends on this quantity.

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).[8] 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. More closely related to this paper, Gambetti et al. (2023) uses forecast disagreement to disentangle fundamental volatility and information noise as drivers of uncertainty, under the conjecture that the first lowers disagreement, while the second increases it. We argue that our approach is more general: in a Bayesian framework, while higher new information noise increases disagreement only in the absence of common/public information, its impact on belief rigidity is positive regardless of the nature of new information.

Finally, 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' surveys. 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 don't find such a decline in the Michigan survey of consumers. Compared to their work, we exploit the higher frequency of the SCE, and, more importantly, we estimate the relationship between individual-level uncertainty and belief rigidity.

The paper proceeds as follows: Section 2 illustrates the general framework we use to guide and interpret our empirical strategy. Section 3 presents our data and empirical strategy. Section 4 investigates the dynamics of belief rigidity before and after the pandemic, and its possible determinants. Section 5 explores the relationship between individual prior and posterior uncertainty on belief rigidity. Lastly, Section 6 offers policy implications, and Section 7 concludes.

[8] See Cascaldi-Garcia et al. (2023) for a review of different measure of macroeconomic uncertainty.

2 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 η_t^i normally distributed mean-zero noise with variance $\sigma^2_{\eta,t}$ which is i.i.d. across time and across households, and (ii) a common component ω_t normally distributed mean-zero noise with variance $\omega^2_{\omega,t}$ 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". This general framework embeds a large set of belief-updating models, such as the rational Bayesian model and the behavioral Diagnostic Expectations model, as described in Appendix A.

3 Households' belief rigidity

3.1 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 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 and prior 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

[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.

[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.

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). We indicate as posterior uncertainty the standard deviation from the variance of the subjective distribution provided in the current month($Post\ Uncertainty_{i,t}$), and as prior uncertainty the one provided in the previous month ($Prior\ Uncertainty_{it}$). Similarly to the point forecast, we assume that the horizon is approximately the same across two consecutive months. 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.

Table 1: Descriptive Statistics

	Mean	SD	Min	Max	N
Beliefs					
$For\ 3y$	4.47	6.69	-60	70	127364
$Revision\ 3y$	-0.15	5.67	-94	100	91925
$Post\ Uncert\ 3y$	2.68	2.76	0	22	127364
$Post\ Uncert\ 3y\ IQR$	3.02	3.12	0	28	127364
$For\ 1y$	4.88	6.24	-45	56	126392
$Revision\ 1y$	-0.12	4.96	-90	70	91212
$Post\ Uncert\ 1y$	2.67	2.78	0	22	126392
$Post\ Uncert\ 1y\ IQR$	3.00	3.17	0	28	126392
$For\ H$	5.25	7.85	-60	90	114545
$Post\ Uncert\ H$	3.04	2.81	0	22	114545
$Revision\ H$	-0.10	6.47	-80	85	84396
$Post\ Uncert\ H\ IQR$	3.45	3.23	0	28	114545
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.

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 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 ($HighNumeracy_{i,t}$).

3.2 Empirical strategy

To estimate belief rigidity in expectation surveys, prior studies often relied on the approach pioneered by Coibion and Gorodnichenko (2015), 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);[11] second, it requires a long time series dimension, rarely available in household surveys. We instead adopt a novel methodology from Goldstein (2023) and Gemmi and Valchev (2023) that accurately estimates rigidity in belief updating, overcoming the challenges posed by common errors and limited data, using only a cross-sectional comparison of prior and posterior forecasts.

Demeaning (2) using consensus forecasts,[12]

$$E_t^i[x_{t+h}] - \bar{E}_t[x_{t+h}] = (1-G)(E_{t-1}^i[x_{t+h}] - \bar{E}_{t-1}[x_{t+h}]) - G\eta_t^i \tag{3}$$

Equation (17) provides an unbiased strategy to measure information rigidity. We run the following panel regression

$$For_{i,t} = \alpha + \beta Prior_{i,t} + \lambda X_{i,t} + \gamma_t + err_t^i \tag{4}$$

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

[12] 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, you don't need to observe x_t to run the regression.

where i indicates the household and t the year-month. We include the year-month fixed effect γ_t to demean the individual forecasts. Moreover, $X_{i,t}$ contains age, gender, race, tenure, numeracy, income, and education fixed effects. The coefficient β 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 β), while lower belief rigidity implies a lower correlation between posterior beliefs and prior beliefs (lower β).

Table 2: Belief rigidity

	(1) $For\ 3y$	(2) $For\ 3y$	(3) $For\ 3y$
$Prior\ 3y$	0.516^{***}	0.496^{***}	0.309^{***}
	(0.012)	(0.011)	(0.025)
$Prior\ 3y \times Tenure_{it}$			0.031^{***}
			(0.003)
$High\ Numeracy_{it}$=1 $\times$ $Prior\ 3y$			0.049^{***}
			(0.017)
Constant	1.947^{***}	2.032^{***}	1.854^{***}
	(0.051)	(0.048)	(0.045)
Year-Month FEs	Y	Y	Y
Socio-demographic FEs	Y	Y	Y
Adjusted R-squared	0.33	0.31	0.34
Observations	90940	87631	90940

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 $p < 0.01$.

Table 2 reports the estimates of belief rigidity β from regression (4). 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 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. 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.

3.3 Heterogeneity in belief updating

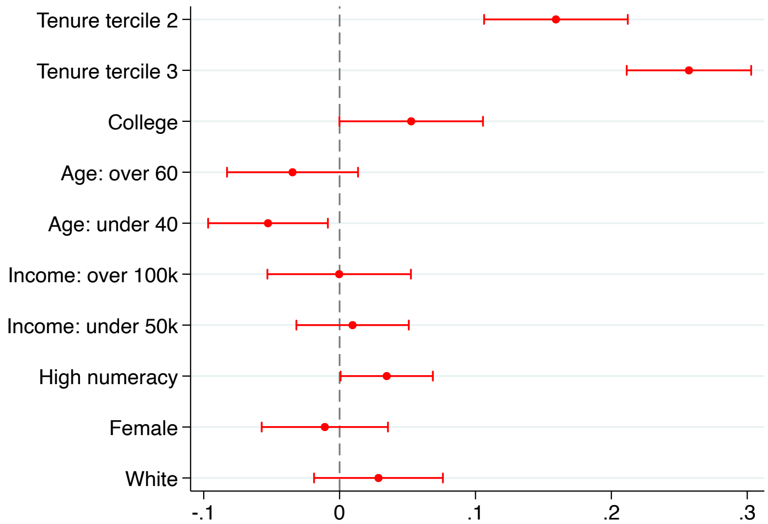
We explore how socioeconomic characteristics affect households' belief formation. To study how these characteristics affect belief rigidity, we interact them with the prior in our regression. That is, we run

$$For_{i,t} = \alpha + \beta_1 Prior_{i,t} + \mathbf{X}_{i,t}\mathbf{B}_2 + Prior_{i,t} \times \mathbf{X}_{i,t}\mathbf{B}_3 + \gamma_t + err_t^i \qquad (5)$$

where $\mathbf{X}_{i,t}$ is a vector containing a set of socioeconomic characteristics 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 qual-

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 (5), i.e. column (7) of Table A.1. Sample period: 2020M3-2023M5.

ity: 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).

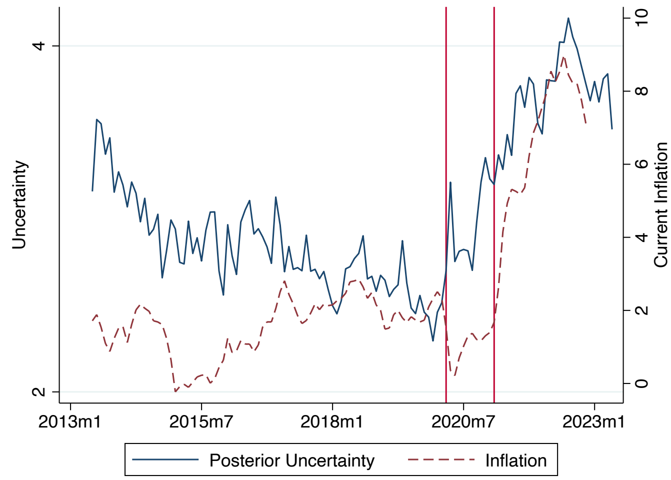
4 Household belief rigidity during uncertain times

4.1 Belief rigidity declines during the pandemic

In this section, we exploit the large panel dimension of the SCE to study the time variation of belief rigidity in the period before and after the pandemic, to shed light on the relation between belief rigidity and uncertainty.

Figure 2 shows the time series of average individual inflation belief uncertainty from the SCE together with the actual current CPI inflation. The start of the COVID pandemic in early 2020 (first vertical line in Figure 2) has been characterized by a

Figure 2: Inflation uncertainty and rigidity in Covid and high inflation periods



Legend: The blue filled line denotes the posterior uncertainty. The red dashed line denotes current inflation. 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 February 2021 (or the start of the Biden term). Data sources: Survey of Consumer Expectations (SCE) and FRED. Sample period: 2013M1 - 2023M5.

striking increase in consumer belief uncertainty Armantier et al. (2021). Uncertainty has remained high when inflation started increasing in 2021 (second vertical line in Figure 2).

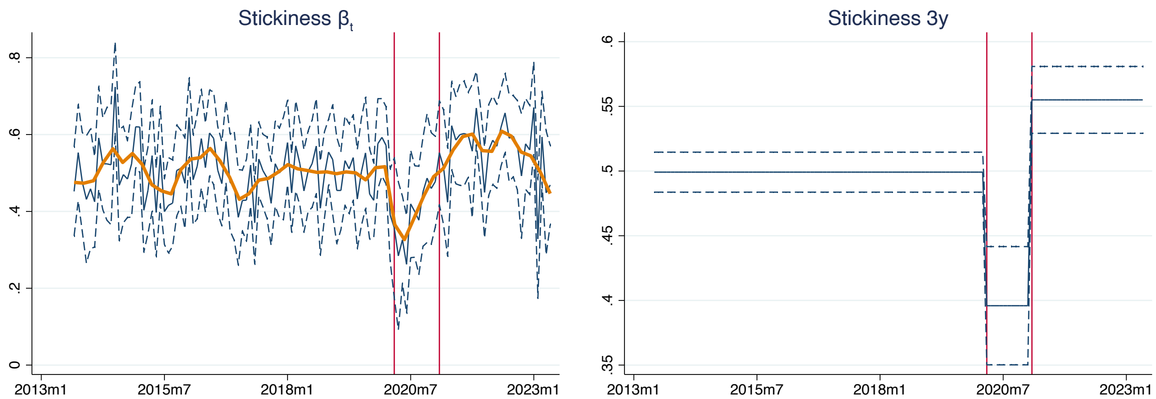
We investigate the evolution of belief rigidity across these two episodes of the COVID pandemic and the subsequent high inflation period. To do that, we compute belief rigidity month-by-month by exploiting the large cross-sectional dimension of the SCE data. For each month t, we run the following regression

$$For_{i,t} = \alpha_t + \beta_t Prior_{i,t} + X_{i,t} + err_t^i \tag{6}$$

The left panel of Figure 3 shows the estimates of belief rigidity β in each month of the sample. Belief rigidity is around 0.5 for the pre-COVID sample, while it decreases to around 0.3 during the COVID period, which translates to weight on new information in belief formation of around $G = 0.7$. After the end of the pandemic, the rigidity reverts back to the pre-pandemic level, but ends at a slightly higher value during the high inflation period. The right panel of Figure 3 shows the estimate of belief rigidity in three different subsamples: pre-COVID period (up to March 2020), COVID period (between March 2020 and February 2021), and high inflation period (after February

Figure 3: Belief rigidity pre- and post-pandemic

Belief rigidity β month-by-month   Belief rigidity β by periods



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 β 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 February 2021 (or the start of the Biden term). Data sources: Our estimates. Sample period: 2013M1 - 2023M5.

2021). Table A.3 reports the estimates, while Figure A.1 reports the same exercise for shorter horizon forecasts with similar results.

This evidence suggests that while uncertainty spikes up during COVID, belief rigidity goes in the opposite direction and instead sharply declines, meaning that consumers incorporate more new information when forming new beliefs. Then, during the high inflation period after COVID belief rigidity increases again, meaning that consumers rely more on their prior beliefs. 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.[13]

[13] Another difference is that we consider a 3-year forecast horizon, Goldstein (2023) considers a short 1-year horizon. Figure A.1 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.

What is driving these large changes in belief rigidity in a period of such high uncertainty? The larger attention paid by consumers during the pandemic might be due to an increase in time available to browse for news, following a set of restrictions on movements implemented by policymakers to stop the spread of the virus. We investigate this hypothesis in the next section.

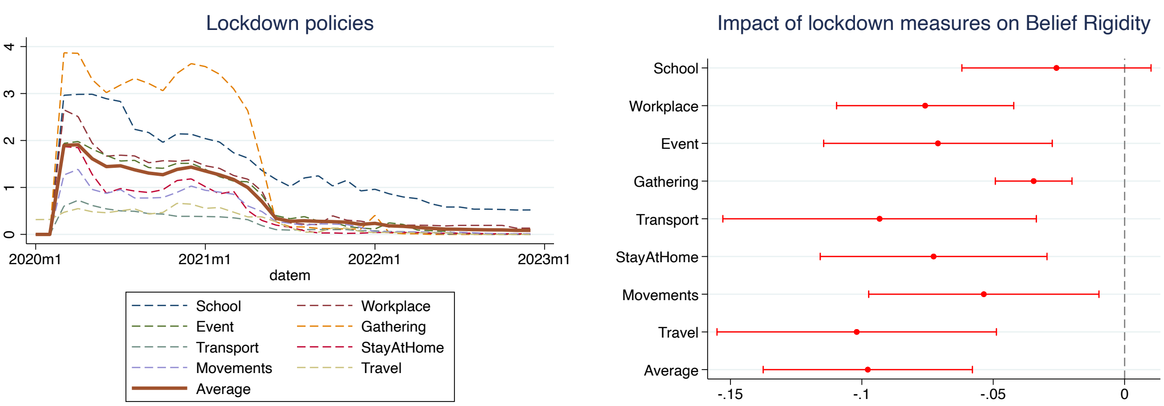
4.2 Information cost and belief rigidity: the case of lockdowns

In this section, we investigate the role of 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.[14] Figure 5(a) reports the time series of the country-level average of each indicator. Moreover, to measure the local impact of the pandemic we use the US state-level monthly level of COVID deaths and cases per capita. Table A.2 reports the summary statistics.

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

Figure 4: 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, β_2 in (7). Sample period: 2020M3-2023M5.

To estimate the impact of lockdown measures on belief rigidity, we interact the prior forecast in regression (4) 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

$$\begin{aligned} For_{i,t} =& \alpha + \beta_1 Prior_{i,t} + \beta_2 Prior_{i,t} \times LockdownIndex_{j,t} + \beta_3 LockdownIndex_{j,t} \\ &+ Prior_{i,t} \times CovidImpact'_{j,t}\Pi + CovidImpact'_{j,t}\Gamma + \lambda X_{i,t} + \gamma_t + err^i_t \end{aligned} \tag{7}$$

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 5(b) reports the estimated impact of lockdown indexes on belief rigidity, β_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 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 3 presents additional evidence. The first column replicates the last column of

Table A.4, using the average index *Severity* to summarize the stringency of state-level lockdown policies. As shown in Figure 5(a), 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.[15] Even controlling for state-level uncertainty, the estimated impact of lockdown policies on belief rigidity is significant and negative.[16]

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.

4.3 The impact of information cost on uncertainty

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

$$x_{t+h} - E_t^i[x_{t+h}] = (1 - G_t)(x_{t+h} - E_{t-1}^i[x_{t+h}]) - G_t e_t^i \tag{8}$$

Equation (8) 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 8 one can derive the posterior belief uncertainty, which equals

$$\Sigma_{t+h,t} = (1 - G_t)^2 \Sigma_{t+h,t-1} + G_t^2 \sigma_{e,t}^2 \tag{9}$$

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 $\sigma_{e,t}^2$. 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;

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

[16] 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 3: Belief rigidity and lockdown measures

	(1) *For 3y*	(2) *For 3y*	(3) *For 3y*	(4) *For 3y*	(5) *For 3y*
Prior 3y	0.558***	0.770***	0.799***	0.815***	0.786***
	(0.115)	(0.143)	(0.152)	(0.147)	(0.147)
Prior 3y × *Lockdown*	-0.098***	-0.113***	-0.123***	-0.121***	-0.117***
	(0.020)	(0.027)	(0.023)	(0.026)	(0.025)
Prior 3y × $ln(DeathsCOVID)$	-0.012	0.014	0.015	0.017	0.014
	(0.013)	(0.021)	(0.022)	(0.023)	(0.022)
Prior 3y × $ln(CasesCOVID)$	0.020	0.011	0.013	0.011	0.012
	(0.020)	(0.020)	(0.019)	(0.021)	(0.020)
Prior 3y × $\Delta ln(EPUState)$			0.021		
			(0.020)		
Prior 3y × $\Delta ln(EPUNational)$				0.028	
				(0.021)	
Prior 3y × $\Delta ln(EPUComposite)$					0.012
					(0.023)
Constant	1.966**	1.457*	1.327*	1.267*	1.390*
	(0.797)	(0.726)	(0.693)	(0.679)	(0.696)
Year-Month FEs	Y	Y	Y	Y	Y
Socio-demographic FEs	Y	Y	Y	Y	Y
Non-interacted variables	Y	Y	Y	Y	Y
Sample	Mar20-May23	Mar20-Jun21	Mar20-Jun21	Mar20-Jun21	Mar20-Jun21
Adjusted R-squared	0.35	0.26	0.26	0.26	0.26
Observations	24769	11146	11146	11146	11146

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 $p < 0.01$.

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 increase in belief uncertainty, as shown in Figure 2. 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

$$\begin{aligned} log(PostUncert_{j,t}) =& \alpha + \beta Lockdown_{j,t} + \gamma log(PriorUncert_{j,t}) \\ &+ CovidImpact'_{j,t}\Gamma + \delta \Delta ln(EPU)_{j,t} + \gamma_j + err_{j,t} \end{aligned} \tag{10}$$

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 proxy for information cost, and $EPU_{j,t}$ is the state-level economic policy uncertainty. Table 4 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.[17] 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 be responsible for both a decline in belief rigidity and an increase in belief uncertainty, which is an increase in fundamental volatility.

4.4 A unified explanation: fundamental volatility

As argued in Section 2, our empirical strategy to estimate belief rigidity does not require us to make any assumption on the belief formation model determining belief rigidity $1 - G_t$. However, our framework embeds the noisy information case with rational

[17] Our uncertainty measure does not reflect the actual precision of consumers' information, but their perceived precision. We don't 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 4: Belief rigidity and lockdown measures

	(1) $ln(PostUncert3y)$	(2) $ln(PostUncert3y)$	(3) $ln(PostUncert3y)$	(4) $ln(PostUncertIQR3y)$
$Lockdown$	-0.236***	-0.242***	-0.129***	-0.099***
	(0.036)	(0.036)	(0.026)	(0.022)
$ln(PriorUncert3y)$			0.442***	
			(0.033)	
$ln(PriorUncertIQR3y)$				0.408***
				(0.033)
$ln(DeathsCOVID)$			-0.002	0.002
			(0.014)	(0.011)
$ln(CasesCOVID)$			-0.002	-0.001
			(0.014)	(0.015)
$\Delta ln(EPUNational)$			0.021*	0.025**
			(0.011)	(0.010)
Constant	1.025***	1.030***	0.540***	0.790***
	(0.033)	(0.023)	(0.103)	(0.078)
State FEs	N	Y	Y	Y
Sample	Mar20-May23	Mar20-May23	Mar20-May23	Mar20-May23
Adjusted R-squared	0.13	0.29	0.46	0.46
Observations	1715	1715	1674	1679

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 state and time levels. $*$ represents $p < 0.10$, $**$ represents $p < 0.05$, and $***$ represents $p < 0.01$.

expectations as a particular case. Consider the rational expectation framework: in this case, the gain G_t equals the Kalman gain, and belief rigidity is given by

$$1 - G_t^{RE} = \frac{\sigma_{e,t}^2}{\sigma_{e,t}^2 + \Sigma_{t+h,t-1}} \tag{11}$$

Belief rigidity $1-G_t$ is time-varying as it depends on changes in information uncertainty. We highlight the importance of differentiating between two different "uncertainty" shocks. First, consider an increase in uncertainty of new information, i.e. an increase in $\hat{\sigma}_{e,t}^2 > \sigma_{e,t}^2$. For the same prior uncertainty, agents receive less accurate signals and therefore update less, $\hat{G}_t < G_t$: belief rigidity increase. For example, households may face a higher cost of collecting information (which we proxy with lockdown policies) or may face a lower supply of information from newspapers, television, or social networks (which we proxy with the economic policy uncertainty index). In the case of lockdown policies, a lower belief rigidity caused by more accurate information would then be associated with a decrease in posterior belief uncertainty, which is consistent with our findings reported in Table 4. However, this would be at odds with the stark jump in uncertainty during the COVID period.

Second, consider an increase in uncertainty (or volatility) of current fundamentals. 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. For example, consider the case where the fundamental follows an AR(1) process:

$$x_{t+h} = \rho x_{t+h-1} + u_{t+h} \tag{12}$$

with $u_{t+h} \sim N(0, \sigma^2_{u,t+h})$. In this case,

$$\Sigma_{t+h,t-1} = \rho^2 \Sigma_{t+h-1,t-1} + \sigma^2_{u,t+h} \tag{13}$$

An increase in fundamental volatility $\hat{\sigma}^2_{u,t+h} > \sigma^2_{u,t+h}$ increase prior uncertainty $\hat{\Sigma}_{t+h,t-1} > \Sigma_{t+h,t-1}$. For the same uncertainty of new information, household prior information is more obsolete and therefore they update more, $\hat{G}_t > G_t$: belief rigidity decreases. Such an increase in fundamental volatility would have made therefore prior information more uncertain and at the same time increased posterior belief uncertainty and encouraged agents to rely more on new information, lowering belief rigidity, consistent with the evidence in the pandemic period.

While we derive this result under the rational expectation assumption, it holds in many models that depart but build on the baseline Bayesian updating in (11). For example, diagnostic expectations (Bordalo et al., 2018, 2020), overconfidence (Broer and Kohlhas, 2018), and over and under-extrapolation (Angeletos et al., 2021) all share the same qualitative impact of prior and new information uncertainty on belief rigidity. 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).

While we do not have a measure able to separate fundamental uncertainty from other sources of uncertainty that we can use to study the COVID period, we can instead exploit the individual prior and posterior uncertainty to test the qualitative implication of the rational expectation framework (11) using the surveys data. We do this in the next section.

5 Belief rigidity and uncertainty

We empirically test two implications of the Bayesian belief updating framework in equation (11), shared by a large set of non-rational belief updating models. First, higher prior uncertainty implies lower belief rigidity. Second, higher new information uncertainty implies higher belief rigidity.

Prior uncertainty The first measure we need to perform this test is prior uncertainty. We use the lagged posterior uncertainty to proxy for today's prior, meaning the uncertainty measured from the density forecasts provided by the same individual in the previous month. 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 and therefore we assume the horizon is approximately the same.

New information uncertainty Measuring new information uncertainty is more challenging as it is not directly observable in the data. We employ three different measures of new information uncertainty, each one with different advantages and drawbacks. First, we use the individual posterior uncertainty provided in the survey controlling for prior uncertainty. Second, we rely on the structural interpretation of our regression to construct a proxy for new information noise. Third, we use the economic policy uncertainty index from U.S. newspaper by Baker et al. (2022).

5.1 Measure 1: Posterior uncertainty

We measure new information noise for each consumer as the individual posterior uncertainty controlling for prior uncertainty. Our benchmark model in (9) implies that posterior uncertainty is a function of prior uncertainty and new information uncertainty. By controlling for the first, we aim to isolate the latter. That is, we run the regression

$$\begin{aligned} For_{i,t} =& \alpha + \beta_1 Prior_{i,t} + \begin{bmatrix} Prior\ Uncertainty_{it} \times Prior_{i,t} \\ Post\ Uncertainty_{it} \times Prior_{i,t} \end{bmatrix}' \begin{bmatrix} \beta_2 \\ \beta_3 \end{bmatrix} \\ & + Z'_{i,t}\Gamma + X_{i,t} + \gamma_t + err_t^i \end{aligned} \tag{14}$$

Table 5: Belief rigidity and uncertainty

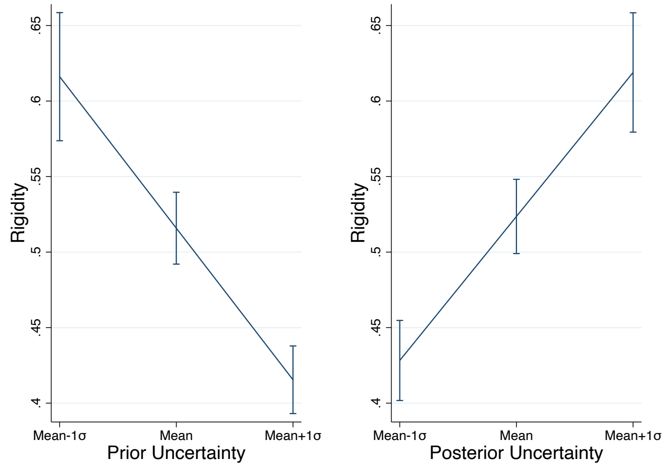
	(1) *For*	(2) *For*	(3) *For*	(4) *For*
PriorFor	0.534***	0.526***		0.548***
	(0.023)	(0.016)		(0.024)
PriorFor × *PriorUncert*	-0.124***		-0.131***	-0.125***
	(0.015)		(0.016)	(0.016)
PriorFor × *PostUncert*	0.116***		0.109***	0.113***
	(0.014)		(0.015)	(0.015)
PriorFor × *Prior Uncert 3y IQR*		-0.014***		
		(0.003)		
PriorFor × *Post Uncert 3y IQR*		0.010***		
		(0.003)		
Constant	0.501***	1.000***	2.793***	0.454***
	(0.095)	(0.082)	(0.083)	(0.098)
Year-Month FEs	Y	Y	Y	Y
Prior-Year-Month FEs	N	N	Y	N
Socio-demographic FEs	Y	Y	Y	Y
Non-interacted variables	Y	Y	Y	Y
Sample	Jun13-May23	Jun13-May23	Jun13-May23	excludeCOVID
Adjusted R-squared	0.36	0.37	0.37	0.37
Observations	90940	90940	90940	83563

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). *PriorFor* is the point forecast about the 3-year horizon provided in the previous month. *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. *PostUncert3yIQR* and *PriorUncert3yIQR* are similar but use the interquartile range to measure uncertainty instead of fitting a generalized beta distribution. 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 $Z_{i,t}$ include the non-interacted terms. The interaction terms β_2 and β_3 capture the impact of a change in, respectively, prior and new information uncertainty on belief rigidity. The Bayesian belief updating model implies that higher prior uncertainty is associated with lower belief rigidity, $\beta_2 < 0$, and higher new information uncertainty with higher belief rigidity, $\beta_3 > 0$.

The results reported in Table 5 confirm our hypothesis. First, the higher the prior uncertainty for a given posterior uncertainty, the lower the belief rigidity (or the higher the weight on new information G_t), i.e. $\hat{\beta}_2 < 0$. If household information is obsolete, they incorporate more new information when forming new beliefs. Second, the higher the posterior uncertainty for a given prior uncertainty, the higher the belief rigidity, i.e. $\hat{\beta}_3 > 0$. If households receive noisier information, they incorporate less of that new information when forming new beliefs. The result is robust to using the interquartile range of subjective probability as a measure of uncertainty (column 2), interacting the

Figure 5: Belief rigidity and uncertainty



Legend: The figure represents graphically the estimated coefficients from column (3) of Table 5. It shows the relationship between belief rigidity β and prior uncertainty (on the left-hand side) and posterior uncertainty (on the right-hand side).

time fixed effect with the prior variable (column 3), and excluding the COVID period (column 4).[18] Moreover, considering the 1-year horizon forecasts in CPI and housing price inflation reported in Tables A.12 and A.13 yields similar results.

Figure 5 plots the estimated effect of prior and posterior uncertainty on belief rigidity in the main specification of Column (3) in Table 5. The effect of uncertainty on belief rigidity is sizable. A one standard deviation increase in the logarithm of prior uncertainty reduces belief rigidity by around 0.1, i.e. 20%. Similarly, a one standard deviation increase in the logarithm of posterior uncertainty increases belief rigidity by around 0.07, i.e. 15%. Figure A.2 shows similar results for shorter forecast horizons.

While using posterior uncertainty as a proxy for new information uncertainty has the advantage of being available at the consumer level, it presents a potential drawback. First, while we hypothesize that posterior uncertainty affects belief rigidity, from equation (9) one can see that the opposite is also true, which might lead to an endogeneity

[18] To proxy for prior uncertainty we use lagged posterior uncertainty, the link between which is given by equation (13). Substituting (13) in (9) gives

$$\Sigma^i_{t+h,t} = (1-G_t)^2\rho^2\Sigma^i_{t+h-1,t-1} + (1-G_t)^2\sigma^2_{u,t+h} + G_t^2\sigma^{i,2}_{e,t} \tag{15}$$

So controlling for lagged posterior, the current posterior depends not only on new information volatility $\sigma^{i,2}_{e,t}$, but also on fundamental volatility $\sigma^2_{u,t+h}$. Interacting time fixed effects to the prior in column (3) demeans the interacted variables and removes the common component $\sigma^2_{u,t+h}$.

bias. To address this issue, we propose an alternative measure for new information uncertainty.

5.2 Measure 2: extract noise from posterior uncertainty

To construct our second measure of new information uncertainty we rely on the general belief updating model presented in section 2. To do that, we consider a group-specific version of the signal structure in (1), which is now

$$s_t^{i,j} = x_{t+h} + e_t^{i,j} \tag{16}$$

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. Suppose the variance of the idiosyncratic component $\eta_t^{i,j}$ is the same for individuals in a specific group, $\eta_t^{i,j} \sim N(0, (\sigma_{\eta,t}^j)^2)$, while the common component is the same, $\omega_t \sim N(0, (\sigma_{\omega,t})^2)$. Therefore a "group" refers to a set of individuals with similar quality of information.

This gives the structural equation

$$E_t^{i,j}[x_{t+h}] - \bar{E}_t^j[x_{t+h}] = (1 - G_t^j)(E_{t-1}^{i,j}[x_{t+h}] - \bar{E}_{t-1}^j[x_{t+h}]) - G_t^j \eta_t^{i,j} \tag{17}$$

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

Our objective is to measure group specific $(\sigma_{\eta,t}^j)^2$. First, we divide consumers into $j = 1, \ldots, J$ groups based on sociodemographic characteristics, which should 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. We estimate regression (4) for each group and in each month.[19] In other words, for each group j, and month t we run

$$For_{i,j,t} = \alpha_{j,t} + \beta_{j,t} Prior_{i,t} + err_{i,j,t} \tag{18}$$

We obtain a series of estimates $\hat{\beta}_{j,t} = 1 - G_{j,t}$. We can use this estimate of group-

[19] 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.

specific gain $G_{j,t}$ to extract the group-specific new information noise from the posterior uncertainty. From (9), the posterior uncertainty of group j at time t equal

$$\Sigma^{j}_{t+h,t} = (1 - G^{j}_{t})^2 \Sigma^{j}_{t+h,t-1} + (G^{j}_{t})^2 (\sigma^{j}_{e,t})^2 \tag{19}$$

We can then extract the group-specific new information noise as

$$\widehat{\sigma}^{j}_{e,t} = \sqrt{\frac{PosteriorUncert^2_{j,t} - \hat{\beta}^2_{j,t} * PriorUncertainty^2_{j,t}}{1 - \hat{\beta}_{j,t}}} \tag{20}$$

where $PosteriorUncert_{j,t}$ is the mean (or median) of individual posterior uncertainty in group j, and similarly for $priorUncert_{j,t}$.

Impact of uncertainty on belief rigidity We can use our measures of new information and prior uncertainty to test the impact of belief rigidity. We run the following group panel regression regression

$$\begin{aligned} For_{i,j,t} =& \alpha + \beta_1 Prior_{i,j,t} + \begin{bmatrix} Prior\ Uncert_{j,t} \times Prior_{i,j,t} \\ \hat{\sigma}^{j}_{e,t} \times Prior_{i,j,t} \end{bmatrix}' \begin{bmatrix} \beta_2 \\ \beta_3 \end{bmatrix} \\ &+ Z'_{j,t}\Gamma + \lambda X_{i,t} + \gamma_t + err_{j,t} \end{aligned} \tag{21}$$

where $Z_{j,t}$ includes the non-interacted terms. The Bayesian belief updating model implies that belief rigidity is higher in groups with higher prior uncertainty, $\beta_2 < 0$, and higher in groups with higher new information noise, $\beta_3 > 0$.

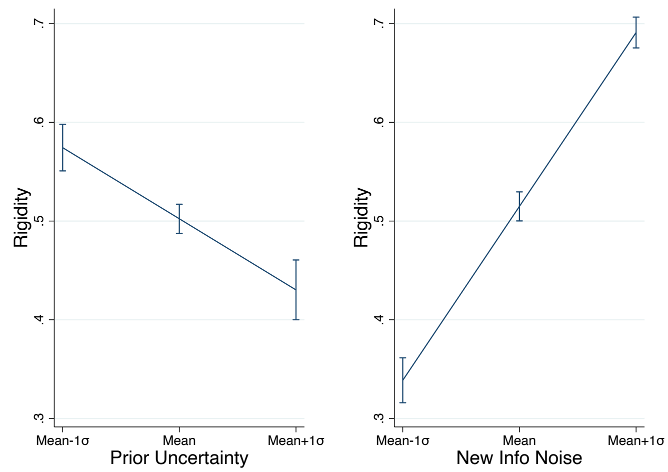
The results reported in the second column of Table 6 are similar to the first approach in Table 5, confirming again the implications of the Bayesian belief updating framework. First, the higher the prior uncertainty, the lower the belief rigidity (or the higher the weight on new information G_t), i.e. $\hat{\beta}_2 < 0$. If household information is obsolete, they incorporate more new information when forming new beliefs. Second, the higher the new information uncertainty, the higher the belief rigidity, i.e. $\hat{\beta}_3 > 0$. If households receive noisier information, they incorporate less of that new information when forming new beliefs. The results are robust to some robustness checks. These results are robust to using individual, group-median, or group-mean of posterior and prior uncertainties to construct the new information noise in equation (20). They are also robust to interact prior with year-month fixed effects (column 4), and to run the regression at

Table 6: Belief rigidity and uncertainty

	(1) *For*	(2) *For*	(3) *For*	(4) *For*	(5) *For*
$PriorFor$	0.296***	0.373***	0.396***		0.568***
	(0.040)	(0.034)	(0.025)		(0.123)
$PriorFor \times PriorUncert$ *(median)*	-0.197***			-0.189***	-0.210**
	(0.032)			(0.036)	(0.083)
$PriorFor \times PriorUncert$ *(mean)*		-0.262***			
		(0.023)			
$PriorFor \times PriorUncert$			-0.127***		
			(0.012)		
$PriorFor \times NewInfoNoise(median)$	0.192***			0.189***	0.080**
	(0.007)			(0.008)	(0.030)
$PriorFor \times NewInfoNoise(mean)$		0.197***			
		(0.006)			
$PriorFor \times NewInfoNoise$			0.101***		
			(0.004)		
Constant	1.205***	0.942**	1.213***	2.422***	0.396
	(0.415)	(0.450)	(0.085)	(0.341)	(0.419)
Year-Month FEs	Y	Y	Y	Y	Y
Non-interacted variables	Y	Y	Y	Y	Y
PriorxYear-Month FEs	N	N	N	Y	N
Sample	Jun13-May23	Jun13-May23	Jun13-May23	Jun13-May23	Jun13-May23
Adjusted R-squared	0.38	0.40	0.43	0.38	0.66
Observations	75639	74095	66193	75639	1021

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). $PriorFor$ is the point forecast about the 3-year horizon provided in the previous month. $PriorUncert$ denotes the individual 1-year ahead forecast of inflation expectations uncertainty starting 24 months into the future provided in the previous month from the NY FED Survey of Consumer Expectations (SCE). In addition to the individual measure, we consider the median and the mean across groups, which are identified by 4 indicators: tercile of tenure, high numeracy, college education, and whether under 40 years old. $NewInfoNoise$ refers to the variable in (20), constructed used the estimate time- and group-specific $\hat{G}_t$ in regression (18) and prior and posterior uncertainty, either individual, group-mean or group-median. We control for year-month fixed effects and for socioeconomic characteristics, such as education, income, age, gender, race, and tenure. Column (4) controls also for year-month fixed effects interacted with $PriorFor$. Column (6) presents the same regression estimated at the group-level, using group-median For and $PriorFor$. 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 6: Belief rigidity and uncertainty



Legend: The figure represents graphically the estimated coefficients from column (1) of Table 6. It shows the relationship between belief rigidity β and prior uncertainty (on the left-hand side) and new information noise (on the right-hand side).

the group level, i.e. group-median posterior and prior point forecasts (column 5).

Figure 6 plots the estimated effect of prior and posterior uncertainty on belief rigidity in the main specification of Column (1) in Table 6. The effect of new information noise on belief rigidity is even more sizable than in Figure 5. A one standard deviation increase in the logarithm of new information noise increases belief rigidity by around 0.2, which close to 40%.

A drawback of this measure is that it relies on the belief updating model of Section 2, even if it does not assume rationality. As an alternative measure, we next consider a proxy for new information noise external to the surveys we are studying.

5.3 Measure 3: newspaper uncertainty

Our third measure for new information uncertainty is the state-level economic policy uncertainty index from Baker et al. (2022). They select sets of daily and weekly newspapers for each U.S., excluding national ones like the New York Times. The EPU indexes measure the fraction of articles that contain terms from term sets regarding the economy, uncertainty, and policy. They provide three indices, regarding national-level policies, state-level policies, and a composite index for both.[20] In order to isolate the

[20]For additional details, see Baker et al. (2022).

changes in EPU indexes, we consider the first difference.

Using changes in EPU as a measure of changes in new information uncertainty, we run the following regression

$$\begin{aligned} For_{i,s,t} =& \alpha + \beta_1 Prior_{i,s,t} + \begin{bmatrix} Prior\ Uncert_{i,s,t} \times Prior_{i,s,t} \\ \Delta EPU_{s,t} \times Prior_{i,s,t} \end{bmatrix}' \begin{bmatrix} \beta_2 \\ \beta_3 \end{bmatrix} \\ & + Z'_{i,s,t}\Gamma + \gamma_t + err_{i,s,t} \end{aligned} \tag{22}$$

where i indicate the consumer, s the U.S. State of residence and t the month, and $Z_{i,s,t}$ includes the non-interacted terms. The interaction terms β_2 and β_3 capture the impact of a change in, respectively, prior and new information uncertainty on belief rigidity. The Bayesian belief updating model implies that higher prior uncertainty is associated with lower belief rigidity, $\beta_2 < 0$, and higher new information uncertainty with higher belief rigidity, $\beta_3 > 0$.

Table 7 reports the results, which are similar to the one obtained with the other measure of new information noise. The impacts of prior and new information noise are consistent with the model's predictions: prior uncertainty decreases information rigidity and new information uncertainty increases it. The results are robust to considering the national news only or a composite indicator of national and local news. We also consider the linear first difference indicator divided by 100 for readability. In the whole sample, the coefficient is still positive but not strongly significant in columns (3), but it becomes significant when we exclude the first months of COVID, February 2020 to January 2021, in column (4).

Figure 7 plots the estimated effect of prior and new information uncertainty, the latter proxied by the Economic Policy Uncertainty index, on belief rigidity in the main specification of Column (1) in Table 7. The effect of new information uncertainty is still positive, but lower in magnitude compared to the alternative proxies in Figures 5 and 6. The impact of an increase of one standard deviation in our proxy for new information uncertainty on rigidity is around 0.03, i.e. 5%.

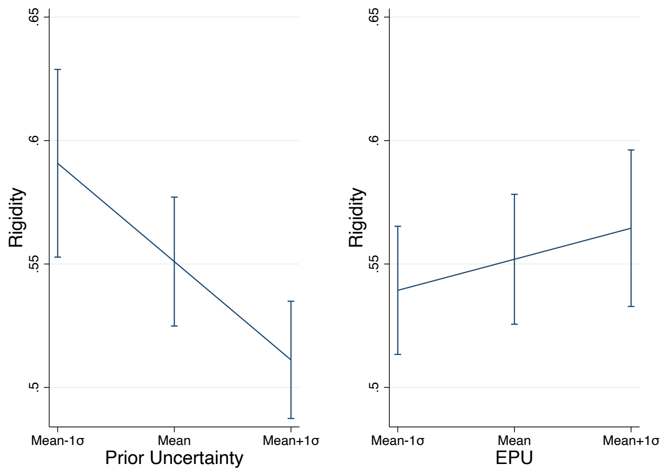
In conclusion, we document a robust positive relationship between belief rigidity and prior uncertainty and a negative one with new information uncertainty. This evidence is consistent with the Bayesian belief updating model (11), but also with a large set of behavioral models that builds on the standard Bayesian framework, such as overconfidence and diagnostic expectations (see Appendix A).

Table 7: Belief rigidity and uncertainty

	(1) *For*	(2) *For*	(3) *For*	(4) *For*
$PriorFor$	0.621***	0.621***	0.621***	0.634***
	(0.025)	(0.025)	(0.025)	(0.026)
$PriorFor \times PriorUncert$	-0.049***	-0.049***	-0.049***	-0.052***
	(0.011)	(0.011)	(0.011)	(0.012)
$PriorFor \times \Delta ln(EPUnational)$	0.019**			
	(0.010)			
$PriorFor \times \Delta EPUcomposite/100$		0.027**		
		(0.013)		
$PriorFor \times \Delta EPUnational/100$			0.016	0.021**
			(0.010)	(0.009)
Constant	0.921***	0.923***	0.923***	0.882***
	(0.091)	(0.091)	(0.091)	(0.095)
Year-Month FEs	Y	Y	Y	Y
Non-interacted variables	Y	Y	Y	Y
Sociodemographic controls	Y	Y	Y	Y
Sample	Jun13-May23	Jun13-May23	Jun13-May23	excludeCOVID
Adjusted R-squared	0.33	0.33	0.33	0.34
Observations	90587	90757	90763	83404

Legend: For denotes the 1-year ahead forecast of inflation expectations starting 24 months into the future from the NY FED Survey of Consumer Expectations (SCE). $Prior$ is the point forecast about the 3-year horizon provided in the previous month. $PriorUncert$ 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), as provided in the previous month. $EPUcomposite$ and $EPUnational$ are state-level uncertainty indexes provided by Baker et al. (2022). We control for year-month fixed effects and for socioeconomic characteristics, such as education, income, age, gender, race, and tenure. The sample in column (4) is Jun13-Feb20 and Feb21-May23. 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 7: Belief rigidity and uncertainty



Legend: The figure represents graphically the estimated coefficients from column (1) of Table 7. It shows the relationship between belief rigidity β and prior uncertainty (on the left-hand side) and economic policy uncertainty (on the right-hand side).

6 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.

6.1 Environment

The model is a simplified version of the framework proposed in Afrouzi and Yang (2021).[21] 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 don't 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

[21] 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.

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 $i \in [0,1]$.

$$\max_{\{(C_{i,t})_{i\in[0,1]}, B_t, L_t\}_{t=0}^{\infty}} \mathbb{E}_0^f \left[\sum_{t=0}^{\infty} \beta^t (\log(C_t) - L_t) \right] \tag{23}$$

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

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 $t+1$, Π_t is the aggregated profits of firms, and T_t is 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:

$$C_{i,t} = C_t \left(\frac{P_{i,t}}{P_t} \right)^{-\theta} \qquad \forall i \in [0,1], \forall t \geq 0, \tag{24}$$

$$1 = \beta R_t \mathbb{E}_t^f \left[\frac{Q_t}{Q_{t+1}} \right] \qquad \forall t \geq 0, \tag{25}$$

$$W_t = Q_t, \qquad \forall t \geq 0 \tag{26}$$

Equation (24) is the demand for variety i at time t, Equation (25) is the consumption Euler Equation and Equation is the intratemporal optimality condition that relates nominal wage and nominal aggregate demand.[22]

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

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

random walk

$$\log(Q_t) = \log(Q_{t-1}) + u_t, \quad u_t \sim \mathcal{N}(0, \sigma_u^2) \tag{27}$$

where u_t is an exogenous shock to monetary policy that affects the nominal rates with a standard deviation of σ_u.[23]

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

$$\max_{\{P_{i,t}\}} E_t^i \left[\frac{1}{P_t C_t} \left(P_{i,t} C_{i,t} - (1 - \theta^{-1}) Q_t L_{i,t} \right) \right] \tag{28}$$

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

$$p_{i,t} = E_t^i[q_t] \tag{29}$$

with small letters denoting the logs of corresponding variables. Equation (29) implies that firms set prices equal to perceived marginal cost, which is exogenous and given by Equation (27).

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

$$s_t^i = q_t + e_t^i \tag{30}$$

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

where the signal noise $e_t^i = \eta_t^i + \omega_t$ contains (i) an idiosyncratic component η_t^i normally distributed mean-zero noise with variance $\sigma^2_{\eta,t}$ which is i.i.d. across time and across households, and (ii) a common component ω_t normally distributed mean-zero noise with variance $\omega^2_{\omega,t}$ 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 firms update their beliefs similarly to the rule in Section 2:

$$E_t^i[q_t] = (1 - G_t)E_{t-1}^i[q_t] + G_t s_t^i \tag{31}$$

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 $G_t = \frac{\Sigma_{t,t-1}}{\Sigma_{t,t-1}+\sigma^2_{e,t}}$ 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 (31) describes also the evolution of firm's i price.

6.2 The Phillips curve with information frictions

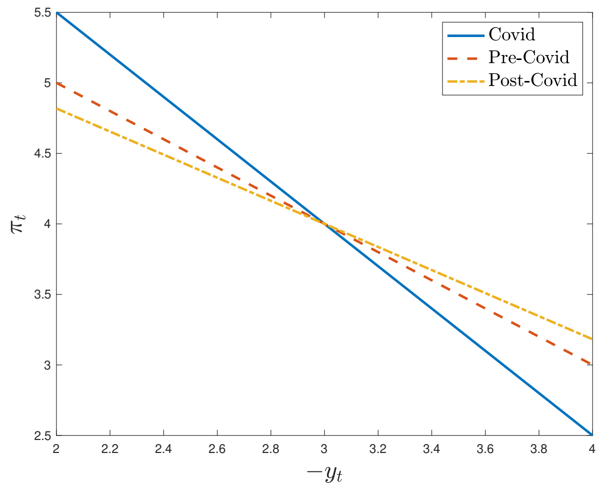
Let $\pi_t \equiv p_t - p_{t-1}$ denote the aggregate inflation rate and $y_t \equiv q_t - p_t$ denote the aggregate output. The Phillips Curve then equals

$$\pi_t = \frac{G_t}{1 - G_t}(y_t + \omega_t) \tag{32}$$

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 8 shows the slope of the Phillips curve in Equation (32) with the belief rigidity in the pre-pandemic, pandemic, and post-pandemic period estimated in section 3.2. 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

Figure 8: Phillips Curve with estimated rigidity



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 (32) 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 (32) 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).

7 Conclusion

In this paper, we investigated the relationship between fundamental uncertainty, news uncertainty, and the household belief updating process. We used the NY Fed Survey of Consumer Expectations and a very general framework of belief updating, encompassing various Bayesian and behavioral models of belief formation, to estimate the empirical relationship between different uncertainty sources and household belief rigidity in recent times.

We found a negative association between household uncertainty and belief rigidity during the Covid outbreak, and a positive relation during the ensuing high inflation period post-Covid. We rationalized these findings with our theoretical framework of belief updating to show that different uncertainty sources influence belief rigidity in distinct ways. In particular, fundamental volatility increases prior uncertainty, which makes households seek information and update more, resulting in lower belief rigidity. On the other hand, an increase in new information uncertainty makes households search and update less, resulting in higher belief rigidity.

We then empirically retested these theoretical mechanisms using naturally occurring variation in information provision, confirming that the relationship between uncertainty and belief rigidity is in line with a large class of behavioral models, including but not limited to the Bayesian framework.

Understanding when households pay attention to information about macroeconomic conditions has important policy implications. When agents' belief rigidity is high, the relationship between employment and inflation loosens, forward guidance is less powerful, and there is a greater risk of facing a liquidity trap. Each of these implications is central to monetary policy decisions, and studying how belief rigidity varies across settings is an important objective for academic and applied research.

References

Afrouzi, H. and C. Yang (2021). Dynamic rational inattention and the phillips curve. Technical report.

Altig, D., S. Baker, J. M. Barrero, N. Bloom, P. Bunn, S. Chen, S. J. Davis, J. Leather, B. Meyer, E. Mihaylov, et al. (2020). Economic uncertainty before and during the covid-19 pandemic. *Journal of public economics 191*, 104274.

Angeletos, G.-M. and Z. Huo (2021, April). Myopia and anchoring. *American Economic Review 111*(4), 1166–1200.

Angeletos, G.-M., Z. Huo, and K. A. Sastry (2021). Imperfect macroeconomic expectations: Evidence and theory. *NBER Macroeconomics Annual 35*(1), 1–86.

Armantier, O., G. Koşar, R. Pomerantz, D. Skandalis, K. Smith, G. Topa, and W. Van der Klaauw (2021). How economic crises affect inflation beliefs: Evidence from the covid-19 pandemic. *Journal of Economic Behavior & Organization 189*, 443–469.

Armantier, O., S. Nelson, G. Topa, W. Van der Klaauw, and B. Zafar (2016). The price is right: Updating inflation expectations in a randomized price information experiment. *Review of Economics and Statistics 98*(3), 503–523.

Armantier, O., G. Topa, W. Van der Klaauw, and B. Zafar (2017). An overview of the survey of consumer expectations. *Economic Policy Review* (23-2), 51–72.

Armona, L., A. Fuster, and B. Zafar (2019). Home price expectations and behaviour: Evidence from a randomized information experiment. *The Review of Economic Studies 86*(4), 1371–1410.

Baker, S. R., N. Bloom, and S. J. Davis (2016). Measuring economic policy uncertainty. *The quarterly journal of economics 131*(4), 1593–1636.

Baker, S. R., S. J. Davis, and J. A. Levy (2022). State-level economic policy uncertainty. *Journal of Monetary Economics 132*, 81–99.

Benhima, K. and E. Bolliger (2022). Do local forecasters have better information? *Available at SSRN 4294565*.

Bloom, N. (2009). The impact of uncertainty shocks. *econometrica 77*(3), 623–685.

Bloom, N., M. Floetotto, N. Jaimovich, I. Saporta-Eksten, and S. J. Terry (2018). Really uncertain business cycles. *Econometrica 86*(3), 1031–1065.

Boehm, C. E. and N. Pandalai-Nayar (2022). Convex supply curves. *American Economic Review 112*(12), 3941–3969.

Bordalo, P., N. Gennaioli, Y. Ma, and A. Shleifer (2020). Overreaction in macroeconomic expectations. *American Economic Review 110*(9), 2748–82.

Bordalo, P., N. Gennaioli, and A. Shleifer (2018). Diagnostic expectations and credit cycles. *The Journal of Finance 73*(1), 199–227.

Broer, T. and A. Kohlhas (2018). Forecaster (mis-) behavior. Technical report.

Cascaldi-Garcia, D., C. Sarisoy, J. M. Londono, B. Sun, D. D. Datta, T. Ferreira, O. Grishchenko, M. R. Jahan-Parvar, F. Loria, S. Ma, et al. (2023). What is certain about uncertainty? *Journal of Economic Literature 61*(2), 624–654.

Cavallo, A., G. Cruces, and R. Perez-Truglia (2017). Inflation expectations, learning, and supermarket prices: Evidence from survey experiments. *American Economic Journal: Macroeconomics 9*(3), 1–35.

Cerrato, A. and G. Gitti (2022, December). Inflation since covid: Demand or supply. https://ssrn.com/abstract=4193594. Available at SSRN: https://ssrn.com/abstract=4193594 or http://dx.doi.org/10.2139/ssrn.4193594.

Coibion, O., D. Georgarakos, Y. Gorodnichenko, G. Kenny, and M. Weber (2021). The effect of macroeconomic uncertainty on household spending. Technical report, National Bureau of Economic Research.

Coibion, O., D. Georgarakos, Y. Gorodnichenko, G. Kenny, and M. Weber (2024). The effect of macroeconomic uncertainty on household spending. *American Economic Review*. Forthcoming.

Coibion, O. and Y. Gorodnichenko (2012). What can survey forecasts tell us about information rigidities? *Journal of Political Economy 120*(1), 116–159.

Coibion, O. and Y. Gorodnichenko (2015). Information rigidity and the expectations formation process: A simple framework and new facts. *American Economic Review 105*(8), 2644–78.

Coibion, O., Y. Gorodnichenko, and R. Kamdar (2018). The formation of expectations, inflation, and the phillips curve. *Journal of Economic Literature 56*(4), 1447–1491.

Coibion, O., Y. Gorodnichenko, and S. Kumar (2018). How do firms form their expectations? new survey evidence. *American Economic Review 108*(9), 2671–2713.

Coibion, O., Y. Gorodnichenko, and M. Weber (2022). Monetary policy communications and their effects on household inflation expectations. *Journal of Political Economy 130*(6), 1537–1584.

Conlon, J. J., L. Pilossoph, M. Wiswall, and B. Zafar (2018). Labor market search with imperfect information and learning. Technical report, National Bureau of Economic Research.

De Bruin, W. B., C. F. Manski, G. Topa, and W. Van Der Klaauw (2011). Measuring consumer uncertainty about future inflation. *Journal of Applied Econometrics 26*(3), 454–478.

Engelberg, J., C. F. Manski, and J. Williams (2009). Comparing the point predictions and subjective probability distributions of professional forecasters. *Journal of Business & Economic Statistics 27*(1), 30–41.

Eusepi, S. and B. Preston (2011). Expectations, learning, and business cycle fluctuations. *American Economic Review 101*(6), 2844–2872.

Fermand, E., C. M. Kuhnen, G. Li, and I. Ben-David (Forthcoming in 2024). Extrapolative uncertainty and household economic behavior. Technical report.

Fuster, A., D. Laibson, and B. Mendel (2010). Natural expectations and macroeconomic fluctuations. *Journal of Economic Perspectives 24*(4), 67–84.

Fuster, A., R. Perez-Truglia, M. Wiederholt, and B. Zafar (2022). Expectations with endogenous information acquisition: An experimental investigation. *Review of Economics and Statistics 104*(5), 1059–1078.

Gabaix, X. (2017). Behavioral inattention. Technical report, National Bureau of Economic Research.

Galí, J. (2015). *Monetary policy, inflation, and the business cycle: an introduction to the new Keynesian framework and its applications*. Princeton University Press.

Gambetti, L., D. Korobilis, J. Tsoukalas, and F. Zanetti (2023). Agreed and disagreed uncertainty. *arXiv preprint arXiv:2302.01621*.

Gemmi, L. and R. Valchev (2023). Biased surveys. Technical report.

Goldstein, N. (2023). Tracking inattention. *Journal of the European Economic Association*, jvad022.

Gudmundsson, T., C. Jackson, and R. Portillo (2024). The shifting and steepening of phillips curves during the pandemic recovery: International evidence and some theory.

Hale, T., N. Angrist, B. Kira, A. Petherick, T. Phillips, and S. Webster (2020). Variation in government responses to covid-19.

Hallas, L., A. Hatibie, S. Majumdar, M. Pyarali, and T. Hale (2021). Variation in us states' responses to covid-19. *University of Oxford*.

Harding, M., J. Lindé, and M. Trabandt (2023). Understanding post-covid inflation dynamics. *Journal of Monetary Economics 140*, S101–S118.

Hazell, J., J. Herreno, E. Nakamura, and J. Steinsson (2022). The slope of the phillips curve: evidence from us states. *The Quarterly Journal of Economics 137*(3), 1299–1344.

Jurado, K., S. C. Ludvigson, and S. Ng (2015). Measuring uncertainty. *American Economic Review 105*(3), 1177–1216.

Kumar, S., Y. Gorodnichenko, and O. Coibion (2023). The effect of macroeconomic uncertainty on firm decisions. *Econometrica 91*(4), 1297–1332.

Link, S., A. Peichl, C. Roth, and J. Wohlfart (2023). Information frictions among firms and households. *Journal of Monetary Economics 135*, 99–115.

Link, S., A. Peichl, C. Roth, and J. Wohlfart (2024). Attention to the macroeconomy. *Available at SSRN 4697814*.

Lusardi, A. (2008). Household saving behavior: The role of financial literacy, information, and financial education programs. Technical report, National Bureau of Economic Research.

Maćkowiak, B., F. Matějka, and M. Wiederholt (2023). Rational inattention: A review. *Journal of Economic Literature 61*(1), 226–273.

Mackowiak, B. and M. Wiederholt (2009). Optimal sticky prices under rational inattention. *American Economic Review 99*(3), 769–803.

Malmendier, U. and S. Nagel (2016). Learning from inflation experiences. *The Quarterly Journal of Economics 131*(1), 53–87.

Mankiw, N. G. and R. Reis (2002). Sticky information versus sticky prices: a proposal to replace the new keynesian phillips curve. *The Quarterly Journal of Economics 117*(4), 1295–1328.

Manski, C. F. (2004). Measuring expectations. *Econometrica 72*(5), 1329–1376.

Manski, C. F. (2018). Survey measurement of probabilistic macroeconomic expectations: progress and promise. *NBER Macroeconomics Annual 32*(1), 411–471.

Mikosch, H., C. Roth, S. Sarferaz, and J. Wohlfart (2024). Uncertainty and information acquisition: Evidence from firms and households. *American Economic Journal: Macroeconomics 16*(2), 375–405.

Negro, M. D., M. Lenza, G. E. Primiceri, and A. Tambalotti (2020). What's up with the phillips curve? *Brookings Papers on Economic Activity*, 301–357.

Ottaviani, M. and P. N. Sørensen (2006). The strategy of professional forecasting. *Journal of Financial Economics 81*(2), 441–466.

Pomatto, L., P. Strack, and O. Tamuz (2023). The cost of information: The case of constant marginal costs. *American Economic Review 113*(5), 1360–1393.

Roth, C., S. Settele, and J. Wohlfart (2022). Risk exposure and acquisition of macroeconomic information. *American Economic Review: Insights 4*(1), 34–53.

Roth, C. and J. Wohlfart (2020). How do expectations about the macroeconomy affect personal expectations and behavior? *Review of Economics and Statistics 102*(4), 731–748.

Sims, C. A. (2003). Implications of rational inattention. *Journal of monetary Economics 50*(3), 665–690.

Wang, T. (2024). How do agents form macroeconomic expectations? evidence from inflation uncertainty. Technical report, Bank of Canada Staff Working Paper.

Weber, M., B. Candia, H. Afrouzi, T. Ropele, R. Lluberas, S. Frache, B. Meyer, S. Kumar, Y. Gorodnichenko, D. Georgarakos, et al. (2024). Tell me something i don't already know: Learning in low and high-inflation settings.

Woodford, M. (2001). Imperfect common knowledge and the effects of monetary policy. Technical report, National Bureau of Economic Research.

Appendix

A Belief formation models

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

- Rational expectations: $G_t^{RE} = \frac{\tau_t}{\tau_t + \Sigma_{t+h,t-1}^{-1}}$, where $\Sigma_{t+h,t-1} \equiv var(x_{t+h} - E_{t-1}^i[x_{t+h}])$ is the prior variance (Sims, 2003; Woodford, 2001; Mackowiak and Wiederholt, 2009). In the case of full-information, the signal is perfectly informative, $\tau_t \to \infty$, and therefore $G_t = 1$.

- Diagnostic expectation: households overreact to new information according to $\theta > 0$, therefore $G_t = (1+\theta)G_t^{RE}$ (Bordalo et al., 2018, 2020).

- Overconfidence: households perceived signal accuracy as more accurate, $\tilde{\tau}_t > \tau_t$, and therefore $G_t = \frac{\tilde{\tau}_t}{\tilde{\tau}_t + \Sigma_{t+h,t-1}^{-1}} > G_t^{RE}$ (Broer and Kohlhas, 2018).

- 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)

- Strategic behavior among forecasters: agents do not reveal true beliefs to the survey but a biased version where $G_t = \frac{G_t^{RE}}{(1-\lambda)+\lambda G_t^{RE}}$. With strategic diversification incentives, $0 > \lambda > 1$ and $G_t > G_t^{RE}$, while with strategic herding incentives $-1 < \lambda < 0$ and $G_t < G_t^{RE}$ (Ottaviani and Sørensen, 2006; Gemmi and Valchev, 2023).

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 λ 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 Additional tables

Table A.1: Heterogeneity in Belief Updating

	(1) *For 3y*	(2) *For 3y*	(3) *For 3y*	(4) *For 3y*	(5) *For 3y*	(6) *For 3y*	(7) *For 3y*
Prior	0.376***	0.480***	0.549***	0.526***	0.500***	0.510***	0.324***
	(0.022)	(0.026)	(0.017)	(0.019)	(0.018)	(0.026)	(0.047)
Tenure=2 × *Prior*	0.159***						0.161***
	(0.027)						(0.027)
Tenure=3 × *Prior*	0.260***						0.261***
	(0.023)						(0.023)
$College_{it}$ =1 × *Prior*		0.055**					0.053*
		(0.028)					(0.027)
*Age Over*60=1 × *Prior*			-0.026				-0.036
			(0.024)				(0.025)
*Age Under*40=1 × *Prior*			-0.060**				-0.053**
			(0.024)				(0.023)
*Income Over*100*k*=1 × *Prior*				0.008			0.001
				(0.027)			(0.027)
*Income Under*50*k*=1 × *Prior*				-0.007			0.008
				(0.021)			(0.021)
High Numeracy=1 × *Prior*					0.047***		0.036**
					(0.017)		(0.017)
Female=1 × *Prior*						-0.018	-0.014
						(0.024)	(0.024)
White=1 × *Prior*						0.033	0.031
						(0.025)	(0.024)
Constant	1.867***	1.897***	1.913***	1.910***	1.873***	1.892***	1.797***
	(0.049)	(0.051)	(0.052)	(0.051)	(0.047)	(0.050)	(0.044)
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	0.33	0.32	0.32	0.32	0.32	0.32	0.34
Observations	90959	90959	90959	90959	90959	90959	90959

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)	(2)	(3)
	For 3y	*For 3y*	*For 3y*
Prior 3y	0.515***	0.486***	0.474***
	(0.011)	(0.011)	(0.011)
Covid=1 × *Prior 3y*		-0.084***	-0.088***
		(0.028)	(0.026)
Post − Covid=1 × *Prior 3y*		0.082***	0.065***
		(0.019)	(0.018)
Constant	1.960***	2.039***	2.106***
	(0.049)	(0.037)	(0.037)
Year-Month FEs	Y	Y	Y
Age, Gender, Race FEs	Y	Y	Y
Tenure FEs	Y	Y	Y
Adjusted R-squared	0.33	0.33	0.31
Observations	83405	83405	80402

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) *For 3y*	(2) *For 3y*	(3) *For 3y*	(4) *For 3y*	(5) *For 3y*	(6) *For 3y*	(7) *For 3y*	(8) *For 3y*	(9) *For 3y*	(10) *For 3y*
Prior 3y	0.492***	0.522***	0.542***	0.529***	0.487***	0.499***	0.480***	0.495***	0.523***	0.558***
	(0.119)	(0.117)	(0.120)	(0.118)	(0.116)	(0.114)	(0.116)	(0.113)	(0.106)	(0.115)
Prior 3y × *ln(DeathsCOVID)*	-0.023*	-0.016	-0.013	-0.015	-0.022*	-0.019	-0.023*	-0.021	-0.014	-0.012
	(0.012)	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Prior 3y × *ln(CasesCOVID)*	0.030	0.023	0.022	0.024	0.031	0.026	0.030	0.030	0.022	0.020
	(0.020)	(0.020)	(0.021)	(0.020)	(0.020)	(0.020)	(0.021)	(0.020)	(0.021)	(0.020)
Prior 3y × *School*	-0.026								0.019	
	(0.018)								(0.024)	
Prior 3y × *Workplace*		-0.076***							-0.053	
		(0.017)							(0.041)	
Prior 3y × *Event*			-0.071***						-0.010	
			(0.022)						(0.038)	
Prior 3y × *Gathering*				-0.035***					-0.016	
				(0.007)					(0.018)	
Prior 3y × *Transport*					-0.093***				-0.039	
					(0.030)				(0.034)	
Prior 3y × *StayAtHome*						-0.073***			0.009	
						(0.022)			(0.039)	
Prior 3y × *Movements*							-0.054**		0.050*	
							(0.022)		(0.028)	
Prior 3y × *Travel*								-0.102***	-0.083**	
								(0.027)	(0.036)	
Prior 3y × *Lockdown*										-0.098***
										(0.020)
Constant	2.111**	2.004**	1.988**	2.058**	2.248***	2.043**	2.243***	2.166***	2.164***	1.966**
	(0.877)	(0.784)	(0.771)	(0.783)	(0.768)	(0.801)	(0.776)	(0.761)	(0.776)	(0.797)
Year-Month FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Socio-democraphic 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	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35
Observations	24051	24769	24769	24769	24769	24769	24769	24769	24769	24769

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) *For 3y*	(2) *For 3y*	(3) *For 3y*	(4) *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 $p < 0.01$.

D Shorter forecast horizon

Table A.6: Belief rigidity

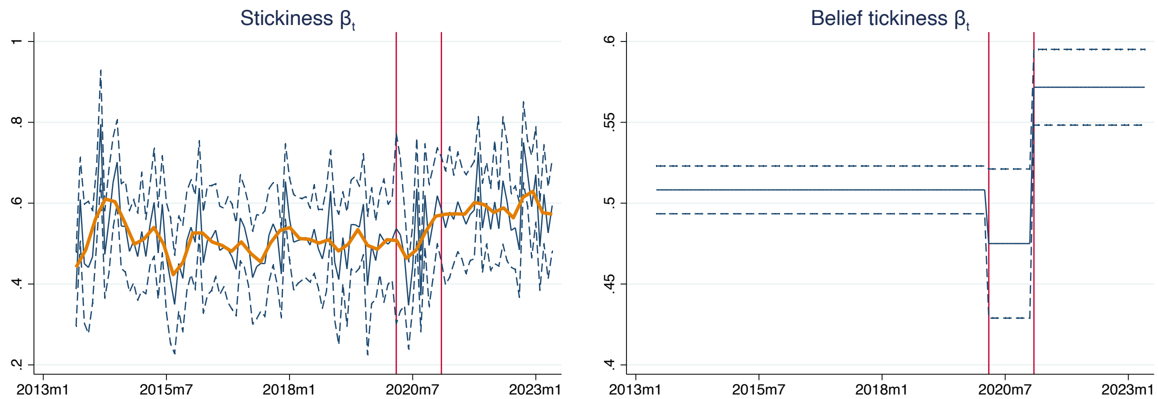
	(1)	(2)	(3)
	For 1y	*For 1y*	*For 1y*
Prior 1y	0.526***	0.506***	0.348***
	(0.010)	(0.010)	(0.019)
$Prior\ 1y \times Tenure_{it}$			0.028***
			(0.002)
$High\ Numeracy_{it}$=1 × *Prior 1y*			0.025
			(0.016)
Constant	2.093***	2.186***	2.013***
	(0.046)	(0.046)	(0.046)
Year-Month FEs	Y	Y	Y
Socio-democraphic FEs	Y	Y	Y
Adjusted R-squared	0.40	0.38	0.41
Observations	90231	86631	90231

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 $p < 0.01$.

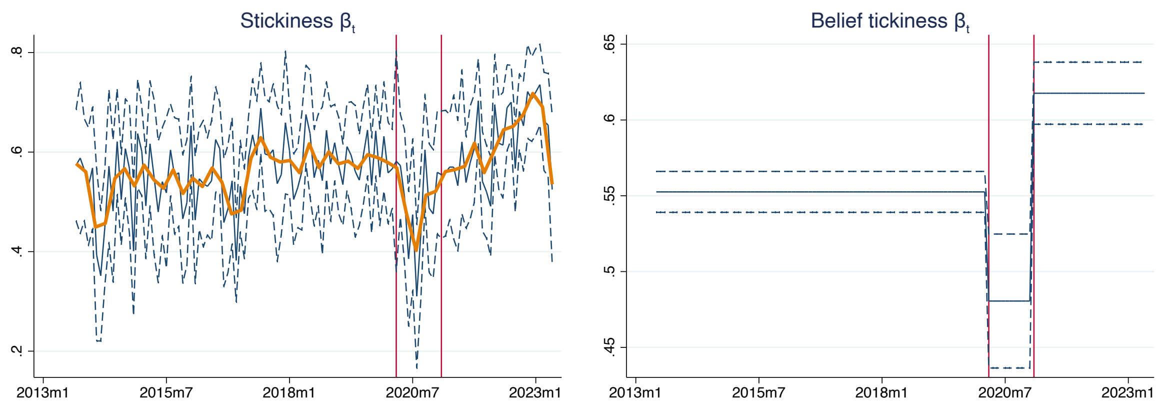
Figure A.1: Belief rigidity pre- and post-pandemic

Belief rigidity β month-by-month | Belief rigidity β by periods

1-year ahead inflation | 1-year ahead inflation



1-year ahead housing price | 1-year ahead housing price



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 β 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)	(2)	(3)
	For H	*For H*	*For H*
Prior H	0.570***	0.555***	0.418***
	(0.011)	(0.010)	(0.026)
$Prior\ H \times Tenure_{it}$			0.020***
			(0.002)
$High\ Numeracy_{it}$=1 $\times$ *Prior H*			0.039**
			(0.018)
Constant	2.165***	2.231***	2.110***
	(0.056)	(0.054)	(0.047)
Year-Month FEs	Y	Y	Y
Socio-democraphic FEs	Y	Y	Y
Adjusted R-squared	0.40	0.39	0.41
Observations	83475	81335	83475

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 $p < 0.01$.

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

	(1) *For 1y*	(2) *For 1y*	(3) *For 1y*	(4) *For 1y*	(5) *For 1y*
Prior 1y	0.535***	0.572**	0.635**	0.612**	0.637**
	(0.136)	(0.254)	(0.253)	(0.262)	(0.255)
$Prior\ 1y \times Lockdown$	-0.044	-0.047	-0.066	-0.053	-0.062
	(0.028)	(0.043)	(0.047)	(0.047)	(0.046)
$Prior\ 1y \times ln(DeathsCOVID)$	-0.009	-0.024	-0.022	-0.021	-0.021
	(0.018)	(0.037)	(0.036)	(0.037)	(0.036)
$Prior\ 1y \times ln(CasesCOVID)$	0.013	0.043	0.046	0.043	0.045
	(0.015)	(0.027)	(0.027)	(0.027)	(0.027)
$Prior\ 1y \times \Delta ln(EPUState)$			0.057**		
			(0.024)		
$Prior\ 1y \times \Delta ln(EPUNational)$				0.032	
				(0.025)	
$Prior\ 1y \times \Delta ln(EPUComposite)$					0.062*
					(0.031)
Constant	3.612***	3.001**	2.700**	2.848**	2.738**
	(0.884)	(1.229)	(1.207)	(1.242)	(1.212)
Year-Month FEs	Y	Y	Y	Y	Y
Socio-democraphic FEs	Y	Y	Y	Y	Y
Non-interacted variables	Y	Y	Y	Y	Y
Sample	Mar20-May23	Mar20-Jun21	Mar20-Jun21	Mar20-Jun21	Mar20-Jun21
Adjusted R-squared	0.40	0.34	0.34	0.34	0.34
Observations	24564	11197	11197	11197	11197

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.

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

	(1) *For H*	(2) *For H*	(3) *For H*	(4) *For H*	(5) *For H*
Prior H	0.494***	0.656***	0.655***	0.664***	0.673***
	(0.110)	(0.181)	(0.167)	(0.171)	(0.164)
Prior H $\times$ *Lockdown*	-0.094***	-0.061*	-0.061*	-0.063*	-0.065**
	(0.022)	(0.033)	(0.030)	(0.032)	(0.030)
Prior H $\times$ $ln(DeathsCOVID)$	-0.002	0.000	0.000	0.001	0.001
	(0.013)	(0.025)	(0.025)	(0.025)	(0.025)
Prior H $\times$ $ln(CasesCOVID)$	-0.020	0.014	0.014	0.014	0.015
	(0.016)	(0.023)	(0.023)	(0.023)	(0.023)
Prior H $\times$ $\Delta ln(EPUState)$			-0.000		
			(0.025)		
Prior H $\times$ $\Delta ln(EPUNational)$				0.006	
				(0.024)	
Prior H $\times$ $\Delta ln(EPUComposite)$					0.017
					(0.028)
Constant	2.508**	1.528	1.531	1.492	1.458
	(1.098)	(1.021)	(0.988)	(1.025)	(0.990)
Year-Month FEs	Y	Y	Y	Y	Y
Socio-democraphic FEs	Y	Y	Y	Y	Y
Non-interacted variables	Y	Y	Y	Y	Y
Sample	Mar20-May23	Mar20-Jun21	Mar20-Jun21	Mar20-Jun21	Mar20-Jun21
Adjusted R-squared	0.43	0.37	0.37	0.37	0.37
Observations	22647	10400	10400	10400	10400

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.

Table A.10: Belief rigidity and lockdown measures

	(1) $ln(PostUncert1y)$	(2) $ln(PostUncert1y)$	(3) $ln(PostUncert1y)$	(4) $ln(PostUncertIQR1y)$
$Lockdown$	-0.266***	-0.272***	-0.124***	-0.091***
	(0.036)	(0.037)	(0.023)	(0.020)
$ln(PriorUncert1y)$			0.491***	
			(0.023)	
$ln(PriorUncertIQR1y)$				0.441***
				(0.020)
$ln(DeathsCOVID)$			-0.010	-0.003
			(0.014)	(0.013)
$ln(CasesCOVID)$			-0.007	-0.007
			(0.010)	(0.011)
$\Delta ln(EPUNational)$			0.025**	0.020**
			(0.011)	(0.009)
Constant	1.110***	1.114***	0.430***	0.695***
	(0.030)	(0.024)	(0.111)	(0.097)
State FEs	N	Y	Y	Y
Sample	Mar20-May23	Mar20-May23	Mar20-May23	Mar20-May23
Adjusted R-squared	0.16	0.33	0.53	0.49
Observations	1713	1713	1674	1681

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 $p < 0.01$.

Table A.11: Belief rigidity and lockdown measures

	(1) $ln(PostUncertH)$	(2) $ln(PostUncertH)$	(3) $ln(PostUncertH)$	(4) $ln(PostUncertIQRH)$
$Lockdown$	-0.205***	-0.213***	-0.098***	-0.081***
	(0.031)	(0.033)	(0.017)	(0.017)
$ln(PriorUncertH)$			0.501***	
			(0.036)	
$ln(PriorUncertIQRH)$				0.484***
				(0.029)
$ln(DeathsCOVID)$			0.012	0.014*
			(0.009)	(0.008)
$ln(CasesCOVID)$			-0.000	-0.008
			(0.009)	(0.007)
$\Delta ln(EPUNational)$			0.018*	0.019**
			(0.010)	(0.008)
Constant	1.192***	1.197***	0.697***	0.843***
	(0.025)	(0.020)	(0.075)	(0.060)
State FEs	N	Y	Y	Y
Sample	Mar20-May23	Mar20-May23	Mar20-May23	Mar20-May23
Adjusted R-squared	0.11	0.20	0.46	0.49
Observations	1699	1699	1656	1667

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 $p < 0.01$.

Table A.12: Belief rigidity and uncertainty

	(1)	(2)	(3)	(4)
	For 1y	*For 1y*	*For 1y*	*For 1y*
Prior 1y	0.537***	0.538***		0.551***
	(0.025)	(0.016)		(0.025)
Prior 1y × *PriorUncert*	-0.135***		-0.139***	-0.136***
	(0.013)		(0.013)	(0.014)
Prior 1y × *PostUncert*	0.129***		0.121***	0.125***
	(0.012)		(0.012)	(0.013)
Prior 1y × *Prior Uncert 1y IQR*		-0.014***		
		(0.003)		
Prior 1y × *Post Uncert 1y IQR*		0.009***		
		(0.003)		
Constant	0.642***	1.151***	3.144***	0.631***
	(0.085)	(0.068)	(0.081)	(0.090)
Year-Month FEs	Y	Y	Y	Y
Prior-Year-Month FEs	N	N	Y	N
Socio-demographic FEs	Y	Y	Y	Y
Non-interacted variables	Y	Y	Y	Y
Sample	Jun13-May23	Jun13-May23	Jun13-May23	excludeCOVID
Adjusted R-squared	0.44	0.44	0.45	0.46
Observations	90231	90231	90231	82857

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 same forecast provided in the previous month. $PostUncert1y$ denotes the individual 1-year ahead forecast of inflation expectations uncertainty from the NY FED Survey of Consumer Expectations (SCE). $PriorUncert1y$ is the same variable but from the previous month. $PostUncert1yIQR$ and $PriorUncert1yIQR$ are similar but use the interquartile range to measure uncertainty instead of fitting a generalized-beta distribution. *Lockdown* is the average of the lockdown policy intensity indicators from Hale et al. (2020). 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 $p < 0.01$.

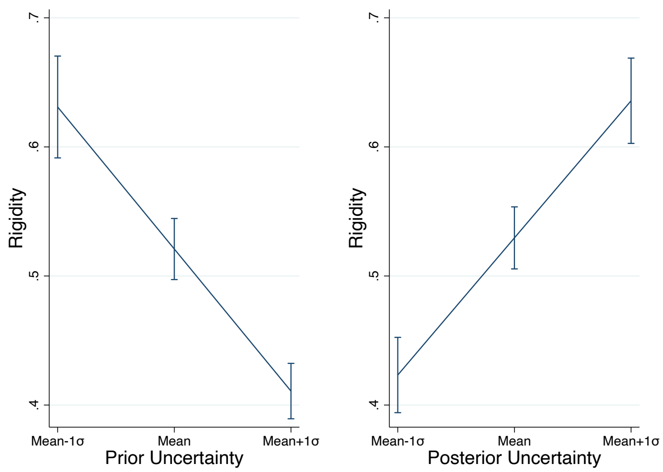
Table A.13: Belief rigidity and uncertainty

	(1)	(2)	(3)	(4)
	For H	*For H*	*For H*	*For H*
Prior H	0.578***	0.577***		0.573***
	(0.022)	(0.014)		(0.022)
Prior H × *PriorUncert*	-0.153***		-0.154***	-0.144***
	(0.010)		(0.010)	(0.010)
Prior H × *PostUncert*	0.152***		0.148***	0.149***
	(0.011)		(0.011)	(0.012)
Prior H		0.000		
		(0.000)		
Prior H × *Prior Uncert H IQR*		-0.020***		
		(0.002)		
Prior H × *Post Uncert H IQR*		0.017***		
		(0.003)		
Constant	0.502***	1.142***	3.494***	0.535***
	(0.116)	(0.081)	(0.096)	(0.109)
Year-Month FEs	Y	Y	Y	Y
Prior-Year-Month FEs	N	N	Y	N
Socio-demographic FEs	Y	Y	Y	Y
Non-interacted variables	Y	Y	Y	Y
Sample	Jun13-May23	Jun13-May23	Jun13-May23	excludeCOVID
Adjusted R-squared	0.44	0.44	0.45	0.45
Observations	83475	83475	83475	76535

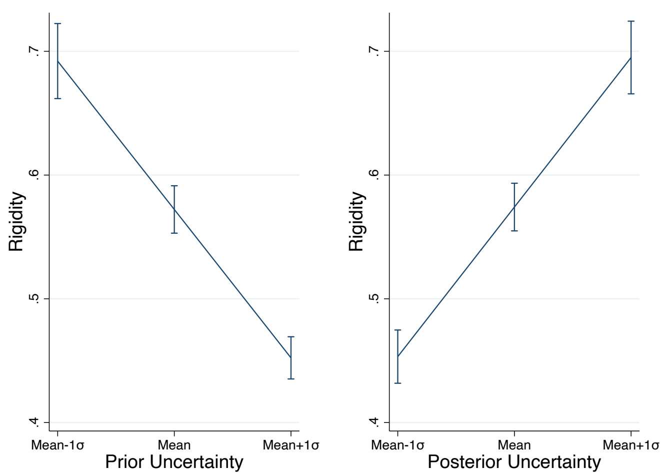
Legend: $Forh_{i,t}$ denotes the 1-year ahead forecast of housing price inflation expectations from the NY FED Survey of Consumer Expectations (SCE). $Prior\ h_{i,t}$ is the same forecast provided in the previous month. $PostUncerth$ denotes the individual 1-year ahead forecast of housing price inflation expectations uncertainty from the NY FED Survey of Consumer Expectations (SCE). $PriorUncerth$ is the same variable but from the previous month. $PostUncerthIQR$ and $PriorUncerthIQR$ are similar but use the interquartile range to measure uncertainty instead of fitting a generalized-beta distribution. *Lockdown* is the average of the lockdown policy intensity indicators from Hale et al. (2020). 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 and uncertainty: shorter horizon

CPI inflation



Housing price inflation



Legend: The figure represents graphically the estimated coefficients from column (1) of Tables A.12 and A.13. It shows the relationship between belief rigidity β and prior uncertainty (on the left-hand side) and posterior uncertainty (on the right-hand side).

Table A.14: Belief rigidity and uncertainty for different numeracy skill

	(1) *For 1y*	(2) *For 1y*	(3) *For 1y*	(4) *For 1y*
Prior 1y	0.540***	0.519***	0.558***	0.556***
	(0.010)	(0.014)	(0.024)	(0.029)
$High\ Numeracy_{it}$=1 × *Prior 1y*		0.026	0.019	0.027
		(0.016)	(0.016)	(0.028)
Prior 1y × *ln*(*Prior Uncert1y*)			-0.156***	-0.088***
			(0.014)	(0.024)
Prior 1y × *ln*(*Post Uncert1y*)			0.131***	0.058***
			(0.013)	(0.019)
$High\ Numeracy_{it}$=1 × *Prior 1y* × *ln*(*Prior Uncert1y*)				-0.121***
				(0.024)
$High\ Numeracy_{it}$=1 × *Prior 1y* × *ln*(*Post Uncert1y*)				0.131***
				(0.023)
Constant	2.030***	2.745***	1.633***	1.528***
	(0.047)	(0.081)	(0.110)	(0.135)
Year-Month FEs	Y	Y	Y	Y
Socio-demographic FEs	Y	Y	Y	Y
Non-interacted variables	Y	Y	Y	Y
Adjusted R-squared	0.39	0.40	0.43	0.43
Observations	91127	91111	74315	74315

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 same forecast provided in the previous month. $PostUncert1y$ denotes the individual 1-year ahead forecast of inflation expectations uncertainty from the NY FED Survey of Consumer Expectations (SCE). $PriorUncert1y$ 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 $p < 0.01$.

Table A.15: Belief rigidity and uncertainty for different numeracy skill

	(1) *For H*	(2) *For H*	(3) *For H*	(4) *For H*
Prior H	0.580***	0.553***	0.534***	0.598***
	(0.011)	(0.019)	(0.021)	(0.035)
High Numeracy$_{it}$=1 × *Prior H*		0.038**	0.064***	-0.038
		(0.018)	(0.017)	(0.039)
Prior H × *ln*(*Prior UncertH*)			-0.156***	-0.120***
			(0.010)	(0.022)
Prior H × *ln*(*Post UncertH*)			0.165***	0.088***
			(0.010)	(0.018)
High Numeracy$_{it}$=1 × *Prior H* × *ln*(*Prior UncertH*)				-0.048*
				(0.025)
High Numeracy$_{it}$=1 × *Prior H* × *ln*(*Post UncertH*)				0.124***
				(0.020)
Constant	2.114***	2.963***	2.235***	1.382***
	(0.057)	(0.114)	(0.140)	(0.189)
Year-Month FEs	Y	Y	Y	Y
Socio-demographic FEs	Y	Y	Y	Y
Non-interacted variables	Y	Y	Y	Y
Adjusted R-squared	0.40	0.40	0.44	0.44
Observations	84316	84298	73669	73669

Legend: $Forh_{i,t}$ denotes the 1-year ahead forecast of housing price inflation expectations from the NY FED Survey of Consumer Expectations (SCE). $Prior\ h_{i,t}$ is the same forecast provided in the previous month. $PostUncerth$ denotes the individual 1-year ahead forecast of housing price inflation expectations uncertainty from the NY FED Survey of Consumer Expectations (SCE). $PriorUncerth$ 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 $p < 0.01$.