Household Belief Formation in Uncertain Times*

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Abstract

We study the relationship between households' belief formation and uncertainty in the pre- and post-pandemic U.S. economy. We find that this relationship crucially depends on the source of uncertainty, in line with the predictions of a broad class of belief-updating models. In particular, we document a decline in belief rigidity at the pandemic's onset, driven by consumers' desire to seek new information to navigate a more uncertain economic landscape, and partly by the lockdown policies lowering information gathering costs. Moreover, we document an increase in belief rigidity in the subsequent period of high inflation, driven by a deterioration in the accuracy of new information, further increasing uncertainty. We show that this opposite impact of uncertainty sources on belief rigidity implies an opposite effect on the Phillips Curve slope, and therefore different macroeconomic implications.

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 emerged as a key feature of the economic landscape. Even before major uncertainty shocks such as COVID-19 and the Ukrainian conflict, Kristalina Georgieva, the Managing Director of the IMF, stated on January 24, 2020: "If I had to identify a theme at the outset of the new decade, it would be increasing uncertainty." A growing literature studies the effect of uncertainty on household spending and firm decisions, both at the macro level (Bloom, 2009; Jurado et al., 2015; Basu and Bundick, 2017) and with experiments and surveys (Coibion et al., 2021; Weber et al., 2023; Kumar et al., 2023). Despite this growing interest, the mechanism through which large shifts in uncertainty influence consumer belief formation and their broader macroeconomic consequences have received comparatively less attention

We investigate the determinants and dynamics of households' inflation expectations in the pre- and post-pandemic U.S. economy. This period is particularly suited for our analysis as it encompasses a significant rise in uncertainty due to the COVID-19 pandemic and subsequent periods of elevated inflation. (Armantier et al., 2021). Additionally, this era is characterized by various shocks to both the supply of and demand for new information, including lockdown measures and economic policy uncertainty. These conditions enable us to pinpoint potential drivers of households' attention choices.

We consider inflation expectations data from the Survey of Consumer Expectations (SCE) as they allow us to measure and compare households' receptiveness to new versus existing information when forming expectations, i.e. belief rigidity, and their belief uncertainty. This survey, which gathers monthly data from a rotating panel of households between June 2013 and May 2023 with approximately 1300 observations each month, offers two important advantages. First, the large cross-sectional dimension allows us to investigate the heterogeneity of belief rigidity and its dynamic over time.[1] Second, the density forecasts collected in the survey allow us to measure individual-level belief uncertainty and study its relation with belief updating.

We first document 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

[1] 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).

beliefs. Notably, this inverse 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.

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 diminishes the reliability of existing information, thereby increasing prior uncertainty. This has two consequences. Firstly, it makes posterior beliefs more uncertain. Secondly, as existing information becomes obsolete, 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 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 in their prior beliefs.

We test the model-predicted correlation between belief uncertainty and rigidity in the households' expectation data and find strong support. Specifically, we investigate the correlation between belief rigidity and both posterior and prior uncertainty, defined as self-reported inflation forecast uncertainty for the current and previous month, respectively.[2] We find that, after controlling for prior uncertainty, posterior 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.[3] 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 experimental data with mixed results, our study leverages naturally occurring variation within a comprehensive dataset of U.S. households.[5]

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.

[2] 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.

[3] 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%.

[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] 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. Finally, experiments considering inflation expectations find results similar to ours (Armantier et al., 2016; Cavallo et al., 2017; Coibion et al., 2018).

(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.[6] 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.

Contribution to the literature This paper contributes to several strands of the literature. A growing literature studies the effect of uncertainty on household spending and firm decisions, both at the macro level (Bloom, 2009; Jurado et al., 2015; Basu and Bundick, 2017) and with experiments and surveys (Coibion et al., 2021; Weber et al., 2023; Kumar et al., 2023). However, the influence of uncertainty on belief formation, particularly the rigidity in belief updating, remains less clear. Belief rigidity is crucial because it critically shapes agents' expectations, influencing individuals' consumption and investment decisions Coibion et al. (2024), as well as business cycle fluctuations and the effectiveness of central bank policies (Mackowiak and Wiederholt (2009), Paciello and Wiederholt (2014), and Reis (2006)). Second, our work contributes to the empirical literature on inflation belief formation (Woodford, 2001; Sims, 2003; Mackowiak and Wiederholt, 2009; Coibion and Gorodnichenko, 2015; Bordalo et al., 2020). Relative to these studies, we focus on households, instead of professional forecasters, because households have high information rigidities as they typically tend to be among the least informed economic agents in the economy. Third, our work contributes to the literature examining the role of information frictions for the Phillips curve. The integration of information frictions into the Phillips curve framework, particularly through the works of (Angeletos et al., 2020; Angeletos and Huo, 2021; Mankiw and Reis, 2002), complicates the traditional inflation-unemployment trade-off. Their research highlights how imperfect, sluggish, and dispersed information affects economic expectations and decisions, challenging the curve's assumptions and suggesting a more nuanced relationship between inflation and unemployment. Their work provides scenarios where

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

information about the economy disseminates slowly and imperfectly among the public, providing a theoretical underpinning for why adjustments in inflation expectations and, subsequently, in wages and prices might be more sluggish than the original Phillips curve model assumes. This body of work implies that economic policies based on the conventional Phillips curve might not fully account for the dynamics of expectation adjustments in response to new information, necessitating refined models that consider these complexities.

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.

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 mode, 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.[7] 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.

[7]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 information.

First, to measure expected mean inflation we use the point forecast provided by respondents.[8] 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 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.

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 ($HighNumeracy_{i,t}$).

[8]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.

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.

3.2 Empirical strategy

To estimate belief rigidity in expectation surveys, prior studies often relied on the approach pioneered by Coibion and Gorodnichenko (2012, 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); second, it requires a long time series dimension, rarely available in household surveys.[9] We instead adopt a novel methodology from Goldstein (2023) and Gemmi and Valchev (2023) that accurately

[9]The bias in the presence of common error in the signals was already recognized in Coibion and Gorodnichenko (2015) appendix. For a detailed description, see Goldstein (2023) and Gemmi and Valchev (2023)

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,[10]

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

Equation (3) provides an unbiased strategy to measure information rigidity. We run the following panel regression

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

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 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

[10] 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.

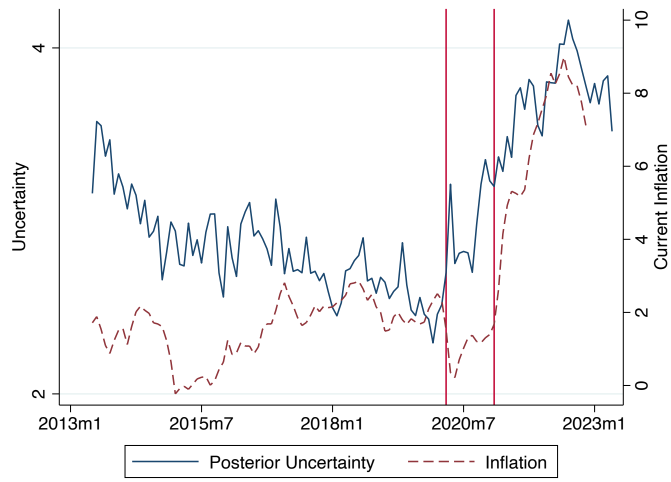
Table 2: Belief rigidity

	(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 × $Tenure_{it}$			0.031***
			(0.003)
$High\ Numeracy_{it}$=1 × *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-democraphic 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 socio-democratic fixed effects, 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 $p < 0.01$.

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.1 and A.2.

Figure 1: 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.

4 Household belief rigidity during uncertain times

4.1 Belief rigidity declines during the pandemic

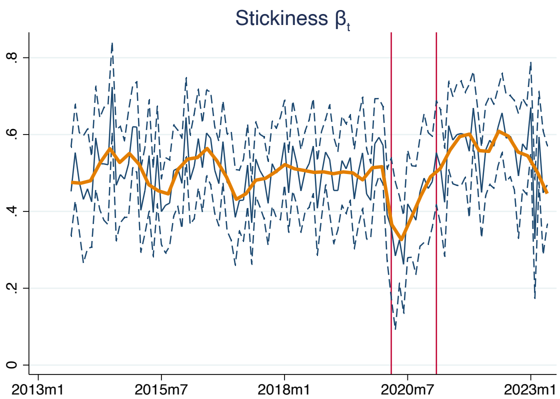
In this section, we exploit the large panel dimension of the SCE to study the time variation of belief rigidity in the period before and after the pandemic, to shed light on the relation between belief rigidity and uncertainty.

Figure 1 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 1) has been characterized by a 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 1).

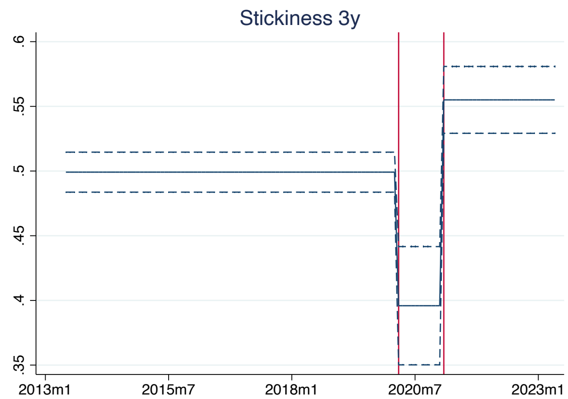
We investigate the evolution of belief rigidity across these two episodes of the COVID pandemic and the subsequent high inflation period. To do that, we compute belief rigidity month-by-month by exploiting the large cross-sectional dimension

Figure 2: 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.

of the SCE data. For each month t, we run the following regression

$$For_{i,t} = \alpha_t + \beta_t Prior_{i,t} + X_{i,t} + err_t^i \tag{5}$$

The left panel of Figure 2 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 2 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 2021). Table 7 reports the estimates, while Figure A.3 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. What is driving these large changes in belief rigidity, since uncertainty is high in both periods? 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.

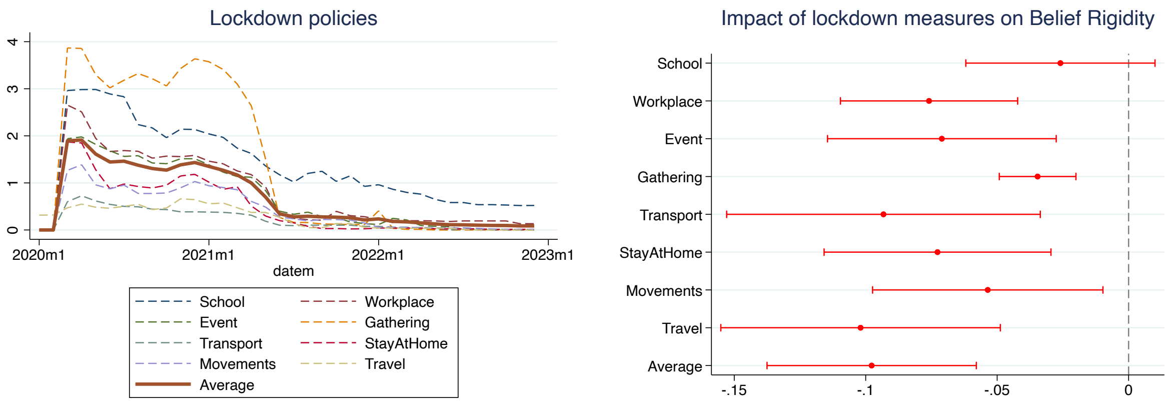
4.2 Information cost and belief rigidity: the case of lockdowns

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.[11] Figure 4(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 6 reports the

[11] 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 3: 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 (6). Sample period: 2020M3-2023M5.

summary statistics.

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

$$\begin{aligned} For_{i,t} =& \alpha + \beta_1 Prior_{i,t} + \beta_2 Prior_{i,t} \times LockdownIndex_{j,t} + \beta_3 LockdownIndex_{j,t} \\ & Prior_{i,t} \times CovidImpact'_{j,t}\Pi + CovidImpact'_{j,t}\Gamma + \gamma_t + err^i_t \end{aligned} \tag{6}$$

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 4(b) reports the estimated impact of lockdown indexes on belief rigidity, β_2, while Table 8 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 8, using the average index *Severity* to summarize the stringency of state-level lockdown policies. As shown in Figure 4(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.[12] Even controlling for state-level uncertainty, the estimated impact of lockdown policies on belief rigidity is significant and negative.[13]

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

$$x_{t+h} - E_t^i[x_{t+h}] = (1 - G_t)(x_{t+h} - E_{t-1}^i[x_{t+h}]) - G_t e_t^i \tag{7}$$

Equation (7) 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 7 one can derive the posterior belief uncertainty, which equals

$$\Sigma_{t+h,t} = (1 - G_t)^2 \Sigma_{t+h,t-1} + G_t^2 \sigma_{e,t}^2 \tag{8}$$

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

[12] Compared to the original measure, we re-scale the measure dividing the original score by 100 to facilitate the reading of the estimated coefficients.

[13] Tables A.3 and A.4 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***	0.794***	0.779***	0.803***
	(0.115)	(0.143)	(0.150)	(0.149)	(0.152)
Prior 3y × *Lockdown*	-0.098***	-0.113***	-0.091**	-0.090**	-0.074*
	(0.020)	(0.027)	(0.035)	(0.039)	(0.038)
Prior 3y × *ln(DeathsCOVID)*	-0.012	0.014	0.022	0.018	0.026
	(0.013)	(0.021)	(0.024)	(0.024)	(0.025)
Prior 3y × *ln(CasesCOVID)*	0.020	0.011	0.001	0.004	-0.004
	(0.020)	(0.020)	(0.023)	(0.022)	(0.023)
Prior 3y × *EPUState*			-0.010		
			(0.007)		
Prior 3y × *EPUNational*				-0.013	
				(0.014)	
Prior 3y × *EPUComposite*					-0.012*
					(0.006)
Constant	1.966**	1.457*	1.436*	1.569*	1.480*
	(0.797)	(0.726)	(0.745)	(0.779)	(0.778)
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	0.35	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 socio-democratic fixed effects, 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 $p < 0.01$.

be thought of as a decrease in new information uncertainty $\sigma^2_{e,t}$ (Maćkowiak et al., 2023; Pomatto et al., 2023). Even with a constant gain G_t, this would lead to a decrease in posterior belief uncertainty $\Sigma_{t+h,t} \equiv var(x_{t+h} - E^i_t[x_{t+h}])$. 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 1. 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

$$\begin{aligned} log(Uncertainty_{j,t}) =& \alpha + \beta Lockdown_{j,t} + CovidImpact'_{j,t}\Gamma \\ &+ \delta EPU_{j,t} + \gamma_j + err_{j,t} \end{aligned} \tag{9}$$

where $Uncertainty_{j,t} = \int_{i \in j} Uncertainty_{i,t} di$ is the average 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.[14] Tables A.5 and A.6 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 expectations as a particular case. Consider the rational expectation framework: in this

[14]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(Uncertainty3y)*	(2) *ln(Uncertainty3y)*	(3) *ln(Uncertainty3y)*	(4) *ln(Uncertainty3y)*
Lockdown	-0.181***	-0.188***	-0.208***	-0.090*
	(0.031)	(0.031)	(0.032)	(0.048)
ln(DeathsCOVID)			0.001	0.012
			(0.013)	(0.023)
ln(CasesCOVID)			-0.005	-0.021
			(0.016)	(0.028)
EPUComposite			0.006	-0.003
			(0.007)	(0.007)
Constant	1.201***	1.205***	1.181***	1.075***
	(0.032)	(0.019)	(0.092)	(0.130)
State FEs	Y	Y	Y	Y
Sample	Mar20-May23	Mar20-May23	Mar20-May23	Mar20-Jun21
Adjusted R-squared	0.10	0.31	0.31	0.29
Observations	1715	1715	1705	799

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 $p < 0.01$.

case, the gain G_t, i.e. Kalman gain, equals

$$G_t^{RE} = \frac{\Sigma_{t+h,t-1}}{\sigma_{e,t}^2 + \Sigma_{t+h,t-1}} \tag{10}$$

The gain 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:

$$x_{t+h} = \rho x_{t+h-1} + u_{t+h} \tag{11}$$

with $u_{t+h} \sim N(0, \sigma^2_{u,t+h})$. In this case, $\Sigma_{t+h,t-1} = \rho^2 \Sigma_{t+h-1,t-1} + \sigma^2_{u,t+h}$. 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, consistently with the evidence in the pandemic period.

While we derive this result under the rational expectation assumption, it holds in a large set of models that depart but build on the baseline Bayesian updating in (10). 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 (10) using the surveys data. We do this in the next section.

5 Belief rigidity and uncertainty

The implication of the basic Bayesian belief updating framework, shared by a large set of non-rational belief updating models and summarized in Proposition 1, is that (i) belief rigidity decreases in prior uncertainty for a given posterior uncertainty, and (ii) and increases in posterior uncertainty for a given prior uncertainty. We formalize this intuition in the following proposition.

Proposition 1. *Consider the belief updating process in equations (2) and (8) with Kalman gain described in equation 10 (Rational Expectations). Then*

(a) *The information rigidity $1 - G_t$ decreases in prior uncertainty,* $\frac{\partial 1-G_t}{\partial \Sigma_{t+1,t-1}} < 0$.

(b) *The information rigidity $1 - G_t$ increases in posterior uncertainty for a given prior uncertainty,* $\left.\frac{\partial 1-G_t}{\partial \Sigma_{t+1,t}}\right|_{\Sigma_{t+1,t-1}} > 0$.

While the result in (a) follows directly from equation (10), the intuition for (b) comes from equation (8): keeping fixed prior uncertainty, posterior uncertainty reflects only new information uncertainty.

We test this implication by investigating how individual prior and posterior uncertainty affect individual belief rigidity. Since we don't have a proper measure of prior uncertainty, we use the posterior uncertainty 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. That is, we run the following regression

$$\begin{aligned} For_{i,t} =& \alpha + \beta_1 Prior_{i,t} + \begin{bmatrix} Prior\ Uncertainty_{it} \times Prior_{i,t} \\ Post\ Uncertainty_{it} \times Prior_{i,t} \end{bmatrix}' \begin{bmatrix} \beta_2 \\ \beta_3 \end{bmatrix} \\ &+ Z'_{i,t}\Gamma + X_{i,t} + \gamma_t + err^i_t \end{aligned} \tag{12}$$

where $Z_{i,t}$ include the non-interacted $Prior\ Uncertainty_{it}$ and $Post\ Uncertainty_{it}$. Proposition 1 implies $\beta_2 < 0$ and $\beta_3 > 0$

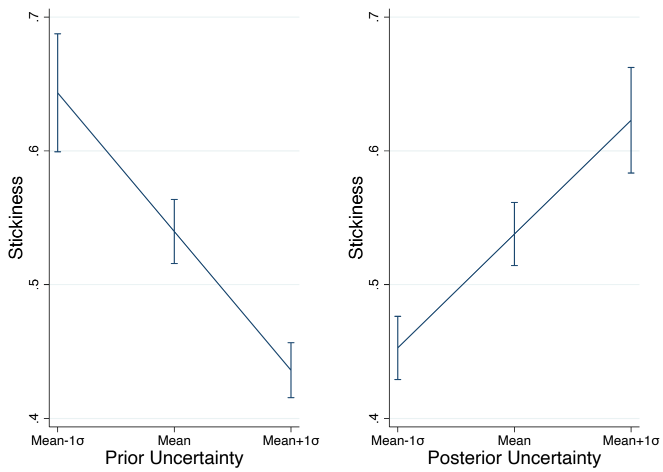
The results reported in Table 5 confirm the implications of the Bayesian belief updating framework summarized in proposition 1. First, the higher the prior uncertainty for a given posterior uncertainty, the lower the belief rigidity (or the higher the weight on new information G_t), i.e. $\hat{\beta}_2 < 0$. 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 considering uncertainty measures linearly (column 2), in logarithm (column 3), using the interquartile range

Table 5: Belief rigidity and uncertainty

	(1) *For 3y*	(2) *For 3y*	(3) *For 3y*	(4) *For 3y*	(5) *For 3y*
Prior 3y	0.516***	0.544***	0.563***	0.498***	0.532***
	(0.012)	(0.015)	(0.018)	(0.017)	(0.044)
Prior 3y × *Prior Uncert 3y*		-0.021***			
		(0.004)			
Prior 3y × *Post Uncert 3y*		0.014***			
		(0.004)			
Prior 3y × *ln(Prior Uncert3y)*			-0.143***		-0.111***
			(0.017)		(0.030)
Prior 3y × *ln(Post Uncert3y)*			0.116***		0.118***
			(0.016)		(0.023)
Prior 3y × *ln(Prior Uncert3yIQR)*				-0.115***	
				(0.015)	
Prior 3y × *ln(Post Uncert3yIQR)*				0.122***	
				(0.013)	
Prior 3y × *LockdownIndex*					-0.097***
					(0.024)
Constant	1.947***	1.019***	1.128***	1.315***	1.551***
	(0.051)	(0.074)	(0.078)	(0.055)	(0.326)
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	Jun13-Jun22	Jun13-Jun22	Jun13-Jun22	Jun13-Jun22	Mar20-Jun21
Adjusted R-squared	0.33	0.36	0.36	0.37	0.30
Observations	90940	90940	74138	90937	9222

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. $PostUncert3y$ 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. $PostUncert3yIQR$ and $PriorUncert3yIQR$ 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 socio-democratic fixed effects, 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 4: 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).

of subjective probability as a measure of uncertainty (column 4), and including the lockdown intensity as a proxy for information cost during the pandemic (column 5). Moreover, considering the 1-year horizon forecasts in CPI and housing price inflation reported in Tables A.7 and A.8 yields similar results.

Figure 4 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.4 shows similar results for shorter forecast horizons.

We test whether the impact of uncertainty on belief rigidity differs between consumers with high and low numeracy skills. We run the following regression

$$
\begin{aligned}
For_{i,t} =& \alpha + \beta_1 Prior_{i,t} + \begin{bmatrix} Prior\ Uncertainty_{it} \times Prior_{i,t} \\ Post\ Uncertainty_{it} \times Prior_{i,t} \end{bmatrix}' \begin{bmatrix} \beta_2 \\ \beta_3 \end{bmatrix} \\
&+ High\ Numeracy_{i,t} \times \begin{bmatrix} Prior\ Uncertainty_{it} \times Prior_{i,t} \\ Post\ Uncertainty_{it} \times Prior_{i,t} \end{bmatrix}' \begin{bmatrix} \beta_4 \\ \beta_5 \end{bmatrix} \\
&+ \beta_6 Prior_{i,t} \times High\ Numeracy_{i,t} + Z'_{i,t}\Gamma + X_{i,t} + \gamma_t + err_t^i
\end{aligned} \tag{13}
$$

where $Z_{i,t}$ include the non-interacted $Prior\ Uncertainty_{it}$, $Post\ Uncertainty_{it}$ and $High\ Numeracy_{i,t}$ as well as their interactions. Coefficient β_2 and β_3 measure respectively the dependence of belief updating on prior and posterior variance for low numeracy households, while $\beta_2 + \beta_4$ and $\beta_3 + \beta_5$ measure respectively the dependence of belief updating on prior and posterior variance for low numeracy households.

Table 9 reports the estimated coefficient and highlights one important result. Once accounting for the different incorporation of uncertainty on belief updating, belief rigidity does not differ systematically between low and high-numeracy households. On the other hand, the relationship between uncertainty and belief rigidity differs systematically between low and high-numeracy households. In particular, belief rigidity of high numeracy households decreases more when posterior uncertainty is higher than for low numeracy households. These results are stronger at the 1-year horizon in table A.9. If one assumes that high numeracy households are the closest to the optimal Bayesian framework, this result implies that lower numeracy households do not incorporate enough information uncertainty in their belief updating.[15]

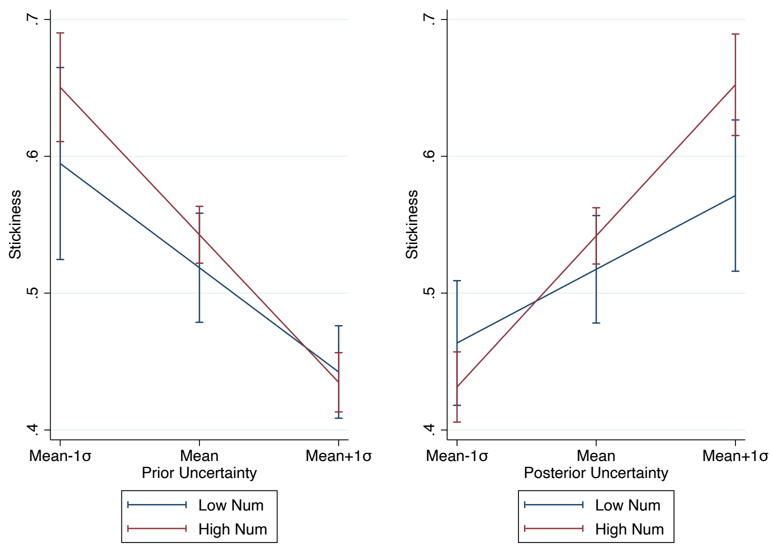
The results suggest that households update their belief according to a basic feature of rational Bayesian updating, meaning updating more when they are less certain and when new information is more accurate. As argued above and discussed in Appendix A, this feature is shared by several of the non-rational belief updating models in the literature, even though not all of them.

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.

[15] While Fermand et al. (2024) documents that high and low numeracy households have different expectation uncertainty, we study the difference in the mapping between uncertainty (which may differ across households) to belief rigidity between the two groups.

Figure 5: Belief rigidity and uncertainty for different numeracy skill



Legend: The figure represents graphically the estimated coefficients from column (3) of Table 5. It shows the relationship between belief rigidity β for high-numeracy households (in red) and low-numeracy households (in blue) and prior uncertainty (on the left-hand side) and posterior uncertainty (on the right-hand side). Numeracy is from the NY FED Survey of Consumer Expectations.

6.1 Environment

The model is a simplified version of the framework proposed in Afrouzi and Yang (2021).[16] 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 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 $i \in [0,1]$.

$$\max_{\{(C_{i,t})_{i\in[0,1]},B_t,L_t\}_{t=0}^{\infty}} \mathbb{E}_0^f \left[\sum_{t=0}^{\infty} \beta^t (\log(C_t) - L_t) \right] \tag{14}$$

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

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

[16]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.

is then summarized by:

$$C_{i,t} = C_t \left(\frac{P_{i,t}}{P_t}\right)^{-\theta} \qquad \forall i \in [0,1], \forall t \geq 0, \tag{15}$$

$$1 = \beta R_t \mathbb{E}_t^f \left[\frac{Q_t}{Q_{t+1}}\right] \qquad \forall t \geq 0, \tag{16}$$

$$W_t = Q_t, \qquad \forall t \geq 0 \tag{17}$$

Equation (15) is the demand for variety i at time t, Equation (16) is the consumption Euler Equation and Equation is the intratemporal optimality condition that relates nominal wage and nominal aggregate demand.[17]

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

$$\log(Q_t) = \log(Q_{t-1}) + u_t, \quad u_t \sim \mathcal{N}(0, \sigma_u^2) \tag{18}$$

where u_t is an exogenous shock to monetary policy that affects the nominal rates with a standard deviation of σ_u.[18]

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

$$\max_{\{P_{i,t}\}} E_t^i \left[\frac{1}{P_t C_t} \left(P_{i,t}C_{i,t} - (1-\theta^{-1})Q_t L_{i,t}\right)\right] \tag{19}$$

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

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

where $E^i_t[\cdot]$ 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

$$p_{i,t} = E^i_t[q_t] \tag{20}$$

with small letters denoting the logs of corresponding variables. Equation (20) implies that firms set prices equal to perceived marginal cost, which is exogenous and given by Equation (18).

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

$$s^i_t = q_t + e^i_t \tag{21}$$

where the signal noise $e^i_t = \eta^i_t + \omega_t$ contains (i) an idiosyncratic component η^i_t 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.

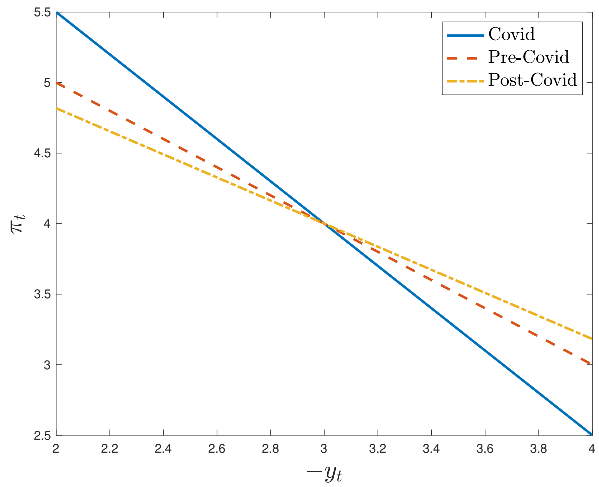
We assume firms update their beliefs similarly to the rule in Section 2:

$$E^i_t[q_t] = (1 - G_t)E^i_{t-1}[q_t] + G_t s^i_t \tag{22}$$

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 $\Sigma_{t,t-1} \equiv var_t(q_t - E^i_{t-1}[q_t])$ 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 $p_{i,t} = E^i_t[q_t]$, Equation (22) describes also the evolution of firm's i price.

Figure 6: Phillips Curve with estimated rigidity



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

$$\pi_t = \frac{G_t}{1 - G_t}(y_t + \omega_t) \tag{23}$$

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 6 shows the slope of the Phillips curve in Equation (23) 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 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 (23) 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 (23) 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.

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Table 6: 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 7: 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 socio-democratic fixed effects, 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 8: 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 $\times$ $ln(DeathsCOVID)$	-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 $\times$ $ln(CasesCOVID)$	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 $\times$ *School*	-0.026								0.019	
	(0.018)								(0.024)	
Prior 3y $\times$ *Workplace*		-0.076***							-0.053	
		(0.017)							(0.041)	
Prior 3y $\times$ *Event*			-0.071***						-0.010	
			(0.022)						(0.038)	
Prior 3y $\times$ *Gathering*				-0.035***					-0.016	
				(0.007)					(0.018)	
Prior 3y $\times$ *Transport*					-0.093***				-0.039	
					(0.030)				(0.034)	
Prior 3y $\times$ *StayAtHome*						-0.073***			0.009	
						(0.022)			(0.039)	
Prior 3y $\times$ *Movements*							-0.054**		0.050*	
							(0.022)		(0.028)	
Prior 3y $\times$ *Travel*								-0.102***	-0.083**	
								(0.027)	(0.036)	
Prior 3y $\times$ *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-demographic FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Non-interacted variables	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R-squared	0.35	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 socio-democratic fixed effects, 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 9: 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 socio-democratic fixed effects, 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 $p < 0.01$.

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

[if Q10 includes codes 1,2,4 or 5 and Q11 ne 0]

Q23v2 Please think ahead to **12 months from now**. Suppose that you are working in the exact same ["main" if Q11>1] job at the same place you currently work, and working the exact same number of hours. What do you expect to have happened to your earnings on this job, before taxes and deductions?

Instruction H8.

Twelve months from now, I expect my earnings to have...

- increase by 0% or more
- decrease by 0% or more

If no response: error E1

[if Q23v2=increase or decrease]

Q23v2part2

By about what percent do you expect your earnings to have [increased/decreased as in Q23]? Please give your best guess.

Instruction H9.

Twelve months from now, I expect my earnings to have [increased/decreased] by __ %

If no response: error E1

Figure A.1

[if Q10 includes codes 1,2,4 or 5 and Q11 ne 0]

Q24

Suppose again that, **12 months from now**, you are working in the exact same ["main" if Q11>1] job at the same place you currently work, and working the exact same number of hours. In your view, what would you say is the percent chance that 12 months from now...

Instruction H4.

Your earnings on this job, before taxes and deductions, will have...

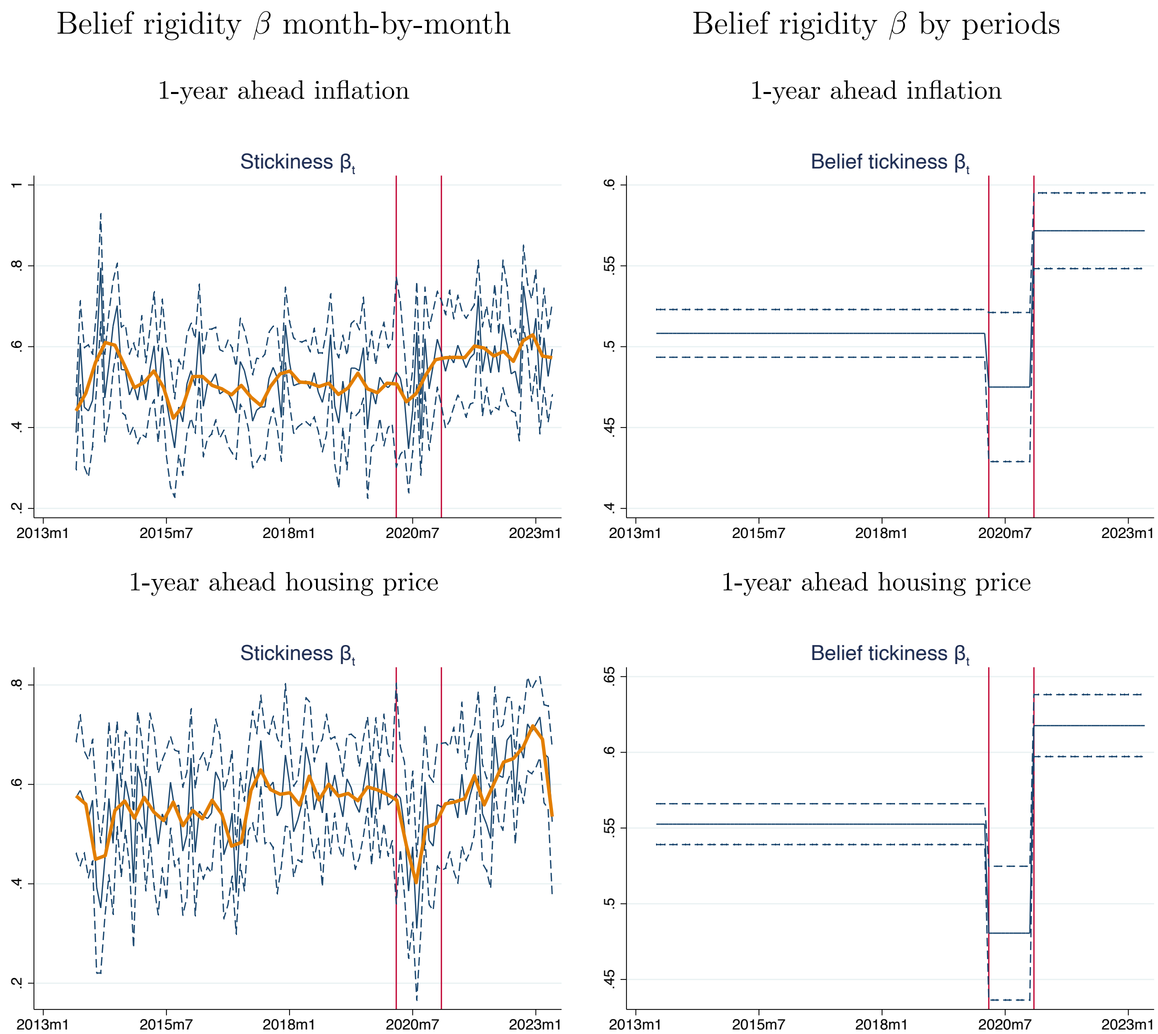
increased by 12% or more	______	percent chance
increased by 8% to 12%	______	percent chance
increased by 4% to 8%	______	percent chance
increased by 2% to 4%	______	percent chance
increased by 0% to 2%	______	percent chance
decreased by 0% to 2%	______	percent chance
decreased by 2% to 4%	______	percent chance
decreased by 4% to 8%	______	percent chance
decreased by 8% to 12%	______	percent chance
decreased by 12% or more	______	percent chance
Total	**100**	

If no response: error E1
If sum not equal to 100: "Your total adds up to XX" followed by error msg E3

Figure A.2

C Shorter forecast horizon

Figure A.3: Belief rigidity pre- and post-pandemic



Legend: The blue solid line represents our estimates of belief rigidity, while the dashed blue lines represent the 95% confidence interval. The orange line is a Kernel-weighted local polynomial smoothing of the estimated coefficient. In the left plot, belief rigidity 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.1: 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 $\times$ *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 socio-democratic fixed effects, 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.2: 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 socio-democratic fixed effects, 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.3: 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**	0.569**	0.574**	0.576**
	(0.136)	(0.254)	(0.264)	(0.254)	(0.258)
Prior 1y × *Lockdown*	-0.044	-0.047	-0.051	-0.043	-0.042
	(0.028)	(0.043)	(0.040)	(0.047)	(0.043)
Prior 1y × $ln(DeathsCOVID)$	-0.009	-0.024	-0.025	-0.023	-0.022
	(0.018)	(0.037)	(0.041)	(0.037)	(0.040)
Prior 1y × $ln(CasesCOVID)$	0.013	0.043	0.045	0.042	0.041
	(0.015)	(0.027)	(0.033)	(0.028)	(0.031)
Prior 1y × $EPUState$			0.001		
			(0.009)		
Prior 1y × $EPUNational$				-0.002	
				(0.009)	
Prior 1y × $EPUComposite$					-0.001
					(0.006)
Constant	3.612***	3.001**	3.069**	3.053**	3.036**
	(0.884)	(1.229)	(1.289)	(1.305)	(1.312)
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: $For1y_{i,t}$ 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 year 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 socio-democratic fixed effects, such as education, income, age, gender, race, and tenure.

Table A.4: 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***	0.634***	0.634***	0.623***
	(0.110)	(0.181)	(0.187)	(0.189)	(0.193)
Prior H × *Lockdown*	-0.094***	-0.061*	-0.083*	-0.100**	-0.103**
	(0.022)	(0.033)	(0.041)	(0.041)	(0.047)
Prior H × *ln(DeathsCOVID)*	-0.002	0.000	-0.008	-0.010	-0.013
	(0.013)	(0.025)	(0.026)	(0.024)	(0.026)
Prior H × *ln(CasesCOVID)*	-0.020	0.014	0.025	0.028	0.032
	(0.016)	(0.023)	(0.024)	(0.020)	(0.023)
Prior H × *EPUState*			0.009		
			(0.011)		
Prior H × *EPUNational*				0.022	
				(0.015)	
Prior H × *EPUComposite*					0.012
					(0.010)
Constant	2.508**	1.528	1.820*	1.651	1.989*
	(1.098)	(1.021)	(0.997)	(0.999)	(0.977)
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 socio-democratic fixed effects, such as education, income, age, gender, race, and tenure.

Table A.5: Belief rigidity and lockdown measures

	(1) $ln(Uncertainty1y)$	(2) $ln(Uncertainty1y)$	(3) $ln(Uncertainty1y)$	(4) $ln(Uncertainty1y)$
Lockdown	-0.194***	-0.198***	-0.233***	-0.082
	(0.029)	(0.029)	(0.030)	(0.050)
$ln(DeathsCOVID)$			-0.006	0.014
			(0.015)	(0.028)
$ln(CasesCOVID)$			-0.000	-0.028
			(0.013)	(0.023)
$EPUComposite$			0.013*	-0.000
			(0.007)	(0.007)
Constant	1.251***	1.254***	1.172***	1.074***
	(0.028)	(0.018)	(0.110)	(0.182)
State FEs	Y	Y	Y	Y
Sample	Mar20-May23	Mar20-May23	Mar20-May23	Mar20-Jun21
Adjusted R-squared	0.11	0.32	0.33	0.32
Observations	1713	1713	1702	796

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.6: Belief rigidity and lockdown measures

	(1) $ln(UncertaintyH)$	(2) $ln(UncertaintyH)$	(3) $ln(UncertaintyH)$	(4) $ln(UncertaintyH)$
Lockdown	-0.162***	-0.169***	-0.174***	-0.173***
	(0.027)	(0.029)	(0.034)	(0.045)
$ln(DeathsCOVID)$			0.026*	0.027
			(0.013)	(0.024)
$ln(CasesCOVID)$			-0.007	-0.014
			(0.013)	(0.026)
$EPUComposite$			0.000	-0.003
			(0.007)	(0.008)
Constant	1.331***	1.335***	1.552***	1.531***
	(0.026)	(0.018)	(0.101)	(0.161)
State FEs	Y	Y	Y	Y
Sample	Mar20-May23	Mar20-May23	Mar20-May23	Mar20-Jun21
Adjusted R-squared	0.09	0.23	0.23	0.29
Observations	1699	1699	1688	788

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.7: Belief rigidity and uncertainty

	(1) *For 1y*	(2) *For 1y*	(3) *For 1y*	(4) *For 1y*	(5) *For 1y*
Prior 1y	0.526***	0.554***	0.568***	0.505***	0.545***
	(0.010)	(0.017)	(0.019)	(0.016)	(0.048)
Prior 1y × *Prior Uncert 1y*		-0.021***			
		(0.003)			
Prior 1y × *Post Uncert 1y*		0.013***			
		(0.003)			
Prior 1y × *ln(Prior Uncert1y)*			-0.155***		-0.172***
			(0.014)		(0.033)
Prior 1y × *ln(Post Uncert1y)*			0.128***		0.156***
			(0.013)		(0.022)
Prior 1y × *ln(Prior Uncert1yIQR)*				-0.131***	
				(0.011)	
Prior 1y × *ln(Post Uncert1yIQR)*				0.139***	
				(0.010)	
Prior 1y × *LockdownIndex*					-0.026
					(0.030)
Constant	2.093***	1.161***	1.283***	1.471***	1.155***
	(0.046)	(0.065)	(0.074)	(0.051)	(0.350)
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	Jun13-Jun22	Jun13-Jun22	Jun13-Jun22	Jun13-Jun22	Mar20-Jun21
Adjusted R-squared	0.40	0.44	0.43	0.45	0.38
Observations	90231	90231	73656	90224	9374

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 socio-democratic fixed effects, 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 $p < 0.01$.

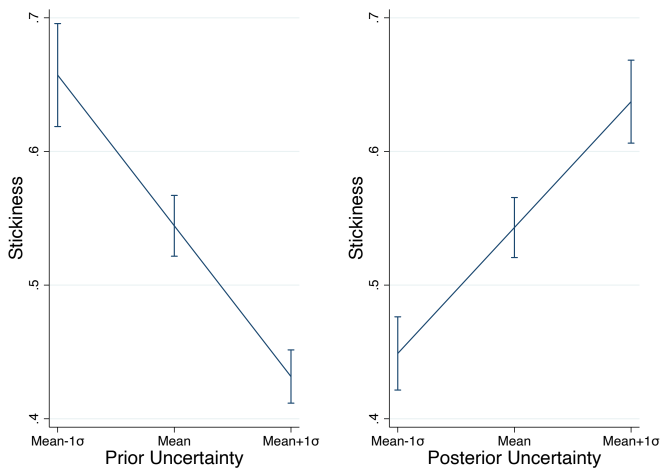
Table A.8: Belief rigidity and uncertainty

	(1) *For H*	(2) *For H*	(3) *For H*	(4) *For H*	(5) *For H*
Prior H	0.570***	0.592***	0.595***	0.545***	0.631***
	(0.011)	(0.014)	(0.016)	(0.014)	(0.064)
Prior H × *Prior Uncert H*		-0.028***			
		(0.003)			
Prior H × *Post Uncert H*		0.024***			
		(0.003)			
Prior H × *ln*(*Prior UncertH*)			-0.164***		-0.160***
			(0.010)		(0.028)
Prior H × *ln*(*Post UncertH*)			0.156***		0.128***
			(0.011)		(0.027)
Prior H × *ln*(*Prior UncertHIQR*)				-0.139***	
				(0.009)	
Prior H × *ln*(*Post UncertHIQR*)				0.157***	
				(0.010)	
Prior H × *LockdownIndex*					-0.053*
					(0.030)
Constant	2.165***	1.149***	1.356***	1.350***	1.474**
	(0.056)	(0.077)	(0.088)	(0.063)	(0.597)
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	Jun13-Jun22	Jun13-Jun22	Jun13-Jun22	Jun13-Jun22	Mar20-Jun21
Adjusted R-squared	0.40	0.43	0.44	0.44	0.38
Observations	83475	83475	72969	83473	9318

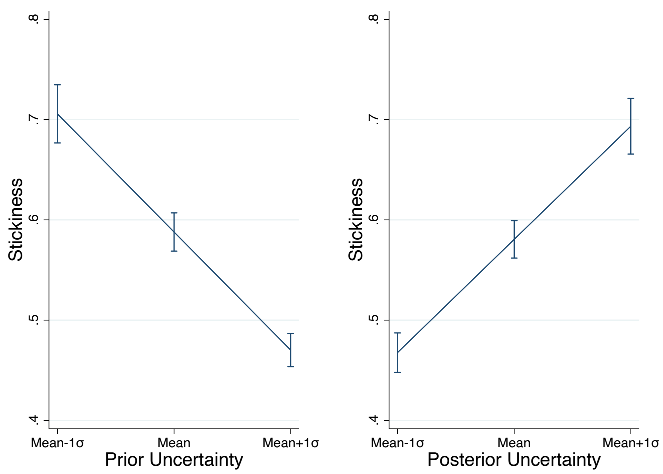
Legend: $Forh_{i,t}$ denotes the 1-year ahead forecast of housing price inflation expectations from the NY FED Survey of Consumer Expectations (SCE). *Prior* $h_{i,t}$ is the same forecast provided in the previous month. *PostUncerth* denotes the individual 1-year ahead forecast of housing price inflation 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 socio-democratic fixed effects, 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.4: Belief rigidity and uncertainty: shorter horizon

CPI inflation



Housing price inflation



Legend: The figure represents graphically the estimated coefficients from column (3) of Tables A.7 and A.8. 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.9: 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 socio-democratic fixed effects, 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.10: 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 socio-democratic fixed effects, 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 $p < 0.01$.