Households' Beliefs Ridigity in the Face of Uncertainty *

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February 26, 2024

Abstract

Households' belief formation is crucial to understand the transmission of economic shocks and their macroeconomic effects. We use survey data on households' inflation expectations to estimate the stickiness in their belief updating, and study how stickiness is affected by belief uncertainty. We show that households update their beliefs more when they report higher prior uncertainty, and less when they report higher posterior uncertainty. This is consistent with the rational Bayesian updating framework, as well as behavioral models building on it (diagnostic expectations, overconfidence) but not with a different set of behavioral models (learning with constant gain, sticky information). We document higher belief stickiness after COVID, and show that it is explained by higher uncertainty of new information. Moreover, we document a large heterogeneity in belief stickiness: older, richer households with higher numeracy score tend to display higher belief stickiness. Our findings have important policy implications, as heterogeneity in belief updating lead to heterogeneous effect of shocks and inequality even in absence of other channels.

Keywords: inflation expectations, surveys, information frictions, uncertainty.

JEL Classification: D81, D83, D84, E31

*This project received financial support from the Sandoz Family Foundation - Monique de Meuron Program for Academic Excellence 2022.

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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 in the last three years raises profound questions about the mechanisms underlying belief formation and decision-making within macroeconomic contexts. It underscores the complexity of economic behavior, hinting at deeper, under-explored factors that influence how individuals and collectives perceive their economic environment.

In this paper, we empirically examine U.S. households economic belief formation and updating in uncertain environments to shed light on potential explanations of the discrepancy between the positive objective data and U.S. households' pessimistic sentiment over the period 2020-2022. This period is ideal to study for multiple reasons: 1) First, it is a period characterized by high uncertainty due to the Covid-19 pandemic and the high-inflation months that followed; 2) Second, it is a period characterized by a large dissonance between real economic statistics and subjective beliefs; 3) Thirdly, it is a period with multiples shocks to the supply and demand of new information (i.e., shocks to households' expectations, uncertainty, attention, and cost of new information) due to repeated lock-downs, which allow us to identify the potential factors that could create such disconnect between real statistics and beliefs. Our contribution fits in a recent literature examining the factors that influence household cognition and expectation formation in uncertain environments (e.g. the scarring impact of crises on beliefs (Kozlowski et al. (2020), Braggion et al. (2024), Fermand et al. (2024)), asymmetric political polarization affecting economic perceptions (Nimark and Sundaresan (2019), Levy and Razin (2019)), the importance of the cost and quality of new information (Woodford (2009), Khaw et al. (2017)), and Ambuehl and Li (2017)), etc.). All these factors suggest a complex interplay between economic reality and public perception.

We empirically examine economic belief formation and updating for a variety of U.S. households for whom forecast data are available. We focus on inflation and house-price forecasts from the Survey of Consumer Expectations (SCE) run by the Federal Reserve Bank of New York during 2013-2022. The dataset contains more than 19,000 U.S. respondents' expectations regarding the rate of inflation and the rate of home price growth nationwide 12 and 36 months ahead, in terms of both their level (first moment) and uncertainty (second moment). The data set is exceptional as it also includes the respondents' socioeconomic characteristics, and measures of economic behaviors such as consumption plans, credit market use, and equity investments. We empirically estimate belief stickiness for 1- and 3-years ahead inflation expectations and 1-year house price expectations in the Survey of Consumer Expectations (SCE) following Goldstein (2023) and Gemmi and Valchev (2023), which improve on the method of Coibion and Gorodnichenko (2012, 2015) to allow common errors and just a cross section of prior and posterior forecasts. Theoretically, the implication of the Bayesian belief updating framework is that belief rigidity decreases in prior uncertainty, conditional on the posterior uncertainty, and increases in posterior uncertainty, conditional on the prior uncertainty. We test this in the Survey of Consumer Expectations (SCE) by including interactions with prior and posterior uncertainties.

We document that households update their beliefs according to the noisy-information Bayesian updating framework, meaning updating more when they are more uncertain and when new information is more accurate. Interestingly, however, the relationship between uncertainty and belief rigidity is not uniform over our sample between 2020 and 2022, which was characterized by increasing short and long-term uncertainty. While inflation and house price uncertainty were increasing throughout, belief rigidity decreased in the early Covid-19 period (up to March 2021), and increased in the later, high-inflation months (after March 2021).

We then investigate the factors driving the time-series trends in belief rigidity. Specifically, our analysis suggests the early pandemic trends of high uncertainty but low belief stickiness are driven by lower costs of information acquisition as remote-working proliferated, depending on the intensity of lock-downs, at different speeds across different states. The trends are not driven by inflation black swan shocks such as scarring of beliefs, or by local media bias and/or uncertain news. The later trends of high uncertainty and high belief stickiness that started in March 2021, at the beginning of the first Biden administration, are driven by increasing costs of information acquisition as households started transitioning back to in-presence work, and amplified by the asymmetric political polarization between Republicans and Democrats. Furthermore, the implied degree of information rigidity is low in the early pandemic, and very high in the late Covid-19 crisis: in the context of noisy-information models it implies that new information receives less than XXX of the weight in the early period, and less than YYY of the weight in the later period that it would under full-information relative to prior beliefs. In addition, we document that qualitatively similar results obtain when including commuting zone fixed effects, considering only high-numeracy households, only non-zero revisions (on the intensive margin), or the monthly share of non-zero revisions (on the extensive margin). This implies that information rigidities are present not just among the general population, but also among highly-sophisticated households, and both on the intensive and extensive margins.

At the heart of our investigation into economic perceptions is the theoretical noisy-information model of belief updating, as in the case of rational expectations (Woodford (2001), Sims (2003), and Mackowiak and Wiederholt (2009)), of diagnostic expectations (Bordalo et al. (2018, 2020)), and of extrapolation (Angeletos et al. (2021)). In this large class of models, agents continuously update their information sets but, because they can never fully observe the true state, they form and update beliefs about the underlying fundamentals via a signal extraction problem. Forecasts are a weighted average of agents' prior beliefs and the new information received, where the weight on prior beliefs can be interpreted as the degree of belief rigidity. 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)). Belief rigidity varied significantly during the pandemic, initially decreasing then increasing with rising inflation and uncertainty. This change is attributed to factors like information acquisition costs and political polarization. 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 macroeconomic outcomes. Our empirical findings offer a new collection of facts that can aid in refining models incorporating belief rigidities beyond noisy information and Bayesian learning.

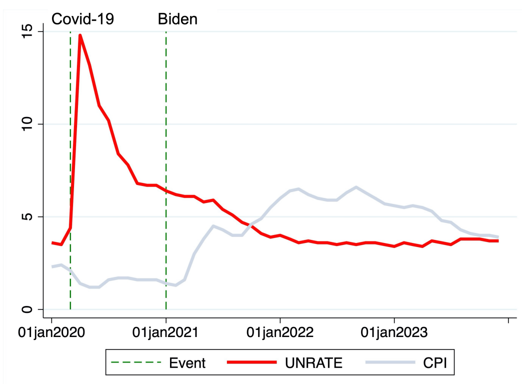
The paper proceeds as follows: Section 2 presents data suggesting a large disconnect between economic statistics and perceptions; Section 3 builds a general theory of belief updating, whose empirical implications are tested in Section 4, focusing on different hypothesis and population subgroups. Section 5 highlights the relationship between different types of uncertainty and belief stickiness, and lastly Section 6 concludes.

2 Disconnect between data and beliefs

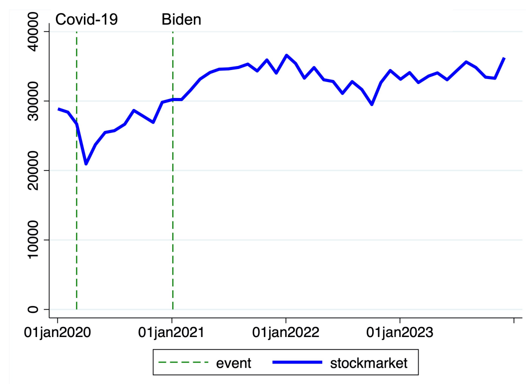
An array of hard data shows that the US economy has been improving lately: inflation has slowed sharply, unemployment is lower than ever , and the stock-market is strong and growing, as shown in Figure 1, Panel A. However, multiple surveys of consumer sentiment are showing indices of optimism that are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

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

A.1. Inflation and unemployment

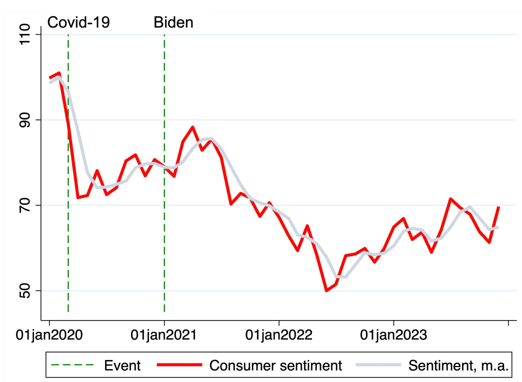


A.2. Stock market

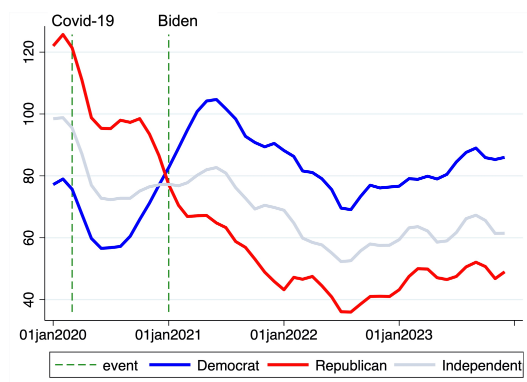


Panel B. But consumer sentiment about the economy remains low

B.1. Michigan consumer sentiment



B.2. Consumer sentiment by politics



Legend: Inflation (CPI-urban, All items less food and energy) and the unemployment rate are from FRED. Stock market index is from DOW. Consumer sentiment by political preference and overall about the U.S. economy are from the University of Michigan.

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 wealth, age, education, etc.), there are large differences in Democrats' and Republicans' perception of the U.S. economy. In Panel B.2., the Democrats' sentiment has slightly risen since early 2020, while Republicans' and Independents' sentiment has fallen dramatically in this period and never recovered.

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) a 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 3, one can write

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

by taking the variance one get

$$\Sigma_{t+h,t} = (1 - G_t)^2 \Sigma_{t+h,t-1} + G_t^2 \sigma_{e,t}^2 \tag{4}$$

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 $\sigma_{e,t}^2$.[1]

This framework embeds the noisy information case with rational expectations, where gain G_t equals the Kalman gain

$$G_t^{RE} = \frac{\Sigma_{t+h,t-1}}{\sigma_{e,t}^2 + \Sigma_{t+h,t-1}} \tag{5}$$

However, this setting is general and it can encompass a large set of belief updating model in the literature, which we discuss in Appendix A.

Consider the baseline rational expectation case in 5. The gain G_t is time-varying as it depends on changes in information uncertainty. However, we highlight the importance to differentiate 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 stickiness increase. For example, households may face a higher cost of collecting information or may face a lower supply of information from newspaper, television or social networks. Second, consider an increase in uncertainty of current fundamentals, i.e. an increase in prior uncertainty $\hat{\Sigma}_{t+h,t-1} > \Sigma_{t+h,t-1}$.[2] For the same uncertainty of new information, agents prior information is more obsolete and therefore update more, $\hat{G}_t > G_t$: belief stickiness decreases. We formalize this intuition in the following proposition.

[1] We will use the term variance and uncertainty interchangeably to refer to the second moment of the distribution of beliefs. We don't consider cases in which the support of the random variable is not known, or where the probability associated with the support is not.

[2] For example, consider the case where horizon is just one period ahead, $h = 1$, and the fundamental follow an AR(1) process: $x_t = \rho x_{t-1} + u_t$ with $u_t \sim N(0, \sigma_{u,t}^2)$. In this case, $E_{t-1}^i x_{t+1} = \rho E_{t-1}^i x_t$ and $\Sigma_{t+1,t-1} = \rho^2 \Sigma_{t,t-1} + \sigma_{u,t}^2$. An increase in fundamental volatility $\sigma_{u,t}^2$ increase prior uncertainty $\Sigma_{t+1,t-1}$.

Proposition 1. *Consider the belief updating process in equations 2 and 4 with Kalman gain described in equation 5 (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 5, the intuition for (b) comes from equation 4: keeping fixed prior uncertainty, posterior uncertainty reflect only new information uncertainty.

While we derive this results under the rational expectation assuming, it holds in a large set of models that depart but build on the baseline Bayesian updating in 5. For example, diagnostic expectations (Bordalo et al., 2018, 2020), overconfidence (Broer and Kohlhas, 2018), over and under-extrapolation (Angeletos et al., 2021) and strategic incentives models (Gemmi and Valchev, 2023) all share the same implications. On the other hand, proposition 1 does 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 this implications. However, more microfounded versions of these models also relate the gain on new information to the model structure, and therefore fundamental and information uncertainty.

4 Data and Results

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.[3] 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

[3]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.

around 1,300 observation per months, 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 provide 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 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 respondent to indicate both their point forecast for future expected inflation and also 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.[4] 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 percentages 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 details in Armantier et al. (2017). We indicate as posterior uncertainty the standard deviation from the variance of the subjective distribution provided in 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 point

[4]While we could alternatively use the mean forecast computed from the subjective distribution, we think that using the answers to two different survey questions lower 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					
$For\ 1y_{it}$	5.17	6.71	-45	56	122158
$For\ 3y_{it}$	4.90	6.99	-50	60	123019
$Prior\ 1y_{it}$	5.06	6.48	-45	56	89061
$Prior\ 3y_{it}$	4.84	6.73	-50	60	89455
$Post\ Uncert\ 1y_{it}$	2.95	3.14	0	22	122158
$Post\ Uncert\ 3y_{it}$	2.97	3.09	0	22	123019
$Post\ Uncert\ 1y\ IQR_{it}$	3.34	3.60	0	28	122158
$Post\ Uncert\ 3y\ IQR_{it}$	3.35	3.52	0	28	123019
Socioeconomic characteristics					
$College_{it}$	0.69	0.46	0	1	135240
$Income\ 50kto100k_{it}$	0.30	0.46	0	1	133884
$Income\ Over100k_{it}$	0.29	0.45	0	1	133884
$Income\ Under50k_{it}$	0.42	0.49	0	1	133884
$High\ Numeracy_{it}$	0.67	0.47	0	1	135187
$Female_i$	0.49	0.50	0	1	135209
Age_{it}	50.73	15.59	17	94	135182
$White_i$	0.84	0.36	0	1	135237
$Tenure_{it}$	5.54	3.38	1	16	135240
$IsWorking_{it}$	0.64	0.48	0	1	135240
$P(default3months)_{it}$	11.70	21.99	0	100	134932

forecast, which is that the horizon is approximately the same across two consecutive month. 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 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 ($HighNumeracy_{i,t}$). Moreover, we consider two additional variables that **?** document significantly affect household inflation uncertainty in the SCE. First, we construct an indicator with value 1 if the respondent is working full-time, part-time or is in a sick leave, and zero otherwise ($Is\ Working_{it}$). Second, a variable indicating the subjective probability of not making the minimum payment on their consumer credit in the following 3 months ($P(default3months)_{it}$). The bottom panel of table 1 presents summary statistics for all these socioeconomic variables.

4.1 Results

4.1.1 Households Belief Stickiness

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 presence of common errors in the signals structure ($\sigma_\omega > 0$ in our theoretical framework). Second, it requires a long time series dimension which is usually not possible to have in household surveys.[5] We instead employ a new methodology developed in Goldstein (2023) and Gemmi and Valchev (2023) which allows to estimate belief updating stickiness even in presence of common errors and with just a cross section of prior and posterior forecasts.

Demeaning 2 using consensus forecasts,[6]

$$E_t^i[x_{t+h}] - \bar{E}_t^i[x_{t+h}] = (1-G)(E_{t-1}^i[x_{t+h}] - \bar{E}_{t-1}[x_{t+h}]) - G\eta_t^i \tag{6}$$

Equation 6 provide an unbiased strategy to measure information stickiness. We run the following panel regression

$$For_{i,t} = \alpha + \beta Prior_{i,t} + X_{i,t} + \gamma_t + err_t^i \tag{7}$$

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

[5]The bias in 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)

[6]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* $3y_{it}$	(2) *For* $3y_{it}$	(3) *For* $3y_{it}$
Prior $3y_{it}$	0.515***	0.375***	0.314***
	(0.011)	(0.011)	(0.023)
Prior $3y_{it}$ $\times$ *Tenure*$_{it}$			0.031***
			(0.002)
High Numeracy$_{it}$=1 $\times$ *Prior* $3y_{it}$			0.038**
			(0.015)
Constant	1.960***	2.666***	1.871***
	(0.049)	(0.053)	(0.046)
Year-Month FEs	Y	Y	Y
Socio-democraphic FEs	Y	Y	Y
Adjusted R-squared	0.33	0.19	0.34
Observations	83405	52012	83405

Standard errors in parentheses
Standard errors are clustered at individual and time level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(lower β).

Table 2 reports the estimates of belief stickiness β from regression (7). 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 uses a similar strategy on the Survey of Professional Forecasters.[7]

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, suggesting that a high level of belief stickiness is not driven by inexperienced respondents.

[7]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.

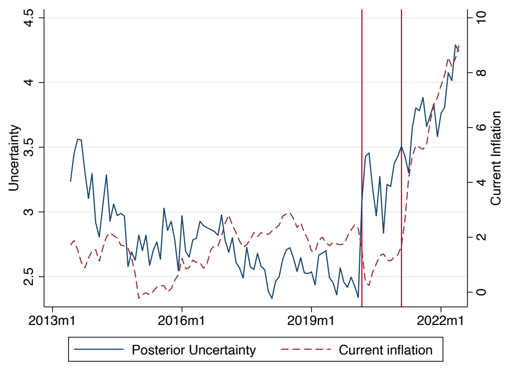


Figure 2: Inflation uncertainty and stickiness in Covid and high inflation periods

4.1.2 Belief stickiness and 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 COVID pandemic and 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

$$For_{i,t} = \alpha_t + \beta_t Prior_{i,t} + X_{i,t} + err_t^i \tag{8}$$

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 sickness in three different subsamples: pre-COVID period (up to March 202), COVID period (between March 2020 and February 2021) and high inflation period (after February

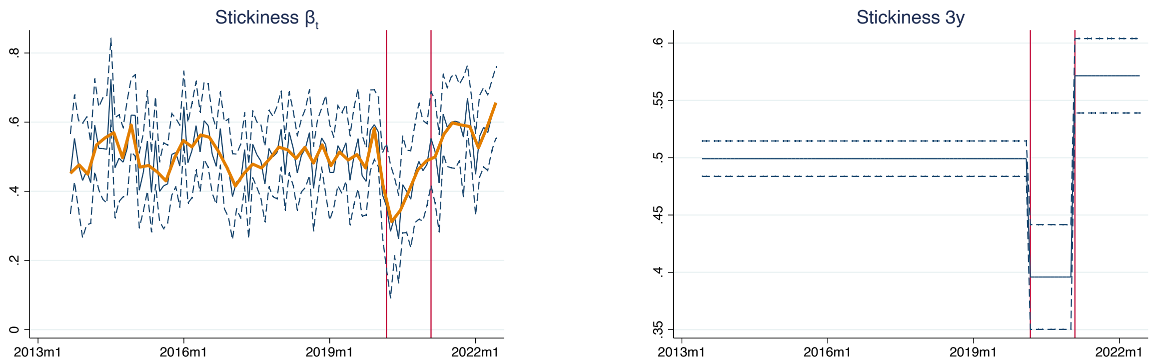


Figure 3: Belief stickiness pre and post pandemic

2021). Table XXX in the appendix reports the estimates.

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.

4.1.3 Information cost and belief stickiness: 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 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 to 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 states 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 differ 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, *severity index*, equal to the simple average of these indicators.[8] Moreover, to measure the local impact of the pandemic we use the US state-level monthly percentage change in COVID deaths per capita.

In order to estimate the impact of lockdown measures on belief stickiness, we interact the prior forecast in regression (7) with each lockdown indicator and the COVID death measure. Intuitively, as the latter measures the impact of the pandemic on the state, the former measures the stringency of the lockdown, which one can think of as a proxy for information acquisition cost. We run the following regression

$$For_{i,t} = \alpha + \beta_1 Prior_{i,t} + Prior_{i,t} \times \Omega'_{i,t}\Pi + \Omega'_{i,t}\Gamma + X_{i,t} + \gamma_t + err^i_t \tag{9}$$

where $\Omega'_{i,t}$ contains the lockdown and the COVID death measure and Π estimates the impact of lockdown and COVID deaths on consumers belief stickiness. We run the regression in the post-pandemic sample, from March 2020. Table 3 reports the 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, in column (10) we use the *Severity* as a summary of the individual indicators. Once again the impact of belief stickiness is negative and robust.

[8] This measure is similar to the *stringency index* in Hale et al. (2020), as they also consider a simple average of each indicators. 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.

Table 3: Belief stickiness and lockdown measures

	(1) *For* $3y_{it}$	(2) *For* $3y_{it}$	(3) *For* $3y_{it}$	(4) *For* $3y_{it}$	(5) *For* $3y_{it}$	(6) *For* $3y_{it}$	(7) *For* $3y_{it}$	(8) *For* $3y_{it}$	(9) *For* $3y_{it}$	(10) *For* $3y_{it}$
Prior $3y_{it}$	0.575***	0.577***	0.573***	0.566***	0.554***	0.559***	0.557***	0.557***	0.553***	0.587***
	(0.027)	(0.017)	(0.017)	(0.016)	(0.018)	(0.017)	(0.017)	(0.016)	(0.029)	(0.018)
Prior $3y_{it} \times DeathsCOVID$	-0.007***	-0.002	-0.004**	-0.004***	-0.006***	-0.004*	-0.006***	-0.008***	-0.004*	-0.002
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
Prior $3y_{it} \times School$	-0.030								0.029	
	(0.024)								(0.029)	
Prior $3y_{it} \times Workplace$		-0.081***							-0.020	
		(0.019)							(0.041)	
Prior $3y_{it} \times Event$			-0.080***						-0.024	
			(0.022)						(0.036)	
Prior $3y_{it} \times Gathering$				-0.039***					-0.024	
				(0.008)					(0.019)	
Prior $3y_{it} \times Transport$					-0.106***				-0.059*	
					(0.034)				(0.034)	
Prior $3y_{it} \times StayAtHome$						-0.086***			0.003	
						(0.027)			(0.042)	
Prior $3y_{it} \times Movements$							-0.070***		0.037	
							(0.024)		(0.029)	
Prior $3y_{it} \times Travel$								-0.113***	-0.094**	
								(0.029)	(0.037)	
Prior $3y_{it} \times Severity$										-0.114***
										(0.022)
Constant	2.100***	2.131***	2.093***	2.222***	2.145***	2.027***	2.082***	2.098***	2.377***	2.232***
	(0.233)	(0.107)	(0.113)	(0.106)	(0.088)	(0.108)	(0.094)	(0.085)	(0.268)	(0.164)
Year-Month FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Socio-democraphic FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Non-interacted variables	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R-squared	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35
Observations	19920	19920	19920	19920	19920	19920	19920	19920	19920	19920

Standard errors in parentheses
Standard errors are clustered at individual and time level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Belief stickiness and lockdown measures

	(1) $For\ 3y_{it}$	(2) $For\ 3y_{it}$	(3) $For\ 3y_{it}$
$Prior\ 3y_{it}$	0.587***	0.605***	0.569***
	(0.018)	(0.089)	(0.024)
$Prior\ 3y_{it} \times Severity$	-0.114***	-0.152**	-0.070
	(0.022)	(0.050)	(0.043)
$Prior\ 3y_{it} \times DeathsCOVID$	-0.002	0.001**	0.096
	(0.001)	(0.001)	(0.206)
$Severity$	0.088	0.100	0.014
	(0.193)	(0.213)	(0.320)
$DeathsCOVID$	0.054***	0.019	0.192
	(0.006)	(0.014)	(1.697)
Constant	2.232***	2.021***	2.423***
	(0.164)	(0.341)	(0.171)
Year-Month FEs	Y	Y	Y
Socio-democraphic FEs	Y	Y	Y
Sample	Mar20-Jun22	Mar20-Feb21	Mar22-Jun22
Adjusted R-squared	0.35	0.21	0.37
Observations	19920	6672	13292

Standard errors in parentheses
Standard errors are clustered at individual and time level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The first column of Table **??** reports the same regression as the last column

4.2 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 test this implication by running the following regression

$$\begin{aligned} For_{i,t} =& \alpha + \beta_1 Prior_{i,t} + \begin{bmatrix} Prior\ Uncertainty_{it} \times Prior_{i,t} \\ Post\ Uncertainty_{it} \times Prior_{i,t} \end{bmatrix}' \begin{bmatrix} \beta_2 \\ \beta_3 \end{bmatrix} \\ &+ Z_{i,t}'\Gamma + X_{i,t} + \gamma_t + err_t^i \end{aligned} \tag{10}$$

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

Table 5 reports the results of regression for inflation expectations at 1 year horizon. The results confirm the implications of the Bayesian belief updating framework summarized in proposition 1. First, the higher is the prior uncertainty for a given posterior

Table 5: Belief stickiness and uncertainty

	(1)	(2)	(3)	(4)
	For $1y_{it}$	*For* $1y_{it}$	*For* $1y_{it}$	*For* $1y_{it}$
Prior $1y_{it}$	0.544**	0.539***	0.563***	0.494***
	(0.022)	(0.018)	(0.021)	(0.017)
Prior $1y_{it}$ × *Prior Uncert* $1y_{it}$		-0.021***		
		(0.004)		
Prior $1y_{it}$ × *Post Uncert* $1y_{it}$		0.015***		
		(0.003)		
Prior $1y_{it}$ × $ln(Prior\ Uncert1y)_{it}$			-0.163***	
			(0.015)	
Prior $1y_{it}$ × $ln(Post\ Uncert1y)_{it}$			0.136***	
			(0.012)	
Prior $1y_{it}$ × $ln(Prior\ Uncert1yIQR)_{it}$				-0.136***
				(0.012)
Prior $1y_{it}$ × $ln(Post\ Uncert1yIQR)_{it}$				0.147***
				(0.010)
Constant	1.953*	1.116***	1.167***	1.441***
	(0.207)	(0.068)	(0.076)	(0.051)
Year-Month FEs	Y	Y	Y	Y
Age, Gender, Race FEs	Y	Y	Y	Y
Tenure FEs	Y	Y	Y	Y
Adjusted R-squared				
Observations	0	0	0	0
N	83685	83685	67225	83678

Standard errors in parentheses
Belief gain estimation interacted with posterior and prior uncertainty.
Controls included the interacted variables without interactions
Standard errors are clustered at individual and time level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

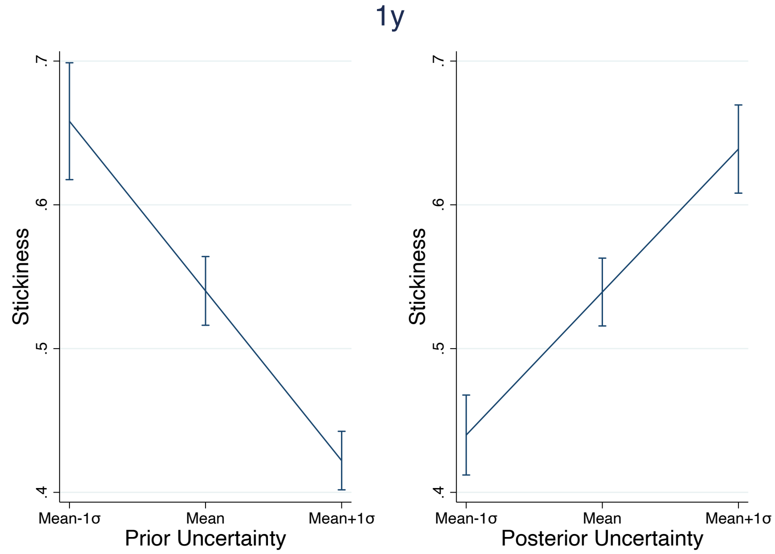


Figure 4: Belief stickiness and uncertainty

uncertainty, the lower is the belief stickiness (or alternatively the higher is the weight on new information G_t), i.e. $\hat{\beta}_2 < 0$. If households information are obsolete, they incorporate more new information when forming new beliefs. Second, the higher is the posterior uncertainty for a given prior uncertainty, the higher is the belief stickiness, i.e. $\hat{\beta}_3 > 0$. If households receive noisier information, they incorporate less of those new information when forming new beliefs. The result is robust to considering only the pre-COVID sample (column 4), to using the interquartile range of subjective probability as a measure of uncertainty (column 5) and to considering a 3 years horizon instead A.1.

Figure 6 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%.

If the relation between households' update stickiness and uncertainty about past and future information is due to a rational Bayesian mechanism, it should be more difficult for households with low numeracy [ADD CITATIONS]. We test this conjecture by interacting the coefficient of interest with the high numeracy indicator.

$$
\begin{aligned}
For_{i,t} =& \alpha + \beta_1 Prior_{i,t} + \begin{bmatrix} Prior\ Uncertainty_{it} \times Prior_{i,t} \\ Post\ Uncertainty_{it} \times Prior_{i,t} \end{bmatrix}' \begin{bmatrix} \beta_2 \\ \beta_3 \end{bmatrix} \\
&+ High\ Numeracy_{i,t} \times \begin{bmatrix} Prior\ Uncertainty_{it} \times Prior_{i,t} \\ Post\ Uncertainty_{it} \times Prior_{i,t} \end{bmatrix}' \begin{bmatrix} \beta_4 \\ \beta_5 \end{bmatrix} \\
&+ \beta_6 Prior_{i,t} \times High\ Numeracy_{i,t} + Z'_{i,t}\Gamma + X_{i,t} + \gamma_t + err^i_t
\end{aligned} \tag{11}
$$

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 6 reports the estimated coefficient for the 1 year horizon and highlight two important results. On the one hand, belief stickiness does not differ systematically between low and high numeracy households. On the other hand, the relation between uncertainty and belief stickiness differs systematically between low and high numeracy households. In particular, belief stickiness of high numeracy households increases more with prior uncertainty is laregr and decreases more when posterior uncertainty is higher than for low numeracy households. There results are similar at the 3 years horizon in table A.2. 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.[9]

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 features is shared by several of the non-rational belief updating models in the literature, even though by not all of them.

[9]While **?** 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.

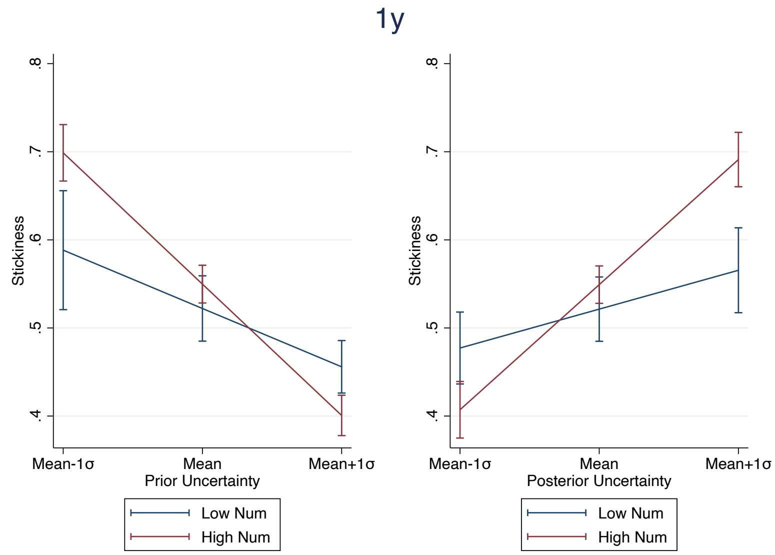


Figure 5: Belief stickiness and uncertainty for different numeracy skill

Table 6: Belief stickiness and uncertainty for different numeracy skill

	(1) $For\ 1y_{it}$	(2) $For\ 1y_{it}$	(3) $For\ 1y_{it}$	(4) $For\ 1y_{it}$
$Prior\ 1y_{it}$	0.532*** (0.011)	0.511*** (0.014)	0.543*** (0.025)	0.547*** (0.032)
$High\ Num{=}1 \times Prior\ 1y_{it}$		0.024 (0.017)	0.019 (0.017)	0.014 (0.031)
$Prior\ 1y_{it} \times ln(Prior\ Uncert1y)_{it}$			-0.161*** (0.015)	-0.092*** (0.026)
$Prior\ 1y_{it} \times ln(Post\ Uncert1y)_{it}$			0.139*** (0.013)	0.060*** (0.018)
$High\ Num{=}1 \times Prior\ 1y_{it} \times ln(Prior\ Uncert1y)_{it}$				-0.115*** (0.025)
$High\ Num{=}1 \times Prior\ 1y_{it} \times ln(Post\ Uncert1y)_{it}$				0.134*** (0.022)
Constant	2.007*** (0.048)	2.709*** (0.076)	1.649*** (0.116)	1.520*** (0.145)
Year-Month FEs	Y	Y	Y	Y
Age, Gender, Race FEs	Y	Y	Y	Y
Tenure FEs	Y	Y	Y	Y
Adjusted R-squared				
Observations	0	0	0	0
N	83685	83669	67215	67215

Standard errors in parentheses
Belief gain estimation interacted with posterior and prior uncertainty.
Controls included the interacted variables without interactions
Standard errors are clustered at individual and time level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.3 Belief stickiness and COVID

Is the higher belief stickiness in the post-COVID sample due to an increase in new information uncertainty or due to other factors (e.g. a structural break in the way agents incorporate uncertainty)? We test this hypothesis by estimating the different effect of prior and posterior uncertainty on belief updating before and after COVID

$$\begin{aligned} For_{i,t} =& \alpha + \beta_1 Prior_{i,t} + \begin{bmatrix} Prior\ Uncertainty_{it} \times Prior_{i,t} \\ Post\ Uncertainty_{it} \times Prior_{i,t} \end{bmatrix}' \begin{bmatrix} \beta_2 \\ \beta_3 \end{bmatrix} \\ &+ PostCovid_t \times \begin{bmatrix} Prior\ Uncertainty_{it} \times Prior_{i,t} \\ Post\ Uncertainty_{it} \times Prior_{i,t} \end{bmatrix}' \begin{bmatrix} \beta_4 \\ \beta_5 \end{bmatrix} \\ &+ \beta_6 Prior_{i,t} \times PostCovid_t + Z'_{i,t}\Gamma + X_{i,t} + \gamma_t + err^i_t \end{aligned} \tag{12}$$

where $Z_{i,t}$ include the non-interacted $Prior\ Uncertainty_{it}$, $Post\ Uncertainty_{it}$ and their interactions with $PostCovid_t$. Coefficients β_2 and β_3 measure respectively the dependence of belief updating on prior and posterior uncertainty in the pre-COVID sample, while $\beta_2+\beta_4$ and $\beta_3+\beta_5$ measure respectively the dependence of belief updating on prior and posterior uncertainty in the post-COVID sample.

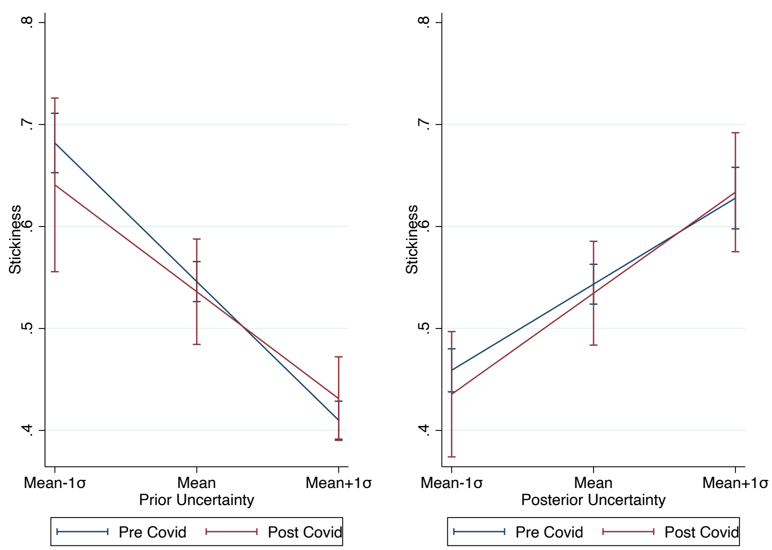


Figure 6: Effect of Uncertainty on Belief Stickiness for Low and High Numeracy

Table 9 reports the estimated coefficient for the 1 year horizon and shows that here is no difference in the impact of prior and posterior uncertainty between the pre and

Table 7: Belief stickiness and uncertainty pre and post COVID

	(1)	(2)	(3)
	For $1y_{it}$	*For* $1y_{it}$	*For* $1y_{it}$
Prior $1y_{it}$	0.532***	0.507***	0.603***
	(0.011)	(0.012)	(0.015)
PostCovid=1 × *Prior* $1y_{it}$		0.049**	-0.060
		(0.020)	(0.046)
Prior $1y_{it}$ × *ln*(*Post Uncert1y*)$_{it}$			0.117***
			(0.012)
Prior $1y_{it}$ × *ln*(*Prior Uncert1y*)$_{it}$			-0.188***
			(0.010)
PostCovid=1 × *ln*(*Post Uncert1y*)$_{it}$			0.445*
			(0.234)
PostCovid=1 × *ln*(*Prior Uncert1y*)$_{it}$			-0.021
			(0.236)
PostCovid=1 × *Prior* $1y_{it}$ × *ln*(*Post Uncert1y*)$_{it}$			0.020
			(0.025)
PostCovid=1 × *Prior* $1y_{it}$ × *ln*(*Prior Uncert1y*)$_{it}$			0.043
			(0.032)
Constant	2.007***	2.043***	1.048***
	(0.048)	(0.043)	(0.070)
Year-Month FEs	Y	Y	Y
Age, Gender, Race FEs	Y	Y	Y
Tenure FEs	Y	Y	Y
Adjusted R-squared	0.38	0.38	0.43
Observations	83685	83685	67225

Standard errors in parentheses
Belief gain estimation interacted with posterior and prior uncertainty.
Controls included the interacted variables without interactions
Standard errors are clustered at individual and time level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Belief stickiness and uncertainty pre and post COVID

	(1)	(2)	(3)	(4)	(5)
	$For\ 1y_{it}$	$For\ 1y_{it}$	$For\ 1y_{it}$	$For\ 1y_{it}$	$For\ 1y_{it}$
$Prior\ 1y_{it}$	0.514***	0.491***	0.580***	0.540***	0.580***
	(0.011)	(0.011)	(0.016)	(0.019)	(0.016)
$PostCovid$=1 × $Prior\ 1y_{it}$		0.046**	-0.068*		-0.065*
		(0.021)	(0.038)		(0.039)
$Prior\ 1y_{it}$ × $ln(Post\ Uncert1y)_{it}$			0.111***	0.134***	0.111***
			(0.011)	(0.011)	(0.011)
$Prior\ 1y_{it}$ × $ln(Prior\ Uncert1y)_{it}$			-0.179***	-0.157***	-0.179***
			(0.011)	(0.013)	(0.011)
$PostCovid$=1 × $ln(Post\ Uncert1y)_{it}$			0.383*		0.342
			(0.231)		(0.233)
$PostCovid$=1 × $ln(Prior\ Uncert1y)_{it}$			0.049		0.088
			(0.202)		(0.203)
$PostCovid$=1 × $Prior\ 1y_{it}$ × $ln(Post\ Uncert1y)_{it}$			0.026		0.029
			(0.023)		(0.023)
$PostCovid$=1 × $Prior\ 1y_{it}$ × $ln(Prior\ Uncert1y)_{it}$			0.042		0.038
			(0.025)		(0.026)
$High\pi$=1 × $Prior\ 1y_{it}$				-0.103***	-0.077*
				(0.028)	(0.043)
$High\pi$=1 × $ln(Post\ Uncert1y)_{it}$				1.687***	1.395***
				(0.187)	(0.281)
$High\pi$=1 × $ln(Prior\ Uncert1y)_{it}$				-1.229***	-1.336***
				(0.146)	(0.240)
$High\pi$=1 × $Prior\ 1y_{it}$ × $ln(Post\ Uncert1y)_{it}$				-0.112***	-0.118***
				(0.024)	(0.030)
$High\pi$=1 × $Prior\ 1y_{it}$ × $ln(Prior\ Uncert1y)_{it}$				0.172***	0.154***
				(0.026)	(0.034)
Constant	2.096***	2.129***	1.155***	1.267***	1.155***
	(0.050)	(0.044)	(0.063)	(0.068)	(0.063)
Year-Month FEs	Y	Y	Y	Y	Y
Age, Gender, Race FEs	Y	Y	Y	Y	Y
Tenure FEs	Y	Y	Y	Y	Y
Commuting-Zone FEs	Y	Y	Y	Y	Y
Adjusted R-squared	0.38	0.38	0.43	0.43	0.43
Observations	91223	91223	72494	72494	72494

Standard errors in parentheses
Belief gain estimation interacted with posterior and prior uncertainty.
Controls included the interacted variables without interactions
Standard errors are clustered at individual and time level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Belief stickiness and uncertainty pre and post COVID

	(1) $For\ 3y_{it}$	(2) $For\ 3y_{it}$	(3) $For\ 3y_{it}$	(4) $For\ 3y_{it}$	(5) $For\ 3y_{it}$
$Prior\ 3y_{it}$	0.504***	0.483***	0.561***	0.542***	0.561***
	(0.011)	(0.010)	(0.017)	(0.017)	(0.017)
$PostCovid$=1 × $Prior\ 3y_{it}$		0.046**	-0.036		-0.033
		(0.020)	(0.039)		(0.039)
$Prior\ 3y_{it}$ × $ln(Post\ Uncert3y)_{it}$			0.106***	0.110***	0.106***
			(0.011)	(0.015)	(0.011)
$Prior\ 3y_{it}$ × $ln(Prior\ Uncert3y)_{it}$			-0.162***	-0.139***	-0.162***
			(0.012)	(0.017)	(0.012)
$PostCovid$=1 × $ln(Post\ Uncert3y)_{it}$			0.205		0.179
			(0.254)		(0.260)
$PostCovid$=1 × $ln(Prior\ Uncert3y)_{it}$			0.105		0.129
			(0.210)		(0.213)
$PostCovid$=1 × $Prior\ 3y_{it}$ × $ln(Post\ Uncert3y)_{it}$			-0.007		-0.003
			(0.033)		(0.033)
$PostCovid$=1 × $Prior\ 3y_{it}$ × $ln(Prior\ Uncert3y)_{it}$			0.052		0.047
			(0.037)		(0.037)
$High\pi$=1 × $Prior\ 3y_{it}$				-0.172***	-0.159***
				(0.020)	(0.033)
$High\pi$=1 × $ln(Post\ Uncert3y)_{it}$				0.880***	0.748***
				(0.166)	(0.281)
$High\pi$=1 × $ln(Prior\ Uncert3y)_{it}$				-0.744***	-0.892***
				(0.098)	(0.188)
$High\pi$=1 × $Prior\ 3y_{it}$ × $ln(Post\ Uncert3y)_{it}$				-0.142***	-0.135***
				(0.018)	(0.031)
$High\pi$=1 × $Prior\ 3y_{it}$ × $ln(Prior\ Uncert3y)_{it}$				0.247***	0.223***
				(0.024)	(0.038)
Constant	2.012***	2.050***	1.092***	1.153***	1.095***
	(0.046)	(0.037)	(0.076)	(0.076)	(0.076)
Year-Month FEs	Y	Y	Y	Y	Y
Age, Gender, Race FEs	Y	Y	Y	Y	Y
Tenure FEs	Y	Y	Y	Y	Y
Commuting-Zone FEs	Y	Y	Y	Y	Y
Adjusted R-squared	0.33	0.33	0.37	0.37	0.37
Observations	91906	91906	73076	73076	73076

Standard errors in parentheses
Belief gain estimation interacted with posterior and prior uncertainty.
Controls included the interacted variables without interactions
Standard errors are clustered at individual and time level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

post-COVID periods. On the other hand, the post-COVID sample is associated with a larger new information uncertainty. There results are similar at the 3 years horizon in table A.5. . Our result suggests that the increase in belief stickiness after COVID is not due to a change in the way agents internalize uncertainty in their belief updating, but to a higher level of uncertainty in the economy.

4.4 Belief stickiness and demographics

We investigate whether stickiness in belief updating depends on socioeconomic characteristics . We run the following regression

$$For_{i,t} = \alpha + \beta_1 Prior_{i,t} + Prior_{i,t} \times \Omega'_{i,t}\Pi + \Omega'_{i,t}\Gamma + X_{i,t} + \gamma_t + err^i_t \tag{13}$$

where $\Omega_{i,t}$ contains a set of socioeconomic characteristics. Tables 10 and 11 report respectively the results for 1 and 3 years forecast horizons. Column (1) shows different results across the two horizons. At the shorter horizon, belief stickiness increases in tenure, while at longer horizons it increases also in education and age. Column (2) adds perceived probability of default on debt obligations, which reduces consistently the sample size but significantly increases stickiness only at the short horizon, which may be due to the short horizon of the perceived default risk itself. All these variables might affect belief stickiness either directly or by altering the perceived prior and posterior uncertainty of households. In order to distinguish between the two cases, in column (3) we control for prior and posterior uncertainty. The coefficients are virtually unaffected, which implies that this heterogeneity in belief stickiness is not due to difference in subjective uncertainty.

[ADD MORE SOCIOECONOMIC CHARACTERISTICS AND OTHER INFORMATION SUPPLY DETERMINANTS BASED ON LOCATION (WE HAVE COMMUTING ZONES)]

5 A Novel Measure of Uncertainty

The existing literature distinguishes between different measures of uncertainty: news-based, survey-based, econometrics-based and market based (ADD CITATIONS). The benefit of survey-based measures is their precision in indicating the segments of so-

Table 10: Belief stickiness heterogeneity

	(1)	(2)	(3)
	$For\ 1y_{it}$	$For\ 1y_{it}$	$For\ 1y_{it}$
$Prior\ 1y_{it}$	0.096	-0.166	-0.043
	(0.125)	(0.165)	(0.181)
$College_{it}$=1 × $Prior\ 1y_{it}$	0.013	0.022	0.015
	(0.028)	(0.033)	(0.032)
$SomeCollege_{it}$=1 × $Prior\ 1y_{it}$	0.016	0.008	0.006
	(0.025)	(0.028)	(0.028)
$Prior\ 1y_{it}$ × $log(Age_{it})$	0.041	0.088**	0.068
	(0.032)	(0.040)	(0.042)
$Income\ 50kto100k_{it}$=1 × $Prior\ 1y_{it}$	0.011	0.021	0.018
	(0.025)	(0.029)	(0.029)
$Income\ Over100k_{it}$=1 × $Prior\ 1y_{it}$	-0.028	-0.015	-0.012
	(0.034)	(0.039)	(0.041)
$High\ Num$=1 × $Prior\ 1y_{it}$	0.005	0.002	-0.002
	(0.020)	(0.024)	(0.025)
$IsWorking_{it}$=1 × $Prior\ 1y_{it}$	0.012	0.049*	0.051*
	(0.023)	(0.028)	(0.028)
$Prior\ 1y_{it}$ × $Tenure$	0.029***	0.028***	0.025***
	(0.003)	(0.004)	(0.004)
$Female_i$=1 × $Prior\ 1y_{it}$	0.005	0.017	0.020
	(0.022)	(0.028)	(0.028)
$White_i$=1 × $Prior\ 1y_{it}$	0.070**	0.063*	0.068*
	(0.030)	(0.034)	(0.035)
$Prior\ 1y_{it}$ × $ln(P(default3months)_{it})$		0.026***	0.028***
		(0.010)	(0.010)
$Prior\ 1y_{it}$ × $ln(Post\ Uncert1y)_{it}$			0.077***
			(0.022)
$Prior\ 1y_{it}$ × $ln(Prior\ Uncert1y)_{it}$			-0.105***
			(0.022)
Year-Month FEs	Y	Y	Y
Age, Gender, Race FEs	Y	Y	Y
Tenure FEs	Y	Y	Y
Commuting-Zone FEs	Y	Y	Y
Adjusted R-squared	0.39	0.40	0.42
Observations	74929	42174	35742

Standard errors in parentheses
Belief gain estimation interacted with posterior and prior uncertainty.
Controls included the interacted variables without interactions
Standard errors are clustered at individual and time level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Belief stickiness heterogeneity

	(1) $For\ 3y_{it}$	(2) $For\ 3y_{it}$	(3) $For\ 3y_{it}$
$Prior\ 3y_{it}$	-0.168	-0.282	-0.212
	(0.200)	(0.239)	(0.263)
$College_{it}$=1 $\times$ $Prior\ 3y_{it}$	0.051**	0.066**	0.061**
	(0.023)	(0.026)	(0.025)
$SomeCollege_{it}$=1 $\times$ $Prior\ 3y_{it}$	0.046**	0.053*	0.048*
	(0.022)	(0.028)	(0.027)
$Prior\ 3y_{it} \times log(Age_{it})$	0.101**	0.125**	0.115*
	(0.048)	(0.059)	(0.060)
$Income\ 50kto100k_{it}$=1 $\times$ $Prior\ 3y_{it}$	0.033	0.014	0.015
	(0.023)	(0.032)	(0.033)
$Income\ Over100k_{it}$=1 $\times$ $Prior\ 3y_{it}$	-0.017	0.001	0.011
	(0.026)	(0.030)	(0.030)
$High\ Num$=1 $\times$ $Prior\ 3y_{it}$	0.020	0.007	0.003
	(0.020)	(0.031)	(0.033)
$IsWorking_{it}$=1 $\times$ $Prior\ 3y_{it}$	0.014	0.023	0.020
	(0.030)	(0.043)	(0.043)
$Prior\ 3y_{it} \times Tenure$	0.034***	0.035***	0.032***
	(0.004)	(0.005)	(0.005)
$Female_i$=1 $\times$ $Prior\ 3y_{it}$	-0.012	-0.012	-0.011
	(0.025)	(0.032)	(0.033)
$White_i$=1 $\times$ $Prior\ 3y_{it}$	0.031	0.029	0.028
	(0.033)	(0.040)	(0.041)
$Prior\ 3y_{it} \times ln(P(default3months)_{it})$		0.002	0.000
		(0.010)	(0.010)
$Prior\ 3y_{it} \times ln(Post\ Uncert3y)_{it}$			0.093***
			(0.015)
$Prior\ 3y_{it} \times ln(Prior\ Uncert3y)_{it}$			-0.099***
			(0.023)
Year-Month FEs	Y	Y	Y
Age, Gender, Race FEs	Y	Y	Y
Tenure FEs	Y	Y	Y
Commuting-Zone FEs	Y	Y	Y
Adjusted R-squared	0.33	0.32	0.34
Observations	75445	42446	35849

Standard errors in parentheses
Belief gain estimation interacted with posterior and prior uncertainty.
Controls included the interacted variables without interactions
Standard errors are clustered at individual and time level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

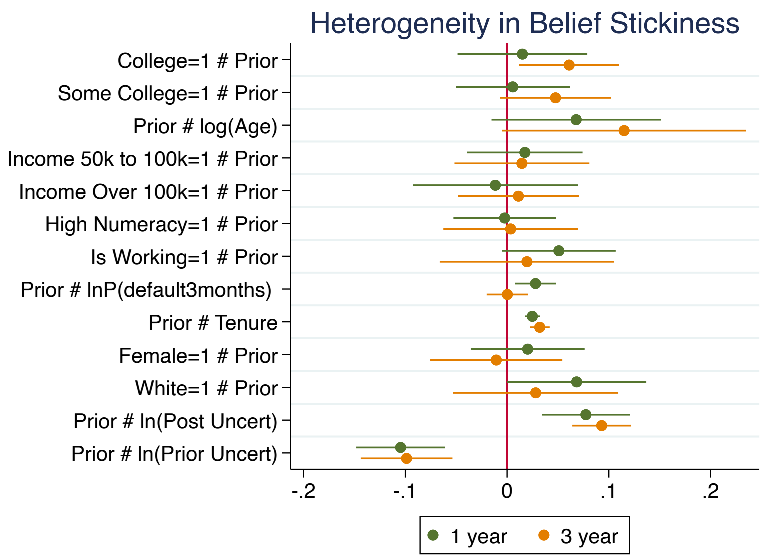


Figure 7

ciety facing uncertainty, the macroeconomic quantity subject to uncertainty and the horizon object of the uncertainty measure. However, the drawback is their potential staleness (Cascaldi-Garcia et al., 2023). First, as documented in section 4.1.1, beliefs are sticky and therefore uncertainty shocks and fast-breaking events take time to be internalized in households' beliefs. From equation 4, posterior uncertainty is not only a function of uncertainty of new information, but also of prior uncertainty. The higher is the degree of information stickiness $1 - G_t$, the less the posterior uncertainty reflects contemporaneous changes in economic uncertainty. To make it worse, as documented in section 4.1.1, higher new information uncertainty results in higher stickiness $1 - G_t$. As a result, periods of high uncertainty induces even higher stickiness in belief updating, making posterior uncertainty is an even less accurate measure of contemporaneous uncertainty shocks.

In order to correct the staleness of the survey-based uncertainty measure, we isolate the uncertainty of new information from the overall posterior households' uncertainty.

$$\sigma_{e,t}^2 = (\Sigma_{t+h,t} - (1 - G_t)^2 \Sigma_{t+h,t-1})/G_t^2 \tag{14}$$

In particular, we use our estimates of $1 - G_t$ from regression 12 together with our measure of belief uncertainty to compute 14.

[do it for both consumer and SPF, and ideally we would find that they are not correlated to each other (because they differ in the stickiness probably?) but the purged measure might be more correlated]

6 Policy implications and conclusion

Throughout the pandemic, the extent to which beliefs remained unchanged fluctuated considerably, with an initial decrease in belief stickiness 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 explains puzzles which 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.

To conclude, in this paper, we investigated the relationship between news uncertainty and households' belief updating and rigidity using the NY Fed Survey of Cosumer 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 Beyesian-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 implications for policy. 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.

References

Ambuehl, S. and S. Li (2017, Sep). Belief updating and the demand for information. Available at SSRN: https://ssrn.com/abstract=2461904 or http://dx.doi.org/10.2139/ssrn.2461904.

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

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

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

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

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

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

Bordalo, P., N. Gennaioli, and A. Shleifer (2020). Memory, Attention, and Choice. *The Quarterly Journal of Economics 135*(3), 1399–1442.

Braggion, F., F. von Meyerinck, N. Schaub, and M. Weber (2024, February). The long-term effects of inflation on inflation expectations. Working Paper 32160, National Bureau of Economic Research.

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

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

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

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

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

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

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

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

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

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

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

Gallegos, J.-E. (2023, February). Inflation persistence, noisy information and the Phillips curve. Working Papers 2309, Banco de España.

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

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

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

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

Khaw, M. W., L. Stevens, and M. Woodford (2017). Discrete adjustment to a changing environment: Experimental evidence. *Journal of Monetary Economics 91*, 88–103.

Kozlowski, J., L. Veldkamp, and V. Venkateswaran (2020). The tail that wags the economy: Beliefs and persistent stagnation. *Journal of Political Economy 128*(8), 2839–2879.

Levy, G. and R. Razin (2019). Echo chambers and their effects on economic and political outcomes. *Annual Review of Economics 11*, 303–328.

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

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

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

Nimark, K. P. and S. Sundaresan (2019). Inattention and belief polarization. *Journal of Economic Theory 180*(C), 203–228.

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

Paciello, L. and M. Wiederholt (2014). Exogenous information, endogenous information, and optimal monetary policy. *Review of Economic Studies 81*(1).

Reis, R. (2006). Inattentive consumers. *Journal of Monetary Economics 53*(8), 1761–1800.

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

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

Woodford, M. (2009). Information-constrained state-dependent pricing. *Journal of Monetary Economics 56*, S100–S124.

Appendix

A Belief formation models

The theoretical framework in equation 2 embeds different model of belief formation in the literature. A first set of models comprise 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 case of full-information, the signal 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 he 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 differ 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: household learn about model's parameters in each period using a constant gain, so that they never learn completely (Eusepi and Preston, 2011).

- Misspecified model: household 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 present a constant gain which does not depend on signal or fundamental accuracy, each of these models can be (and has be) microfounded to endogenize the information stickiness to the economic environment, including uncertainty.

B Point estimates and subjective distribution of inflation in the SCE

Figure A.1

Figure A.2

C Robustness

Table A.1: Weight on new information in beliefs update

	(1) *For* $3y_{it}$	(2) *For* $3y_{it}$	(3) *For* $3y_{it}$	(4) *For* $3y_{it}$
Prior $3y_{it}$	0.535**	0.537***	0.558***	0.486***
	(0.019)	(0.014)	(0.017)	(0.015)
Prior $3y_{it}$ × *Prior Uncert* $3y_{it}$		-0.019***		
		(0.004)		
Prior $3y_{it}$ × *Post Uncert* $3y_{it}$		0.013***		
		(0.004)		
Prior $3y_{it}$ × $ln(Prior\ Uncert3y)_{it}$			-0.138***	
			(0.018)	
Prior $3y_{it}$ × $ln(Post\ Uncert3y)_{it}$			0.113***	
			(0.015)	
Prior $3y_{it}$ × $ln(Prior\ Uncert3yIQR)_{it}$				-0.111***
				(0.014)
Prior $3y_{it}$ × $ln(Post\ Uncert3yIQR)_{it}$				0.124***
				(0.012)
Constant	1.876*	1.011***	1.075***	1.343***
	(0.169)	(0.071)	(0.076)	(0.053)
Year-Month FEs	Y	Y	Y	Y
Age, Gender, Race FEs	Y	Y	Y	Y
Tenure FEs	Y	Y	Y	Y
Adjusted R-squared				
Observations	0	0	0	0
N	84280	84280	67917	84277

Standard errors in parentheses
Belief gain estimation interacted with posterior and prior uncertainty.
Controls included the interacted variables without interactions
Standard errors are clustered at individual and time level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Belief stickiness and uncertainty for different numeracy skill

	(1) $For\ 3y_{it}$	(2) $For\ 3y_{it}$	(3) $For\ 3y_{it}$	(4) $For\ 3y_{it}$
$Prior\ 3y_{it}$	0.527***	0.500***	0.521***	0.545***
	(0.012)	(0.016)	(0.022)	(0.033)
$High\ Num{=}1 \times Prior\ 3y_{it}$		0.041***	0.038**	-0.002
		(0.015)	(0.016)	(0.036)
$Prior\ 3y_{it} \times ln(Prior\ Uncert3y)_{it}$			-0.132***	-0.106***
			(0.018)	(0.027)
$Prior\ 3y_{it} \times ln(Post\ Uncert3y)_{it}$			0.118***	0.074***
			(0.015)	(0.022)
$High\ Num{=}1 \times Prior\ 3y_{it} \times ln(Prior\ Uncert3y)_{it}$				-0.044
				(0.027)
$High\ Num{=}1 \times Prior\ 3y_{it} \times ln(Post\ Uncert3y)_{it}$				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
Age, Gender, Race FEs	Y	Y	Y	Y
Tenure FEs	Y	Y	Y	Y
Adjusted R-squared				
Observations	0	0	0	0
N	84280	84263	67904	67904

Standard errors in parentheses
Belief gain estimation interacted with posterior and prior uncertainty.
Controls included the interacted variables without interactions
Standard errors are clustered at individual and time level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Belief stickiness and uncertainty for different tenure

	(1)	(2)	(3)
	For $1y_{it}$	*For* $1y_{it}$	*For* $1y_{it}$
Prior $1y_{it}$	0.497***	0.333***	0.383***
	(0.013)	(0.023)	(0.050)
Prior $1y_{it}$ × *Tenure*		0.028***	0.025***
		(0.003)	(0.007)
Prior $1y_{it}$ × $ln(Post\ Uncert1y)_{it}$			0.044
			(0.030)
Prior $1y_{it}$ × $ln(Prior\ Uncert1y)_{it}$			-0.085**
			(0.034)
Tenure × $ln(Post\ Uncert1y)_{it}$			-0.032
			(0.035)
Tenure × $ln(Prior\ Uncert1y)_{it}$			-0.036
			(0.033)
Prior $1y_{it}$ × *Tenure* × $ln(Post\ Uncert1y)_{it}$			0.009**
			(0.005)
Prior $1y_{it}$ × *Tenure* × $ln(Prior\ Uncert1y)_{it}$			-0.007
			(0.005)
Constant	2.335***	2.265***	1.317***
	(0.063)	(0.062)	(0.089)
Year-Month FEs	Y	Y	Y
Age, Gender, Race FEs	Y	Y	Y
Tenure FEs	Y	Y	Y
Commuting-Zone FEs	Y	Y	Y
Adjusted R-squared	0.38	0.39	0.43
Observations	75893	75893	60498

Standard errors in parentheses
Belief gain estimation interacted with posterior and prior uncertainty.
Controls included the interacted variables without interactions
Standard errors are clustered at individual and time level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Belief stickiness and uncertainty for different tenure

	(1)	(2)	(3)
	$For\ 3y_{it}$	$For\ 3y_{it}$	$For\ 3y_{it}$
$Prior\ 3y_{it}$	0.482***	0.292***	0.378***
	(0.013)	(0.025)	(0.052)
$Prior\ 3y_{it} \times Tenure$		0.032***	0.024***
		(0.003)	(0.007)
$Prior\ 3y_{it} \times ln(Post\ Uncert3y)_{it}$			0.107***
			(0.026)
$Prior\ 3y_{it} \times ln(Prior\ Uncert3y)_{it}$			-0.154***
			(0.036)
$Tenure \times ln(Post\ Uncert3y)_{it}$			0.043
			(0.040)
$Tenure \times ln(Prior\ Uncert3y)_{it}$			-0.098**
			(0.049)
$Prior\ 3y_{it} \times Tenure \times ln(Post\ Uncert3y)_{it}$			-0.003
			(0.005)
$Prior\ 3y_{it} \times Tenure \times ln(Prior\ Uncert3y)_{it}$			0.006
			(0.007)
Constant	2.250***	2.185***	1.230***
	(0.057)	(0.056)	(0.110)
Year-Month FEs	Y	Y	Y
Age, Gender, Race FEs	Y	Y	Y
Tenure FEs	Y	Y	Y
Commuting-Zone FEs	Y	Y	Y
Adjusted R-squared	0.32	0.33	0.36
Observations	76415	76415	60917

Standard errors in parentheses
Belief gain estimation interacted with posterior and prior uncertainty.
Controls included the interacted variables without interactions
Standard errors are clustered at individual and time level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Belief stickiness and uncertainty pre and post COVID

	(1) $For\ 3y_{it}$	(2) $For\ 3y_{it}$	(3) $For\ 3y_{it}$
$Prior\ 3y_{it}$	0.527***	0.500***	0.586***
	(0.012)	(0.011)	(0.017)
$PostCovid{=}1 \times Prior\ 3y_{it}$		0.056***	-0.049
		(0.020)	(0.039)
$Prior\ 3y_{it} \times ln(Post\ Uncert3y)_{it}$			0.103***
			(0.013)
$Prior\ 3y_{it} \times ln(Prior\ Uncert3y)_{it}$			-0.164***
			(0.013)
$PostCovid{=}1 \times ln(Post\ Uncert3y)_{it}$			0.144
			(0.245)
$PostCovid{=}1 \times ln(Prior\ Uncert3y)_{it}$			0.062
			(0.204)
$PostCovid{=}1 \times Prior\ 3y_{it} \times ln(Post\ Uncert3y)_{it}$			0.008
			(0.034)
$PostCovid{=}1 \times Prior\ 3y_{it} \times ln(Prior\ Uncert3y)_{it}$			0.053
			(0.038)
Constant	1.911***	1.959***	0.999***
	(0.049)	(0.039)	(0.077)
Year-Month FEs	Y	Y	Y
Age, Gender, Race FEs	Y	Y	Y
Tenure FEs	Y	Y	Y
Adjusted R-squared	0.32	0.33	0.37
Observations	84280	84280	67917

Standard errors in parentheses
Belief gain estimation interacted with posterior and prior uncertainty.
Controls included the interacted variables without interactions
Standard errors are clustered at individual and time level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

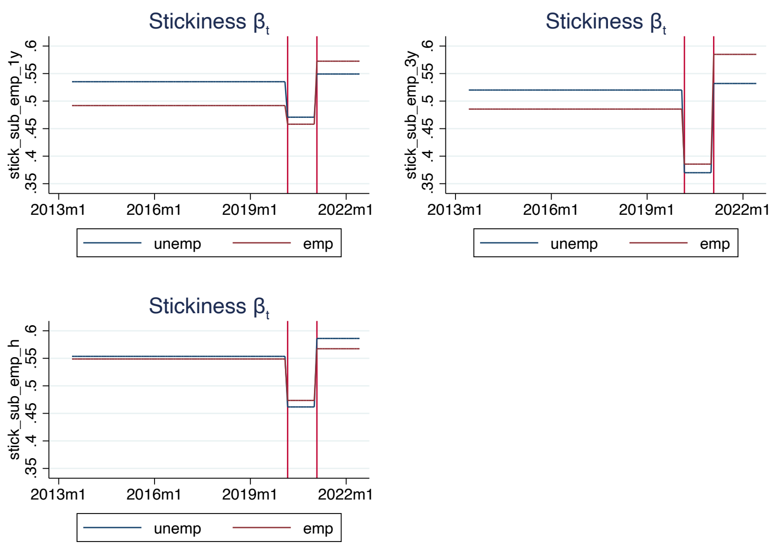


Figure A.3

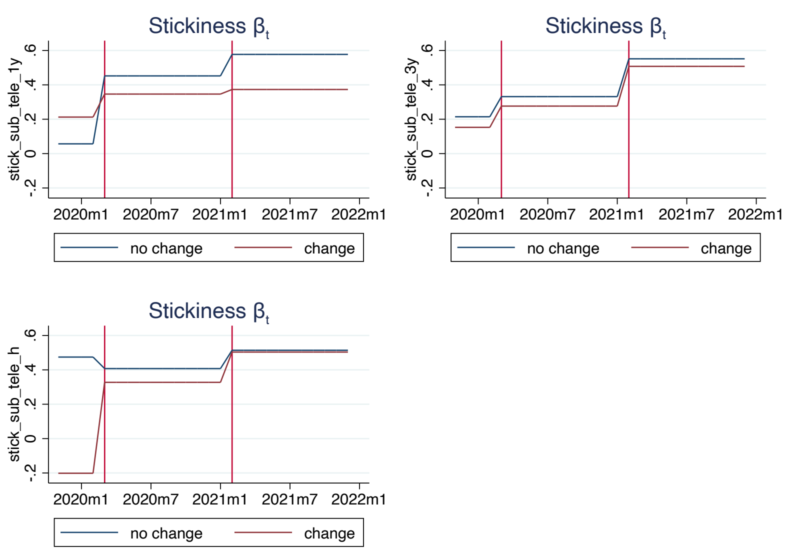


Figure A.4