Household Belief Formation in Uncertain Times*

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Abstract

We investigate the impact of heightened uncertainty in the post-pandemic economy on households' inflation belief formation. Utilizing data from the Survey of Consumer Expectations, we document a marked decline in belief rigidity at the pandemic's onset, indicating an increased receptiveness of households to new information. Through the lenses of a Bayesian belief updating model, we pinpoint two contributing causes: first, lockdown and stay-at-home policies significantly reduced the marginal cost of gathering information; second, increased volatility in economic fundamentals rendered existing information obsolete, thus prompting households to increase relative attention to new information. We document strong empirical support for the model's implications in households' expectations data. Our findings not only contribute to the understanding of belief formation mechanisms but also shed light on post-pandemic inflation dynamics, including possible alterations to the slope of the Philips Curve.

Keywords: beliefs, expectations, household surveys, information frictions, uncertainty.
JEL Classification: D81, D83, D84, E31.

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1 Introduction

The contemporary economic landscape presents a paradox that challenges conventional wisdom: despite strong economic indicators suggesting prosperity - including a decline in inflation rates and a strong job market since the early, uncertain days of the Covid-19 pandemic, public sentiment in the United States remains decidedly negative. This dissonance between objective data and subjective perception raises profound questions about the mechanisms underlying belief formation and decision-making within macroeconomic contexts. Furthermore, the process of belief formation could play a pivotal role in shaping post-pandemic macroeconomic dynamics, including the relationship between inflation and economic activity.

In this paper, we empirically investigate the determinants and dynamics U.S. households' inflation expectations before and after the pandemic. This period is particularly suited for our analysis for several reasons: first, it encompasses a period of increased uncertainty triggered by the COVID-19 pandemic and subsequent months of high inflation (Armantier et al., 2021); second, it is a period characterized by a large dissonance between real economic indicators and subjective beliefs (Frankel, 2024); third, it is a period with multiples shocks to the supply and demand of new information, such as lockdown policies and economic policy uncertainty, which allow us to identify the potential factors driving households' attention choice.

We investigate the dynamics and determinants of households' belief rigidity, meaning the relative weight consumers attach to new versus existing information when forming expectations. We follow the empirical strategy developed in Goldstein (2023) and Gemmi and Valchev (2023). We focus on 3 and 1-year ahead CPI inflation and house-price forecasts from the Survey of Consumer Expectations (SCE) conducted by the Federal Reserve Bank of New York. This survey, which gathers monthly data from a rotating panel of households between June 2013 and June 2022—with approximately 1300 observations each month—offers two advantages. First, the large cross-sectional dimension allows us to investigate the heterogeneity of belief updating and its dynamic over time. Second, the density forecasts collected in the survey allow us to measure individual-level belief uncertainty and study its relation with belief updating.

We document three important facts about households' belief updating. First, we document a sharp drop in belief rigidity at the onset of the Covid-19 pandemic in March 2020. This increase in households' attention to new information is accompanied by a stark increase in uncertainty about their beliefs. Interestingly, this inverse correlation between belief rigidity and uncertainty shifts during the high inflation period starting in February 2021, with households showing instead a higher degree of belief rigidity and higher belief uncertainty. These shifts in belief rigidity during the pandemic might have important macroeconomic consequences for the inflation dynamics and for the estimation of the New Keynesian Philips Curve slope, which strongly depends on inflation expectations (Coibion et al., 2018). Furthermore, the changing relationship between belief rigidity and uncertainty sheds light on the mechanism behind households' belief formation, which we investigate in the remainder of this paper.

Second, we show that the large drop in belief rigidity during the Covid-19 period is at least partly driven by the lockdown policies implemented to stop the spread of the virus. By leveraging the variation in the intensity of state-level lockdown policies, measured by the Oxford Covid-19 Government Response Tracker (OxCGRT), we identify 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 a larger amount of new information. Nevertheless, lockdown policies alone do not explain the simultaneous rise in belief uncertainty observed during this period. We show that the impact of lockdown policies on belief uncertainty is, in fact, negative. This aligns with conventional belief formation models, where reduced information-gathering costs allow the collection of more accurate data, and therefore a larger relative weight on new information when forming new beliefs. Hence, while diminished information costs contribute to decreased belief rigidity during the pandemic, they do not account for the heightened uncertainty.

Third, we argue that an increase in volatility of the economic fundamentals can explain the simultaneous decrease in belief rigidity and increase in belief uncertainty documented during the pandemic. Within a benchmark rational expectation Bayesian belief formation model, we show that an increase in the volatility of the stochastic process of the variable forecasted, such as inflation, has two effects. First, it makes forecasts more uncertain. Second, it diminishes the accuracy of existing information about inflation, thereby increasing the uncertainty of prior beliefs. As existing information becomes obsolete, households incorporate a greater volume of new information in forming beliefs, lowering their belief rigidity. In other words, a structural shift in the economic environment such as the pandemic could significantly transform the economic landscape, prompting households to seek new information to navigate through an increasingly uncertain world.

We find robust empirical support for the noisy information Bayesian belief updating model's implication on household expectation data. 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.[1] We find that controlling for prior uncertainty, posterior uncertainty is positively correlated with belief rigidity: noisier signals induce agents to update less and be more uncertain about their forecast. Conversely, prior uncertainty is inversely correlated with belief rigidity: higher uncertainty in existing information prompts agents to place greater weight on new information when forming beliefs.[2] Our findings align not only with the rational expectation belief model, but also with a large set of models that diverge from yet are built upon the Bayesian updating model[3] Unlike existing literature, which primarily explores the uncertainty-belief rigidity relationship through experimental data yielding mixed results, our study leverages naturally occurring variation within a substantial dataset of U.S. households.[4]

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

[1] 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.

[2] A one standard deviation increase in the logarithm of prior uncertainty reduces belief stickiness by around 0.1, i.e. 20%. Similarly, a one standard deviation increase in the logarithm of posterior uncertainty increases belief stickiness by around 0.07, i.e. 15%.

[3] 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 stickiness.

[4] In particular, Fuster et al. (2022) document the opposite effect of prior uncertainty on housing price expectation stickiness. 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).

(2014), and Reis (2006)). Finally, 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).

The paper proceeds as follows: Section 2 presents some motivational evidence on beliefs disconnect. Section 3 illustrates the general framework we use to guide and interpret our empirical strategy. Section 4 presents our data and empirical strategy. Section 5 investigate the dynamics of belief rigidity before and after the pandemic, and its possible determinants. Section 6 explores the relationship between individual prior and posterior uncertainty on belief stickiness. Lastly Section 7 offers implications for policy and Section 8 concludes.

2 Disconnect between data and beliefs

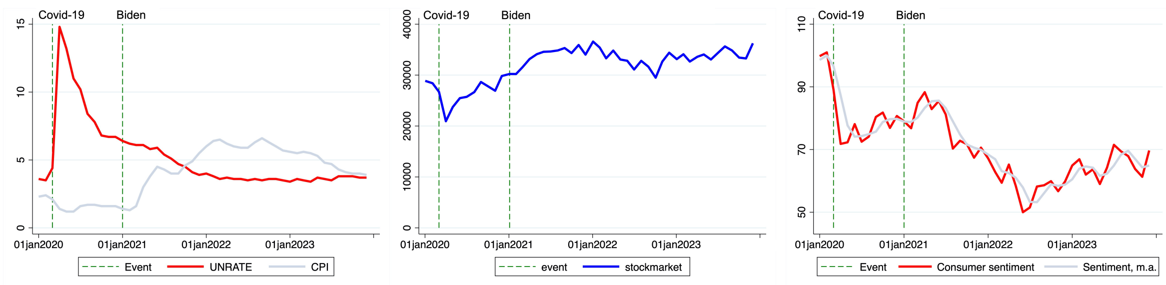
An array of hard data shows that the US economy has been improving lately: inflation has slowed sharply, unemployment is lower than ever, and the stock market is strong and growing, as shown in Figure 1, Panel A. However, multiple surveys of consumer sentiment are showing indices of optimism that are 30% below their recent peak on the eve of the Covid-19 crisis in early 2020, as shown in Figure 1, Panel A.3.

The discrepancy between strong U.S. economic indicators and the public's perception highlights a complex issue. Despite low unemployment, reduced inflation, rising wages, and a surge in stock prices, many households perceive the economy negatively. This persistent pessimism is puzzling, especially as consumer confidence remains below average despite recent improvements. The gap between objective economic health and subjective economic sentiment raises questions about the factors influencing public perceptions, suggesting a deeper exploration into how US households interpret and react to economic information.

While there are no polarizing consumer sentiment beliefs between other sub-groups (e.g. by age, education, etc.) as shown in Figure 1, Panel B, there are large differences in Democrats' and Republicans' perception of the U.S. economy. In Panel B.1., the Democrats' sentiment has slightly risen since early 2020, while Republicans' and Independents' sentiment has fallen dramatically in this period and never recovered.

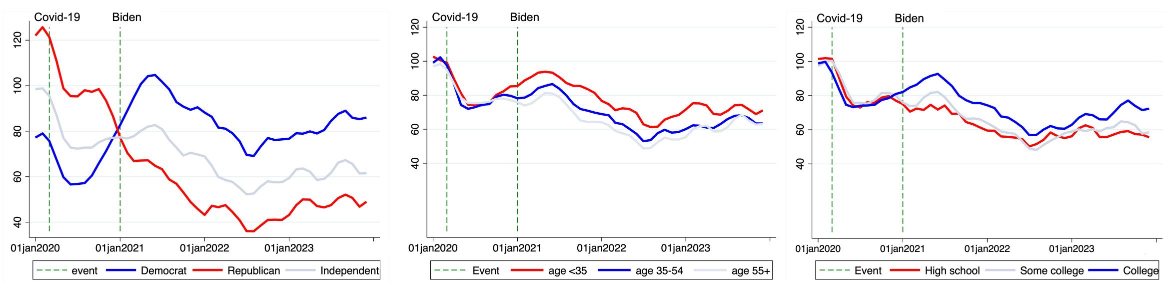
Figure 1: Panel A. The economy has been doing better

1. Inflation, unemployment 2. Stock market 3. Consumer sentiment



Panel B. But consumer sentiment about the economy remains low

1. By politics 2. By age 3. By education



Legend: Inflation (CPI-urban, All items less food and energy) and unemployment are from FRED. The stock market index is from DOW. Consumer sentiment about the U.S. economy is from the University of Michigan. The time period is 2020-2023. Covid-19 corresponds to March 2020. Biden corresponds to January 2021.

3 A general framework of belief updating

We present a general theoretical framework embedding different models of belief updating, from which we derive implications to test in the data. 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 $\tilde{E}_t^i[x_{t+h}]$ at time t about the variable at h periods ahead according to

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

where G_t is the weight households assign to new information, E is a potentially non-optimal expectation operator, and forecast errors are defined as the difference between realization and posterior expectations. We follow the literature in referring to G_t as "gain" and to $1 - G_t$ as "stickiness".

From (2), one can write

$$x_{t+h} - E_t^i[x_{t+h}] = (1 - G_t)(x_{t+h} - E_{t-1}^i[x_{t+h}]) - G_t e_t^i \tag{3}$$

Equation (3) describes how forecast error relate to belief rigidity $1 - G_t$ and prior information $E_{t-1}^i[x_{t+h}]$. This framework is general and embeds a large set of belief-updating models, such as the rational Bayesian model, described in Appendix A.

4 Households' belief rigidity

4.1 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.[5] 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 June 2022, 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 131,299 total month-respondent observations from around 19,106 unique respondents. We consider point forecasts only if respondents provide a meaningful density forecast (i.e. the survey provides the

[5]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.

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") and expected inflation/deflation over the 12 months starting from 24 months in the future (which we define as "3 years"). The SCE asks respondents to indicate both their point forecast for future expected inflation and their subjective distribution over all possible inflation realization. We use both of these variables.

First, to measure expected mean inflation we use the point forecast provided by respondents.[6] We use this measure to construct (i) expected mean inflation ($For_{i,t}$) as the point forecast about inflation at horizon 1 and 3 years provided in month t, and (ii) prior mean expectation as the point forecast about horizon 1 and 3 years 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 and therefore we assume the horizon is approximately the same.

Second, we use the subjective distribution to construct a measure of 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 for the 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 ($Prior\ Uncertainty_{it}$). We make the same assumption as for the point forecast, which is 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

[6]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.

distributions. The top panel of Table 1 presents summary statistics for forecasts and uncertainty.

Table 1: Descriptive Statistics

	Mean	SD	Min	Max	N
Beliefs					
For 3y	4.49	6.19	-50	60	116867
Revision 3y	-0.15	5.19	-94	100	84344
Post Uncert 3y	2.61	2.71	0	22	116867
Post Uncert 3y IQR	2.94	3.07	0	28	116867
For 1y	4.71	5.95	-45	56	116039
Revision 1y	-0.09	4.73	-90	70	83749
Post Uncert 1y	2.58	2.74	0	22	116039
Post Uncert 1y IQR	2.91	3.12	0	28	116039
For H	5.46	7.36	-60	85	105231
Post Uncert H	2.97	2.78	0	22	105231
Revision H	-0.09	6.21	-80	79	77601
Post Uncert H IQR	3.37	3.20	0	28	105231
Socioeconomic characteristics					
$College_{it}$	0.89	0.31	0	1	124829
$Income\ 50kto100k_{it}$	0.36	0.48	0	1	123496
$Income\ Over100k_{it}$	0.30	0.46	0	1	123496
$Income\ Under50k_{it}$	0.34	0.48	0	1	123496
$High\ Numeracy_{it}$	0.74	0.44	0	1	124770
$Female_i$	0.47	0.50	0	1	124783
Age_{it}	50.71	15.25	17	94	124721
$White_i$	0.85	0.35	0	1	124823
$Tenure_{it}$	5.58	3.37	1	16	124829

Legend: This table provides descriptive statistics for beliefs and household socioeconomic characteristics derived from the Survey of Consumer Expectations (SCE). The sample period is 2013M6-2022M6.

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, which is 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 ($HighNumeracy_{i,t}$).

4.2 Empirical strategy

In order to estimate the stickiness in belief updating in survey expectations, the previous literature followed the seminal papers by Coibion and Gorodnichenko (2012, 2015) in regressing consensus forecast error on consensus forecast revisions. However, this measure suffers from two important drawbacks. 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 which is usually not possible to have in household surveys.[7] We instead employ a new methodology developed in Goldstein (2023) and Gemmi and Valchev (2023) which allows us to estimate belief updating stickiness even in the presence of common errors and with just a cross-section of prior and posterior forecasts.

Demeaning (2) using consensus forecasts,[8]

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

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

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

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

[7] 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)

[8] Demeaning allows you to eliminate the actual realization of the underlying process forecasted, which could be 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 stickiness

	(1) *For 3y*	(2) *For 3y*	(3) *For 3y*
Prior 3y	0.515***	0.494***	0.314***
	(0.011)	(0.010)	(0.023)
Prior 3y × $Tenure_{it}$			0.031***
			(0.002)
$High\ Numeracy_{it}$=1 × *Prior 3y*			0.038**
			(0.015)
Constant	1.960***	2.044***	1.871***
	(0.049)	(0.043)	(0.046)
Year-Month FEs	Y	Y	Y
Socio-democraphic FEs	Y	Y	Y
Adjusted R-squared	0.33	0.31	0.34
Observations	83405	80402	83405

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 2013M6-2022M6. Column (2) excludes respondents who never revised their forecasts. Standard errors (in parentheses) are clustered at individual and time levels. $*$ represents $p < 0.10$, $**$ represents $p < 0.05$, and $***$ represents $p < 0.01$.

Table 2 reports the estimates of belief stickiness β from regression (5). Column (1) reports the belief stickiness 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 strategy on the Survey of Professional Forecasters. Notice that this empirical strategy is not informative on whether this belief stickiness is optimal or not, as this would require knowing the distribution of households' signals.

This gain estimate reflects a combination of both the extensive and intensive margin of information adjustment, meaning some consumers do not update their beliefs from one month to the other and some consumers do update their beliefs. One possible concern is that this measure could be biased by respondents who do not make the effort to change their answer from one month to the other, even if their beliefs changed. To address this concern, estimate the belief stickiness excluding consumers that never changed their forecasts. Column (2) reports this estimate, which is lower but comparable to column (1). Moreover, we investigate whether this estimate is driven by inexperienced consumers who might not pay attention to the survey questions. Column (3) shows that belief stickiness is higher for consumers with higher tenure in the survey and for consumers with a high level of numeracy. This result suggests that the large estimated belief rigidity is not driven by inexperienced respondents. Similar results are documented for 1 year ahead and housing inflation, Tables A.1 and A.2.

5 Households' belief rigidity during uncertain times

5.1 Belief rigidity declines during the pandemic

In this section, we exploit the large cross-sectional dimension of the SCE to study the time variation of belief stickiness in the period before and after the pandemic.

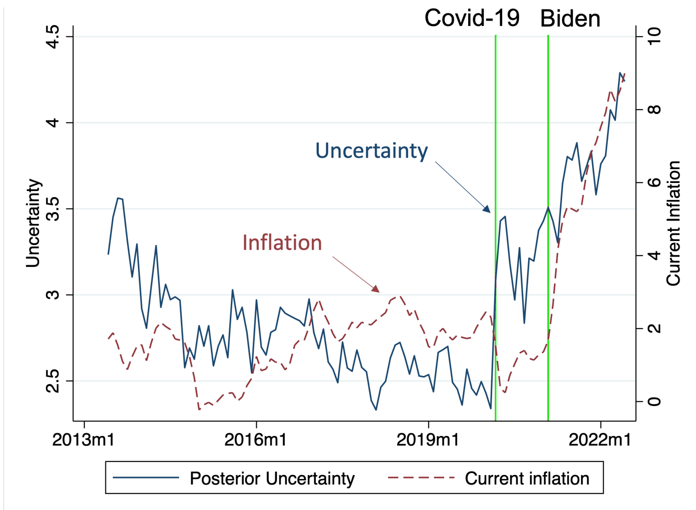
Figure 2 shows the time series of average individual inflation belief uncertainty from the SCE together with the actual current CPI inflation. The start of the COVID pandemic in early 2020 (first vertical line in Figure 2) has been characterized by a striking increase in consumer belief uncertainty Armantier et al. (2021). Uncertainty has remained high when inflation started increasing in 2021 (second vertical line in Figure 2).

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

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

The left panel of Figure 3 shows the estimates of belief stickiness β in each month of the sample. Belief stickiness 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 stickiness reverts back to the pre-pandemic level, but ends at a slightly higher value during the high inflation period. The right panel of Figure 3 shows the estimate of belief stickiness in three different subsamples: pre-COVID period (up to March 2020), COVID period (between March 2020 and February 2021), and high inflation period (after February

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



Legend: The blue filled line denotes the posterior uncertainty. The red dashed line denotes current inflation. 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: Survey of Consumer Expectations (SCE) and FRED. Sample period: 2013M1 - 2022M6.

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 stickiness goes in the opposite direction and instead sharply declines in the same period, just to increase back after COVID. This finding seems inconsistent with the Bayesian belief updating model, which implies that more uncertain news would lead consumers to weigh less new information when forming new beliefs and instead rely more on their pre-existing priors. However, the increase in 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.

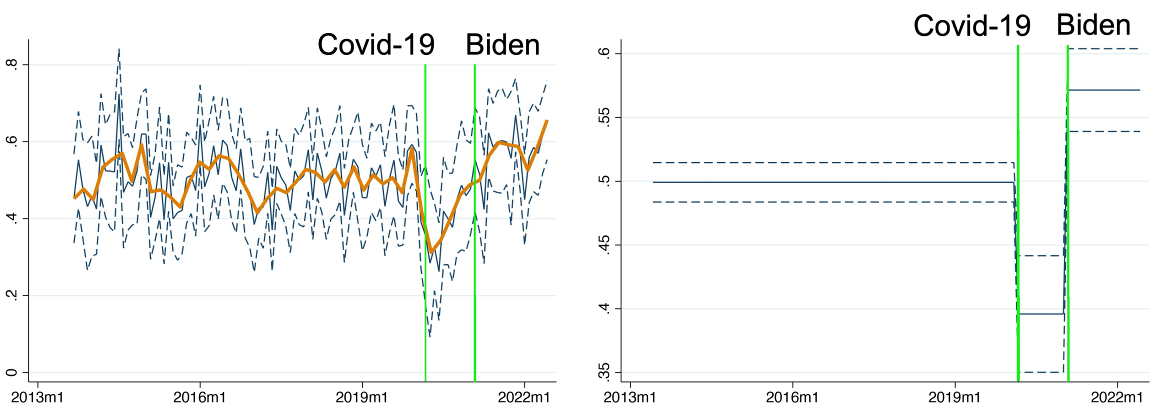
5.2 Information cost and belief rigidity: the case of lockdowns

In this section, we investigate the role of lockdown policies in the decrease in belief stickiness 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

Figure 3: Belief stickiness pre- and post-pandemic

Belief stickiness β month-by-month

Belief stickiness β by periods



Legend: The blue solid line represents our estimates of belief stickiness, 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 stickiness 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 - 2022M6.

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.[9] Figure 5(a) reports the time series of the country-level average of each indicator. Moreover, to measure the local impact of the pandemic we use the US state-level monthly level of COVID deaths and cases per capita. Table 6 reports the summary statistics.

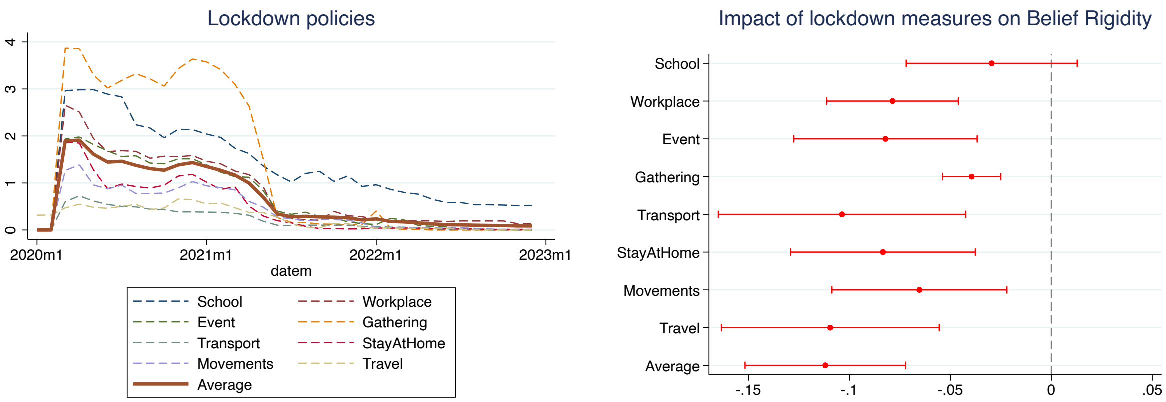
To estimate the impact of lockdown measures on belief stickiness, we interact the prior forecast in regression (5) with each lockdown indicator and the COVID cases and death measures. Intuitively, controlling for the impact of COVID in each state in terms of cases and deaths allows us to isolate the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

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

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

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

Figure 4: Belief stickiness and uncertainty



Legend: The left figure represents the average state-level lockdown policies intensity for different social activities, weighted by state population. The data source for lockdowns is the Oxford Covid-19 Government Response Tracker (OxCGRT). The right plot shows the impact of lockdown measures on our estimate of belief rigidity, β_2 in (7). Sample period: 2020M3-2022M6.

Figure 5(b) reports the estimated impact of lockdown indexes on belief stickiness, β_2, while Table 8 reports the detailed result. While all the indicators have a robust and negative effect on belief stickiness, including all of them together might create collinearity issues. As a result, we use the average of the indexes as a summary of the individual indicators. Once again the impact on belief stickiness is negative and robust. This result suggests that lockdown policies might have lowered the cost of collecting information for consumers, leading them to adjust their beliefs more than before.

Table 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 5(a), these policies were mainly in place until June 2021. Therefore, we run the same regression considering only this subsample. The impact of lockdown policies on belief stickiness 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.[10] Even controlling for state-level uncertainty, the estimated impact of lockdown policies on belief rigidity is significant

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

Table 3: Belief stickiness and lockdown measures

	(1) *For 3y*	(2) *For 3y*	(3) *For 3y*	(4) *For 3y*	(5) *For 3y*
Prior 3y	0.503***	0.770***	0.794***	0.779***	0.803***
	(0.102)	(0.143)	(0.150)	(0.149)	(0.152)
Prior 3y × *Lockdown*	-0.112***	-0.113***	-0.091**	-0.090**	-0.074*
	(0.020)	(0.027)	(0.035)	(0.039)	(0.038)
Prior 3y × *ln(DeathsCOVID)*	-0.013	0.014	0.022	0.018	0.026
	(0.013)	(0.021)	(0.024)	(0.024)	(0.025)
Prior 3y × *ln(CasesCOVID)*	0.007	0.011	0.001	0.004	-0.004
	(0.021)	(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	2.299***	1.457*	1.436*	1.569*	1.480*
	(0.801)	(0.726)	(0.745)	(0.779)	(0.778)
Year-Month FEs	Y	Y	Y	Y	Y
Socio-demographic FEs	Y	Y	Y	Y	Y
Non-interacted variables	Y	Y	Y	Y	Y
Sample	Mar20-Jun22	Mar20-Jun21	Mar20-Jun21	Mar20-Jun21	Mar20-Jun21
Adjusted R-squared	0.35	0.26	0.26	0.26	0.26
Observations	20615	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 $p < 0.01$.

and negative.[11]

5.3 The impact of lockdown policies on uncertainty

Lower information cost can explain the decrease in belief stickiness, but the spike in belief uncertainty seems at odds with a standard model of information choice. Lower information cost would imply a more precise signal, which would lower and not increase the belief uncertainty.

Formally, consider the general framework in Section 3. Taking the squared of belief

[11] 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.

updating equation 3 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 be thought of as a decrease in new information uncertainty $\sigma_{e,t}^2$ (Maćkowiak et al., 2023; Pomatto et al., 2023). Even with a constant gain G_t, this would lead to a decrease in posterior belief uncertainty $\Sigma_{t+h,t} \equiv var(x_{t+h} - E_t^i[x_{t+h}])$. An increase in gain G_t (i.e. a decline in belief rigidity $1 - G_t$), would strengthen further this effect and lead to even lower belief uncertainty. However, in the COVID period, we observe a sharp increase in belief uncertainty, as shown in Figure 2. Therefore, a lower information cost would not be consistent by itself with both a decline in belief stickiness 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 observe signal volatility only by acquiring more signals. In this case, a lower information cost would allow consumers to acquire more signals and learn about the increase in the signal's noise, which could explain both the lowering belief stickiness and the higher belief uncertainty.

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

Table 4: Belief stickiness and lockdown measures

	(1) $ln(Uncertainty3y)$	(2) $ln(Uncertainty3y)$	(3) $ln(Uncertainty3y)$	(4) $ln(Uncertainty3y)$
$Lockdown$	-0.173***	-0.185***	-0.215***	-0.090*
	(0.036)	(0.035)	(0.036)	(0.048)
$ln(DeathsCOVID)$			0.012	0.012
			(0.013)	(0.023)
$ln(CasesCOVID)$			-0.014	-0.021
			(0.016)	(0.028)
$EPUComposite$			0.009	-0.003
			(0.008)	(0.007)
Constant	1.189***	1.197***	1.231***	1.075***
	(0.038)	(0.025)	(0.085)	(0.130)
State FEs	Y	Y	Y	Y
Sample	Mar20-Jun22	Mar20-Jun22	Mar20-Jun22	Mar20-Jun21
Adjusted R-squared	0.09	0.30	0.30	0.29
Observations	1414	1414	1407	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 $p < 0.01$.

to more precise information.[12] Tables A.5 and A.6 show similar results for shorter horizon forecasts.

Our results show that, while lockdown policies have lowered belief stickiness 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.

5.4 A unified explanation: fundamental volatility

As argued in Section 3, 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

[12]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.

case, the gain G_t, or Kalman gain, equals

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

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 $\hat{\sigma}^2_{e,t} > \sigma^2_{e,t}$. For the same prior uncertainty, agents receive less accurate signals and therefore update less, $\hat{G}_t < G_t$: belief stickiness 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 stickiness 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, $E^i_{t-1}x_{t+h} = \rho E^i_{t-1}x_{t+h}$ and $\Sigma_{t+h,t-1} = \rho^2\Sigma_{t+h-1,t-1} + \sigma^2_{u,t+h}$. 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, households' prior information is more obsolete and therefore they update more, $\hat{G}_t > G_t$: belief stickiness 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 data.

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 stickiness. On the other hand, these results do not hold in models where the gain G_t does not depend on the uncertainty of the economy but only on some fixed parameter. For example, the baseline case of sticky information (Mankiw and Reis, 2002), adaptive learning with a constant gain (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.

6 Belief stickiness 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 stickiness* $1 - G_t$ *decreases in prior uncertainty,* $\frac{\partial 1-G_t}{\partial \Sigma_{t+1,t-1}} < 0$.

(*b*) *The information stickiness* $1 - G_t$ *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 stickiness. 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

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

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 stickiness (or the higher the weight on new information G_t), i.e. $\hat{\beta}_2 < 0$. If households' 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 stickiness, 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 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 5 plots the estimated effect of prior and posterior uncertainty on belief stickiness in the main specification of Column (3) in Table 5. The effect of uncertainty on belief stickiness is sizable. A one standard deviation increase in the logarithm of prior uncertainty reduces belief stickiness by around 0.1, i.e. 20%. Similarly, a one standard deviation increase in the logarithm of posterior uncertainty increases belief stickiness by around 0.07, i.e. 15%. Figure A.4 shows similar results for shorter forecast horizons.

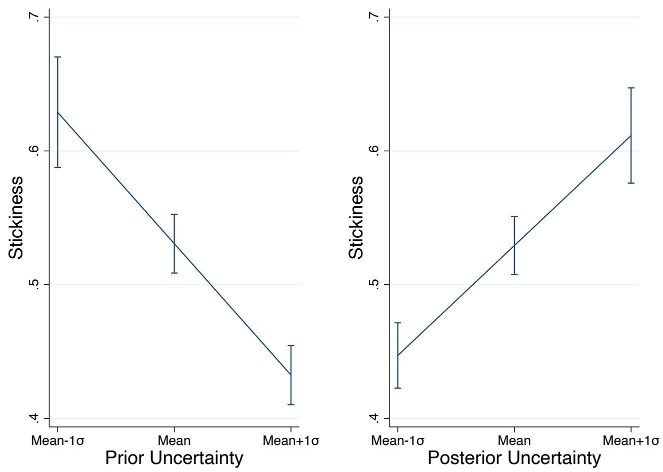
We test whether the impact of uncertainty on belief rigidity differs between con-

Table 5: Belief stickiness and uncertainty

	(1) *For 3y*	(2) *For 3y*	(3) *For 3y*	(4) *For 3y*	(5) *For 3y*
Prior 3y	0.515***	0.533***	0.551***	0.484***	0.532***
	(0.011)	(0.014)	(0.017)	(0.015)	(0.044)
Prior 3y × *Prior Uncert 3y*		-0.019***			
		(0.004)			
Prior 3y × *Post Uncert 3y*		0.013***			
		(0.004)			
Prior 3y × *ln*(*Prior Uncert3y*)			-0.137***		-0.111***
			(0.018)		(0.030)
Prior 3y × *ln*(*Post Uncert3y*)			0.113***		0.118***
			(0.015)		(0.023)
Prior 3y × *ln*(*Prior Uncert3yIQR*)				-0.112***	
				(0.014)	
Prior 3y × *ln*(*Post Uncert3yIQR*)				0.124***	
				(0.012)	
Prior 3y × *LockdownIndex*					-0.097***
					(0.024)
Constant	1.960***	1.072***	1.188***	1.391***	1.551***
	(0.049)	(0.069)	(0.073)	(0.051)	(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	0.37	0.36	0.38	0.30
Observations	83405	83405	67228	83402	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 5: Belief stickiness and uncertainty



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

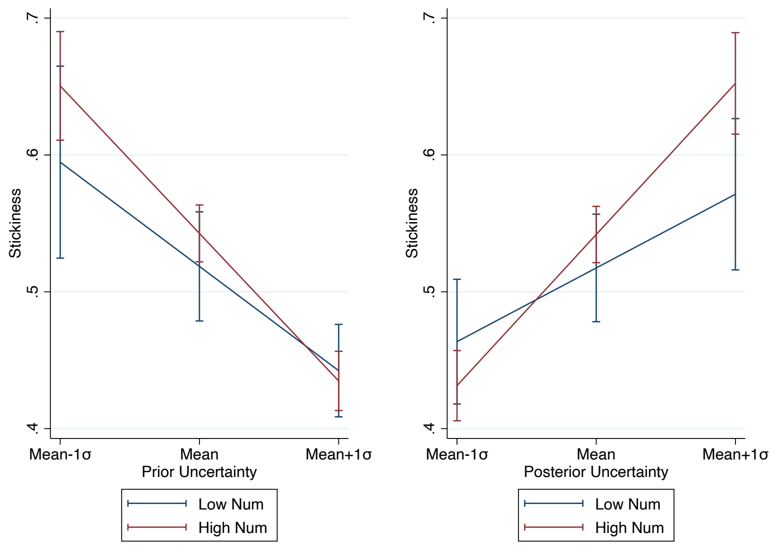
sumers with high and low numeracy skills. We run the following regression

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

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 stickiness does not differ systematically between low and high-numeracy households. On the other hand, the relationship between uncertainty and belief stickiness differs systematically between low and high-numeracy households. In particular, belief stickiness of high numeracy households decreases more when posterior uncertainty is higher than

Figure 6: Belief stickiness 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 stickiness 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.

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.[13]

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.

[13]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 stickiness between the two groups.

7 Policy implications

Throughout the pandemic, the extent to which households incorporate new information in their beliefs fluctuated considerably, with an initial decrease in belief rigidity followed by an increase as inflation and uncertainty grew. This variation is linked to elements such as the cost of acquiring information and the influence of political polarization. Notably, the later stages of the COVID-19 crisis and the beginning of President Biden's term saw a marked rise in the steadfastness of inflation expectations, pointing to its profound influence on the recent macroeconomic environment. This underscores the importance of developing economic models that more effectively account for the persistence of beliefs to accurately forecast economic trends. Our research provides a fresh set of data that can help improve the accuracy of models that include belief rigidity and guide policy-making. The high estimated level of belief rigidity in inflation forecasts in the later part of the Covid-19 crisis and during the early months of the Biden administration indicates a significant impact on macroeconomic dynamics in the recent period and highlights the need for models that better incorporate belief rigidities to understand and predict economic outcomes. This is important for explaining and anticipating the impact of information frictions on real macro relationships, such as the Phillips curve.

Information frictions, according to Angeletos and Huo (2021), contribute to flattening the Phillips Curve. This flattening implies that the inverse relationship between inflation and unemployment becomes less pronounced due to these frictions. Essentially, when information about the economy is not perfectly disseminated among all market participants, responses to changes in economic conditions (like inflation) are delayed or muted, weakening the expected trade-off between inflation and unemployment. Our paper suggests that the sharp drop in belief rigidity would have led to the Phillips curve becoming steeper in the early days of the pandemic, while the sharp increase in belief rigidity in the later part of the crisis to a flattening of the Philipps curve. This is consistent with evidence from Gallegos (2023), which shows that once information frictions are incorporated in models of expectation formation, the Phillips curve flattens. Moreover, this helps explain the slope of the U.S. Philipps curve estimated in Cerrato and Gitti (2022). Cerrato and Gitti (2022) document that the slope of the Phillips curve dropped to zero in the early months of the pandemic and more than tripled relative to pre-COVID from March 2021 onward, which could be rationalized with non-linearities, but would have been estimated exactly opposite had they considered information frictions as well.

Consequently, these empirical findings offer a new collection of facts that can aid in refining models incorporating belief rigidities and explain puzzles that cannot be rationalized with simple microfoundations. Moreover, they suggest that variations in belief rigidity can explain the observed dynamics of the Phillips Curve during the pandemic. These insights are pivotal for refining economic models and have profound implications for monetary policy, highlighting the importance of understanding how public perception and information processing influence macroeconomic policies and outcomes.

8 Conclusion

We investigated the relationship between news uncertainty and households' belief updating and rigidity using the NY Fed Survey of Consumer Expectations. Empirically, we find a negative association between uncertainty and belief rigidity during the Covid outbreak, and a positive relation during the ensuing high inflation period post-Covid. We rationalize these findings using a Bayesian-like belief updating model to show that different uncertainty sources influence belief rigidity in distinct ways. In particular, fundamental volatility increases prior uncertainty, which makes households want to search for information and update more, resulting in lower belief rigidity. On the other hand, higher new information uncertainty makes households want to search less and update less, resulting in higher belief rigidity. We then empirically retest these theoretical mechanisms using naturally occurring variation of 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 mechanisms 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	1.63	0.92	0	3	29998
Workplace	0.95	0.93	0	3	29998
Event	0.85	0.79	0	2	29998
Gathering	1.72	1.82	0	4	29998
Transport	0.29	0.49	0	2	29998
StayAtHome	0.57	0.70	0	2	29998
Movements	0.53	0.69	0	2	29998
Travel	0.28	0.63	0	2	29998
CasesCOVID	0.01	0.01	0.0000234	0.103	29998
DeathsCOVID	0.00	0.00	0	0.00108	29998
Economic Polic Uncertainty					
EPUState	2.29	2.03	0	14.66	29998
EPUNational	2.14	1.67	0	15.63	29998
EPUComposite	3.59	2.69	0.151	19.64	29998

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 2020M3-2022M6.

Table 7: Belief stickiness

	(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 2013M6-2022M6. 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 stickiness 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	0.431***	0.468***	0.489***	0.483***	0.444***	0.457***	0.439***	0.451***	0.481***	0.503***
	(0.107)	(0.098)	(0.105)	(0.106)	(0.100)	(0.099)	(0.099)	(0.099)	(0.103)	(0.102)
Prior 3y × *ln*($DeathsCOVID$)	-0.025*	-0.017	-0.014	-0.015	-0.022*	-0.018	-0.022	-0.021	-0.012	-0.013
	(0.012)	(0.013)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Prior 3y × *ln*($CasesCOVID$)	0.020	0.011	0.010	0.012	0.020	0.014	0.018	0.019	0.008	0.007
	(0.021)	(0.021)	(0.022)	(0.021)	(0.021)	(0.021)	(0.022)	(0.022)	(0.021)	(0.021)
Prior 3y × *School*	-0.030								0.026	
	(0.022)								(0.028)	
Prior 3y × *Workplace*		-0.079***							-0.022	
		(0.017)							(0.039)	
Prior 3y × *Event*			-0.082***						-0.027	
			(0.023)						(0.038)	
Prior 3y × *Gathering*				-0.039***					-0.025	
				(0.007)					(0.019)	
Prior 3y × *Transport*					-0.104***				-0.055	
					(0.031)				(0.034)	
Prior 3y × *StayAtHome*						-0.083***			0.004	
						(0.023)			(0.041)	
Prior 3y × *Movements*							-0.065***		0.044	
							(0.022)		(0.029)	
Prior 3y × *Travel*								-0.109***	-0.092**	
								(0.028)	(0.036)	
Prior 3y × *Lockdown*										-0.112***
										(0.020)
Constant	2.449**	2.358***	2.298***	2.325***	2.502***	2.259***	2.479***	2.425***	2.489***	2.299***
	(0.903)	(0.747)	(0.767)	(0.779)	(0.749)	(0.793)	(0.747)	(0.737)	(0.815)	(0.801)
Year-Month FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Socio-dемocraphic 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	19897	20615	20615	20615	20615	20615	20615	20615	20615	20615

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 stickiness and uncertainty for different numeracy skill

	(1) *For 3y*	(2) *For 3y*	(3) *For 3y*	(4) *For 3y*
Prior 3y	0.527***	0.500***	0.521***	0.545***
	(0.012)	(0.016)	(0.022)	(0.033)
$High\ Numeracy_{it}$=1 × *Prior 3y*		0.041***	0.038**	-0.002
		(0.015)	(0.016)	(0.036)
Prior 3y × *ln(Prior Uncert3y)*			-0.132***	-0.106***
			(0.018)	(0.027)
Prior 3y × *ln(Post Uncert3y)*			0.118***	0.074***
			(0.015)	(0.022)
$High\ Numeracy_{it}$=1 × *Prior 3y* × *ln(Prior Uncert3y)*				-0.044
				(0.027)
$High\ Numeracy_{it}$=1 × *Prior 3y* × *ln(Post Uncert3y)*				0.078***
				(0.026)
Constant	1.911***	2.617***	1.651***	1.369***
	(0.049)	(0.085)	(0.108)	(0.164)
Year-Month FEs	Y	Y	Y	Y
Socio-demographic FEs	Y	Y	Y	Y
Non-interacted variables	Y	Y	Y	Y
Adjusted R-squared	0.32	0.33	0.36	0.37
Observations	84280	84263	67904	67904

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 microfounded to endogenize the information stickiness 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...

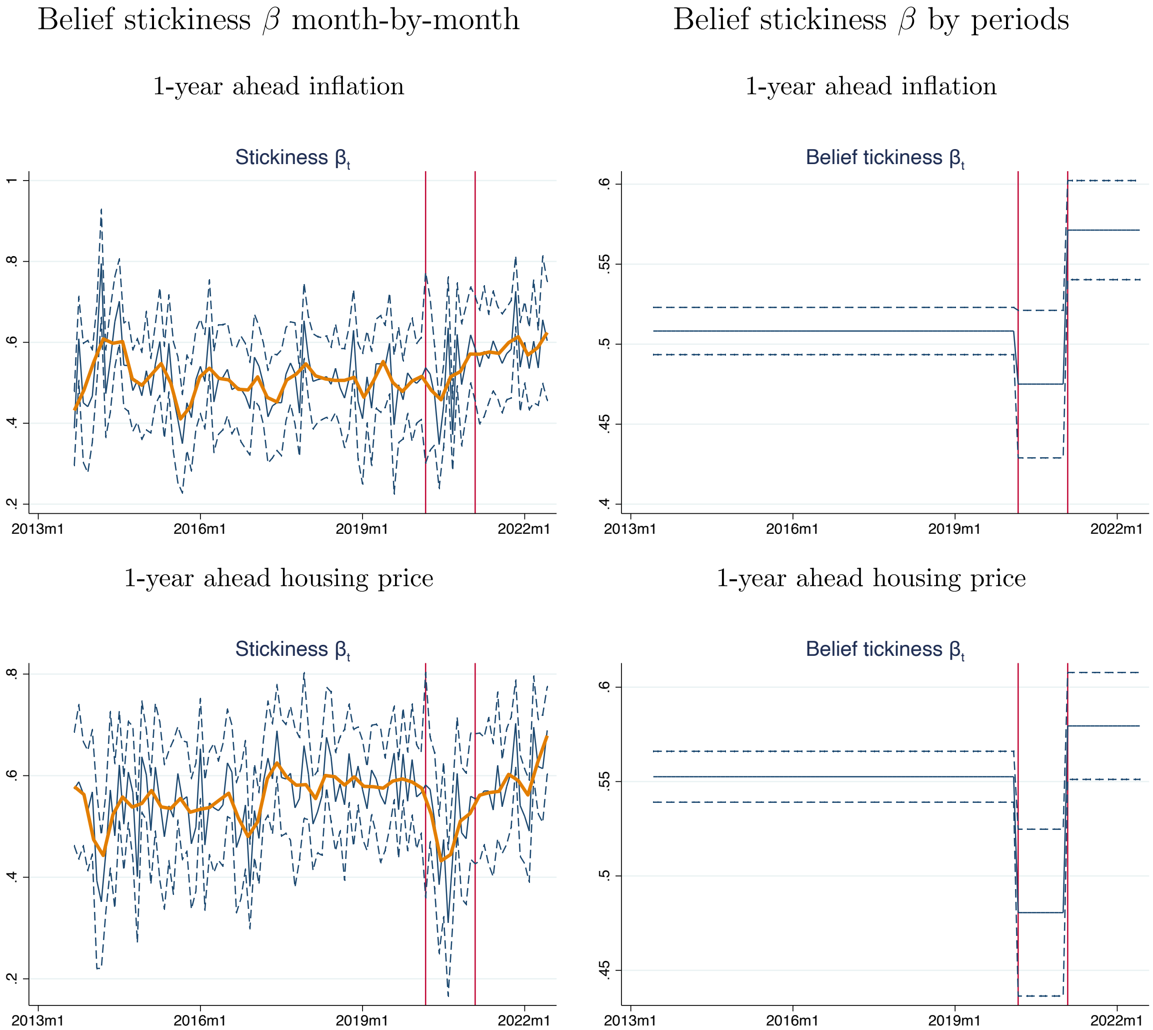
increased by 12% or more	______________	percent chance
increased by 8% to 12%	______________	percent chance
increased by 4% to 8%	______________	percent chance
increased by 2% to 4%	______________	percent chance
increased by 0% to 2%	______________	percent chance
decreased by 0% to 2%	______________	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 stickiness pre- and post-pandemic



Legend: The blue solid line represents our estimates of belief stickiness, 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 stickiness 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 - 2022M6.

Table A.1: Belief stickiness

	(1) $For\ 1y$	(2) $For\ 1y$	(3) $For\ 1y$
$Prior\ 1y$	0.518***	0.497***	0.327***
	(0.011)	(0.011)	(0.021)
$Prior\ 1y \times Tenure_{it}$			0.030***
			(0.002)
$High\ Numeracy_{it}$=1 $\times$ $Prior\ 1y$			0.027
			(0.017)
Constant	2.067***	2.160***	1.977***
	(0.047)	(0.047)	(0.048)
Year-Month FEs	Y	Y	Y
Socio-democraphic FEs	Y	Y	Y
Adjusted R-squared	0.39	0.37	0.40
Observations	82815	79378	82815

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 2013M6-2022M6. 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 stickiness

	(1)	(2)	(3)
	For H	*For H*	*For H*
Prior H	0.548***	0.536***	0.374***
	(0.010)	(0.010)	(0.025)
$Prior\ H \times Tenure_{it}$			0.022***
			(0.002)
$High\ Numeracy_{it}$=1 $\times$ $Prior\ H$			0.056***
			(0.018)
Constant	2.378***	2.435***	2.292***
	(0.054)	(0.052)	(0.044)
Year-Month FEs	Y	Y	Y
Socio-democraphic FEs	Y	Y	Y
Adjusted R-squared	0.38	0.36	0.38
Observations	76724	74807	76724

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 2013M6-2022M6. 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 stickiness and lockdown measures: 1 year inflation

	(1) *For 1y*	(2) *For 1y*	(3) *For 1y*	(4) *For 1y*	(5) *For 1y*
Prior 1y	0.502***	0.572**	0.569**	0.574**	0.576**
	(0.146)	(0.254)	(0.264)	(0.254)	(0.258)
Prior 1y × *Lockdown*	-0.037	-0.047	-0.051	-0.043	-0.042
	(0.029)	(0.043)	(0.040)	(0.047)	(0.043)
Prior 1y × *ln(DeathsCOVID)*	-0.017	-0.024	-0.025	-0.023	-0.022
	(0.020)	(0.037)	(0.041)	(0.037)	(0.040)
Prior 1y × *ln(CasesCOVID)*	0.022	0.043	0.045	0.042	0.041
	(0.017)	(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	3.660***	3.001**	3.069**	3.053**	3.036**
	(0.929)	(1.229)	(1.289)	(1.305)	(1.312)
Year-Month FEs	Y	Y	Y	Y	Y
Socio-demographic FEs	Y	Y	Y	Y	Y
Non-interacted variables	Y	Y	Y	Y	Y
Sample	Mar20-Jun22	Mar20-Jun21	Mar20-Jun21	Mar20-Jun21	Mar20-Jun21
Adjusted R-squared	0.40	0.34	0.34	0.34	0.34
Observations	20506	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 stickiness and lockdown measures: 1 year house prices

	(1) *For H*	(2) *For H*	(3) *For H*	(4) *For H*	(5) *For H*
Prior H	0.548***	0.656***	0.634***	0.634***	0.623***
	(0.121)	(0.181)	(0.187)	(0.189)	(0.193)
Prior H × *Lockdown*	-0.081***	-0.061*	-0.083*	-0.100**	-0.103**
	(0.023)	(0.033)	(0.041)	(0.041)	(0.047)
Prior H × *ln*(*DeathsCOVID*)	0.006	0.000	-0.008	-0.010	-0.013
	(0.015)	(0.025)	(0.026)	(0.024)	(0.026)
Prior H × *ln*(*CasesCOVID*)	-0.020	0.014	0.025	0.028	0.032
	(0.017)	(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	2.685**	1.528	1.820*	1.651	1.989*
	(1.118)	(1.021)	(0.997)	(0.999)	(0.977)
Year-Month FEs	Y	Y	Y	Y	Y
Socio-demographic FEs	Y	Y	Y	Y	Y
Non-interacted variables	Y	Y	Y	Y	Y
Sample	Mar20-Jun22	Mar20-Jun21	Mar20-Jun21	Mar20-Jun21	Mar20-Jun21
Adjusted R-squared	0.40	0.37	0.37	0.37	0.37
Observations	18898	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 stickiness and lockdown measures

	(1) $ln(Uncertainty1y)$	(2) $ln(Uncertainty1y)$	(3) $ln(Uncertainty1y)$	(4) $ln(Uncertainty1y)$
$Lockdown$	-0.182***	-0.187***	-0.234***	-0.082
	(0.033)	(0.033)	(0.033)	(0.050)
$ln(DeathsCOVID)$			0.006	0.014
			(0.015)	(0.028)
$ln(CasesCOVID)$			-0.008	-0.028
			(0.013)	(0.023)
$EPUComposite$			0.016**	-0.000
			(0.008)	(0.007)
Constant	1.234***	1.238***	1.237***	1.074***
	(0.034)	(0.024)	(0.116)	(0.182)
State FEs	Y	Y	Y	Y
Sample	Mar20-Jun22	Mar20-Jun22	Mar20-Jun22	Mar20-Jun21
Adjusted R-squared	0.10	0.32	0.33	0.32
Observations	1412	1412	1404	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 stickiness and lockdown measures

	(1) $ln(UncertaintyH)$	(2) $ln(UncertaintyH)$	(3) $ln(UncertaintyH)$	(4) $ln(UncertaintyH)$
$Lockdown$	-0.171***	-0.183***	-0.191***	-0.173***
	(0.030)	(0.031)	(0.037)	(0.045)
$ln(DeathsCOVID)$			0.025	0.027
			(0.015)	(0.024)
$ln(CasesCOVID)$			-0.010	-0.014
			(0.014)	(0.026)
$EPUComposite$			0.002	-0.003
			(0.008)	(0.008)
Constant	1.343***	1.351***	1.539***	1.531***
	(0.028)	(0.022)	(0.111)	(0.161)
State FEs	Y	Y	Y	Y
Sample	Mar20-Jun22	Mar20-Jun22	Mar20-Jun22	Mar20-Jun21
Adjusted R-squared	0.09	0.22	0.22	0.29
Observations	1402	1402	1394	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 stickiness and uncertainty

	(1) *For 1y*	(2) *For 1y*	(3) *For 1y*	(4) *For 1y*	(5) *For 1y*
Prior 1y	0.518***	0.533***	0.553***	0.489***	0.545***
	(0.011)	(0.018)	(0.021)	(0.017)	(0.048)
Prior 1y × *Prior Uncert 1y*		-0.021***			
		(0.004)			
Prior 1y × *Post Uncert 1y*		0.015***			
		(0.004)			
Prior 1y × *ln(Prior Uncert1y)*			-0.159***		-0.172***
			(0.015)		(0.033)
Prior 1y × *ln(Post Uncert1y)*			0.136***		0.156***
			(0.012)		(0.022)
Prior 1y × *ln(Prior Uncert1yIQR)*				-0.134***	
				(0.012)	
Prior 1y × *ln(Post Uncert1yIQR)*				0.146***	
				(0.010)	
Prior 1y × *LockdownIndex*					-0.026
					(0.030)
Constant	2.067***	1.196***	1.302***	1.504***	1.155***
	(0.047)	(0.066)	(0.075)	(0.050)	(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	0.39	0.44	0.43	0.45	0.38
Observations	82815	82815	66580	82808	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 $p < 0.01$.

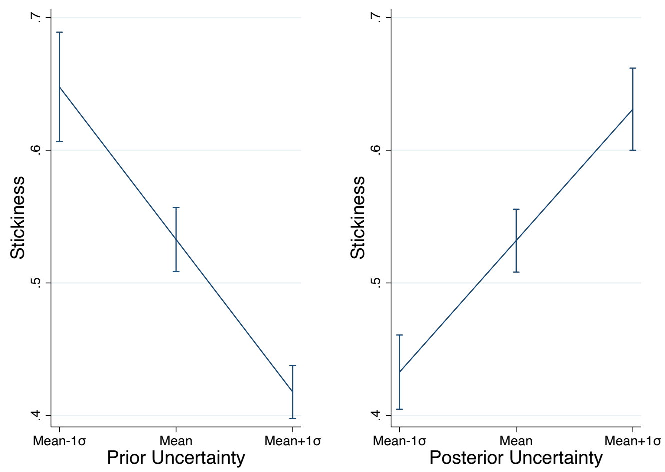
Table A.8: Belief stickiness and uncertainty

	(1) *For H*	(2) *For H*	(3) *For H*	(4) *For H*	(5) *For H*
Prior H	0.548***	0.581***	0.584***	0.532***	0.631***
	(0.010)	(0.014)	(0.017)	(0.015)	(0.064)
Prior H × *Prior Uncert H*		-0.026***			
		(0.003)			
Prior H × *Post Uncert H*		0.019***			
		(0.004)			
Prior H × *ln*(*Prior UncertH*)			-0.156***		-0.160***
			(0.011)		(0.028)
Prior H × *ln*(*Post UncertH*)			0.138***		0.128***
			(0.011)		(0.027)
Prior H × *ln*(*Prior UncertHIQR*)				-0.133***	
				(0.010)	
Prior H × *ln*(*Post UncertHIQR*)				0.142***	
				(0.010)	
Prior H × *LockdownIndex*					-0.053*
					(0.030)
Constant	2.378***	1.260***	1.469***	1.481***	1.474**
	(0.054)	(0.083)	(0.095)	(0.068)	(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	0.38	0.41	0.41	0.42	0.38
Observations	76724	76724	66667	76722	9318

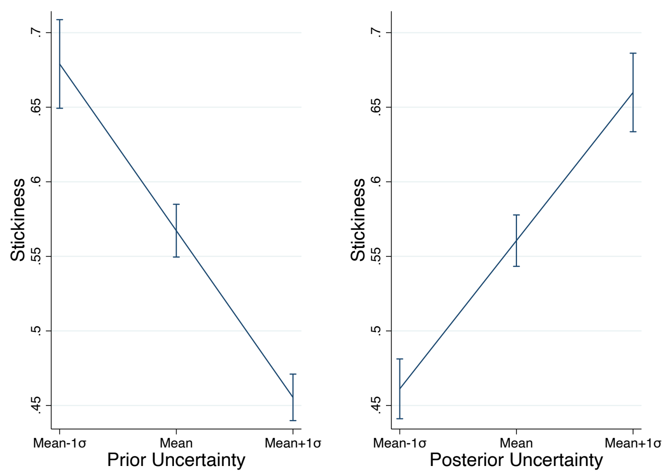
Legend: $Forh_{i,t}$ denotes the 1-year ahead forecast of housing price inflation expectations from the NY FED Survey of Consumer Expectations (SCE). $Prior\ h_{i,t}$ is the same forecast provided in the previous month. *PostUncerth* denotes the individual 1-year ahead forecast of housing price inflation 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 stickiness 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 stickiness β and prior uncertainty (on the left-hand side) and posterior uncertainty (on the right hand side).

Table A.9: Belief stickiness and uncertainty for different numeracy skill

	(1) *For 1y*	(2) *For 1y*	(3) *For 1y*	(4) *For 1y*
Prior 1y	0.532***	0.511***	0.543***	0.547***
	(0.011)	(0.014)	(0.025)	(0.032)
$High\ Numeracy_{it}$=1 × *Prior 1y*		0.024	0.019	0.014
		(0.017)	(0.017)	(0.031)
Prior 1y × *ln*(*Prior Uncert1y*)			-0.161***	-0.092***
			(0.015)	(0.026)
Prior 1y × *ln*(*Post Uncert1y*)			0.139***	0.060***
			(0.013)	(0.018)
$High\ Numeracy_{it}$=1 × *Prior 1y* × *ln*(*Prior Uncert1y*)				-0.115***
				(0.025)
$High\ Numeracy_{it}$=1 × *Prior 1y* × *ln*(*Post Uncert1y*)				0.134***
				(0.022)
Constant	2.007***	2.709***	1.649***	1.520***
	(0.048)	(0.076)	(0.116)	(0.145)
Year-Month FEs	Y	Y	Y	Y
Socio-demographic FEs	Y	Y	Y	Y
Non-interacted variables	Y	Y	Y	Y
Adjusted R-squared	0.38	0.39	0.43	0.43
Observations	83685	83669	67215	67215

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-demecratic 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 stickiness and uncertainty for different numeracy skill

	(1) *For H*	(2) *For H*	(3) *For H*	(4) *For H*
Prior H	0.557***	0.520***	0.509***	0.609***
	(0.010)	(0.018)	(0.020)	(0.035)
High Numeracy$_{it}$=1 × *Prior H*		0.056***	0.078***	-0.082**
		(0.018)	(0.017)	(0.038)
Prior H × *ln*(*Prior UncertH*)			-0.146***	-0.132***
			(0.011)	(0.024)
Prior H × *ln*(*Post UncertH*)			0.148***	0.074***
			(0.011)	(0.019)
High Numeracy$_{it}$=1 × *Prior H* × *ln*(*Prior UncertH*)				-0.014
				(0.026)
High Numeracy$_{it}$=1 × *Prior H* × *ln*(*Post UncertH*)				0.125***
				(0.020)
Constant	2.332***	3.193***	2.391***	1.429***
	(0.054)	(0.118)	(0.147)	(0.196)
Year-Month FEs	Y	Y	Y	Y
Socio-demographic FEs	Y	Y	Y	Y
Non-interacted variables	Y	Y	Y	Y
Adjusted R-squared	0.37	0.38	0.41	0.41
Observations	77540	77522	67343	67343

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 $p < 0.01$.