

How Inflation Expectations De-Anchor: The Role of Selective Memory Cues

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Abstract

A selective recall model predicts how inflation expectations should change with current cues. Data from the New York Fed's Survey of Consumer Expectations and the University of Michigan's Consumer Survey confirm these predictions, yielding two new insights. First, households' expectations are rigid when inflation is anchored but highly unstable when surges in inflation trigger the retrieval of forgotten high-inflation episodes. This effect quantitatively accounts for the post-pandemic rise in inflation expectations, particularly among the elderly. Second, cued recall explains a striking failure of rationality: a state-dependent discrepancy between people's point and density-based expectations of future inflation. The structure of memory offers new tests and insights on inflation expectations and their measurement.

1. Introduction

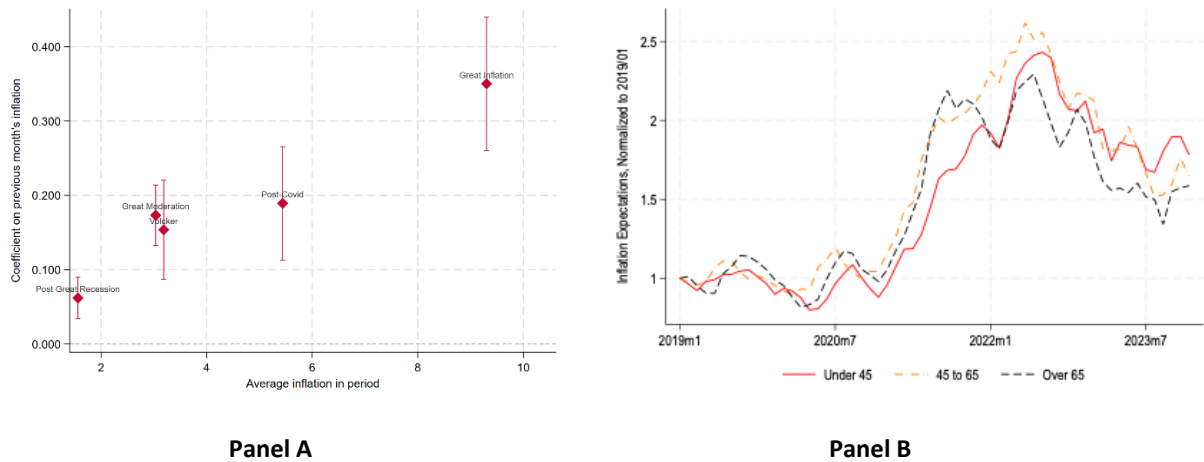
The post-Covid inflation surge has renewed interest in understanding how people form inflation expectations. The leading view is that these expectations are sticky due to inattention to data. Inattention could be rational (Sims 2003, Woodford 2009, Coibion and Gorodnichenko 2015) or alternatively driven by adaptive learning from experiences (Evans and Honkapohja 2001, Malmendier and Nagel 2011, 2016, 2021) or a focus on local prices (d’Acunto et al. 2023, 2024, Cavallo et al. 2017, Coibion and Gorodnichenko 2015, Gelman et al. 2023, Binder 2018, Weber et al. 2022). These mechanisms reduce the sensitivity of expectations to aggregate inflation. This low sensitivity is different from other macro-financial outcomes, for which beliefs tend to overreact (Bordalo et al. 2020, 2022).

Looking through history, the picture is more nuanced: expected inflation does not exhibit uniform rigidity, but rather a highly state dependent sensitivity. Sometimes it reacts sharply to changes in inflation, other times it does not. Using the Michigan Survey of Consumers (MSC), Panel A in Figure 1 reports a measure of belief sensitivity: the coefficient estimated from regressing a respondent’s current inflation expectations on past month’s inflation. Across five major inflation regimes, state dependence is sharp: beliefs are highly sensitive when current inflation is high and volatile (the Great Inflation of 1978-1982), but insensitive when it is low (the Great Recession), with the Post-Covid regime in the middle.

The Post-Covid episode is particularly interesting because it came after a long low inflation period. Panel B zooms into it. Actual inflation rose from 1.4% in January 2021 to 5.3% in June 2021, reaching 9% in June 2022. We see pronounced sensitivity of expectations to this trend. Around April 2021, expectations increased from around 3.2%, where they hovered for years, to above 4.2% and then continued rising to 7.9%. The sensitivity varies across cohorts: the elderly (black line) reacted faster and more strongly than the young (red line), who caught up after roughly one year. The difference is large (1.9 p.p.) both in absolute terms and compared to the pre-Covid period, during which the beliefs of different cohorts moved

in similar ways. We show later that this pattern also holds in other countries. This is surprising: if anything, the elderly should be *less* sensitive to a recent episode, given their larger set of past experiences.¹

Figure 1: Updating of Inflation Expectations and Experienced Inflation by Age Groups



Notes: **Panel A (left)** plots the estimated sensitivity of individual inflation expectations to inflation in the previous month across five episodes: the Great Inflation (1978–1982), the Volcker disinflation (1983–1986), the Great Moderation (1987–2007), the post-Great Recession low-inflation (2009–2019), and the post-Covid episode (2021–2023). The regressions control for income, education, sex, and marital status. The x-axis reports average quarterly inflation during the period. Vertical bars report confidence intervals. Standard errors are clustered by month of the survey. **Panel B (right)** shows the index of inflation expectations initialized in January 2019 of 12-month ahead weighted average inflation expectations from the University of Michigan’s Survey of Consumers for respondents younger than 45 years old (red line), 45-65 years old (maroon line) or 65+ years old (black line).

What shapes the sensitivity of beliefs in the time series and the cross section? We present an account based on similarity-driven memory. This mechanism has strong support in cognitive science and intuitively explains Figure 1.B: during Covid, the elderly reacted fast because they recalled similar past experiences (from Great Inflation), which the young did not live through due to the pre-2021 low inflation regime. After inflation stays high for several months, the young also recall recent high inflation, again by similarity. They then catch up with the elderly, eventually becoming sensitive to the shock and explaining generalized higher sensitivity during high inflation regimes. The key idea of the model is that the “belief function” is unstable because experiences build over time and are endogenously recalled and forgotten.

¹ Also inconsistent with rational inattention, the elderly respond more sharply even though they experience a smaller increase in their CPI index (Appendix Figure B1).

Such instability is disciplined by regularities of human memory, which yield new testable predictions compared to other rational and non-rational models, which can be tested using survey data in new ways.

Based on vast memory research (Baddeley 1997, Kahana 2012), we assume that recall of a past inflation events increases in their frequency, in their similarity to current cues, and declines in interference from other events. Frequency causes the *primacy effect*: early experiences are *ceteris paribus* easier to recall because they have been rehearsed more often, so they come to mind when thinking about inflation (see also Conlon 2026). Similarity acts through time and the forecasting task. Recent inflation is easier to recall because its temporal context is similar to the present. The forecasting task instead causes *numerical anchoring*: when a person sees or thinks about inflation at 3%, similar 3% episodes are easier to recall. Interference means that, due to recall limits, these forces compete and cause forgetting of information.

Mnemonic beliefs make three predictions that depart from inattention and Bayesian learning and are tightly disciplined by two observables: the databases of different people (the inflation history they lived through), and the current cues (time and the inflation rate). First, due to primacy, a cohort exhibits *persistently* higher expected inflation if it experienced high inflation early in life compared to a cohort having the same experience later. This is inconsistent with Bayesian learning, in which recent rates should, if anything, matter more (Marcet and Sargent 1989, Sargent 1999, Evans and Honkapohja 2001).

Second, numerical similarity causes cohort-dependent instability: when they see high inflation, cohorts that have lived through high inflation respond fast, but younger cohorts without the same experiences quickly catch up if high inflation persists, due to similarity. The latter pattern is not explained by Bayesian regime switching – the young have not experienced a high inflation regime – but it can be explained by similarity: as high inflation populates their database, its recall interferes with recalling many low inflation episodes from their past. Mental regimes are endogenous to memory.

Third, beliefs are incoherent across the events a person is thinking about. When making point forecasts, people neglect deflation: they rarely experienced it, so it faces strong interference from current inflation. Perceived deflation risk however sharply increases when the same person is asked to assess deflation states, which then enter the memory cue. This incoherence is a stark departure from *any* model in which beliefs are a probability measure. Critically, memory makes predictions about this phenomenon: the incoherence should exhibit state- and cohort-dependence based on current inflation and past inflation experiences. These predictions allow us to test memory against the possibility that elicitation procedures may distort reported beliefs through frictions such as rounding, scale and order effects (Danz, Vesterlund, and Wilson 2022, Becker et al. 2023, Goldfayn-Frank, Kieren, and Trautmann 2026).

We find significant support for the model’s predictions using micro data from the MSC and the Federal Reserve Bank of New York’s Survey of Consumer Expectations (SCE). Two results showcase the explanatory power of frequency and similarity. First, memory disciplines incoherence. Consistent with neglect of rare deflation states, in the data a household’s point inflation forecast is systematically higher than the forecast computed using its separately elicited probability density. Consistent with memory and inconsistent with mechanical accounts where incoherence reflects “elicitation frictions”, this gap is state- and cohort-dependent: it is smaller when current inflation is higher, and larger for cohorts that experienced more deflation. Indeed, the latter cohorts revise up their deflation perception more strongly when asked to assess it, causing density-based expectations to fall and hence the gap to increase.

Second, memory is needed to explain belief dynamics. Malmendier and Nagel (2016) show that higher inflation experiences trigger higher expectations today, which they explain with experience-based Bayesian learning. We estimate this model and show that it cannot explain the observed state- and cohort-dependent sensitivity around 2021. Similarity parameters estimated from the MSC data instead account for: i) the sharp increase in beliefs around April 2021, ii) catch up by the young, and iii) the subsequent decline in expectations. Crucially, this holds in the US and other advanced economies.

Much empirical work on household inflation expectations points to the roles of demographics (Manski 2004, 2018; d’Acunto et al. 2021a, 2021b, Bruine de Bruin et al. 2010, Armantier et al. 2013),² experiences (Hajdini et al. 2024, Goldfayn and Wohlfart 2020, Braggion et al. 2024, Salle et al. 2026), mental models (Andre et al. 2022, Zuellig 2024), or inattention (Carroll 2003, Carroll et al. 2020, Bracha and Tang 2025). We instead rely on the structure of memory, which reconciles seemingly inconsistent patterns of high and low sensitivity as well as incoherence across elicitations. These effects may be economically important: state-dependent sensitivity can lead to anchoring when inflation is low and hence a stubbornly low inflation regime despite expansionary monetary policy, but also swift switches to high expectations and realized inflation regimes after a streak of inflationary shocks. Incoherence further suggests that this instability can be importantly shaped by context (consistent with Bordalo et al. 2026): repeated discussion of deflation risk reinforce a low inflation regime, concerns about high inflation do the opposite, with possibly important implications for policy communication and the role of the media.

Following Bordalo et al. (2023, 2025) we build and quantify a mnemonic model based on cues and similarity. Bonaglia and Gennaioli (2026) study a general mnemonic learning model. Bonaglia et al. (2026) use it to study investor inflation expectations across countries and horizons, and link memory to excess volatility in interest rates. Compared to diagnostic expectations (Bordalo et al. 2018, Maxted 2024, L’Huillier et al. 2024, Bianchi et al. 2024, 2026), modeling selective recall allows us to endogenize belief distortions, yielding new predictions that reconcile the rigidity and excess sensitivity of beliefs as well as their incoherence. Memory models also help account for beliefs about novel risks (Bordalo et al. 2025), expected stock returns (Jiang et al. 2025), the effects of idiosyncratic experiences (Cenzon 2026, Taubinsky et al. 2026), and animal spirits (Bordalo et al. 2026a).

² Afrouzi et al (2015), Afrouzi (2024), Kumar et al. (2023), and Coibion et al. (2018, 2020) study firms’ expectations.

Section 2 provides evidence from other countries that older households reacted more swiftly to the recent inflation surge than younger ones. It also presents our memory model and derives its key predictions. In Section 3 we test predictions about point inflation expectations using the MSC and SCE surveys. In Section 4 we test predictions for forecast densities and their inconsistency with point expectations. Section 5 shows how the model explains the evolution of expected inflation in the US, in and out of sample, also compared to experience-based learning. Section 6 concludes.

2. Why Memory is Needed and how it Works

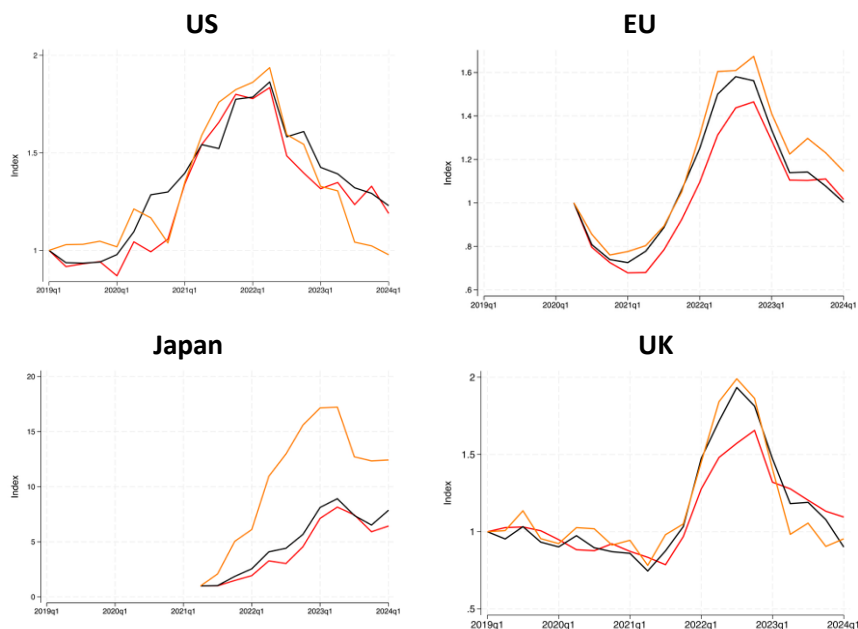
2.1 Additional Motivating Evidence

We report broader evidence about the state- and cohort- dependent sensitivity of expectations during the Post-Covid episode, for which expectations data is available for many countries. Figure 2 shows quarterly 12-month-ahead inflation point expectations of different cohorts around 2022-23 from the New York Fed Survey of Consumer Expectations (SCE) (our second US sample), the Bank of England's Inflation Attitudes Survey (IAS), the EU the monthly European Central Bank's Consumer Expectations Survey (CES), the monthly Canadian Survey of Consumer Expectations (CSCE), and the monthly Indirect Consumer Inflation Expectations (ICIE) for Australia and Japan (see Hajdini et al. (2024) for details). To ensure consistency with Figure 1B we normalize each series to 1 pre-COVID in 2019 or at the earliest available data point which is 2020Q2 for the EU, and 2021Q2 for Australia and Japan. We then compute quarterly expectations and remove outliers (Figure B2 reports for the US also the ICIE series and the median inflation expectations published by the New York Fed's SCE). See the appendix for details.³

³ The CSCE and IAS are quarterly, while the CES and ICIE (Australia and Japan) are monthly. The five data sets contain roughly 1,700, 2,500, 16,560, 800, and 800 observations respectively of inflation point expectations per wave, but are limited in socio-demographics, for example provide only three to four age brackets rather than continuous measures of age. The samples span 2014 to 2025 for Canada, 2001 to 2025 for the UK, 2020 to 2025 for the ECB CES, and 2021 to 2024 for Australia and Japan. We winsorize point expectations at the bottom and top 5th percentiles for the BoC, corresponding to -3% and 30%, and at bottom and top 2.5th percentiles for the ECB CES, corresponding

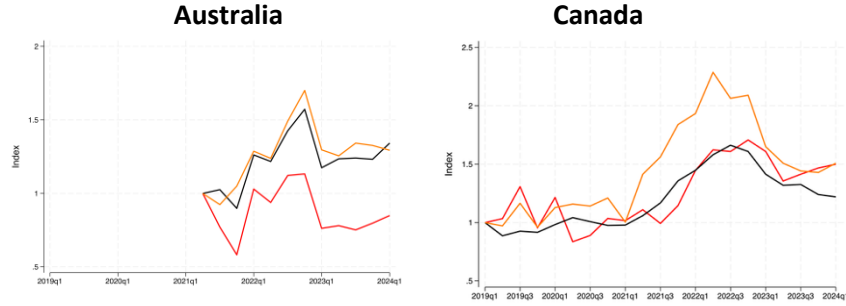
There are cross-country nuances due to different inflation dynamics. Inflation surged earlier in Canada and the US in spring 2021, perhaps partly due to stronger fiscal stimulus, particularly in the US, followed later that year by the EU and UK, while lagging further behind in Australia (late 2021 to early 2022) and Japan (spring 2022). However, the key facts of Figure 1B are confirmed across countries. First, there is a sharp upward reaction of expectations to the shock, as they swiftly de-anchor from their previous low level. Second, the elderly (yellow) de-anchor first, while the young (red) initially do not update much. The divergence in the speed of updating is most striking for Canada, Japan, the UK, and Australia, but also evident in the other datasets. Third, younger households eventually also de-anchor, broadly following the dynamics of older households with a delay, with their upward response often becoming more pronounced around the time older households' expectations reach their peak.

Figure 2: International Inflation Expectations by Age Groups



to -3.8% and 30%. The ICIE data for Australia and Japan come trimmed at the bottom and top 10% of signed point expectations within each survey month, with average cutoffs of about -0.1% and 27.7% for Australia and 0% and 12% for Japan. For the UK IAS, expectations are elicited in bins rather than as continuous point forecasts, so our midpoint coding mechanically bounds the variable between -5.5% and 15.5%.

⁴ We use “de-anchoring” to denote a marked departure of household inflation expectations from their previously stable level, although it is more typically used for long-run expectations to the central bank’s inflation target. For the United States, where medium-term expectations are available, we observe a more muted but still significant change at the 24–36-month horizon. Five-year-ahead expectations are available only from 2022 onward.



Notes: We show quarterly 12-month ahead inflation expectations by age group for the US using the NY Fed’s Survey of Consumer Expectations (SCE) , for the UK using the Bank of England’s Inflation Attitudes Survey (IAS), for the Euro area using the European Central Bank’s Consumer Expectations Survey (CES),for Australia and Japan using Morning Consult’s Indirect Consumer Inflation Expectations (ICIE) and for Canada using the Canadian Survey of Consumer Expectations (CSCE). Each series reports the weighted mean within the relevant age group. For the US, respondents are grouped directly into under 45, ages 45-64, and ages 65 and older. For the IAS, ages 15-24, 25-34, and 35-44 are combined into under 45, while ages 45-54 and 55-64 are combined into ages 45-64. For Japan, ages 18-34 and 35-44 are combined into under 45. For the CES, ages 18-34 and 35-49 are combined into ages 18-49; the middle and older groups are ages 50-70 and 71 and older, respectively. For Australia and Canada, ages 18-34 and 35-44 are combined into under 45, while ages 45-64 and 65 and older define the middle and older groups. In each panel, the youngest cohort is shown in red, the middle cohort in black, and the oldest cohort in orange. Series are normalized to 1 in 2019Q1 for Canada, the US, and the UK; in 2020Q2 for the CES; and in 2021Q2 for Australia and Japan.

This evidence is inconsistent with Bayesian learning from experience in which inflation expectations are anchored to average past experiences. It is also hard to square with a Bayesian model in which the elderly switch to the persistently high inflation regime they experienced in the 1970s in all these countries: the young also de-anchor after a few months, despite not having been exposed to any persistent high inflation regime. In Section 5 we show that our model estimated on US data can account for the main features of these cross-country episodes out of sample.

We next present a model of mnemonic beliefs that can account for state and cohort dependence belief sensitivity in Figures 1 and 2. The model makes specific predictions about this phenomenon, which we test, as well as about the incoherence of beliefs across elicitation methods, which rules out any Bayesian learning model, be it experience based or regime switching.

2.2 Selective Recall and Inflation Expectations

At each time t , the agent forms her beliefs by sampling past inflation experiences in her memory database based on their similarity to the inflation cue.

The Database, Cues, and Similarity. The database $\Pi_t = (\pi_{t-s})_{s=1,\dots,a_t}$ collects the inflation rates observed by the agent in the past, starting from a_t periods ago. a_t is “effective age” at t , namely the age of the agent’s inflation records. The cue is a signal prompting recall from Π_t by similarity (Baddeley 1997, Kahana 2012). In free recall experiments, people retrieve words from a previously studied list. One regularity is that the first (primacy) and last (recency) words studied are recalled best. Primacy reflects the fact that frequent experiences are more likely to be recalled: the first word is in fact rehearsed more often. Recency reflects similarity between the mental context when the last word was studied (her thoughts about the list, her mood etc.) and the mental context during recall. Similarity is also shaped by the task, which is shown by manipulating cues (e.g. Anderson 1974): when asked to recall “things in the kitchen”, people may retrieve “milk” because it is often seen in kitchens. The cue is the question\event (kitchen) that must be assessed, which prompts retrieval of similar events (milk). An object can also act as a cue (e.g. a glass of milk on the person’s desk while doing the task).

We capture these forces by assuming that, when evaluating future inflation, the agent is cued by time and numerical inflation. Time combines repeated rehearsal as in primacy effects and the contextual similarity of recency effects. Numerical context captures the idea that inflation levels similar to the one the agent is currently seeing are more likely to be retrieved, as in cued recall experiments.

Formally, the cue at time t when forecasting inflation event $E \subseteq \mathbb{R}$ at $t + 1$ is denoted by $\pi_{t,E}$. The cue has three features, embedded in vector $\pi_{t,E} \equiv (t, \pi_t, \bar{\pi}_{E,t})$: i) the time t at which the forecast is made, the ii) numerical inflation level π_t the agent is currently experiencing, and iii) a numerical level $\bar{\pi}_{E,t}$ representative of the inflation event $E \subseteq \mathbb{R}$ the agent is estimating. We specify $\bar{\pi}_{E,t}$ below. Vector $\pi_{t,E}$ ignites retrieval based on its similarity with past inflation π_{t-s} . The latter is stored in Π_t as a three-

dimensional trace reporting the episode’s temporal and numerical features $(t - s, \pi_{t-s}, \pi_{t-s})$. Similarity falls in the distance between the features of this vector and those of the cue $\pi_{t,E}$, as we describe next.

Absolute temporal distance between π_{t-s} and the cue $\pi_{t,E}$ is s years. For the agent’s similarity perception, this distance is normalized by effective age a_t , because an experience of $s = 20$ years ago is “early” – and hence distant – for a person of $a_t = 30$ years, but “mid-life” – and hence not so distant – for a person of $a_t = 60$ years. Temporal distance reduces retrieval based on the inverse U-shaped quadratic $\beta(s/a_t) = -\beta_1 \cdot (s/a_t)^2 + \beta_2 \cdot (s/a_t)$, where $\beta_1, \beta_2 \geq 0$ respectively capture the strength of primacy and recency. Higher temporal distance s increases distance from current context, $\beta_2 > 0$, reducing recall of remote inflation experiences. On the other hand, early experiences $s = a_t$, are more rehearsed than recent ones, which makes them less dissonant ($\beta_1 > 0$) and hence more likely to be recalled when estimating inflation. Temporal similarity may depend on macroeconomic states, e.g. during war we more easily recall wartime inflation. We adopt a parsimonious time function and see how far we can go with it.

Consider numerical similarity next. Episode π_{t-s} is less similar to $\pi_{t,E}$ if it differs from current inflation π_t , captured by the quadratic discrepancy $(\pi_{t-s} - \pi_t)^2$. Intuitively, if current inflation is 3%, a 10% state is less similar and hence harder to recall than a 2% one. Numerical similarity also acts based on the event E the agent is estimating and falls in the quadratic distance $(\pi_{t-s} - \bar{\pi}_{E,t})^2$. The reference $\bar{\pi}_{E,t}$ is the average inflation the agent has lived in event E , namely $\bar{\pi}_{E,t} = \frac{\sum_{E \cap \Pi_t} \pi_{t-s}}{|E \cap \Pi_t|}$. Intuitively, when assessing E , the agent is cued to recall episodes similar to her experiences with this set.⁵ For instance, if the agent is estimating the probability of inflation in $E = [2\%, 3\%]$, she finds it easier to retrieve $\pi_{t-s} =$

⁵ One foundation is that an agent thinking about E randomly recalls an experience in it, which then acts as a cue for subsequent retrieval, as in free recall models (see Kahana 2012). In our quadratic structure, this process can be approximated using the certainty equivalent $\bar{\pi}_{E,t}$ (abstracting from changing variance in E). Taking the average as a reference implies that different people may recall slightly different events when thinking about $E = [2\%, 3\%]$. An agent who only experienced 3% inflation will be cued by $\bar{\pi}_{E,t} = 3\%$ while an agent with uniform experiences would be cued by $\bar{\pi}_{E,t} = 2.5\%$. These differences are arguably small, so we abstract from them in our analysis.

2.5% than $\pi_{t-s} = 10\%$. This effect is key to generating belief incoherence: an agent may have rare deflation experiences, e.g. in the range $E = [-2\%, 0\%]$, but thinking about deflation selectively cues them, increasing the belief that they may happen again in the future.

Numerical similarity may act on additional features, which could allow us to capture the temporal contiguity of past episodes, including inflation persistence (Bonaglia et al. 2026). Again, we adopt a parsimonious similarity structure and show that it gives significant explanatory power. In fact, both recency and numerical similarity already cause beliefs to reflect inflation persistence.

Put together, temporal and numerical cues imply that similarity decreases in the discrepancy:

$$d(\pi_{t-s}, \pi_{t,E}) = \sigma_1 \cdot (\pi_{t-s} - \bar{\pi}_{E,t})^2 + \sigma_2 \cdot (\pi_{t-s} - \pi_t)^2 + \beta(s/a), \quad (1)$$

where σ_1 and σ_2 are nonnegative weights on numerical similarity to the target event E and to current inflation, respectively. In what follows, we assume that $\sigma_1 = \sigma \cdot (1 - q)$ and $\sigma_2 = \sigma \cdot q$, with $q \in [0,1]$ capturing the relative weight of each dimension and σ reflecting the strength of numerical similarity. In psychology similarity weights reflect attention to features (Nosofsky 1992). Link et al. (2026) measure attention to inflation and find that it varies across people, based on past experiences, and over time, based on inflation changes. In the interest of parsimony, we assume constant weights.

Recall. The agent forms her expectation by recalling past experiences based on their similarity to the cue. Similarity decreases exponentially with distance, $S(\pi_{t-s}, \pi_{t,E}) = e^{-d(\pi_{t-s}, \pi_{t,E})}$, a common assumption in memory models. Similarity is additive, so the similarity of $B \subseteq \Pi_t$ to the cue is $S(B, \pi_{t,E}) = \sum_{\pi_{t-s} \in B \cap \Pi_t} S(\pi_{t-s}, \pi_{t,E})$. The likelihood of recalling π_{t-s} based on $\pi_{t,E}$ then satisfies:

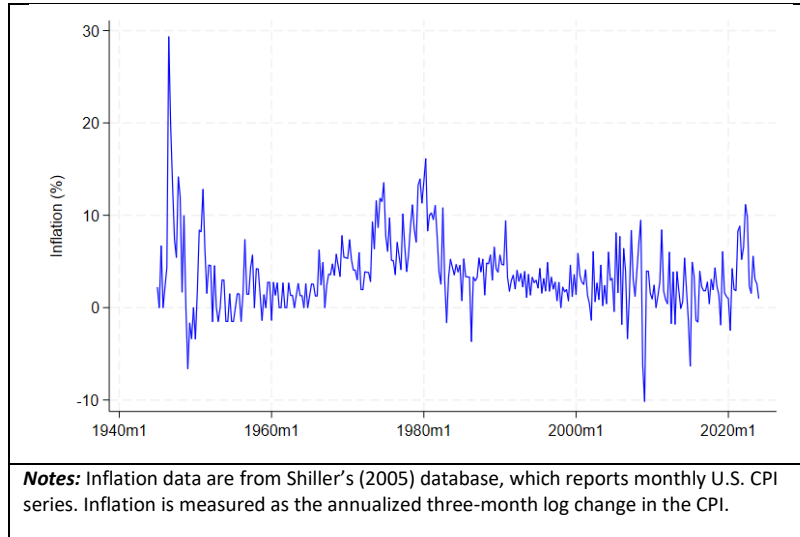
$$\Pr(\pi_{t-s} | \pi_{t,E}) \propto S(\pi_{t-s}, \pi_{t,E}), \quad (2)$$

where the normalization constant implies that, in the current forecasting task, probabilities add up to one. Normalization captures interference: experiences compete in recall. *Ceteris paribus*, it is easier to retrieve

a specific inflation level, say $\pi = 10\%$, compared to another, say $\pi' = 2\%$, if the former is more similar to the cue $\pi_{t,E}$ both along temporal and numerical context, and if it is relatively more frequent in Π_t .

The agent samples her database Π_t sufficiently many times that the distribution of recollections can be approximated by (2). Memory makes distinctive predictions based on two drivers: differences in the database that interact with current cues, and differences in how a forecasting task is described. To see the role of the database, Figure 3 reports quarterly US inflation from 1945 to 2024. The database at date t of a US household then collects realized inflation in Figure 3 from her 16 years of age to t .

Figure 3: U.S. Inflation Series



A person whose inflation database starts in 1971 has experienced more high inflation rates than a person whose database starts in 1980. If beliefs merely reflect the averaging of experiences, the older person should have higher inflation expectations than the latter. A full model of memory contains a countervailing force. A person whose inflation database starts in 1980 experiences very high inflation early. By primacy, she may end up with equal or even higher expected inflation than the older person.

Consider similarity next. Until 2021, a person with first record in 2006 has seen low inflation on average, much like a person with first record in 2011. If beliefs merely reflect average recorded inflation,

these two people should react in the same way to the 2021 shock. Memory adds a countervailing force. The person whose database starts in 2006 has witnessed higher inflation volatility during the commodity shock of 2007-2008 and then the Great Recession. By similarity, she may react more strongly to the 2021 shock than the younger person. Stronger updating is not a prerogative of the elderly, who have lived in a persistent high inflation regime. It is also caused by high experienced volatility around a given mean.

Propositions 1 and 2 in the next section derive econometric tests that systematically test these effects. Proposition 3 then derives predictions on the description of the forecasting task. To see those, consider a person asked to report her point expectation. She recalls past episodes based on a broad cue, capturing any possible inflation level, $E = \mathbb{R}$. By Equation (1), then, in this task similarity depends on the average inflation in the agent's database $\bar{\pi}_{\mathbb{R},t} = \bar{\pi}_t$. The agent's point forecast is then given by:

$$\mathbb{E}(\pi_{t+1}|\pi_{t,\mathbb{R}}) = \sum_{\pi_{t-s} \in \Pi_t} \Pr(\pi_{t-s}|\pi_{t,\mathbb{R}}) \cdot \pi_{t-s}, \quad (3)$$

where probabilities in (2) are normalized in the full database, $\Pr(\pi_{t-s}|\pi_{t,\mathbb{R}}) = S(\pi_{t-s}, \pi_{t,\mathbb{R}})/S(\Pi_t, \pi_{t,\mathbb{R}})$.⁶

Suppose however that the same person is asked to report the forecast density. Here the agent estimates the probabilities of the explicitly described cells of a partition $E_1, \dots, E_k$ of future inflation (so $\cup_j E_j = \mathbb{R}$). There are now multiple and narrower cues. She thinks about each E_j and normalizes across ranges, estimating the probability of E_j by its relative self-similarity compared to the other elicited ranges:

$$\Pr(E_j|\pi_{t,E_j}) = \frac{S(E_j \cap \Pi_t, \pi_{t,E_j})}{\sum_{r=1,\dots,k} S(E_r \cap \Pi_t, \pi_{t,E_r})}. \quad (4)$$

⁶ We can define an implicit estimate for event $E \subset \mathbb{R}$ as $\Pr(E|\pi_{t,\mathbb{R}}) = \sum_{\pi_{t-s} \in E \cap \Pi_t} S(\pi_{t-s}, \pi_{t,\mathbb{R}})/S(\Pi_t, \pi_{t,\mathbb{R}})$. The value of $\Pr(E|\pi_{t,\mathbb{R}})$ is not observed because in this task the agent only reports the point estimate. It however provides a benchmark for understanding how different forecasting tasks influence beliefs.

Equation (4) entails an implicit point expectation $\mathbb{E}(\pi_{t+1}|\pi_{t,E_1}, \dots \pi_{t,E_k}) = \sum_{j=1,\dots,k} \Pr(E_j|\pi_{t,E_j}) \cdot \pi_{E_j}$, where π_{E_j} is the similarity weighted average inflation lived in range E_j (i.e. across experiences in $E_j \cap \Pi_t$). The cue for ranges is more specific than that for point forecasts, so recall from the same database differs across the two tasks. These differences then lead to a gap between the density-based forecast $\mathbb{E}(\pi_{t+1}|\pi_{t,E_1}, \dots \pi_{t,E_k})$ and the explicit point forecast in Equation (3).⁷

The role of the forecasting task (point expectation vs forecast density) in shaping recall and beliefs is a striking new implication of the memory model. It distinguishes this mechanism from any rational model in which the agent holds a coherent belief system, including Bayesian learning. Incoherence is well documented in work on judgment and related to the “disjunction fallacy” (Fischhoff et al. 1978): decomposing an event facilitates retrieval of its components and can alter assessed probabilities. Here, explicitly eliciting inflation ranges cues neglected deflation states and because probabilities sum to one, this shifts mass toward the lower tail and reduces the density-implied mean. Using our model and the SCE elicitation of point expectations and range probabilities, we can assess this inconsistency in the key field context of household inflation expectations.

2.3 Deriving Memory Predictions

Our predictions rely on: i) the database Π_t , which varies across people of different ages a_t and over time due to realized inflation π_t , and on ii) the cue, $\pi_{t,E}$, which includes the estimation task. These elements interact because the cue ignites retrieval of past states π_{t-s} from the database Π_t based on the distance in Equation (1). We derive implications for two common elicitations: point and density forecasts.

⁷ Equation (4) follows Bordalo et al. (2023) in having the agent sample different hypotheses separately but adopts a simpler form of normalization. If an agent is asked to assess only one strict subset $E \subset \mathbb{R}$ we intuitively assume that she also samples based on its unmentioned alternative $-E = \mathbb{R} \setminus E$.

Point Expectations. This elicitation is available in the Michigan Survey of Consumers (MSC) and the Federal Reserve Bank of New York’s Survey of Consumer Expectations (SCE), and concerns expected inflation 12 months ahead or even farther. The point forecast cue is broad, $E = \mathbb{R}$, which facilitates retrieval of rates near the respondent’s average experienced inflation, $\bar{\pi}_{E,t} = \bar{\pi}_t$. We obtain a first test.

Proposition 1 *The linear approximation of a respondent’s point inflation expectation at time t with respect to β_1 , β_2 and σ around $\beta_1 = \beta_2 = \sigma = 0$, is given by:*

$$\begin{aligned} \mathbb{E}(\pi_{t+1} | \pi_{t,\mathbb{R}}) &\approx \bar{\pi}_t + \beta_1 \cdot \text{cov}[(s/a_t)^2, \pi_{t-s}] - \beta_2 \cdot \text{cov}(s/a_t, \pi_{t-s}) \\ &\quad - \sigma \cdot (1 - q) \cdot \text{cov}[\pi_{t-s}, (\pi_{t-s} - \bar{\pi}_t)^2] - \sigma \cdot q \cdot \text{cov}[\pi_{t-s}, (\pi_{t-s} - \pi_t)^2]. \end{aligned} \quad (5)$$

The first determinant of the point forecast is a respondent’s average experienced inflation $\bar{\pi}_t$ when entering time t . This is a database effect: *ceteris paribus*, people who have experienced higher average inflation $\bar{\pi}_t$ expect higher future inflation, whatever the cue. The other covariance terms reflect the interaction between cues and the database, for they are computed using the features of the cue and the distribution of experiences in Π_t .

The first two covariances $\beta_1 \cdot \text{cov}[(s/a)^2, \pi_{t-s}]$ and $-\beta_2 \cdot \text{cov}(s/a, \pi_{t-s})$ encode primacy and recency, respectively. Holding a person’s average experience constant, the first term implies that people whose above average inflation experiences occurred early in life persistently estimate higher inflation than people who lived above average inflation later (the former people have higher $\text{cov}[(s/a_t)^2, \pi_{t-s}]$). The second term captures recency: a person whose above average inflation experiences occurred recently expects higher inflation compared to a person for whom such inflation experiences occurred some time ago (the former people have lower $\text{cov}(s/a_t, \pi_{t-s})$).

Primacy is a stark departure from Bayesian models: it implies that a person’s early experiences are more heavily weighted in beliefs than recent ones, as if they were objectively “more informative”.

Recency is more standard: it is embedded in constant gain and experience-based learning models (Marcet and Sargent 1989, Sargent 1999, Evans and Honkapohja 2001, Malmendier and Nagel 2011, 2016, Nagel and Xu 2022). With memory the two forces pull beliefs in different directions. Recency is a stronger pull if and only if $\beta_2 > \beta_1$, in which case the very last episode has a higher weight than the very first one.

The two other covariances reflect numerical similarity. They imply that – for a given Π_t – a surge in current inflation π_t boosts expectations by cueing recall of similarly high inflation rates compared to low inflation ones. This effect is cohort-specific. Holding average prior experiences constant, higher π_t especially boosts the belief of a person whose above average inflation experiences are similar to π_t or $\bar{\pi}_t$ compared to a person whose above average inflation experiences are different from π_t or $\bar{\pi}_t$ (for the former people the two covariances are lower). The first similarity term acts through $\bar{\pi}_t$, which is slow moving, the second covariance term changes quickly with π_t .

Numerical similarity implies that higher current inflation π_t can trigger strong de-anchoring, and especially so for people who have lived through many high inflation episodes similar to π_t , *regardless of how remote they are in the past*. At the same time, during an upward trend in inflation the expectations of “low inflation” cohorts catch up: their database gets filled with high inflation as they live it, boosting their recall by similarity. A Bayesian regime switching model cannot capture this state dependence: the young have not experienced a regime with persistently high inflation. Memory explains why they can develop it on the spot: based on similarity. Memory can thus account for the patterns in Figure 1: fast de-anchoring by the elderly and the subsequent catch up by the young.

Density Forecasts. As described in Section 4, the SCE asks people to report the probability of ten inflation ranges: inflation greater than 12%, 8% to 12%, 4% to 8%, 2% to 4%, 0% to 2%, and deflation 0 to -2%, -2% to -4%, -4% to -8%, -8% to -12% and less than -12%. To study belief formation about ranges, assume for simplicity that peoples’ databases are concentrated at each range midpoints π_j for $j =$

1,...,10, so that cohort differences are captured by ranges' experienced frequencies. When assessing the probability of range j , the respondent is cued by it, $\bar{\pi}_{t,E_j} = \pi_j$, and by current inflation π_t .

Proposition 2 *Let n_j be the database frequency of π_j . The linear approximation of a respondent's estimate for the odds of π_j versus a base π_b at t with respect to β_1 , β_2 and σ around $\beta_1 = \beta_2 = \sigma = 0$, is given by:*

$$\begin{aligned} \frac{\Pr(\pi_j|\pi_j, \pi_t)}{\Pr(\pi_b|\pi_b, \pi_t)} \approx & \frac{n_j}{n_b} + \beta_1 \cdot \frac{n_j}{n_b} \cdot (\bar{s}_j^2 - \bar{s}_b^2)/a_t^2 - \beta_2 \cdot \frac{n_j}{n_b} \cdot (\bar{s}_j - \bar{s}_b)/a_t \\ & - \sigma \cdot q \cdot \frac{n_j}{n_b} \cdot [(\pi_j - \pi_t)^2 - (\pi_b - \pi_t)^2]. \end{aligned} \quad (6)$$

The memory forces affecting point forecasts influence the estimated relative probability of different ranges. The first term in Equation (6) is a pure database effect: the relative probability attached to range j relative to range b increases in its relative frequency n_j/n_b . The other terms capture the interaction between cues and the database, which produce state- and cohort- dependence. There is a primacy effect: when $\beta_1 > 0$, range j is deemed more likely than b if j is experienced on average more remotely than b , $\bar{s}_j^2 > \bar{s}_b^2$. On the other hand, $\beta_2 > 0$ captures recency: range j is deemed more likely than b if j was experienced more recently than b , $\bar{s}_j < \bar{s}_b$. Critically, the strength of primacy and recency are both stronger if range j is experienced relatively more frequently than b , higher n_j/n_b . This is the interaction between the temporal cue and the database.

When $\sigma > 0$ there is also a numerical similarity term: range j is deemed more likely if current inflation is closer to it than to range b , and more so if range j experiences were more frequent relative to range b ones, higher n_j/n_b . If inflation increases from 2% to 10%, the judged probability of the 10% range should go up for everybody, but especially so for people who have lived more 10% inflation episodes. Beliefs about ranges are state- and cohort-dependent in the same way as point expectations are.

A key difference between point expectations and density forecasts is that, when forming the latter, the average inflation cue $\bar{\pi}_t$ plays no role, namely it is absent from Equation (6). When people estimate range E_j , they are directly cued to think about its corresponding inflation π_j , even if it was rarely experienced. Thus, the forecast density $\Pr(E_j|\pi_{t,E_j})$ in Equation (4) differs from the belief $\Pr(E_j|\pi_{t,\mathbb{R}})$ implicitly formed over the same range E_j when making point expectations.

Work on density forecasts has documented several anomalies, including smearing of probabilities across events and outsized probabilities attached to events elicited at the beginning of the list. The typical explanations include “frictions” such as low numeracy, rounding of probabilities (Binder 2018), order effects (Tversky and Kahneman 1974, Hogarth and Einhorn 1992), and the 1/n heuristic (Benartzi and Thaler 2001). Memory makes precise predictions on how cues and the database shape these anomalies. Consider the link between point and density forecasts. Equations (3) and (4) imply:

$$\mathbb{E}(\pi_{t+1}|\pi_{t,\mathbb{R}}) = \sum_j w_{j,t} \cdot \Pr(E_j|\pi_{t,E_j}) \cdot \pi_j. \quad (7)$$

That is, mnemonic point expectations are a *weighted* sum of ranges’ expected values, where the weight $w_{j,t}$ on range j identifies the ratio of the implicit estimate of E_j used for making the point forecast to the directly elicited estimate for the same range, $w_{j,t} = \frac{\Pr(E_j|\pi_{t,\mathbb{R}})}{\Pr(E_j|\pi_{t,E_j})}$.

If the two estimates are coherent (as should be the case in any rational model), then $w_{j,t} = 1$: a person’s point expectation should be equal to the average inflation computed using her separately elicited forecast density. With memory, however, rarely experienced ranges are not recalled and hence are underweighted in point expectations, so $w_{j,t} < 1$. For instance, if people rarely experienced deflation, the lowest ranges elicited in the SCE, then point forecasts will underweight deflation scenarios compared to forecast densities (indeed, the latter elicitation cues deflation). Critically, memory predicts that the gap between point and density-based forecasts depends on current inflation π_t and average experience $\bar{\pi}_t$.

Proposition 3 Let $\mathbb{E}(X_k|\text{DF}) = \sum_k \Pr(E_k|\pi_{t,E_k}) \cdot X_k$ be the density-based expectation of X_k . Let $d_{j,t} = (\pi_j - \bar{\pi}_t)^2$ be the distance between range j and a person's average experience, and $\bar{d}_t$ the average distance of ranges based on their experienced frequencies. A linear approximation of $w_{j,t}$ with respect to β_1 , β_2 and σ around $\beta_1 = \beta_2 = \sigma = 0$ implies that the respondent's point estimate at t satisfies:

$$\mathbb{E}(\pi_{t+1}|\pi_{t,\mathbb{R}}) \approx \mathbb{E}(\pi_{t+1}|\text{DF}) + \sigma \cdot q \cdot \mathbb{E}[\pi_j \cdot (\bar{d}_t - d_{j,t})|\text{DF}]. \quad (8)$$

Point and density-based forecasts differ only if similarity matters, $\sigma > 0$. In this case, the point forecast is higher than the density-based one if high inflation ranges are more similar to the average experience than deflation ones, namely $d_{j,t} < \bar{d}_t$ at positive inflation levels $\pi_j > 0$ and $d_{j,t} > \bar{d}_t$ at negative ones $\pi_j < 0$. Low experience with deflation causes underweighting of this event when forming point expectations compared to forecast densities. In turn, this causes a positive gap $\mathbb{E}(\pi_{t+1}|\pi_{t,\mathbb{R}}) - \mathbb{E}(\pi_{t+1}|\text{DF}) > 0$.

Memory then makes two predictions about the belief gap. First, the gap is state dependent: it should shrink when inflation rises. Higher π_t in fact triggers a sharp downward revision of deflation ranges, causing the density-based forecast to increase sharply. The point expectation increases proportionately less: it is anchored to the slow-moving average experience $\bar{\pi}_t$. Higher current inflation π_t thus causes $\mathbb{E}(\pi_{t+1}|\text{DF})$ to get proportionally closer to $\mathbb{E}(\pi_{t+1}|\pi_{t,\mathbb{R}})$. Second, the gap should be database dependent: larger for people with more deflation experiences. Because deflation is rare for everyone, people similarly underweight it in point forecasts. When deflation is cued, however, people with more deflation experiences increase its probability more, as shown by the frequency-similarity interaction in Equation (6). This implies that the density-based forecast is lower for people with more deflation experiences, who should then exhibit a larger gap $\mathbb{E}(\pi_{t+1}|\pi_{t,\mathbb{R}}) - \mathbb{E}(\pi_{t+1}|\text{DF})$.

This state-dependent discrepancy between point and density-based expectations is a clear test of memory and has important real-world implications. It means that people may neglect unlikely risks when

forecasting the future, but also sharply increase the weight on such risks when those are made salient. When deflation becomes salient, people may switch from under to overestimating its risk, reducing the central bank's ability to raise inflation expectations. This effect can also matter if decisions are made under the influence of different cues. The same person may buy gold after hearing about the risk of high inflation but prefer a cheap over an expensive car because the car dealer's context does not cue high inflation risk.

3. Testing the Model's Predictions for Point Expectations

We examine point expectations in Equation (5) using the Michigan Survey of Consumers, MSC, and the New York Fed's SCE. We use the SCE because, despite its shorter time series, it has the crucial advantage of measuring also households' density forecasts, which are key for our tests.

3.1 Data

The MSC is a rotating monthly survey panel conducted by the University of Michigan starting from January 1978. Six months after the interview, about 40% of the sample is interviewed again (each respondent can be interviewed up to three times). The MSC collects socio-demographics and expectations about a range of indicators. On inflation, each respondent is asked whether he/she believes that prices will go up, down, or stay the same in the following 12 months, and by which percentage. The latter estimate is our point expectations proxy, which we winsorize at the bottom and top 1st percentiles at -7% and 30% expected inflation. Before 1978, the survey was delivered quarterly, respondents were fewer, and questions were slightly different. We thus focus on the post-1978 period until March 2024.

The New York Fed's SCE is also a rotating panel. It comprises about 1,300 nationally representative US household heads who are interviewed every month over a 12-month period. Our data cover the period from the inception of the survey in June 2013 until March 2024. Similar to the MSC, the SCE collects socio-

demographic characteristics and a wide array of expectations. The point expectations question asks respondents whether they expect an increase or decrease in inflation, and then to specify their estimates, which we winsorize at the bottom and top 5th percentiles at -4% and 25% expected inflation.

Current and experienced realized inflation comes from the Shiller (2005) database, which reports the monthly CPI back to 1871. We measure experiences at a quarterly frequency, using the annualized quarterly growth rate of the CPI. Quarterly inflation is a reasonable compromise between the high volatility of monthly inflation, whose fluctuations may fail to be noticed by households, and the stability of annual inflation, which may create a false impression that most households have never experienced significant price increases or deflation. In each month of forecast, the respondent's database consists of all experienced inflation rates before the current quarter, starting at age 16, so for testing the model in each period we compute a respondent's effective age as $a_t = (\text{actual years of age at } t - 16) * 4$. Results remain robust if we allow for an earlier starting point of the memory database at age 12.

Consistent with the construction of the database, we measure the current cue, π_t in the model, as the annualized quarterly inflation rate realized in the three months before the forecast (the forecast month is included). We adopt the same method to construct the database and cues in the SCE dataset. We take realized inflation to be perfectly observed by households. Relaxing this assumption does not radically change our qualitative results if the mapping between true and perceived inflation is monotonic.⁸ We also use data on professional CPI inflation forecasts from the Survey of Professional Forecasters (SPF).

3.2 Cues and Point Expectations

We test Equation (5) by estimating:

⁸ In particular, the current analysis goes through under a linear approximation in which perceived inflation is affine in true inflation, so that $\hat{\pi}_t = a + b \cdot \pi_t$. In this case, parameter a would affect the level of beliefs but not similarity, and the slope b would enter quadratically in the numerical similarity weights.

$$\begin{aligned}
\pi_{i,t}^e = & \gamma_0 + \gamma_1 \cdot \bar{\pi}_{t-1} + \gamma_2 \cdot cov[(s/a)^2, \pi_{t-s}] + \gamma_3 \cdot cov[(s/a), \pi_{t-s}] \\
& + \gamma_4 \cdot cov[\pi_{t-s}, (\pi_{t-s} - \bar{\pi}_t)^2] + \gamma_5 \cdot cov[\pi_{t-s}, (\pi_{t-s} - \pi_t)^2] \\
& + \gamma_6 \cdot \pi_{SPF,t}^e + \delta'_1 X_i + \delta'_2 Z_t + u_{it},
\end{aligned}$$

where $\pi_{i,t}^e$ is the point expectations at time t by respondent i , X_i controls for i 's gender, education, income brackets, and marital status, and Z_t are year dummies, which are included in most specifications to control for common shocks and to assess memory's ability to account for cross cohort belief variation. In some specifications we add the SPF inflation forecast $\pi_{SPF,t}^e$: professional forecasts are salient in the media, so we want to control for them as an alternative source of de-anchoring.

The parameters linked to Equation (5) are γ_1 , which should be positive if experiences matter, γ_2 and γ_3 , which determine the temporal primacy ($\gamma_2 > 0$) and recency ($\gamma_3 < 0$) effects, and γ_4 and γ_5 , which should be negative if numerical similarity matters. Table 1 reports estimates for the MSC (Panel A) and the SCE (Panel B). We include different memory effects in progression from columns (1) to (4). In column (6) we exclude year dummies and the SPF forecast to assess the explanatory power of memory alone, without accounting for unobservable time-varying factors.

In Column (1) respondents who experienced higher average inflation $\bar{\pi}_t$ report higher inflation expectations compared to the others, $\gamma_1 > 0$. Holding $\bar{\pi}_t$ constant, does selective retrieval matter? Column (2) assesses temporal context. Estimates in the SCE support the predicted U-shaped pattern of higher expected inflation if a respondent's above average inflation experiences are either early or recent, $\gamma_2 > 0$ and $\gamma_3 < 0$. In the MSC, estimates of γ_2 and γ_3 are directionally consistent with the theory but not statistically significant. They become significant as we add the other memory effects, as we show next.

In Column (3) we allow for all effects in Equation (5). Consistent with the model, the numerical similarity coefficients are negative, $\gamma_4 < 0$ and $\gamma_5 < 0$. Holding average experience constant, the

respondent over weights her above average inflation experiences when these are more similar to current inflation π_t or to the average experienced inflation $\bar{\pi}_t$, which both act as cues. Now primacy and recency effects become robust predictors, also in the MSC. We thus find strong evidence for selective recall. These effects are robust to adding the SPF forecast, Column (4), and to dropping year dummies, Column (5). In fact, year dummies have a small impact on the R^2 , showing the capability of memory to account for cohort and time variation in beliefs. As we show in Section 5, standard models with time dependent weights, including experience-based learning (Malmendier and Nagel 2016) cannot account for these patterns.

Estimated coefficients are economically meaningful. Consider temporal context. As Appendix Table B2 shows for the MSC, in our preferred specification (Table 1, Column 4) a one-standard deviation increase in the first covariance term (second row) is associated with a 0.82 percentage point increase in inflation expectations. The second covariance term (third row) is associated with -1.04 percentage points decrease. Realistic variation in database statistics give meaningful disagreement. Statistically, frequency and primacy have the same magnitude. Using point estimates, the temporally hardest experiences to recall occur at $s/a = \beta_2/2\beta_1 = 0.685$, which is about one third into a person's effective age.

Consider numerical similarity next. The effect of this force is strong, which is needed to explain de-anchoring. A one-standard deviation higher dissimilarity of above average experienced inflation to average inflation (fourth row), and to current inflation (fifth row), is associated with decreases in expected inflation of 0.11 and 0.29 percentage points, respectively.

Similar conclusions apply to the SCE (Appendix Table B3). Here, a one-standard deviation increase in the primacy term leads to an increase in inflation expectations by 1.42 percentage points while a one-standard deviation increase in the recency term is associated with a decrease in inflation expectations of 1.66 percentage points. As for numerical similarity to the database and current inflation, a one-standard deviation higher covariance decreases expectations by 0.18 and 0.20 percentage points, respectively.

Table 1. Inflation Expectations, Experience and Selective Recall

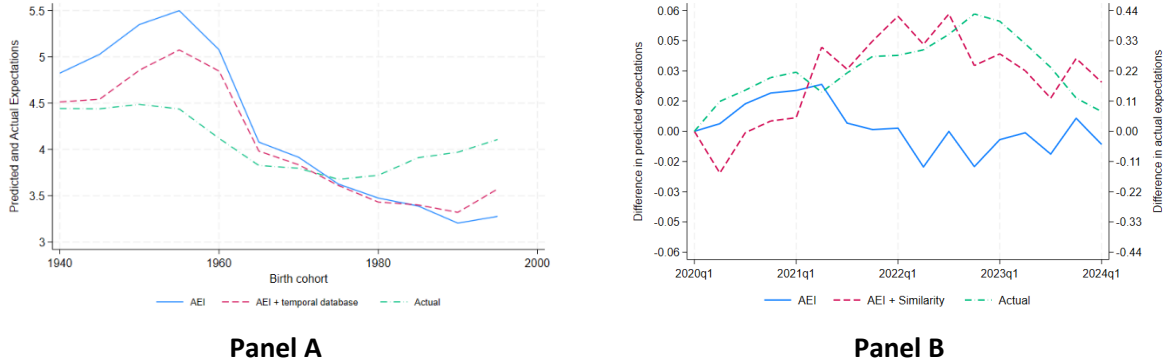
	One-Year-Ahead Inflation Expectation					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. MSC						
Average Experienced Inflation: $\bar{\pi}_{t-1}$:	0.280*** (0.027)	0.331*** (0.062)	0.549*** (0.070)	0.529*** (0.067)	0.298*** (0.051)	0.626*** (0.038)
Temporal Context Quadratic Component: $\text{Cov}(s^2, \pi_{t-s}) / a^2$		0.008 (0.531)	2.237*** (0.603)	1.801*** (0.539)	1.189** (0.479)	4.980*** (0.552)
Temporal Context Linear Component: $\text{Cov}(s, \pi_{t-s})/a$		-0.301 (0.708)	-3.090*** (0.796)	-2.464*** (0.722)	-1.096* (0.598)	-5.991*** (0.646)
Dissimilarity average inflation: $\text{Cov}((\pi_{t-s} - \bar{\pi}_{t-1})^2, \pi_{t-s})$			-0.003*** (0.001)	-0.003** (0.001)	-0.002* (0.001)	-0.003*** (0.001)
Dissimilarity current inflation: $\text{Cov}((\pi_{t-s} - \pi_t)^2, \pi_{t-s})$			-0.002*** (0.001)	-0.003*** (0.000)	-0.005*** (0.001)	-0.006*** (0.001)
SPF inflation forecast				0.672*** (0.135)	0.262*** (0.055)	
Constant	2.990*** (0.121)	2.793*** (0.249)	2.133*** (0.264)	0.023 (0.460)	2.238*** (0.101)	2.034*** (0.121)
Observations	229,495	229,495	229,495	217,818	217,818	229,495
R-squared	0.092	0.092	0.094	0.061	0.044	0.069
Panel B. SCE						
Average Experienced Inflation: $\bar{\pi}_{t-1}$:	0.212*** (0.074)	0.464* (0.242)	1.046*** (0.392)	0.931** (0.395)	2.175*** (0.374)	2.481*** (0.337)
Temporal Context Quadratic Component : $\text{Cov}(s^2, \pi_{t-s}) / a^2$		5.292** (2.555)	7.218** (2.853)	6.371** (2.835)	19.083*** (2.790)	22.322*** (2.457)
Temporal Context Linear Component: $\text{Cov}(s, \pi_{t-s})/a$		-6.543* (3.564)	-9.608** (4.061)	-8.351** (4.040)	- 26.657*** (3.942)	-31.184*** (3.440)
Dissimilarity average inflation: $\text{Cov}((\pi_{t-s} - \bar{\pi}_{t-1})^2, \pi_{t-s})$			-0.010 (0.007)	-0.009 (0.007)	-0.001 (0.007)	0.001 (0.007)
Dissimilarity current inflation: $\text{Cov}((\pi_{t-s} - \pi_t)^2, \pi_{t-s})$			-0.002*** (0.001)	-0.002*** (0.001)	-0.008*** (0.001)	-0.010*** (0.001)
SPF inflation forecast				0.646* (0.354)	0.937*** (0.306)	
Constant	5.699*** (0.216)	5.263*** (0.452)	3.810*** (0.884)	2.639** (1.061)	-0.163 (0.959)	1.331 (0.820)
Observations	139,583	139,583	139,583	139,583	139,583	139,583
R-squared	0.114	0.115	0.115	0.115	0.104	0.103
Demographic Characteristics	YES	YES	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES	NO	NO
SPF Forecast Included	NO	NO	NO	YES	YES	NO

Notes: The table reports the estimates of the first-order approximation of our model, augmented with similarity and a quadratic recency term, given by the regression specification $\pi_{i,t}^e = \gamma_0 + \gamma_1 \cdot \bar{\pi}_{t-1} + \gamma_2 \cdot \text{cov}[(s/a)^2, \pi_{t-s}] + \gamma_3 \cdot \text{cov}[(s/a), \pi_{t-s}] + \gamma_4 \cdot \text{cov}[\pi_{t-s}, (\pi_{t-s} - \bar{\pi}_{t-1})^2] + \gamma_5 \cdot \text{cov}[\pi_{t-s}, (\pi_{t-s} - \pi_t)^2] + \gamma_6 \cdot \pi_{i,t}^{\text{SPF}} + \delta_1' \mathbf{X}_i + \delta_2' \mathbf{Z}_t + u_{i,t}$. Demographic characteristics include sex, education, income quintile and marital status. The database of inflation experiences includes the quarter-on-quarter experienced inflation rate and is updated each month. Inflation experience stops at the quarter before the quarter in which the forecast is made. Current inflation is the inflation experienced during the three months before the forecast. We assume that for each cohort, learning starts when 16. Observations are weighted using survey weights. Standard errors clustered at the cohort and forecast date level in parentheses.

To further illustrate explanatory power, we compare predicted beliefs for cohorts whose databases differ in dimensions that are relevant for the memory effects. Panel A in Figure 4 focuses on

primacy. Using the specification of column (4), it reports average expected inflation for different cohorts in the MSC across all sample periods. The blue line is the predicted belief using only average experiences $\bar{\pi}_t$. The red line is the prediction using also primacy and recency. The green line is the data.

Figure 4: Predicted and Actual Expectations



Notes: **Panel A (left)** plots actual and counterfactual inflation expectations by five-year birth cohort, computed from the full specification by shutting down selected memory components. The blue line keeps only average experienced inflation (AEI), the red dashed line adds the temporal-database component, the green dashed line reports actual expectations. The right **Panel B (right)** plots the difference in expectations between respondents born in 1995–1999 and those born in 1990–1994. The blue line reports the counterfactual difference implied by AEI only, the red dashed line adds the similarity component, and the green dashed line reports the actual difference. Before computing the right-panel differences, actual and predicted expectations are smoothed using a four-quarter moving average and normalized to their values in the first quarter of 2020.

Memory improves explanatory power by reducing the expectations of cohorts born between 1945 and 1960 compared to those born later. This is the primacy effect discussed in Figure 3. Take for instance the 1950 cohort. It lives through the Great Inflation rise and peak, so its average database $\bar{\pi}_t$ is very high (reflected in a higher point in the blue curve for this cohort). However, this cohort sees the 1980 peak later in life than the 1963 cohort. Including primacy reduces the average belief of 1955 cohort more than that of the 1963 one, improving the model's prediction.

Consider how similarity shapes sensitivity to the 2021 shock. Panel B shows the over-time difference between the belief of the average person born in 1990–94 and of a person born between 1995–99. In the data, the older cohort reacted more swiftly than the younger one (the green line is positive). Using only $\bar{\pi}_t$ (blue line) does not give meaningful belief differences, failing to capture this feature. Allowing for similarity (red line) gives a directionally correct effect: the older cohort is predicted to react

more swiftly to the shock than the younger one (the peak difference is about 1/7th of the observed one). As discussed, this occurs because – despite not living through Great Inflation – the older cohort has the inflationary shocks of 2007-8 in her database, so it has more memories to imagine high future inflation than the younger cohort. It reacts more swiftly to 2021, consistent with the data, even though people born in 1990-94 do not have a persistent high inflation regime like the 1970’s in their experience set.

The examples of Figure 4 convey a broader message: primacy and similarity effects in recall make new predictions on state and cohort belief sensitivity. Primacy yields sensitivity to early experiences, creating persistent gaps across cohorts, similarity yields cohort-specific extrapolation even based on occasional events. To quantify explanatory power, we collapse the data to month-by-five-year-cohort cells and regress average observed inflation expectations on the corresponding model-implied predictions. Allowing for memory effects raises the R^2 for cross-cohort and over-time variation in expectations from about 0.04 to 0.30, compared to a model based solely on average experiences.

Our key results are robust to different measures and methods. We estimate our regression using longer term inflation expectations (between 24 and 36 months ahead), which are available from the New York Fed’s SCE, but not for the MSC. These expectations are highly relevant for individual decisions as well as for monetary policy. Our results on temporal context and numerical similarity carry over to them, with one interesting nuance: for longer term expectations similarity to experienced mean inflation $\bar{\pi}_t$ is more important than similarity to current inflation π_t , the opposite of what we found for short term beliefs. Intuitively, long-term expectations are shaped by longer-term experiences, so that different cohorts have different long-run inflation anchors. The results hold if we apply robust regressions (Appendix Table B1) or if we define inflation experiences annually rather than quarterly (Appendix Table B5). Annual aggregation weakens the effect of the short-run memory cue and some coefficients are less precisely estimated with year effects; we therefore view the annual specification as qualified robustness evidence.

In sum, selective memory has significant explanatory power for point expectations. Regularities in recall improve on adaptive models in which cues play no role and only recency matters, as well as on Bayesian models that exhibit no primacy effects. In Section 5 numerical similarity is key for swift de-anchoring by the elderly and quick catch up by the young in Figure 1. We next compare point and density forecasts in the data. This analysis rejects any standard model of people holding a coherent belief system which they use for different elicitation and allows us to test additional predictions of memory.

4. The Model's Predictions for Forecast Densities and Belief Inconsistency

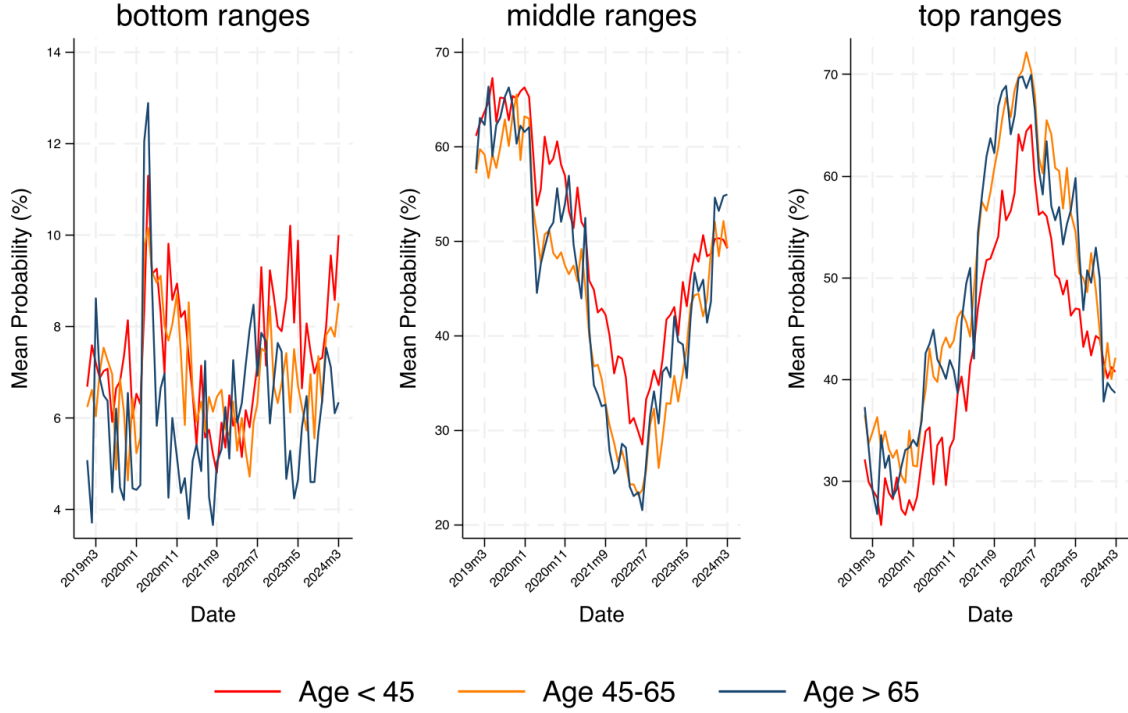
Section 4.1 shows that forecast densities are also influenced by temporal and numerical cues based on estimates of Equation (6). Section 4.2 shows that a household's density-based and point expectations are inconsistent, in a way that can be explained by our model, based on Equation (8).

4.1. Temporal and Numerical Similarity in Forecast Density Estimation

The forecast density elicitation in the SCE asks households to report their probability estimates of inflation falling into each of 10 ranges using numbers that sum to 100 percent. Figure 5 aggregates the lowest ($\pi_{t+1} < -4\%$), middle ($\pi_{t+1} \in [-4, 4\%]$), and top ($\pi_{t+1} > 4\%$) ranges, and reports the average estimates of young (<45, red), middle-aged (45-65, orange), and older (>65, blue) cohorts during 2019-24.

Consistent with Figure 1, upon seeing the inflation surge older respondents increase the probability of the top ranges ($\pi_{t+1} > 4\%$) more sharply than younger ones and correspondingly revise more sharply downward the probability of the middle ranges ($\pi_{t+1} \in [-4, 4\%]$). The probability attached to the deflationary range ($\pi_{t+1} < -4\%$) is much smaller and economically quite similar across cohorts: The young place a probability of 7.4% on this range, the middle-aged 6.9% and the older 6.1%.

Figure 5 Cohort Specific State-Dependence in Range Estimation



Notes: We report the mean probability that respondents assign in the New York Fed SCE to the bottom, middle and top ranges of future inflation. Bottom ranges span <-12%, -12% to -8% and -8 to -4% future inflation; middle ranges -4% to -2%, -2% to 0% , 0% to 2% and 2% to 4% future inflation; top ranges 4% to 8%, 8% to 12% and >12% future inflation. Means are computed using survey weights.

This pattern lines up with the interaction between cues and the database in Equation (6): the effect of changing inflation π_t in range E_j estimation is mediated by its experienced frequency n_j/n_b . Across cohorts, as the elderly see high inflation, they more sharply increase their estimated probability $\Pr(\pi_{t+1} > 4\%)$ due to their higher frequency n_j/n_b compared to the young, who experienced few such episodes. Over time, much action in forecast densities comes from middle and high inflation ranges, the probability attached to deflation moves much less. This is again consistent with memory: changes in the inflation cue π_t affect deflation ranges less, due to their lower frequency n_j/n_b , for all cohorts. We next present a structured test of our model, which also allows for additional forces, including recency and primacy. We take the model-implied Equation (6) to the data, which we implement by estimating several variants of the specification:

$$\frac{\hat{\pi}_{j,i,t}}{\hat{\pi}_{b,i,t}} = \theta_0 + \theta_1 \cdot \frac{n_{j,i,t}}{n_{b,i,t}} + \theta_2 \cdot \frac{n_{j,i,t}}{n_{b,i,t}} \cdot (\bar{s}_{j,i,t}^2 - \bar{s}_{b,i,t}^2) / a_t^2 + \theta_3 \cdot \frac{n_{j,i,t}}{n_{b,i,t}} \cdot (\bar{s}_{j,i,t} - \bar{s}_{b,i,t}) / a_t +$$

$$\theta_4 \cdot \frac{n_{j,i,t}}{n_{b,i,t}} \cdot [(\pi_j - \pi_t)^2 - (\pi_b - \pi_t)^2] + \omega'_1 \mathbf{R}_j \times \mathbf{X}_i + \omega'_2 \mathbf{R}_j \times \mathbf{Z}_t + \omega_3 \pi_{SPF,t}^e + v_{ijt},$$

where the left-hand side reports the odds of range j over a baseline $b \neq j$, selected for each respondent as the range with the lowest non-zero probability assessment. On the right hand side, $n_{j,it}/n_{b,it}$ is the corresponding relative experience frequency, $(\bar{s}_{j,i,t}^2 - \bar{s}_{b,i,t}^2)/a_t^2$ and $(\bar{s}_{j,i,t} - \bar{s}_{b,i,t})/a_t$ the relative recency, $[(\pi_j - \pi_t)^2 - (\pi_b - \pi_t)^2]$ the relative dissimilarity; $\mathbf{X}_i$ contains demographics to account for individual-specific characteristics, $\mathbf{Z}_t$ captures year dummies, $\pi_{SPF,t}^e$ the SPF inflation forecast, and $\mathbf{R}_j$ contains indicators for range j which we interact with $\mathbf{X}_i$ and $\mathbf{Z}_t$. Including range*date-specific dummies allows us to assess state*cohort differences in the assessment of a specific range. To avoid creating fat tails in experience ratios and to use Huber-robust weights, we aggregate tail ranges to >8%, 4% to 8%, 2% to 4%, 0% to 2%, -2% to 0%, -4% to -2%, and <-4% and we exclude single-valued density forecasts.

Key parameters in the specifications include θ_1 , which should be positive if the relative experience n_j/n_b with the target range j matters, θ_2 , which should be positive if greater primacy of the target range j boosts its estimated odds, θ_3 , which should be negative if more recently experienced ranges are more likely, and θ_4 , which should be negative if the higher similarity of the target range j to the current inflation cue boosts its estimated odds. All effects here are relative to the benchmark range b .

The results in Table 2 confirm the memory channel. The database matters (positive coefficient on “frequency ratio”): cohorts that have experienced a higher relative frequency of inflation in, say [2%,4%], report a relatively higher probability for this range compared to cohorts that experienced it less. Cues also matter. Temporally, the negative coefficient on “time delay” shows a recency effect, the [2%,4%] range is deemed as relatively more likely if it was experienced recently, while the positive coefficient on “time

delay square” shows primacy, the same [2%,4%] range is also deemed relatively more likely by a cohort that experienced it early in life. These effects are again especially strong if the range was experienced more frequently. These temporal effects are inconsistent with Bayesian or adaptive models.

Table 2. Memory and Range Probabilities

	Odds Ratio				
	(1)	(2)	(3)	(4)	(5)
Frequency Ratio	0.0162*** (0.000682)	0.0230*** (0.00131)	0.0242*** (0.00131)	0.0230*** (0.00131)	0.0242*** (0.00132)
Relative Frequency Ratio x Relative Time Delay Squared	0.104*** (0.00464)	0.0251*** (0.00728)	0.0350*** (0.00755)	0.0251*** (0.00728)	0.0350*** (0.00755)
Relative Frequency Ratio x Relative Time Delay	-0.106*** (0.00412)	-0.0731*** (0.00629)	-0.0866*** (0.00687)	-0.0731*** (0.00629)	-0.0866*** (0.00687)
Relative Frequency Ratio x Relative Dissimilarity	-2.26e-05*** (2.38e-06)	-8.20e-06** (3.43e-06)	-1.06e-05*** (3.87e-06)	-8.23e-06** (3.42e-06)	-1.06e-05*** (3.87e-06)
SPF				0.000858 (0.00615)	0.00814 (0.00521)
Constant	0.0453*** (0.00251)	0.171*** (0.00293)	0.173*** (0.00280)	0.171*** (0.00305)	0.173*** (0.00272)
Observations	491,072	567,767	570,799	567,775	570,822
R-squared	0.255	0.295	0.307	0.295	0.307
Demographic x Range Fixed Effects	No	Yes	Yes	Yes	Yes
Year x Range Fixed Effects	No	No	Yes	No	Yes

Notes: This table reports estimated coefficients and standard errors from estimating $\frac{\pi_{j,lt}}{\pi_{b,lt}} = \theta_0 + \theta_1 \cdot \frac{n_{j,lt}}{n_{b,lt}} + \theta_2 \cdot \frac{n_{j,lt}}{n_{b,lt}} \cdot (\bar{s}_{j,lt}^2 - \bar{s}_{b,lt}^2) / a^2 + \theta_3 \cdot \frac{n_{j,lt}}{n_{b,lt}} \cdot (\bar{s}_{j,lt} - \bar{s}_{b,lt}) / a + \theta_4 \cdot \frac{n_{j,lt}}{n_{b,lt}} \cdot [(\pi_j - \pi_t)^2 - (\pi_b - \pi_t)^2] + \omega_1' R_j \times X_i + \omega_2' R_j \times Z_t + \omega_3 \pi_{SPF,t}^e + v_{ijt}$ where the data come from the New York Fed SCE. Columns 1 and 2 include interactions of inflation range indicators R_j with demographic fixed effects X_i as well as year fixed effects Z_t , while Columns 3 and 4 additionally include an indicator variable for the SPF forecast falling in the range, captured by the *SPF* entry. Regressions use Huber-robust survey weights. Standard errors clustered at the cohort-range and forecast-range date level in parentheses.

Numerical cues also matter, see column (4): a target range is deemed more likely if it is relatively more similar to current inflation (see the negative coefficient on “relative dissimilarity”), especially if the household experienced this range more frequently. As in Figure 5, upon seeing high inflation in 2021, the elderly sharply increase their high-inflation range estimates compared to the young, who have fewer high inflation experiences. The interaction between the database and cues, the signature of memory, sheds light on both point and density forecasts. Table B6 in the Appendix shows that the results are robust to trimming cells with very low baseline probabilities, fixing the baseline bucket to the 0–2 percent range,

and using a fixed-baseline log-ratio approximation. Coefficients are stable, indicating that the findings are not driven by rare probability bins, the choice of baseline bucket, or the log-ratio approximation.

4.2 The Incoherence between Point Expectations and Forecast Densities

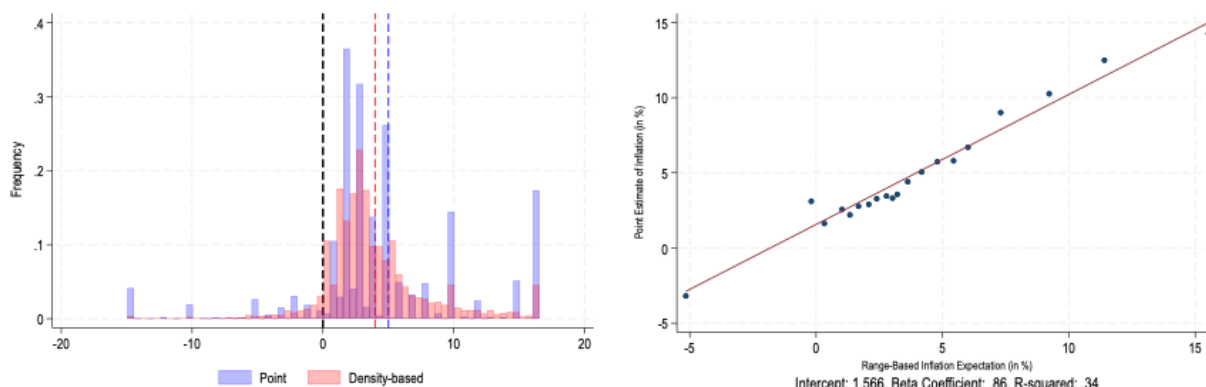
A rational person forms a probability density over future inflation rates and uses it to: i) estimate the probabilities of various ranges, and to ii) form a point forecast. This is not the case with selective memory: density estimates cue recall of rarely lived ranges that are neglected when making a point forecast. As a result, beliefs are incoherent across elicitations. We next show that such incoherence is present in our data, in line with Bruine de Bruin et al. (2011). Crucially, memory disciplines its size.

For each household i and time period t , we compute the density-based forecast $\pi_{i,t,DF}^e$ using the reported range probabilities by household i at time t and the 1931-2020 average inflation rate in each range. The latter choice addresses the difficulty of assigning a numerical value to unbounded ranges $>12\%$ and $<-12\%$ and gives estimates of 16.19% and -14.95%. For other ranges, this procedure assigns 9.80% to the 8% to 12%, 5.50% to the 4% to 8%, 3.02% to the 2% to 4%, 1.25% to the 0% to 2%, -0.42% to the -2% to -0%, -2.90% to the -4% to -2%, -5.55% to the -4% to -8% and -10.32% to the -8% to -12% inflation ranges. To avoid mechanical gaps between point and density-based forecasts, we also winsorize point forecasts at the top and bottom range values, 16.19% and -14.95%. Our results are robust to using average personal experiences over ranges (using midpoints or population averages in case of zero experiences).

Figure 6 reports in Panel A the distribution of point and density-based expectations in the SCE. We see a systematic discrepancy between the two measures: the distribution of density-based expectations is shifted to the left relative to that of point forecasts, so the point expectation tends to exceed the density-based one. The survey-weighted mean (median) point expectation is 5.01% (4%) while the survey-weighted mean (median) density-based expectation is 3.98% (3.08%), with differences that

are highly statistically significant. Consistent with memory, this discrepancy is at least in part due to neglect of deflation.⁹ Appendix Table B7 regresses point expectations on the elicited probabilities of the ten ranges. The coefficients on deflation ranges are generally not significant or in some cases are even positive, indicating that point expectations do not account for separately estimated deflation risk.

Figure 6: Systematic Point-Density Gap



Notes: Panel A (left) plots the distribution of point forecasts and density-based means. The dashed black line marks 0, the dashed blue line the survey-weighted mean of the point estimates, and the red line the survey-weighted mean of the density-based means. Panel B (right) binscatter-plots point estimates against range-based inflation expectations and shows associated regression estimates. The data come from the NY Fed SCE and are winsorized at -14.95% and 16.19% as discussed in the text.

The key prediction of memory is that the gap should be state- and database-dependent. Panel B of Figure 6 reports the binned scatterplot of a univariate regression of a respondent's point expectation on her density-based expectation. The slope coefficient is 0.86, significantly smaller than 1 (p-value < 0.001). This means that a 1 p.p. higher density-based expectation is associated with a less than 1 p.p. increase in the point expectation. Consistent with memory, a unit increase in density forecasts results in a $(1-0.86) = 0.14$ closing of their gap with point forecasts. When inflation increases, people attach a sharply higher weight to high inflation ranges (as in Figure 5) and density-based expectations increase. Point expectations also increase, but less in proportion to the density-based ones. As a result, the gap between the two narrows, consistent with the memory model.

⁹ Looking at databases we indeed see that deflation is experienced rarely, and that the average inflation experienced by respondents is far from it: In January 2020, before the recent inflation surge, 89.7% of the population inflation experiences are positive, with the young at 83.2%, the middle-aged at 90.3%, and the old at 92.4%.

To test for cohort-dependence we next regress the gap between point and density-based expectations on the share of deflation experiences in a respondent's database. Deflation is rare, but its experience meaningfully varies across SCE respondents. For instance, by the end of 2021, deflation episodes accounted for about 7 percent of the inflation histories of respondents born in 1940, compared with roughly 21 percent for respondents born in 1996. According to memory, respondents with more deflation experiences should exhibit a wider gap. To avoid capturing the effect of cognitive decline or low IQ, we control for age and numeracy in the regression. Table 3 reports the regression results.

Respondents with more deflation experiences exhibit a sizably wider gap. A one-standard deviation higher share of deflation experiences is associated with a 0.3 percentage point increase in the point-density gap (roughly 30% of the weighted average gap), after controlling for age, numeracy and demographics. Consistent with memory, people with more deflation experiences are thus more sensitive to the deflation cue in density elicitation, resulting in a sensibly lower density-based forecast than people with fewer experiences. Memory produces realistic state- and cohort- dependence in belief incoherence.

Table 3. Deflation Experiences and Point-Density Gap

	Point-Density Gap			
	(1)	(2)	(3)	(4)
Deflation Episodes Experienced (share)		10.312*** (1.948)		6.671*** (1.826)
Numeracy Score	-0.502*** (0.030)	-0.544*** (0.031)	-0.316*** (0.026)	-0.351*** (0.028)
Age	0.007*** (0.002)	0.034*** (0.006)	0.003 (0.002)	0.021*** (0.006)
Constant	3.180*** (0.195)	0.824* (0.467)	2.437*** (0.170)	0.944** (0.447)
Demographic Controls	NO	NO	YES	YES
Observations	138,959	138,959	137,551	137,551
R-squared	0.024	0.026	0.038	0.039

Notes: Deflation Episodes Experienced (share) is the share of deflation episodes experienced over an individual's lifetime, starting at age 16. Numeracy is the number of correct answers to the survey's numeracy questions. Respondents for which all numeracy answers are missing are dropped. Two-way clustered standard errors at the forecast date and cohort levels are reported in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Compare memory with canonical frictional accounts of incoherence such as: i) order effect (i.e. the first elicited ranges are overestimated), ii) rounding of probabilities (the density is "discretized"), or ii)

the 1/n heuristic (the probability of ranges is smeared toward 1/n). These mechanisms may play a role but cannot explain Figure 6 and Table 3. With order effects, people should overestimate top ranges, which are elicited first, counterfactually implying that density-based expectations should be higher than point forecasts. Rounding of probabilities or 1/n create smearing of densities, which also does not explain why point forecasts are higher than density-based ones. None of these mechanisms explains the state and cohort dependence of the gap we see in the data, which is instead consistent with memory cues.¹⁰

We conclude the analysis by directly testing Equation (8) of Proposition 3, which ties the state and database effect of our previous tests to a similarity index. Specifically, when current inflation π_t increases, similarity prompts households to sharply increase the probability of high inflation ranges, in turn sharply increasing density-based expectations more than point forecasts (which are more anchored to slow moving average experiences $\bar{\pi}_{i,t}$). We test this mechanism in Equation (8) by estimating:

$$\pi_{i,t}^e = \mu_0 + \mu_1 \cdot \pi_{i,t,DF}^e + \mu_2 \cdot [\pi \cdot d]_{i,t,DF}^e + \boldsymbol{\varphi}'_1 \mathbf{Z}_i + \boldsymbol{\varphi}'_2 \mathbf{Z}_t + e_{i,t}.$$

The left-hand side is the point estimate by respondent i , $\mathbf{Z}_i$ her demographics and $\mathbf{Z}_t$ year dummies. The first regressor, $\pi_{i,t,DF}^e$, is the density-based expectation. The second regressor, $[\pi \cdot d]_{i,t,DF}^e$ measures the relative similarity of high inflation ranges to the respondent's database of experiences up to the previous quarter (computed using Equation (8)). If the database $\bar{\pi}_{i,t}$ is more similar to high inflation ranges, point expectations (which anchor to the database) are more inflated compared to density-based ones, so $\mu_2 > 0$. Parameter μ_1 should instead be positive and equal to one if point expectations and range beliefs are formed using the same database of experiences. Table 4 reports the results, including also fixed effects. In columns (2) and (4) we also add squared and cubed similarity terms. These higher order terms can help capture the exponential similarity function, where similarity increases in a convex way as distance shrinks.

¹⁰ Danz, Vesterlund, and Wilson (2022) show that incentive-compatible elicitation can induce center-biased reporting. This mechanism cannot explain the state and cohort dependent incoherence we see in the data.

Table 4: Inflation Point Expectations, Density-Based Expectations and Similarity

	One-Year-Ahead Inflation Expectation			
	(1)	(2)	(3)	(4)
Range-based inflation expectations	1.094*** (0.024)	1.078*** (0.029)	0.981*** (0.024)	0.919*** (0.024)
Similarity of high inflation ranges to personal experiences	1.49e-03*** (1.72e-04)	1.46e-03*** (3.08e-04)	1.28e-03*** (1.31e-04)	3.533e-04 (2.33e-04)
(Similarity of high inflation ranges to personal experiences)^2		1.17e-07*** (4.06e-08)		-9.88e-08*** (3.69e-08)
(Similarity of high inflation ranges to personal experiences)^3		-7.647e-13 (1.79e-11)		7.16e-11*** (1.43e-11)
Constant	0.873*** (0.102)	0.858*** (0.111)	1.258*** (0.090)	1.455*** (0.086)
Observations	140053	140053	136794	136794
Year fixed effects	No	No	Yes	Yes
Individual fixed effects	No	No	Yes	Yes
R ²	0.3458	0.3470	0.6074	0.6085
Adj. R ²	0.3458	0.3470	0.5556	0.5568

Notes: This table reports estimated coefficients and standard errors from estimating $\pi_{i,t}^e = \mu_0 + \mu_1 \cdot \pi_{i,t,B}^e + \mu_2 \cdot [\pi \cdot d]_{i,t,B}^e + \phi_1' Z_i + \phi_2' Z_t + e_{i,t}$. The data come from the New York Fed SCE. Regressions use survey weights and standard errors are clustered at the cohort-year level.

The results are consistent with our model. The positive sign of the similarity regressor in columns (1) and (3) says that – holding density-based expectations constant – point expectations increase when average experiences are more similar to higher inflation ranges. This is precisely what happens when forecast densities attach higher probability to moderately high inflation, say in the range 3%-6% which is close to the average experiences $\bar{\pi}_{it}$ of many people compared to deflation. When instead inflation sharply increases and forecast densities attach a high probability to very high inflation ranges (which are

different from average experiences) the similarity term falls. Now point expectations increase less in proportion to density-based estimates so the gap between the two shrinks.

This effect accounts for the dampened sensitivity of point expectations to density-based ones in Figure 6 Panel B. Indeed, once we add the similarity term, in columns (1) and (3) the coefficient on density-based expectations rises to one, consistent with Equation (9). Higher-order similarity terms in turn suggest nonlinear curvature, but their mixed signs do not establish global convexity. Point expectations increase sharply as people attach higher probabilities to moderately high ranges close to $\bar{\pi}_{it}$. The results are robust to controlling for time fixed effects, so they are not due to special periods, and for respondent fixed effects. Inconsistencies in survey responses are not due to some respondents being lazy, have low acuity, or numeracy. They are due, at least in part, to the interplay between cues and experiences.

These findings rule out any rational model, including highly flexible Bayesian structures, and rule in selective memory. Quantitatively, the effects are significant. Even though the explanatory power of the regression improves only marginally when we add the similarity terms¹¹, the economic importance of similarity is large: a one-standard deviation increase in density-based inflation expectations increases reported inflation point forecasts by 3.75 to 4.36 pp (based on Columns 1 and 2). But a one-standard deviation increase in the similarity of high-inflation ranges around zero similarity is also associated with a 0.28 to 1.03 pp. increase in point inflation forecasts (based on Columns 1 and 2). Respondents substantially overweight ranges they are familiar with and underweight those they are unfamiliar with, resulting in state dependent inconsistencies across different methods of elicitation.

5. How Inflation Expectations De-Anchor and Re-Anchor

¹¹ In Column (1), the adjusted R2 is 34.58% relative to 33.98% in the specification without the linear similarity term in Figure 6. Going to a higher cubic order raises the adjusted R2 to 34.70%.

We go back to our motivation on state- and cohort-dependent de-anchoring of expectations in April 2021. We first evaluate our model’s explanatory power in the US but also for the other datasets and countries in Section 2. We use the specification in Column 6 of Table 1, focusing on MSC expectations, available for a longer period. In addition to memory terms and demographic controls, we use neither the SPF forecast nor time dummies as belief predictors because we wish to isolate the role of a person’s past inflation experiences – mediated by cued recall – in generating meaningful time variation in beliefs.

To showcase memory, we directly compare our model to experience-based learning (Malmendier and Nagel 2016, hereafter MN), where agents optimally estimate the long run mean and persistence of an AR(1) inflation process using their lived inflation history. We again focus on MSC expectations and nonlinearly estimate their gain parameter θ using data from 1978 on, when the monthly forecasts become regularly available. The appendix Figure B4 includes model comparison based on the restricted frame of the SCE, which shows robustness of the results. We include survey respondents of all ages, relaxing the MN restriction to ages 25–74. Moreover, to compare models to observed time variation in beliefs, we simulate expectations using monthly variation in inflation (while the AR(1) parameters are updated quarterly as in MN).¹² We then regress observed MSC inflation expectations on the AR(1)-implied ones, estimating equation (5) in Malmendier and Nagel (2016) without including time dummies or SPF forecasts, which would obscure learning-driven de-anchoring. The estimation yields a θ of 1.96. Using the fitted MSC expectations for each respondent i and time t we obtain a learning proxy π_{it}^e . This proxy does not allow for forgetting and selective retrieval based on changing temporal and numerical cues. We make comparisons by normalizing the initial predictions of all cohorts and across models.¹³

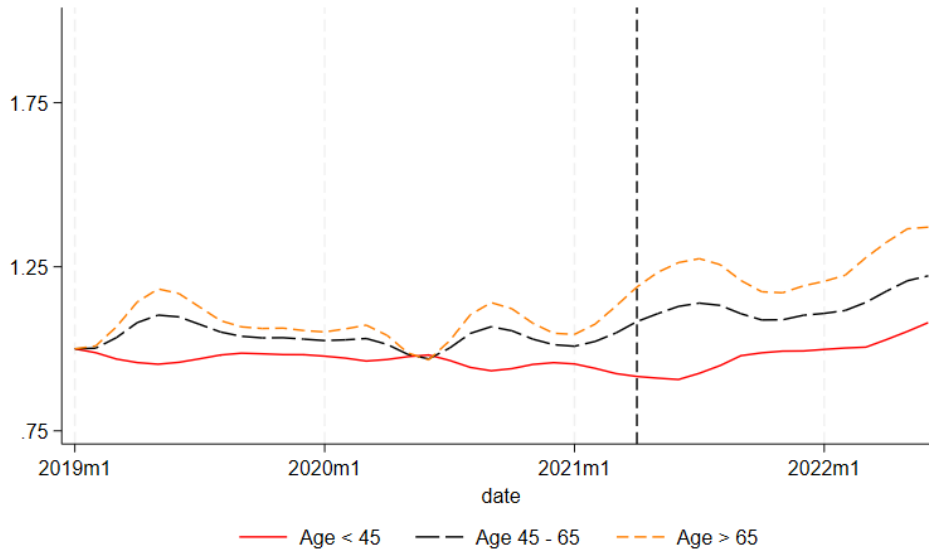
¹² The estimation results are robust to restricting the sample to respondents aged 25–74 and to alternative choices for the timing of the inflation cue and the frequency of parameter updating.

¹³ Here we report the learning-from-experience proxy π_{it}^e directly. Allowing measured expectations to load on π_{it}^e with a freely estimated coefficient barely affects the result.

Figure 7. De-Anchoring of Inflation Expectations and the Importance of Similarity



Panel A: Selective Memory Model



Panel B: Malmendier and Nagel Model

Notes: The top panel (Memory Model) shows predicted inflation expectations by cohort when including as regressors experienced average inflation, temporal context and similarity measures as well as demographic controls, as in Column 6 of Table 1 (thus excluding the SPF term). The bottom panel (Malmendier and Nagel Model) shows predicted inflation expectations from the learning-from-experience model described by Equations (1) and (2) in Malmendier and Nagel (2016). All individual-level predictions are averaged within each cohort group using survey weights. Data come from the Michigan Consumer Survey. In order to maintain comparability, the model is calibrated on the MCS timeframe (January 1978 – March 2024). The actual forecast and the predictions are expressed as a fraction of their value in January 2019. The dashed vertical line marks April 2021.

Our state-dependent selective-retrieval model can reproduce the de-anchoring of Figures 1 and 2 while experience-based learning cannot. Panel A of Figure 7 shows our model's predictions, and Panel

B those from experience-based learning. In Panel A, state-dependent cues play a quantitatively important role in accounting for both overall de-anchoring and for the stronger initial de-anchoring by the elderly. Panel B shows that experience-based learning fails to capture these dynamics. The elderly are somewhat more sensitive than the young, because they experience and hence estimate a higher inflation persistence. But such excess sensitivity is not in the data before 2021 and, most important, it is too small to account for significant de-anchoring during 2021. Bayesian learning is just too linear and muted, even when restricted to personal experiences. Due to many experiences with stable inflation, the beliefs of older cohorts are too rigid, and barely move from the starting point. The learning from experience model also fails to capture de-anchoring by the young, whose beliefs are also too rigid (their cohort only experienced stable inflation). Experience based learning can capture level differences in expectations across cohorts, which are not shown in the figure. However, it does not give the state and cohort dependent sensitivity that we see in the data and that memory can account for.

We next consider the ability of the two models to account for the post-2021 behavior of expectations out of sample. We perform a nowcasting exercise in which we use the model's coefficient estimates before July 2022 to predict inflation expectations until February 2024. To properly calibrate the beliefs parameters to the conditions around 2021, we estimate the two models in the June 2013 – June 2022, which also allows us to compare results to the SCE. Our target are the beliefs of the average respondent because we do not have clear predictions on cohort differences in re-anchoring (both the young and the elderly have experienced many recent high-inflation periods), and neither does the experience-based learning model.¹⁴ We then compare model predictions to the average MSC expectation, whose values in the nowcasting subperiods have not influenced model estimations.

¹⁴ In fact, there are no clear cohort differences in re-anchoring in the data.

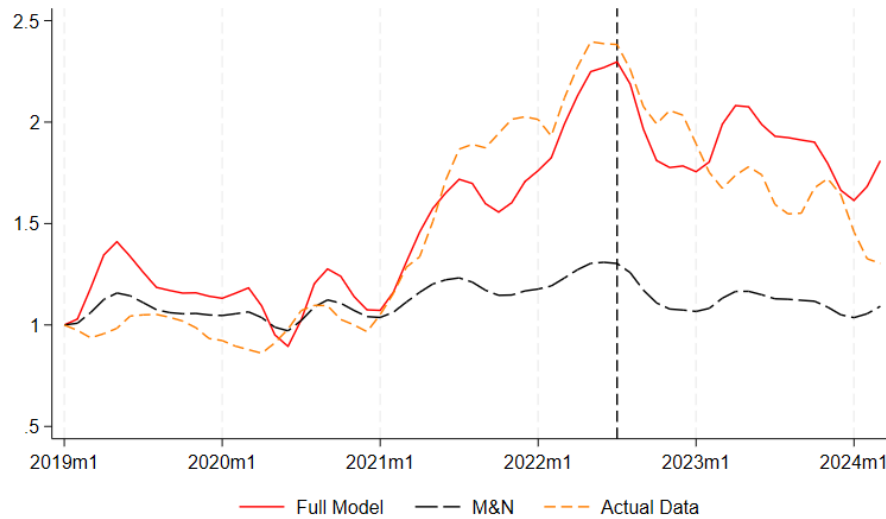


Figure 8. Nowcasting: Re-Anchoring of Inflation Expectations

Notes: The figure shows the predictions from the “Full Model” which includes as regressors experienced average inflation, temporal context and similarity measures as well as demographic controls, as in Column 6 of Table 1, which excludes the forward-looking SPF term. The “M&N” model estimates the learning-from-experience model described by Equations (1) and (2) in Malmendier and Nagel (2016). Nowcasting takes as inputs the period inflation rate and the period’s age distribution of all respondents, feeding them into the respective models and regressors to generate nowcasts. Nowcasting holds the estimated coefficients constant. All individual-level predictions and nowcasts are averaged using survey weights. Both models are calibrated on the SCE timeframe (June 2013 – June 2022). The estimated learning speed in the Malmendier and Nagel model is 0.86. All predictions are expressed as a fraction of their value in January 2019. The dashed vertical line marks June 2022, the end of our estimation period and the beginning of the nowcasting period.

The results in Figure 8 confirm the importance of selective memory. First, just as Figure 7 shows, the predicted aggregate inflation expectations in the memory model (red line) are a good match to the actual evolution of inflation expectations in the data (yellow line). We already saw that, due to similarity, the model generates a rise of aggregate inflation expectations in the face of surging inflation. The same force allows the model to produce re-anchoring of expectations when inflation subsequently declines. Numerical similarity (not just recency) is key to obtaining this pattern: if one uses only the temporal context terms as predictors, the rise and fall of predicted inflation expectations is much more attenuated than what we see in Figure 8. Notably, similarity does not hinder model performance before 2021, when observed inflation expectations are stable and so are the expectations predicted by a memory model. The reason is that with stable inflation similarity generates stability in inflation expectations.

The experience-based learning model cannot produce realistic anchoring and re-anchoring. This is so because in this model past experiences are not selectively recalled and forgotten based on current cues, so predicted beliefs are too rigid compared to reality. Standard experience effects are empirically important drivers of cross-sectional differences in beliefs, but do not alone offer a satisfactory model of belief formation in the time series. To reproduce realistic expectations in the time series, it is important to explicitly characterize the mechanism whereby experiences affect beliefs: selective memory.

We finally perform a demanding external-validation test by asking whether a common set of memory parameters estimated from US data can reproduce the cross-country patterns documented in Figure 2: state-dependent de-anchoring and differential cohort dynamics in Australia, Canada, the Euro area, Japan, and the UK. We use memory coefficients from MSC specifications closely matching Column 6 of Table 1, adjusted only to allow for international comparability (see Appendix C). We combine the coefficients with country-specific data for each of the right-hand-side memory variables to predict inflation expectations for every respondent and then plot the cohort-specific predictions alongside the actual data from Figure 2.¹⁵ Despite the limitations inherent to the international microdata, the mechanism predicts the international patterns remarkably well.

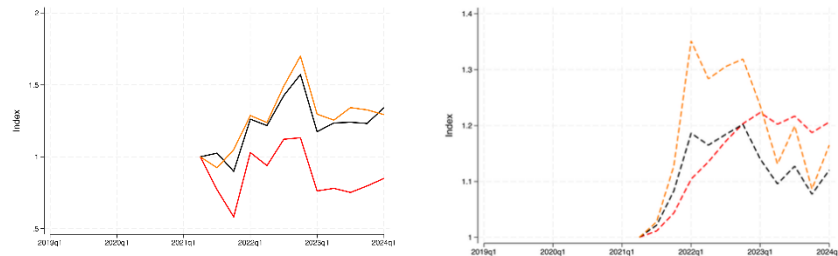
Figure 9: External Validation of Inflation Expectation Predictions

Actual Inflation Expectations

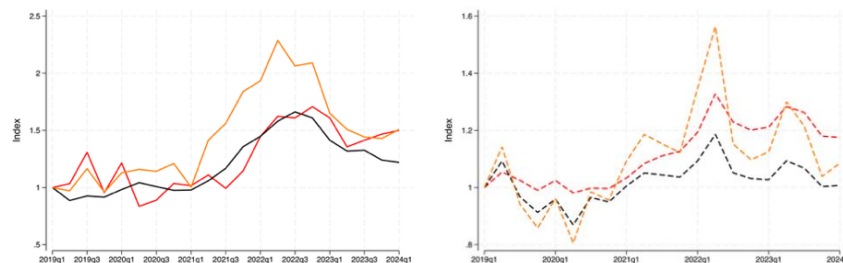
Predicted Inflation Expectations

¹⁵ We construct databases and cues as follows. For Australia, we use the Royal Bank of Australia's (RBA) G1 Consumer Price Inflation workbook, drawn from Australian Bureau of Statistics (ABS) CPI publications and linked to earlier retail price index data before the modern ABS CPI. For Canada, we use Statistics Canada Table 18-10-0004-01. For the UK, we use the Bank of England's monthly spliced consumer price index from the Millennium of Macroeconomic Data project, accessed through FRED series SCPIUKM. For Japan, we splice annual CPI from the Jordà-Schularick-Taylor Macroeconomy Database to official monthly CPI from Japan's e-Stat government statistics portal. For the EU/ECB CES countries, we clean BIS monthly CPI data and extend them backward using annual historical CPI data from the "European Consumer Price Indices Since 1870" by Ljungberg (2025), interpolated and spliced by country; the extended CPI file is then used to construct inflation variables for the ECB CES point-expectation analysis.

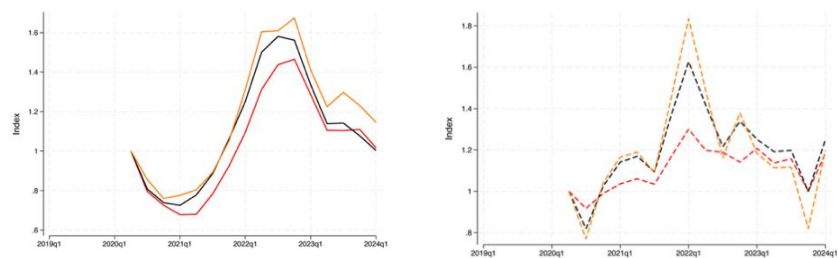
Australia



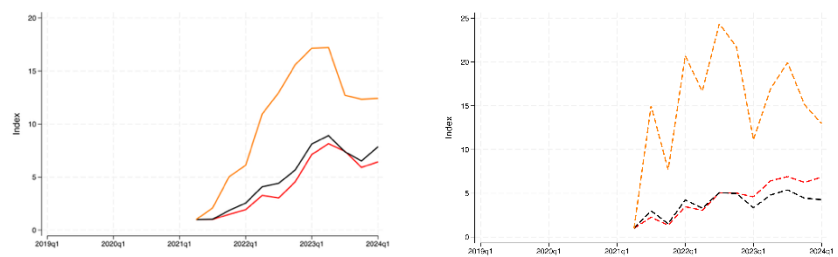
Canada



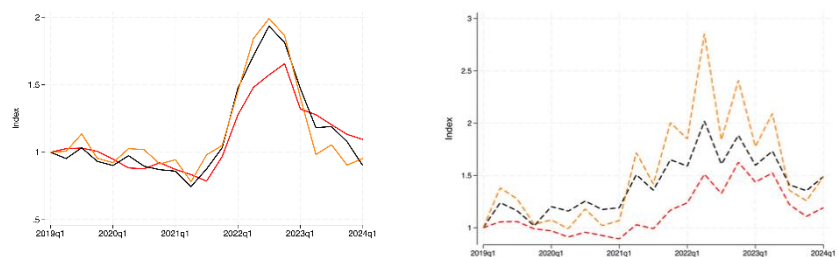
EU



Japan



UK



Note: Actual and predicted inflation expectations by age group and country. Predictions apply the coefficients from Table 1, specification 6, estimated on US MSC data, to country-specific memory variables. Actual expectations come from the UK IAS, Canadian CSCE, ECB CES, and Australian and Japanese ICIE surveys. Age groups are harmonized across surveys using population weights. Predictions are initialized at observed values, and both series are normalized to one. Orange, black, and red denote ages 65+, 45–64, and under 45, respectively.

As the right column in Figure 9 shows, applying the US estimates to the memory databases of respondents outside the US predicts the two organizing facts emphasized in the introduction and Section

2.1 (replicated in the left column of Figure 9). First, predicted beliefs are strongly state-dependent: they rise sharply across countries as the post-pandemic inflation surge makes high-inflation experiences more similar to the current cue and therefore more retrievable; as inflation declines, they partly re-anchor. The model produces this realistic pattern across all countries. Moreover, the timing of the predicted increase and subsequent moderation follows the observed cycles—with an earlier increase in Canada, a later increase in the UK and Euro area, and a later increase still in Australia and Japan.

Second, memory produces realistic cohort-dependent responses, with a striking divergence in the speed of updating. Across the panels, the oldest cohort generally begins to increase expectations sharply first and reaches the highest peak, while younger respondents initially move less and react strongly only after a few periods of high inflation make the episode a recent, repeated experience. Because each cohort is normalized to one at its own initial value, this ordering is generated by fixed coefficients from the US data interacting with cohort-specific memory databases, and not by any baseline initialization.

Notably, among the countries in the prediction exercise, Japan constitutes a principal qualification in terms of scale. The reason is that initial inflation expectations in the data are unusually low, reflecting the country's long history of low inflation and deflation, which are masked by the beginning of period normalization. Yet most importantly, Japan also sharpens the cohort-sensitivity test: initially, its oldest respondents are the only group with meaningful lived exposure to the high inflation of the 1970s and, for some, the hyperinflationary post–World War II period. And it is precisely these cohorts that respond first and by far the most when inflation rises, while younger cohorts respond only as the new episode enters their recent experience, consistent with memory. Thus, despite differences in national inflation dynamics and survey measures, the state-dependent expectations response and the differential de-anchoring of older and younger households remains robust across countries, with predictions based on each country's inflation-memory database and a common set of coefficients estimated solely from US data.

6. Conclusion

Memory models, with their emphasis on similarity, frequency, and interference, offer a promising way to study household inflation expectations. The role of past experiences for belief formation has long been documented in social science (e.g. Weinstein 1989). In economics, Malmendier and Nagel (2011, 2016) showed the importance of inflation or stock market experiences for belief formation. The key question becomes: what is the mechanism through which experiences matter?

Our analysis shows that regularities in selective recall offer a concrete and promising approach to this question. By featuring a rich interaction between the experience database and time varying cues, these regularities allow us to capture realistic state and cohort dependence in belief formation, as well as a time varying inconsistency across different belief elicitation. These features cannot be explained by full Bayesian learning or by learning from experience models. Recent evidence such as Cenzon (2026) or Taubinsky et al (2026) shows that memory can also help explain why wholly normatively irrelevant personal experience shape beliefs about the aggregate economy. Mnemonic retrieval of future states based on time varying cues can also influence learning, causing beliefs to follow a distorted version of the true data generating process, “as if” the agent makes forecasts by using a subjective statistical model. Bonaglia and Gennaioli (2026) and Bonaglia et al. (2026) show that this mechanism endogenizes observed belief rigidity and overreaction based on measurable features of the DGP and the forecast horizon.

More broadly, explicitly incorporating cognitive forces in models of belief formation can yield a realistic theory of expectations in macroeconomics and finance. This paper and the work described above focus on memory. Selective attention may also play an important role. Link et al. (2026) show that German households and firm managers who experienced high inflation tend to attend to inflation more and raise their attention to inflation more during the 2021-2 surge, thereby revising up their expected inflation

more strongly than other people. These effects can be captured in a cognitive model combining memory with endogenous attention to features, along the lines of Bordalo et al. (2026a).

Our approach may also be relevant for the theory of monetary policy. Interest rate policies or announcements that are normatively optimal under rationality may be suboptimal with associative memory, for instance because they may cue episodes of market instability, destabilizing investor beliefs. Formally evaluating these policy implications would require an equilibrium extension with an explicit central bank and endogenous inflation and output, which we leave for future research. More immediately, the approach to studying household beliefs laid out in this paper may be a useful, practical tool for policymakers at central banks. Our now-casting exercise can be used to obtain real-time inflation expectations exactly when no real-time expectations measurements are available, but desirable to have. All that is needed is knowledge of the current inflation rate (and its history), the representative age distribution of consumers, and a theory embedding regularities of selective recall. To develop the theory further, it may be useful to explicitly measure household recollections, so as to learn which cues are most relevant in the context of interest. A simple calculation can then exploit, for example, releases at different dates of inflation measures (CPI versus PCE), which are asynchronous to the release dates of inflation expectations, or even daily online inflation measures such as those by the Billion Prices Project, to compute real-time inflation expectations.

References

- Afrouzi, H. (2024). Strategic inattention, inflation dynamics, and the non-neutrality of money. *Journal of Political Economy*, 132(10), 3378–3420.
- Afrouzi, H., Coibion, O., Gorodnichenko, Y., & Kumar, S. (2015). Inflation targeting does not anchor inflation expectations: Evidence from firms in New Zealand. *Brookings Papers on Economic Activity* (Fall), 151–225.
- Anderson, J. (1974). Retrieval of propositional information from long-term memory. *Cognitive Psychology*, 6(4), 451–474.
- Andre, P., Pizzinelli, C., Roth, C., & Wohlfart, J. (2022). Subjective models of the macroeconomy: Evidence from experts and representative samples. *The Review of Economic Studies*, 89(6), 2958–2991.
- Armantier, O., Bruine de Bruin, W., Potter, S., Topa, G., van der Klaauw, W., & Zafar, B. (2013). Measuring inflation expectations. *Annual Review of Economics*, 5, 273–301.
- Baddeley, A. (1997). *Human memory: Theory and practice* (Rev. ed.). Psychology Press.
- Becker, C., Duersch, P., & Eife, T. (2023). Measuring inflation expectations: How the response scale shapes density forecasts (AWI Discussion Paper Series No. 727). Heidelberg University, Alfred Weber Institute for Economics. <https://doi.org/10.11588/heidok.00033232>
- Benartzi, S., & Thaler, R. (2001). Naive diversification strategies in defined contribution saving plans. *American Economic Review*, 91(1), 79–98.
- Bianchi, F., Ilut, C., & Saijo, H. (2024). Diagnostic business cycles. *The Review of Economic Studies*, 91(1), 129–162.
- Bianchi, F., Ilut, C., & Saijo, H. (2026). Smooth diagnostic expectations. *The Review of Economic Studies*. Advance online publication. <https://doi.org/10.1093/restud/rdag077>
- Binder, C. (2017). Measuring uncertainty based on rounding: New method and application to inflation expectations. *Journal of Monetary Economics*, 90, 1–12.
- Binder, C. (2018). Inflation expectations and the price at the pump. *Journal of Macroeconomics*, 58, 1–18.
- Boctor, V., Coibion, O., Gorodnichenko, Y., & Weber, M. (2024). On eliciting subjective probability distributions of expectations (NBER Working Paper No. 32406).
- Bonaglia, E., D'Arienzo, D., Fallico, N., Gennaioli, N., & Iovino, L. (2026). The volatility of inflation expectations and interest rates. Working paper.
- Bonaglia, E., & Gennaioli, N. (2026). Mnemonic expectations. Working paper.
- Bordalo, P., Burro, G., Coffman, K., Gennaioli, N., & Shleifer, A. (2025). Imagining the future: Memory, simulation, and beliefs. *The Review of Economic Studies*, 92(3), 1532–1563.

- Bordalo, P., Conlon, J., Gennaioli, N., Kwon, S., & Shleifer, A. (2023). Memory and probability. *The Quarterly Journal of Economics*, 138(1), 265–311.
- Bordalo, P., Gennaioli, N., Lanzani, G., & Shleifer, A. (2026). A cognitive theory of reasoning and choice. *The Quarterly Journal of Economics*, 141(3), 1921–1963.
- Bordalo, P., Gennaioli, N., Lopez-de-Silanes, F., Schröder, S. G., Shleifer, A., & van Rooij, M. (2026a). The psychology of macroeconomic expectations (NBER Working Paper No. 35214).
- Bordalo, P., Gennaioli, N., Ma, Y., & Shleifer, A. (2020) Overreaction in Macroeconomic Expectations. *American Economic Review*, 110(9), 2748-2792.
- Bordalo, P., Gennaioli, N., & Shleifer, A. (2018). Diagnostic expectations and credit cycles. *The Journal of Finance*, 73(1), 199–227.
- Bordalo, P., Gennaioli, N., & Shleifer, A. (2022). Overreaction and diagnostic expectations in macroeconomics. *Journal of Economic Perspectives*, 36(3), 223–244.
- Bracha, A., & Tang, J. (2025). Inflation levels and (in)attention. *The Review of Economic Studies*, 92(3), 1564–1594.
- Braggion, F., von Meyerinck, F., Schaub, N., & Weber, M. (2024). The long-term effects of inflation on inflation expectations (NBER Working Paper No. 32160).
- Bruine de Bruin, W., Manski, C. F., Topa, G., & van der Klaauw, W. (2011). Measuring consumer uncertainty about future inflation. *Journal of Applied Econometrics*, 26(3), 454–478.
- Bruine de Bruin, W., van der Klaauw, W., Downs, J. S., Fischhoff, B., Topa, G., & Armantier, O. (2010). Expectations of inflation: The role of demographic variables, expectation formation, and financial literacy. *Journal of Consumer Affairs*, 44(2), 381–402.
- Carroll, C. (2003). Macroeconomic expectations of households and professional forecasters. *The Quarterly Journal of Economics*, 118(1), 269–298.
- Carroll, C., Crawley, E., Slacalek, J., Tokunaka, K., & White, M. (2020). Sticky expectations and consumption dynamics. *American Economic Journal: Macroeconomics*, 12(3), 40–76.
- Cavallo, A., Cruces, G., & Perez-Truglia, R. (2017). Inflation expectations, learning, and supermarket prices: Evidence from survey experiments. *American Economic Journal: Macroeconomics*, 9(3), 1–35.
- Cenzon, J. (2026). Credit market experiences and macroeconomic expectations: Evidence and theory. Working paper.
- Coibion, O., & Gorodnichenko, Y. (2015). Is the Phillips curve alive and well after all? Inflation expectations and the missing disinflation. *American Economic Journal: Macroeconomics*, 7(1), 197–232.
- Coibion, O., Gorodnichenko, Y., & Kumar, S. (2018). How do firms form their expectations? New survey evidence. *American Economic Review*, 108(9), 2671–2713.
- Coibion, O., Gorodnichenko, Y., & Ropele, T. (2020). Inflation expectations and firm decisions: New causal evidence. *The Quarterly Journal of Economics*, 135(1), 165–219.

- Coibion, O., Gorodnichenko, Y., & Weber, M. (2022). Monetary policy communications and their effects on household inflation expectations. *Journal of Political Economy*, 130(6), 1537–1584.
- Conlon, J. (2026). Memory rehearsal and belief biases. Working paper.
- Danz, D., Vesterlund, L., & Wilson, A. (2022). Belief elicitation and behavioral incentive compatibility. *American Economic Review*, 112(9), 2851–2883.
- D’Acunto, F., Malmendier, U., Ospina, J., & Weber, M. (2021). Exposure to grocery prices and inflation expectations. *Journal of Political Economy*, 129(5), 1615–1639.
- D’Acunto, F., Malmendier, U., & Weber, M. (2021). Gender roles produce divergent economic expectations. *Proceedings of the National Academy of Sciences*, 118(21), e2008534118.
- D’Acunto, F., Malmendier, U., & Weber, M. (2023). What do the data tell us about inflation expectations? In R. Bachmann, G. Topa, & W. van der Klaauw (Eds.), *Handbook of economic expectations* (pp. 133–161). Academic Press.
- D’Acunto, F., & Weber, M. (2024). Memory & beliefs: Evidence from the field. Mimeo.
- D’Acunto, F., & Weber, M. (2024). Why survey-based subjective expectations are meaningful and important. *Annual Review of Economics*, 16, 329–357.
- Evans, G., & Honkapohja, S. (2001). *Learning and expectations in macroeconomics*. Princeton University Press.
- Fischhoff, B., Slovic, P., & Lichtenstein, S. (1978). Fault trees: Sensitivity of estimated failure probabilities to problem representation. *Journal of Experimental Psychology: Human Perception and Performance*, 4(2), 330–344.
- García-Lembergman, E., Hajdini, I., Leer, J., Pedemonte, M., & Schoenle, R. (2024). The expectations of others (IDB Working Paper No. IDB-WP-1642). Inter-American Development Bank.
- Gelman, M., Gorodnichenko, Y., Kariv, S., Koustas, D., Shapiro, M., Silverman, D., & Tadelis, S. (2023). The response of consumer spending to changes in gasoline prices. *American Economic Journal: Macroeconomics*, 15(2), 129–160.
- Goldfayn-Frank, O., P. Kieren, & S. T. Trautmann (2026). “A Choice-Based Approach to the Measurement of Inflation Expectations.” *Journal of Monetary Economics*, 157, 103882.
- Goldfayn-Frank, O., & Wohlfart, C. (2020). Expectation formation in a new environment: Evidence from the German reunification. *Journal of Monetary Economics*, 115, 301–320.
- Graeber, T., Roth, C., & Zimmermann, F. (2024). Stories, statistics, and memory. *The Quarterly Journal of Economics*, 139(4), 2181–2225.
- Haaland, I., Roth, C., Stantcheva, S., & Wohlfart, J. (2025). Understanding economic behavior using open-ended survey data. *Journal of Economic Literature*, 63(4), 1244–1280.
- Hajdini, I., Knotek, E. S., II, Leer, J., Pedemonte, M., Rich, R., & Schoenle, R. (2024). Indirect consumer inflation expectations: Theory and evidence. *Journal of Monetary Economics*, 145, 103568.

- Hogarth, R., & Einhorn, H. (1992). Order effects in belief updating: The belief-adjustment model. *Cognitive Psychology*, 24(1), 1–55.
- Jaravel, X. (2019). The unequal gains from product innovations: Evidence from the U.S. retail sector. *The Quarterly Journal of Economics*, 134(2), 715–783.
- Jiang, Z., Liu, H., Peng, C., & Yan, H. (2025). Investor memory and biased beliefs: Evidence from the field. *The Quarterly Journal of Economics*, 140(4), 2749–2804.
- Kahana, M. (2012). *Foundations of human memory*. Oxford University Press
- Kuchler, T., & Zafar, B. (2019). Personal experiences and expectations about aggregate outcomes. *The Journal of Finance*, 74(5), 2491–2542.
- Kumar, S., Gorodnichenko, Y., & Coibion, O. (2023). The effect of macroeconomic uncertainty on firm decisions. *Econometrica*, 91(4), 1297–1332.
- L’Huillier, J. P., Singh, S. R., & Yoo, D. (2024). Incorporating diagnostic expectations into the New Keynesian framework. *The Review of Economic Studies*, 91(5), 3013–3046.
- Link, S., Peichl, A., Pfäuti, O., Roth, C., & Wohlfart, J. (2026). Attention to the macroeconomy (CESifo Working Paper No. 10858).
- Ljungberg, J. (2025). European consumer price indices since 1870. *Cliometrica*, 19, 29–80.
- Malmendier, U., & Nagel, S. (2011). Depression babies: Do macroeconomic experiences affect risk taking? *The Quarterly Journal of Economics*, 126(1), 373–416.
- Malmendier, U., & Nagel, S. (2016). Learning from inflation experiences. *The Quarterly Journal of Economics*, 131(1), 53–87.
- Malmendier, U., Nagel, S., & Yan, Z. (2021). The making of hawks and doves. *Journal of Monetary Economics*, 117, 19–42.
- Manski, C. (2004). Measuring expectations. *Econometrica*, 72(5), 1329–1376.
- Manski, C. (2018). Survey measurement of probabilistic macroeconomic expectations: Progress and promise. *NBER Macroeconomics Annual*, 32, 411–471.
- Marcet, A., & Sargent, T. (1989). Convergence of least squares learning mechanisms in self-referential linear stochastic models. *Journal of Economic Theory*, 48(2), 337–368.
- Maxted, P. (2024). A macro-finance model with sentiment. *The Review of Economic Studies*, 91(1), 438–475.
- Nagel, S., & Xu, Z. (2022). Asset pricing with fading memory. *The Review of Financial Studies*, 35(5), 2190–2245.
- Nosofsky, R. (1992). Similarity scaling and cognitive process models. *Annual Review of Psychology*, 43, 25–53.

- Salle, I., Gorodnichenko, Y., & Coibion, O. (2026). Lifetime memories of inflation: Evidence from surveys and the lab. *Journal of Political Economy: Macroeconomics*, forthcoming.
- Sargent, T. (1999). *The conquest of American inflation*. Princeton University Press.
- Shiller, R. (2005). *Irrational exuberance* (2nd ed.). Princeton University Press.
- Sims, C. (2003). Implications of rational inattention. *Journal of Monetary Economics*, 50(3), 665–690.
- Taubinsky, D., Butera, L., Saccharola, M., & Lian, C. (2026). Beliefs about the economy are excessively sensitive to household-level shocks: Evidence from linked survey and administrative data. *The Quarterly Journal of Economics*.
- Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, 185(4157), 1124–1131.
- Weber, M., D’Acunto, F., Gorodnichenko, Y., & Coibion, O. (2022). The subjective inflation expectations of households and firms: Measurement, determinants, and implications. *Journal of Economic Perspectives*, 36(3), 157–184.
- Weinstein, N. (1989). Effects of personal experience on self-protective behavior. *Psychological Bulletin*, 105(1), 31–50.
- Woodford, M. (2009). Convergence in macroeconomics: Elements of the new synthesis. *American Economic Journal: Macroeconomics*, 1(1), 267–279.
- Züllig, G. (2023). Consumer memory, inflation expectations and the interpretation of shocks. Mimeo.

APPENDIX A: Proofs.

Proof of Proposition 1. Using all model ingredients, we can write Equation (4) as:

$$\mathbb{E}(\pi_{t+1}|\pi_{t,\mathbb{R}}) = \frac{\sum_{s=1,\dots,a} e^{\beta_1 \left(\frac{s}{a}\right)^2 - \beta_2 \left(\frac{s}{a}\right) - \sigma \cdot q \cdot (\pi_{t-s} - \pi_t)^2 - \sigma \cdot (1-q) \cdot (\pi_{t-s} - \bar{\pi}_{t-1})^2} \cdot \pi_{t-s}}{\sum_{s=1,\dots,a} e^{\beta_1 \left(\frac{s}{a}\right)^2 - \beta_2 \left(\frac{s}{a}\right) - \sigma \cdot q \cdot (\pi_{t-s} - \pi_t)^2 - \sigma \cdot (1-q) \cdot (\pi_{t-s} - \bar{\pi}_{t-1})^2}},$$

where to ease notation we set $a_t = a$. This expectation features, at $\beta = \sigma = 0$, the value:

$$\mathbb{E}(\pi_{t+1}|\pi_{t,\mathbb{R}}) = \frac{\sum_{s=1,\dots,a} \pi_{t-s}}{a} = \bar{\pi}_t,$$

and first derivatives:

$$\begin{aligned} \frac{\partial \mathbb{E}(\pi_{t+1}|\pi_{t,\mathbb{R}})}{\partial \beta_2} &= \frac{-a \left[\sum_{s=1,\dots,a} \frac{s}{a} \cdot \pi_{t-s} \right]}{a^2} + \frac{\left[\sum_{s=1,\dots,a} \pi_{t-s} \right] \left[\sum_{s=1,\dots,a} \frac{s}{a} \right]}{a^2} \\ &= \frac{- \left[\sum_{s=1,\dots,a} \left(\frac{s}{a} \right) \cdot \pi_{t-s} \right]}{a} + \frac{\left[\sum_{s=1,\dots,a} \pi_{t-s} \right] \left[\sum_{s=1,\dots,a} \frac{s}{a} \right]}{a^2} \\ &= - \overline{\left(\frac{s}{a} \right) \cdot \pi_{t-s}} + \overline{\pi_{t-s}} \cdot \overline{\left(\frac{s}{a} \right)} = -cov \left(\frac{s}{a}, \pi_{t-s} \right) \\ \frac{\partial \mathbb{E}(\pi_{t+1}|\pi_{t,\mathbb{R}})}{\partial \beta_1} &= \frac{a \left[\sum_{s=1,\dots,a} \left(\frac{s}{a} \right)^2 \cdot \pi_{t-s} \right]}{a^2} - \frac{\left[\sum_{s=1,\dots,a} \pi_{t-s} \right] \left[\sum_{s=1,\dots,a} \left(\frac{s}{a} \right)^2 \right]}{a^2} \\ &= \frac{\left[\sum_{s=1,\dots,a} \left(\frac{s}{a} \right)^2 \cdot \pi_{t-s} \right]}{a} - \frac{\left[\sum_{s=1,\dots,a} \pi_{t-s} \right] \left[\sum_{s=1,\dots,a} \left(\frac{s}{a} \right)^2 \right]}{a^2} \\ &= \overline{\left(\frac{s}{a} \right)^2 \cdot \pi_{t-s}} - \overline{\pi_{t-s}} \cdot \overline{\left(\frac{s}{a} \right)^2} = cov \left(\left(\frac{s}{a} \right)^2, \pi_{t-s} \right) \end{aligned}$$

where upper bars denote arithmetic averages, and

$$\frac{\partial \mathbb{E}(\pi_{t+1}|\pi_{t,\mathbb{R}})}{\partial \sigma} = - \frac{\left[\sum_{s=1,\dots,a} q \cdot (\pi_{t-s} - \pi_t)^2 \cdot \pi_{t-s} + (1-q) \cdot (\pi_{t-s} - \bar{\pi}_{t-1})^2 \cdot \pi_{t-s} \right] a}{a^2}$$

$$\begin{aligned}
& + \frac{[\sum_{s=1,\dots,a} \pi_{t-s}][\sum_{s=1,\dots,a} q \cdot (\pi_{t-s} - \pi_t)^2 + (1-q) \cdot (\pi_{t-s} - \bar{\pi}_{t-1})^2]}{a^2} \\
& = -q \cdot \text{cov}[\pi_{t-s}, (\pi_{t-s} - \pi_t)^2] - (1-q) \cdot \text{cov}[\pi_{t-s}, (\pi_{t-s} - \bar{\pi}_{t-1})^2],
\end{aligned}$$

which yields the desired result.

Proof of Proposition 2 Using all model ingredients, the probability of bin j obeys:

$$\Pr(E_j | \pi_{t,E_j}) \propto \sum_{\pi_{t-s}=\pi_j} e^{\beta_1 \left(\frac{s}{a}\right)^2 - \beta_2 \left(\frac{s}{a}\right) - \sigma \cdot q \cdot (\pi_j - \pi_t)^2},$$

so that, given the common normalization the odds of bin j compared to a base bin b is:

$$\frac{\Pr(E_j | \pi_{t,E_j})}{\Pr(E_b | \pi_{t,E_b})} = \frac{\sum_{\pi_{t-s}=\pi_j} e^{\beta_1 \left(\frac{s}{a}\right)^2 - \beta_2 \left(\frac{s}{a}\right) - \sigma \cdot q \cdot (\pi_j - \pi_t)^2}}{\sum_{\pi_{t-s}=\pi_b} e^{\beta_1 \left(\frac{s}{a}\right)^2 - \beta_2 \left(\frac{s}{a}\right) - \sigma \cdot q \cdot (\pi_b - \pi_t)^2}},$$

which features, at $\beta = \sigma = 0$, the value:

$$\frac{\Pr(E_j | \pi_{t,E_j})}{\Pr(E_b | \pi_{t,E_b})} = \frac{\sum_{\pi_{t-s}=\pi_j} 1}{\sum_{\pi_{t-s}=\pi_b} 1} = \frac{n_j}{n_b},$$

where n_j is the experienced frequency of a generic π_j , and first derivatives:

$$\frac{\partial}{\partial \beta} \frac{\Pr(E_j | \pi_{t,E_j})}{\Pr(E_b | \pi_{t,E_b})} = \frac{n_j}{n_b} \cdot (\bar{s}_j^2 - \bar{s}_b^2)/a^2 - \frac{n_j}{n_b} \cdot (\bar{s}_j - \bar{s}_b)/a,$$

and

$$\frac{\partial}{\partial \sigma} \frac{\Pr(E_j | \pi_{t,E_j})}{\Pr(E_b | \pi_{t,E_b})} = -q \cdot \frac{n_j}{n_b} \cdot [(\pi_j - \pi_t)^2 - (\pi_b - \pi_t)^2],$$

which yields the desired result.

Proof of Proposition 3 Using all model ingredients, we can write:

$$\begin{aligned}
\mathbb{E}(\pi_{t+1}|\pi_{t,\mathbb{R}}) &= \sum_j \left[\frac{\sum_{\pi_{t-s}=\pi_j} e^{\beta_1\left(\frac{s}{a}\right)^2 - \beta_2\left(\frac{s}{a}\right) - \sigma \cdot q \cdot (\pi_j - \pi_t)^2 - \sigma \cdot q \cdot (\pi_j - \bar{\pi}_{t-1})^2}}{\sum_{\pi_{t-s}=\pi_j} e^{\beta_1\left(\frac{s}{a}\right)^2 - \beta_2\left(\frac{s}{a}\right) - \sigma \cdot q \cdot (\pi_j - \pi_t)^2}} \right. \\
&\quad \cdot \left. \frac{\sum_u \sum_{\pi_{t-s}=\pi_u} e^{\beta_1\left(\frac{s}{a}\right)^2 - \beta_2\left(\frac{s}{a}\right) - \sigma \cdot q \cdot (\pi_u - \pi_t)^2}}{\sum_u \sum_{\pi_{t-s}=\pi_u} e^{\beta_1\left(\frac{s}{a}\right)^2 - \beta_2\left(\frac{s}{a}\right) - \sigma \cdot q \cdot (\pi_u - \pi_t)^2 - \sigma \cdot q \cdot (\pi_u - \bar{\pi}_{t-1})^2}} \right] \cdot \Pr(E_j|\pi_{t,E_j}) \cdot \pi_j \\
&= \sum_j \left[\frac{e^{-\sigma \cdot q \cdot (\pi_j - \bar{\pi}_{t-1})^2} \sum_u \sum_{\pi_{t-s}=\pi_u} e^{\beta_1\left(\frac{s}{a}\right)^2 - \beta_2\left(\frac{s}{a}\right) - \sigma \cdot q \cdot (\pi_u - \pi_t)^2}}{\sum_u e^{-\sigma \cdot q \cdot (\pi_u - \bar{\pi}_{t-1})^2} \sum_{\pi_{t-s}=\pi_u} e^{\beta_1\left(\frac{s}{a}\right)^2 - \beta_2\left(\frac{s}{a}\right) - \sigma \cdot q \cdot (\pi_u - \pi_t)^2}} \right] \cdot \Pr(E_j|\pi_{t,E_j}) \cdot \pi_j.
\end{aligned}$$

At $\sigma = 0$, this expressions takes the value:

$$\mathbb{E}(\pi_{t+1}|\pi_{t,\mathbb{R}}) = \sum_j \Pr(E_j|\pi_{t,E_j}) \cdot \pi_j = \mathbb{E}(\pi_{t+1}|\text{DF}),$$

and first derivatives:

$$\frac{\partial \mathbb{E}(\pi_{t+1}|\pi_{t,\mathbb{R}})}{\partial \beta} = 0$$

and

$$\frac{\partial \mathbb{E}(\pi_{t+1}|\pi_{t,\mathbb{R}})}{\partial \sigma} = \sum_j q \cdot \left[\frac{\sum_u (\pi_u - \bar{\pi}_{t-1})^2 n_u}{a} - (\pi_j - \bar{\pi}_{t-1})^2 \right] \cdot \Pr(E_j|\pi_{t,E_j}) \cdot \pi_j,$$

which yields the desired result:

$$\begin{aligned}
\mathbb{E}(\pi_{t+1}|\pi_{t,\mathbb{R}}) &\approx \mathbb{E}(\pi_{t+1}|\text{DF}) + \sigma \cdot q \cdot \sum_j \left[\overline{(\pi_u - \bar{\pi}_{t-1})^2} - (\pi_j - \bar{\pi}_{t-1})^2 \right] \cdot \Pr(E_j|\pi_{t,E_j}) \cdot \pi_j \\
&= \mathbb{E}(\pi_{t+1}|\text{DF}) + \sigma \cdot q \cdot \mathbb{E}[\pi_{t+1} \cdot (\bar{d}_{j,t} - d_{t+1,t})|\text{DF}].
\end{aligned}$$

Appendix B: Tables and Figures

Table B1. Robustness: Huber Robust Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
One-year ahead Infl. Exp.						
Panel A. MSC						
Average Experienced Inflation	0.205*** (0.015)	0.276*** (0.033)	0.444*** (0.036)	0.419*** (0.034)	0.154*** (0.028)	0.376*** (0.021)
$\text{Cov}(s^2, \pi_{t-s}) / a^2$		0.128 (0.273)	1.460*** (0.307)	1.141*** (0.289)	-0.405 (0.286)	2.058*** (0.321)
$\text{Cov}(s, \pi_{t-s}) / a$		-0.481 (0.360)	-2.194*** (0.400)	-1.715*** (0.382)	0.713** (0.353)	-2.458*** (0.374)
$\text{Cov}((\pi_{t-s} - \bar{\pi}_{t-1})^2, \pi_{t-s})$			-0.002*** (0.000)	-0.002*** (0.000)	-0.004*** (0.000)	-0.005*** (0.000)
$\text{Cov}((\pi_{t-s} - \pi_t)^2, \pi_{t-s})$			-0.001 (0.000)	-0.000 (0.001)	0.001** (0.001)	0.001* (0.001)
SPF				0.533*** (0.069)	0.139*** (0.032)	
Constant	2.453*** (0.065)	2.190*** (0.128)	1.649*** (0.132)	0.035 (0.227)	2.205*** (0.054)	1.990*** (0.064)
Observations	224,223	224,238	224,203	213,299	213,271	223,874
R-squared	0.101	0.101	0.104	0.054	0.030	0.059
Panel B. SCE						
Average Experienced Inflation	0.451*** (0.027)	0.726*** (0.088)	1.098*** (0.142)	0.895*** (0.126)	2.066*** (0.124)	2.452*** (0.130)
$\text{Cov}(s^2, \pi_{t-s}) / a^2$		1.330 (0.984)	2.923*** (1.055)	1.432 (0.949)	10.155*** (1.072)	14.481*** (0.990)
$\text{Cov}(s, \pi_{t-s}) / a$		-2.640* (1.345)	-5.100*** (1.480)	-2.881** (1.316)	-15.993*** (1.524)	-22.002*** (1.366)
$\text{Cov}((\pi_{t-s} - \bar{\pi}_{t-1})^2, \pi_{t-s})$			-0.002*** (0.000)	-0.002*** (0.000)	-0.005*** (0.000)	-0.008*** (0.001)
$\text{Cov}((\pi_{t-s} - \pi_t)^2, \pi_{t-s})$			-0.003 (0.003)	-0.002 (0.003)	-0.006** (0.002)	-0.003 (0.003)
SPF				1.153*** (0.190)	1.426*** (0.109)	
Constant	2.219*** (0.074)	1.748*** (0.164)	0.881*** (0.328)	-1.203** (0.528)	-4.132*** (0.347)	-1.693*** (0.309)
Observations	126,595	126,543	126,577	126,580	126,676	126,942
R-squared	0.135	0.136	0.138	0.141	0.121	0.105
Demographic Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	NO	NO

Notes: The table reports the estimates of the first-order approximation of learning from experience model, augmented with similarity and a quadratic recency term, using the Huber-robust to downweigh outliers. Demographic characteristics include sex, education, income quintile and marital status. The database of inflation experiences includes the quarter-on-quarter experienced inflation rate and is updated each month. Inflation experience stops at the quarter before the quarter in which the forecast is made. Current inflation is the inflation experienced in three months before the forecast. We assume that for each cohort, learning starts when 16. Observations are weighted using survey weights. Standard errors clustered at the cohort and forecast date level in parentheses.

Table B2. Quantification Table, MSC

	Effect SD Increase	Average	SD
Average Experienced			
Inflation	0.72	4.04	1.31
$\text{Cov}(s^2, \pi_{t-s}) / a^2$	0.82	0.07	0.40
$\text{Cov}(s, \pi_{t-s}) / a$	-1.04	0.08	0.37
$\text{Cov}((\pi_{t-s} - \bar{\pi}_{it-1})^2, \pi_{t-s})$	-0.11	24.37	38.33
$\text{Cov}((\pi_{t-s} - \pi_t)^2, \pi_{t-s})$	-0.29	52.40	98.20
SPF	0.74	3.03	1.21

Notes: The table reports the effect of a standard deviation increase of each component of the linearized model. Coefficients are obtained using the specification in Column 4 of Table 1, panel A. To ease interpretability, for each measure, we also report the values of the mean and the standard deviation, computed using survey weights.

Table B3. Quantification Table, SCE

	Effect SD Increase	Average	SD
Average Experienced			
Inflation	0.74	3.00	0.80
$\text{Cov}(s^2, \pi_{t-s}) / a^2$	1.42	0.28	0.22
$\text{Cov}(s, \pi_{t-s}) / a$	-1.66	0.27	0.20
$\text{Cov}((\pi_{t-s} - \bar{\pi}_{it-1})^2, \pi_{t-s})$	-0.18	-3.71	20.29
$\text{Cov}((\pi_{t-s} - \pi_t)^2, \pi_{t-s})$	-0.20	11.19	90.36
SPF	0.21	2.18	0.32

Notes: The table reports the effect of a standard deviation increase of each component of the linearized model. Coefficients are obtained using the specification in Column 4 of Table 1, panel B. To ease interpretability, for each measure, we also report the values of the mean and the standard deviation, computed using survey weights.

Table B4. Medium-Term Inflation Expectations, Experience and Selective Recall

	(1)	(2)	(3)	(4)	(5)
	Medium-Term Inflation Expectations (t+24, t+36)				
Average Experienced Inflation: $\bar{\pi}_{t-1}$:	0.148*	0.259	0.945**	0.940**	1.707***
	(0.082)	(0.253)	(0.359)	(0.377)	(0.352)
Temporal Context Quadratic Component : $\text{Cov}(s^2, \pi_{t-s})/a^2$		0.406	0.585*	0.581	1.397***
		(0.334)	(0.347)	(0.362)	(0.333)
Temporal Context Linear Component: $\text{Cov}(s, \pi_{t-s})/a$		-1.443	-2.375	-2.355	5.926***
		(1.368)	(1.431)	(1.501)	(1.389)
Dissimilarity average inflation: $\text{Cov}((\pi_{t-s} - \bar{\pi}_{it-1})^2, \pi_{t-s})$			0.018***	-0.018***	-0.017**
			(0.007)	(0.007)	(0.006)
Dissimilarity current inflation: $\text{Cov}((\pi_{t-s} - \pi_t)^2, \pi_{t-s})$			-0.000	-0.000	-0.002**
			(0.001)	(0.001)	(0.001)
SPF inflation forecast				0.023	-0.433
				(0.265)	(0.323)
Constant	5.518***	5.386**	3.586***	3.549***	3.118***
	(0.246)	(0.450)	(0.803)	(0.823)	(0.892)
Observations	139,700	139,700	139,700	139,700	139,700
R-squared	0.079	0.079	0.079	0.079	0.074
Demographic Fixed Effects	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	NO

Notes: The table reports the estimates of the first-order linear approximation of a learning from experience model, augmented with similarity and a quadratic recency term. Demographic characteristics include sex, education, income quintile and marital status. The database of inflation experiences includes the quarter-on-quarter experienced inflation rate and is updated each month. Inflation experience stops at the quarter before the quarter in which the forecast is made. Current inflation is the inflation experienced in three months before the forecast. The dependent variable is the inflation expectation of an individual for months 24 to 36 in the future (rather than over the next 12 months). We assume that for each cohort, learning starts when 16. Observations are weighted using survey weights. Standard errors clustered at the cohort and forecast date level in parentheses.

Table B5. Robustness: Annually Recorded Inflation Experiences

	(1)	(2)	(3)	(4)	(5)	(6)
One-year ahead Infl. Exp.						
Panel A. MSC						
Average Experienced Inflation	0.215*** (0.026)	0.295*** (0.049)	0.412*** (0.055)	0.378*** (0.050)	0.114** (0.046)	0.488*** (0.031)
$\text{Cov}(s^2, \pi_{t-s}) / a^2$		0.221*** (0.063)	0.319*** (0.070)	0.216*** (0.058)	0.222*** (0.052)	0.712*** (0.079)
$\text{Cov}(s, \pi_{t-s}) / a$		-0.758*** (0.227)	-1.091*** (0.253)	-0.713*** (0.212)	-0.351** (0.162)	-2.134*** (0.239)
$\text{Cov}((\pi_{t-s} - \bar{\pi}_{t-1})^2, \pi_{t-s})$			-0.003*** (0.001)	-0.004*** (0.001)	-0.006*** (0.001)	-0.011*** (0.001)
$\text{Cov}((\pi_{t-s} - \pi_t)^2, \pi_{t-s})$			-0.001 (0.002)	-0.001 (0.002)	0.002 (0.002)	0.004* (0.002)
SPF				0.716*** (0.132)	0.416*** (0.060)	
Constant	3.215*** (0.121)	2.933*** (0.203)	2.570*** (0.211)	0.321 (0.434)	2.321*** (0.092)	2.458*** (0.114)
Observations	241,498	241,498	241,498	228,668	228,668	241,498
R-squared	0.097	0.097	0.098	0.059	0.041	0.069
Panel B. SCE						
Average Experienced Inflation	0.209*** (0.075)	0.041 (0.370)	0.361 (0.402)	0.264 (0.394)	2.058*** (0.363)	2.281*** (0.367)
$\text{Cov}(s^2, \pi_{t-s}) / a^2$		0.082 (0.465)	0.173 (0.457)	0.053 (0.445)	2.444*** (0.447)	3.156*** (0.433)
$\text{Cov}(s, \pi_{t-s}) / a$		-0.013 (1.986)	-0.384 (1.946)	0.128 (1.895)	-10.016*** (1.868)	-12.872*** (1.800)
$\text{Cov}((\pi_{t-s} - \bar{\pi}_{t-1})^2, \pi_{t-s})$			-0.002 (0.001)	-0.002 (0.001)	-0.010*** (0.002)	-0.018*** (0.003)
$\text{Cov}((\pi_{t-s} - \pi_t)^2, \pi_{t-s})$			-0.011 (0.010)	-0.011 (0.010)	0.000 (0.010)	0.022** (0.011)
SPF				0.932** (0.384)	1.946*** (0.327)	
Constant	5.705*** (0.219)	6.033*** (0.604)	5.359*** (0.706)	3.482*** (1.079)	-1.547 (0.983)	2.539*** (0.705)
Observations	139,555	139,555	139,555	139,555	139,555	139,555
R-squared	0.115	0.115	0.115	0.115	0.102	0.097
Demographic Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	NO	NO

Notes: The table reports the estimates of the first-order approximation of learning from experience model, augmented with similarity and a quadratic recency term. Demographic characteristics include sex, education, income quintile and marital status. The database of inflation experiences includes the year-on-year experienced inflation rate and is updated each quarter. Inflation experience stops at the quarter before the quarter in which the forecast is made. Current inflation is the inflation experienced in three months before the forecast. We assume that for each cohort, learning starts when 16. Observations are weighted using survey weights. Standard errors clustered at the cohort and forecast date level in parentheses.

Table B6. Robustness

	Table 2		Trimmed sample		Fixed baseline bucket (0-2%)		Log-ratio approximation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Frequency Ratio	0.0242*** (0.00131)	0.0242*** (0.00132)	0.0215*** (0.000979)	0.0215*** (0.000979)	0.109*** (0.0196)	0.108*** (0.0197)	0.219*** (0.0189)	0.219*** (0.0189)
Primacy	0.0350*** (0.00755)	0.0350*** (0.00755)	0.0484*** (0.00576)	0.0484*** (0.00576)	0.506*** (0.101)	0.500*** (0.101)	0.135 (0.153)	0.136 (0.153)
Recency	-0.0866*** (0.00687)	-0.0866*** (0.00687)	-0.0906*** (0.00525)	-0.0905*** (0.00525)	-0.814*** (0.136)	-0.805*** (0.137)	-0.634*** (0.197)	-0.636*** (0.197)
Dissimilarity	-1.06e-05*** (3.87e-06)	-1.06e-05*** (3.87e-06)	-1.91e-05*** (2.82e-06)	-1.91e-05*** (2.82e-06)	-3.61e-04*** (6.34e-05)	-3.61e-04*** (6.35e-05)	-4.68e-04*** (1.18e-04)	-4.67e-04*** (1.18e-04)
SPF		0.00814 (0.00521)		0.00801* (0.00409)		0.00907 (0.00574)		-0.00892 (0.00997)
Constant	0.173*** (0.00280)	0.173*** (0.00272)	0.115*** (0.00191)	0.114*** (0.00186)	0.277*** (0.00629)	0.276*** (0.00629)	0.281*** (0.0221)	0.283*** (0.0224)
Observations	570,799	570,822	517,119	517,143	483,975	483,950	337,428	337,428
R-squared	0.307	0.307	0.347	0.347	0.414	0.415	0.209	0.209
Demographic x Range FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year x Range FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

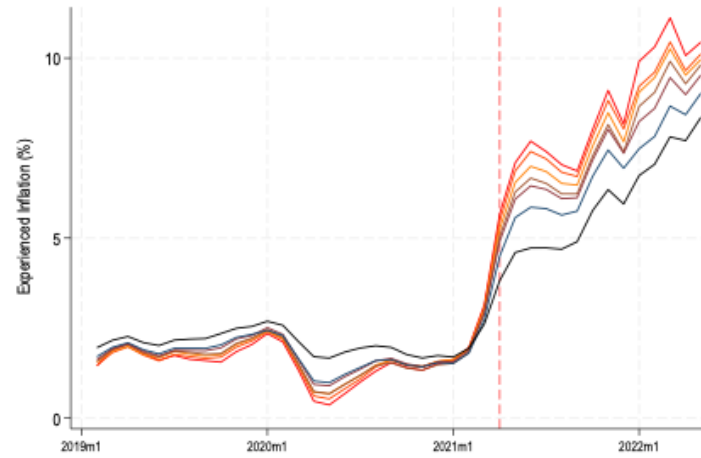
Notes: Dependent variable is the (log) odds ratio of the probability assigned to an inflation range relative to a baseline range. Columns (1)-(2) reproduce Table 2 (columns 3 and 5); columns (3)-(4) use the trimmed robust-weighted sample; columns (5)-(6) fix the baseline range at 0-2%; Columns (7)-(8) report a log-ratio approximation. Within each block, the second column adds the SPF control. Clustered standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table B7. Inflation Point Expectations and Range Probabilities

	Inflation Expectations Point Estimate	
	(1)	(2)
Inflation > 12%	0.196*** (0.009)	0.198*** (0.010)
8% < Inflation < 12%	0.144*** (0.009)	0.156*** (0.010)
4% < Inflation < 8%	0.088*** (0.009)	0.114*** (0.010)
2% < Inflation < 4%	0.060*** (0.009)	0.091*** (0.009)
0% < Inflation < 2%	0.048*** (0.009)	0.080*** (0.009)
-2% < Inflation < 0%	0.021** (0.009)	0.054*** (0.009)
-4% < Inflation < -2%	0.014 (0.010)	0.038*** (0.010)
-8% < Inflation < -4%	0.005 (0.011)	0.012 (0.010)
-12% < Inflation < -8%	0.002 (0.012)	-0.025* (0.013)
Constant	-2.879*** (0.918)	-5.165*** (0.932)
Observations	138,769	135,518
R-squared	0.382	0.615
Individual Fixed Effects	No	Yes
Year Fixed Effects	No	Yes

Notes: This table reports estimated coefficients and standard errors from estimating $\pi_{i,t}^e = \beta_0 + \sum_k \beta_{1k} \cdot Prob(\pi_{t+1} = b_k) + e_{i,t}$ where $\pi_{i,t}^e$ denotes respondent i's point expectations and $Prob(\pi_{t+1} = b_k)$ their reported probabilities for inflation range k . Data come from the NY Fed SCE. Regressions use survey weights and standard errors in parentheses are clustered at the cohort and date level.

Figure B1. Inflation Experiences by Age



Notes: The figure shows inflation rates experienced during the last 12 months by different age cohorts as in Jaravel (2019). Cohorts comprise ages <25, 25 – 34, 35 – 44, 45 – 54, 55 – 64, 65 – 74, and 75+, with colors reflecting this increasing order going from red to black.

Figure B2. Inflation Expectations by Age Groups

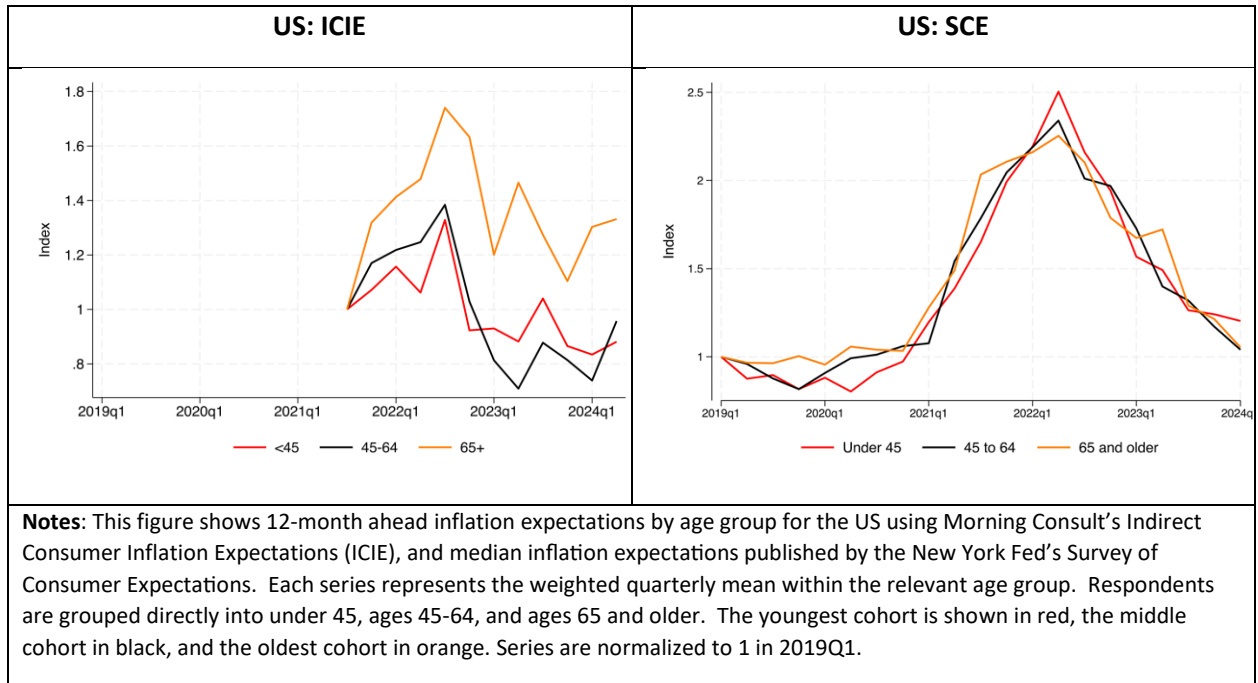
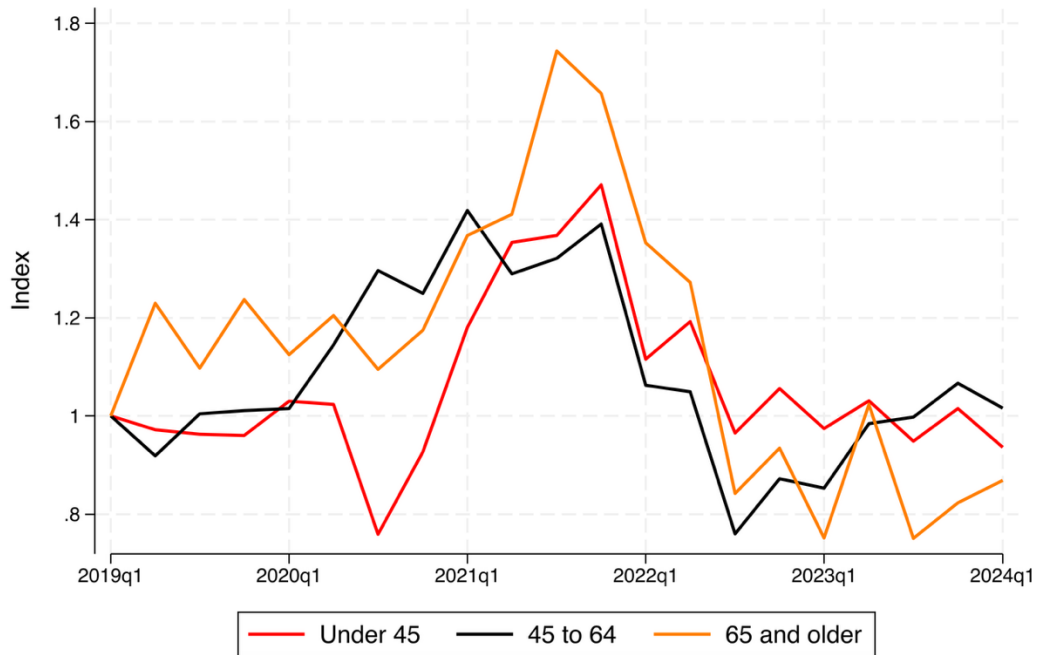
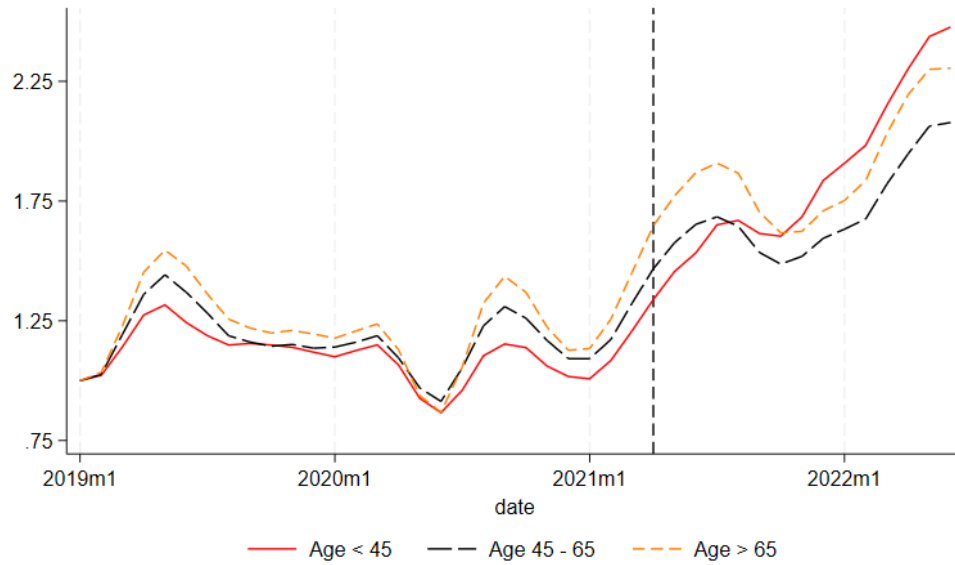


Figure B3. Inflation Expectations at a Medium Horizon

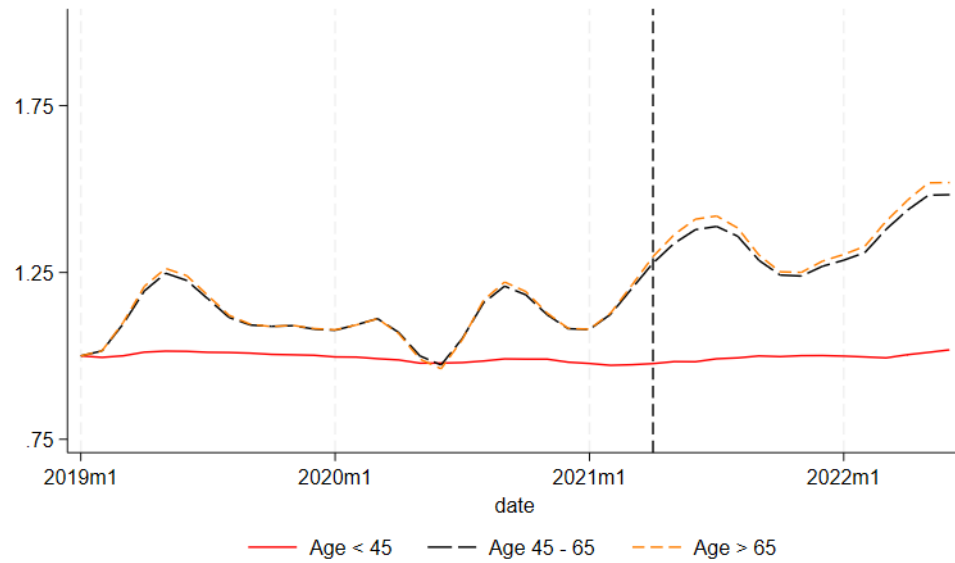


Notes: The figure shows quarterly inflation expectations from the NY Fed SCE for a medium ($t+24, t+36$) horizon. Each line, respectively, shows the weighted means for respondents age <45, age 45-65 and age >65, normalized to 1 in 2019Q1.

Figure B4. De-Anchoring of Inflation Expectations and the Importance of Similarity, Robustness



Panel A: Selective Memory Model



Panel B: Malmendier and Nagel Model

Notes: The top panel (Selective Memory Model) shows predicted inflation expectations by cohort from a model which includes as regressors experienced average inflation, temporal context and similarity measures as well as demographic controls, as in Column 6 of Table 1, which excludes the SPF term to retain consistency with the nowcasting exercise. The bottom panel (Malmendier and Nagel Model) shows predicted inflation expectations from the learning-from-experience model described by Equations (1) and (2) in Malmendier and Nagel (2016). All individual-level predictions are averaged within each cohort group using survey weights. Data come from the Michigan Consumer Survey. The model is calibrated for the 2013-2022 period. The actual forecast and the predictions are expressed as a fraction of their value in January 2019. The dashed vertical line marks April 2021.

Appendix C: External Validation Exercise

This section describes further details of the validation exercise in Section 5 with regards to data and methodology. Specifically, our validation exercise requires three specific adjustments to maintain comparability across micro datasets. First, age in the international data is reported in survey brackets rather than continuously, as in the Michigan data. Only the Canadian data report exact age, which we also bin to ensure comparability. We therefore assign, country by country, the midpoints of the age brackets and the average population age within the upper bracket as age measures (Australia and Canada: 26, 40, 55, and 75; Japan: 26, 40, 55, and 77; UK: 22, 30, 40, 50, 60, 70, and 75; euro area: 26, 42, 60, and 79). We then map these measures into young, middle-aged, and older cohorts, using appropriate weights where needed (under 45, 45–64, and 65+ in Australia, Canada, Japan, and the UK; 18–49, 50–70, and 71+ in the Euro area). Second, we adjust the MSC specifications used to obtain the prediction coefficients so that they include only demographic variables that are also available in the respective target country, as demographic coverage differs across countries. For example, marital status is unavailable in the UK data. Thus, we use only gender and income for Australia, Canada, and Japan; gender and education for the UK; and gender, education, household income, and marital or partnered status for the ECB Consumer Expectations Survey. Moreover, because the associated MSC coefficients are themselves estimated conditional on demographics, we residualize the explanatory variables in the target-country data with respect to demographics, so as not to conflate the memory channel with variation arising from differences in demographic composition. Third, when constructing our cohort-specific indices, we set the initial value of each predicted quarterly series equal to the corresponding actual inflation expectation for that cohort and normalize to one at the beginning of the available sample. The exercise therefore evaluates subsequent dynamics rather than the fit of initial levels: later predicted movements reflect the target country's inflation database and cue, evaluated using fixed MSC coefficients.