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.

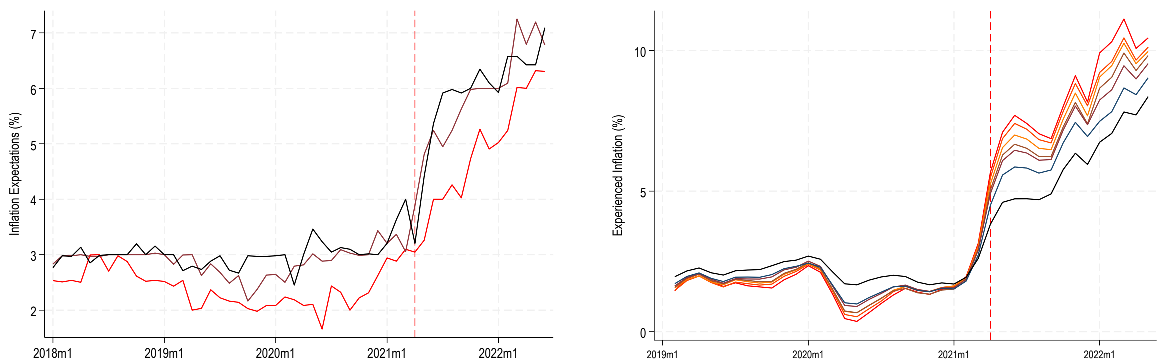
1. Introduction

Inflation expectations play a central role in macroeconomics. They shape wage and price setting, durable good consumption, investment decisions, and the conduct of monetary policy. How are they formed? Current research views these expectations as sticky and slow moving, due to gradual learning, which can be either adaptive (Evans and Honkapohja 2001) or restricted by inflation experiences (Malmendier and Nagel 2011, 2016, 2021), or to rational inattention (Sims 2003, Woodford 2009, Coibion and Gorodnichenko 2015). The evidence also shows that households rely on recent prices of groceries and gasoline (d'Acunto et al. 2022, 2023, 2024, Cavallo et al. 2017, Coibion and Gorodnichenko 2015, Gelman et al. 2016, Binder 2018). While amplifying disagreement, the dependence of beliefs on these local signals also creates rigidity by reducing the sensitivity of expectations to aggregate inflation changes.

Evidence from the recent inflation surge however suggests that, contrary to the above models, inflation expectations de-anchor quickly, not slowly. Figure 1, Panel A, reports US inflation expectations from 2019 to 2023 in the Survey of Consumer Expectations by the New York Fed. Around April 2021, these expectations increased from around 3%, where they hovered for years, to above 5% and then continued rising to 7%. Over the same period, actual inflation rose from 1.4% in January 2021 to 5.3% in June 2021, reaching 9% in June 2022. "De-anchoring"[1] occurred for all age groups, but the elderly (blue line) reacted faster and more strongly than the young (green line). This pattern, which we later document in other datasets and countries, is surprising: in standard accounts, the elderly should react to recent events *less* than the young, because a recent experience has less impact on their large database than on the smaller database of the young. Deepening the puzzle, the elderly de-anchor despite the fact, shown in Panel B, that around April 2021 they experience a smaller increase in their CPI index than do younger consumers.

[1] De-anchoring in this paper refers to the *state-dependent* nature of dynamics of shorter-term inflation expectations. In the central banking context, de-anchoring is conventionally understood as movement of inflation expectations at longer, 5-year horizons, away from inflation targets.

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



Panel A (left) shows the 12-month ahead median inflation expectations published by the New York Fed's Survey of Consumer Expectations for respondents 45 years old or younger (lower-envelope red line), 45-65 years old (maroon line) or 65+ years old (black line). The vertical line marks April 2021 in both panels. **Panel B (right)** shows inflation rates experienced during the last 12 months by different age cohorts as in Jaravel (2019). Cohorts comprise ages <25, 24 – 34, 35 – 44, 45 – 54, 55 – 64, 65 – 74, and 75+, with colors reflecting this increasing order going from red to black.

We present a model of mnemonic beliefs showing that these and other patterns can be explained based on associative human memory (Baddeley 1997, Kahana 2012). Recall of a past inflation episode increases in its similarity with current cues, where cues are shaped by: i) temporal context, and ii) the forecasting task. Temporal context yields well-known primacy and recency effects. *Ceteris paribus*, recent inflation is easier to recall because its temporal context is similar to the present. Early experiences are also easier to recall because they have been rehearsed often, so they come to mind when thinking about inflation. The inflation forecasting task cues recall based on numerical similarity: when a person sees or thinks about inflation at 3%, she scans for similar episodes in her database, making 3% episodes easier to retrieve. Critically, because different cohorts have lived different histories and thus have different databases, the same cue leads them to recall different episodes. People react differently to the same current inflation change, causing cohort and state-dependent disagreement.

Our memory model endogenizes known features of inflation expectations but also yields new predictions for their formation. Due to temporal cues, mnemonic beliefs overweight recent inflation, as in constant gain learning models (Marcet and Sargent 1989, Sargent 1999, Evans and Honkapohja 2001).

Due to primacy, however, they also overweight early life inflation. The combination of these forces causes a strong departure from Bayesian learning: *persistently* higher expected inflation by a cohort that experienced high inflation early compared to a cohort having the same experience later in life. Numerical similarity in turn causes two forms of belief *instability*. The first is cohort-specific state-dependence: an inflation surge from 2% to 10% prompts recall of 10% inflation. This effect is especially strong for people with more of the 10% experiences (even if remote, like for the elderly during the recent inflation surge). The second instability depends on the event a person is thinking about: people put higher weight on a rare inflation state when explicitly asked to estimate its probability than when forming overall point expectations. Intuitively, the latter task does not describe the rare state, causing its neglect. This instability is a stark departure from *any* model, including Bayesian learning, in which people have a coherent belief system. Critically, such incoherence is state-dependent, in a way that we can test.

We test the model's predictions using micro data from the University of Michigan's Survey of Consumers (MSC) and the Federal Reserve Bank of New York's Survey of Consumer Expectations (SCE). The data shows that a model of beliefs embedding recall mechanisms that are robustly documented in cognitive science greatly improves the account of real-world expectations. We find strong support for the role of temporal similarity, so inflation experiences affect expected inflation via primacy and recency effects, as well as for the role of numerical similarity. The latter force delivers two key new findings.

First, it accounts for a striking inconsistency between different belief elicitations we see in the data: a household's point inflation expectation is systematically higher than its expectation computed using its separately elicited density forecast. In our model this occurs because households forget rarely experienced deflation states when forming point expectations but not when explicitly asked to assess such states in density forecast elicitations. Memory predicts that this inconsistency should be state-dependent: during inflation surges, estimated deflation densities drop sharply, causing density-based expectations to increase faster than point forecasts. We confirm this mechanism in the data, showing that underweighting of deflation in point forecasts is key and works through similarity.

The second key finding is that similarity is qualitatively and quantitatively needed to account for de-anchoring of expectations around April 2021 as well as for their subsequent re-anchoring. In seminal work, Malmendier and Nagel (2016) documented that people who lived through higher inflation have higher inflation expectations today. They explain this finding with a model of Bayesian learning from experiences. We show that to understand the role of experiences in belief formation it is necessary to explicitly model selective recall. In the context of the 2021 events, learning from experiences cannot explain the sharp de-anchoring of expected inflation in April 2021, the stronger reaction by the elderly, and the subsequent re-anchoring by all cohorts. Memory is needed to capture incoherence and instability.

The literature on household inflation expectations is large and also points to the role of demographics (Manski 2004, 2018; d'Acunto et al. 2021a, 2021b, Bruine de Bruin et al. 2010 and Armantier et al. 2013).[2] Hajdini et al. (2024) confirm the role of experiences in recent and in international data while Goldfayn and Wohlfart (2020), Braggion et al. (2024), and Salle et al. (2024) provide evidence on historical experiences and inflation expectations. Andre et al. (2022) stress mental models and Zuellig (2022) quantifies them for inflation expectations. Carroll (2003), Carroll et al. (2020), and Bracha and Tang (2022) study belief rigidity due to inattention.

Following Bordalo et al. (2023, 2025a) we build a model of selective recall based on the cognitive structure of cues and similarity, and quantify its effects. Bonaglia and Gennaioli (2025) formalize and study the long run properties of a general mnemonic learning model, and Bonaglia et al. (2025) use it to study investor inflation expectations and their link to excess interest rate volatility. Compared to diagnostic expectations models of over-reaction in Bordalo et al. (2018), Maxted (2024), L'Huillier et al. (2023), or

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

Bianchi et al. (2024a, 2024b), modeling selective recall expands explanatory power. Selective recall based on frequency and similarity helps account for assessments of novel risks (Bordalo et al. 2025a), expected stock returns (Jiang et al. 2025), and the effects of idiosyncratic experiences on beliefs about the macroeconomy (Cenzon 2025, Butera et al. 2024). In our context, they reconcile pre-pandemic rigidity with the volatility of expectations in 2021 and explain the inconsistency between point expectations and density forecasts. Our mechanism accounts for the broader role of cues in eliciting inflation expectations (Armantier et al. 2013), including the role of survey response scales documented in Becker et al. (2023).

The paper is organized as follows. Section 2 starts by providing additional evidence, coming from other surveys and countries, that older households reacted more swiftly to the recent inflation surge than younger respondents. We then present our memory model and derive its key predictions. In Section 3 we test the model's predictions about point inflation expectations using the MSC and SCE surveys. In Section 4 we test the model's predictions for forecast densities and for their inconsistency with point expectations. Section 5 shows the importance of memory for explaining the evolution of expected inflation in the US, in and out of sample, also compared to experience-based learning. Section 6 concludes.

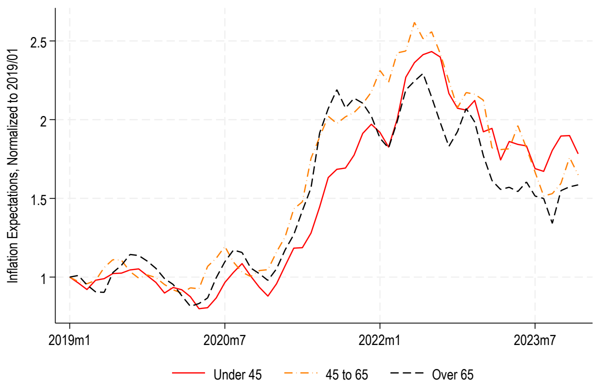
2. The Model

Before presenting our model, we offer additional evidence – from the US and other countries – showing the robustness of two key features of inflation expectations during the post-pandemic inflation surge: i) older households de-anchored faster than younger ones, but ii) younger households caught up quickly. For the US, we use the monthly Michigan Survey of Consumers (MSC). For the UK we use the quarterly Bank of England's Inflation Attitudes Survey (IAS), for the EU the European Central Bank's monthly Consumer Expectations Survey (CES), for Japan the Cabinet Office's monthly Consumer Trend Survey (CTS). The first three data sets report 12-month ahead point expectations, in the CTS expectations are constructed by integrating forecast densities. Figure 2 reports three-month moving averages of beliefs for different age groups, normalized to 1 in January 2019 and June 2020 for the CES. The IAS is already at quarterly frequency, so we do not smooth it further.

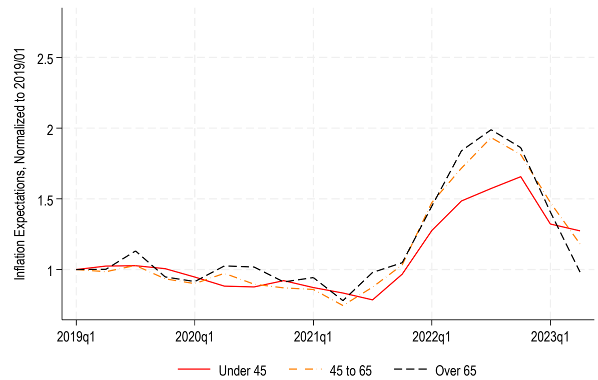
The path of expectations varies across countries due to differences in inflation dynamics: Inflation surged earlier in the US in 2021 perhaps due to a stronger fiscal stimulus, it rose later in 2021 in Europe, and only in mid-to-late 2022 in Japan. However, and crucially, the pattern in Figure 1 is robust across survey measurements and countries. Older cohorts (yellow, gray and black lines) de-anchored their inflation expectations faster than the younger cohorts (orange lines). The divergence in the speed of updating is most striking for the US and the UK, but also evident in the EU and Japanese series. As in Figure 1, younger households eventually catch up, usually around the time in which older households' expectations reach their peak.

Why did the elderly de-anchor faster as inflation rose, but then the young fairly quickly caught up? This behavior is inconsistent with Bayesian (including experience-based) adaptive learning, in which inflation expectations are rigid and, if anything, the young should react more quickly than the elderly. Perhaps the data is consistent with a Bayesian regime-switching model in which the elderly hold a "high inflation" regime in their mind due to past experiences. This is prima facie unsatisfactory, for it requires the young to form a "high inflation" regime right after seeing a few high inflation datapoints. But even if that were the case, a Bayesian regime-switching (or any other rational) model would be at odds with the belief inconsistency across different belief elicitations, another feature of survey expectations (see Section 4). We next present a model of beliefs based on well-established and domain general regularities of human recall. This model accounts for the pattern of Figures 1 and 2 as well as the observed inconsistency of beliefs. It rules out learning models and yields several new testable predictions that we test.

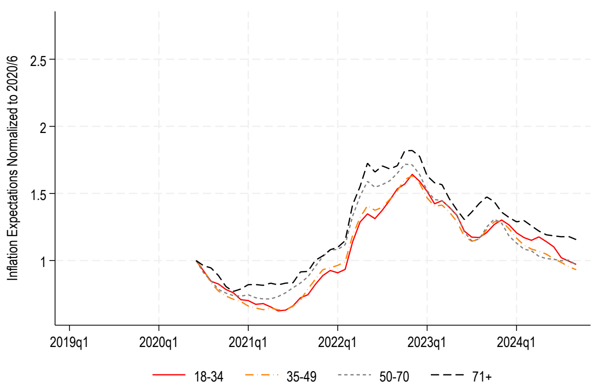
Figure 2: Inflation Expectations Internationally



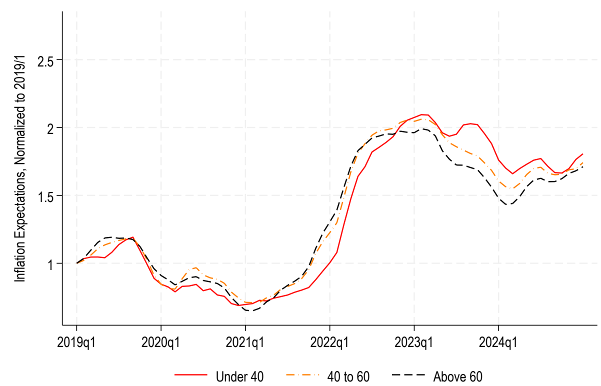
Panel A: Michigan Survey of Consumers (US)



Panel B: Inflation Attitudes Survey (UK)



Panel C: Consumer Expectations Survey (EU)



Panel D: Consumer Trend Survey (Japan)

Note: This figure shows inflation expectations by age group, for the US from the University of Michigan Survey of Consumers (MSC, monthly), for the UK from the Bank of England's Inflation Attitudes Survey (IAS, quarterly), for the Euro area from the European Central Bank's Consumer Expectations Survey (CES, monthly) and for Japan from the Japanese Cabinet Office's Consumer Trend Survey (CTS, monthly). In the IAS, ages 15-24, 25-34 and 35-44 are combined into "under 45"; ages 45-54 and 55-64 into "45 to 65". Age brackets are preset in the CES, and set to the NY Fed brackets in the MSC. In the CTS, age-specific inflation expectations are constructed by integrating over range-midpoints of age-specific average forecast densities; age groups <29 and 30-39 are combined into "Under 40"; age groups 40-49 and 50-59 into "40 to 60" using 2022 population weights from Japan's National Institute of Population and Social Security Research. Panels display three-month backward-looking moving averages for the MSC, CES and CTS. Series are normalized to 1 in January 2019, and June 2020 for the CES.

2.1 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 $\Pi_t = (\pi_{t-s})_{s=1,\ldots,a_t}$ collects the inflation levels observed by the agent in the past, starting from a_t periods ago. a_t is the "effective age" of the agent at t, namely the age of her 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. These effects are explained by similarity between a person's current context (her thoughts about the list, her mood etc.) – which acts as a spontaneous cue – and her context when the word was studied. The last word's context was similar to the present. The first word is often rehearsed, so it is similar to the context of the list the person is thinking about. In both cases, similarity is higher and recall easier.

Similarity is also shaped by the task itself, as shown by cued recall experiments (e.g. Anderson 1974). Here cues are explicitly manipulated. If asked to recall "things in the kitchen", people may retrieve "plates" because they are often seen in kitchens. If asked to recall "white things in the kitchen", they may recall "milk" and forget plates, due to color. Here the cue is the question\event (kitchen, white) that must be assessed, which prompts retrieval of similar experiences (plates, milk). An object in the environment can also act as a cue (e.g. a glass of milk in the person's desk while doing the task).

We capture these forces by assuming that, when evaluating future inflation, the agent is cued by the current temporal and numerical inflation contexts. Temporal context captures the idea that inflation levels experienced in conditions (economic, political, etc.) similar to the present or rehearsed for a long time are more likely to be retrieved, as in recency and primacy effects. Numerical context captures the idea that inflation levels similar to the one the agent is currently experiencing or thinking about 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 currently thinking about. We specify $\bar{\pi}_{E,t}$ later. 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 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. Perceived temporal dissimilarity is modelled using 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. When thinking about future inflation, early inflation experiences ($s = a_t$) are similar and hence likely to be recalled, because they have often been rehearsed. But yesterday's inflation ($s = 1$) is also similar and hence likely to be recalled because its personal or social context is similar to the present. Temporal similarity may depend on macroeconomic states, so that during war or economic depression we more easily recall wartime or depression inflation. Here 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, which we approximate by the quadratic discrepancy $(\pi_{t-s} - \pi_t)^2$. Intuitively, if current inflation is $\pi_t = 3\%$, episode $\pi_{t-s} = 10\%$ is less similar and hence harder to recall than $\pi_{t-s'} = 2\%$. Numerical similarity also acts based on the event E the agent is estimating and in particular falls in the quadratic distance $\left(\pi_{t-s} - \bar{\pi}_{E,t}\right)^2$. 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 spontaneously cued to recall episodes similar to her experiences with this set.[3] For instance, if the agent is estimating the probability of inflation in $E = [2\%, 3\%]$, she finds it easier to retrieve $\pi_{t-s} = 2.5\%$ 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, e.g. it may retrieve states that followed conditions similar to current ones, or it may depend on inflation changes. These features could allow to capture the temporal contiguity of past episodes, including inflation persistence. Again, here we adopt a parsimonious similarity structure and show that it suffices to obtain significant explanatory power. In fact, both recency and numerical similarity already cause beliefs to embed inflation persistence.

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

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

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 (Nosofsky 1992), in our case to inflation and its specific features. In our analysis, these weights are fixed across people and over time, and we estimate them from the data. Link et al. (2025) measure attention to inflation and find that it systematically varies across people, based on past experiences, and over time, based on inflation changes. In the interest of

[3] 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 certain equivalent $\overline{\pi}_{E,t}$ (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 $\overline{\pi}_{E,t} = 3\%$ while an agent with uniform experiences would be cued by $\overline{\pi}_{E,t} = 2.5\%$. These differences are arguably small, so we abstract from them in our analysis.

parsimony, we abstract from this effect, focusing on objective distance in the feature space. In the conclusion we argue that these forces can be naturally embedded in our cognitive approach.

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 models of recognition and recall (Nosofsky 1992). Furthermore, similarity extends to sets additively, 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:

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

where the normalization constant is set so that, in the current forecasting task, probabilities add up to one. Normalization captures interference. From the cue-stimulus, different 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 relatively more similar to the cue $\pi_{t,E}$ both along temporal and numerical context, and if it occurs relatively more frequently in Π_t.

The agent samples her database Π_t sufficiently many times that the distribution of recollections can be approximated by (2). Critically, a change in the available cues, including a normatively irrelevant change in the way the forecasting task is described, affects recall and forecasts. In particular, two alternative such descriptions are important for our purposes. The first elicits the point expectation. Here the agent 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 $\overline{\pi}_{\mathbb{R},t} = \overline{\pi}_t$. The agent's point forecast is then equal to the average recollection under features t, π_t and $\overline{\pi}_t$:

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

The agent weights past inflation using the probabilities obtained by normalizing Equation (2) in the entire database, so that $\Pr(\pi_{t-s}|\pi_{t,\mathbb{R}}) = S(\pi_{t-s}, \pi_{t,\mathbb{R}})/S(\Pi_t, \pi_{t,\mathbb{R}})$. Using this probability, 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.

The second description of the forecasting task entails estimating a 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: the agent samples each range E_j by thinking about E_j itself. She then normalizes across the different ranges, estimating the probability of a specific range E_j by its relative self-similarity compared to the other elicited ranges:

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

This density forecast entails an implicit point expectation $\mathbb{E}(\pi_{t+1}|\pi_{t,E_1}, \dots \pi_{t,E_k}) = \sum_{j=1,\dots,k} \Pr\left(E_j|\pi_{t,E_j}\right) \cdot \pi_{E_j}$, where π_{E_j} is the similarity weighted average inflation lived in range E_j (namely across experiences in $E_j \cap \Pi_t$). The cue for ranges is more specific compared to $\mathbb{R}$, so recall from the same database differs compared to recall when a point forecast is elicited. Differences in recall in turn produce 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).[4]

The role of the forecasting task (point expectation versus forecast density) in shaping recall and beliefs is a striking new implication of selective memory. It distinguishes this mechanism from any rational model in which the agent holds a consistent belief system, including highly flexible Bayesian learning

[4] 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 $-E = \mathbb{R} \backslash E$.

structures. The inconsistency of beliefs elicited under different cues is well documented in work on judgment and known as the "disjunction fallacy": people attach a higher probability to an event if its description is broken down into constituent parts, which facilitates retrieval of instances (Fischoff et al. 1978). 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.

We next derive the model's predictions for point expectations in Equation (3), then for forecast densities in Equation (4), and finally for the inconsistency between point and density-based expectations. These predictions underscore a structured dependence of these objects on changing current inflation π_t, on cohort differences in the database Π_t, and on the interaction between the two. This structure organizes our empirical tests in Sections 3 and 4.

2.2 Model Predictions

The model's predictions rely on: i) the database Π_t, which varies across respondents with different ages a_t and over time due to realized inflation π_t, and on ii) the features of the cue, $\pi_{t,E}$, which include the estimation task. These elements interact because following Equation (2) the cue ignites retrieval of past episodes π_{t-s} based on the distance in Equation (1), but critically the retrieval is restricted by the database. Thus, the same cue affects beliefs differently across databases, producing systematic belief disagreement. We derive testable implications of this interaction for the common belief elicitations in household surveys: point forecasts and density forecasts of future inflation.

Point Expectations. This is the most common elicitation of expectations, available in the University of Michigan's 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 farther. When forming a point forecast the cue is broad, $E = \mathbb{R}$, which facilitates retrieval of episodes near the respondent's average experienced inflation, $\bar{\pi}_{E,t} = \bar{\pi}_t$. The model then implies the following result.

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

$$\mathbb{E}(\pi_{t+1}|\pi_{t,\mathbb{R}}) \approx \bar{\pi}_t + \beta_1 \cdot cov[(s/a_t)^2, \pi_{t-s}] - \beta_2 \cdot cov(s/a_t, \pi_{t-s})$$

$$-\sigma \cdot (1-q) \cdot cov[\pi_{t-s}, (\pi_{t-s} - \bar{\pi}_t)^2] - \sigma \cdot q \cdot cov[\pi_{t-s}, (\pi_{t-s} - \pi_t)^2]. \quad (5)$$

The first determinant of expectations is a respondent's average experienced inflation $\bar{\pi}_t$ when entering time t. This term reflects the database Π_t: people who have experienced higher inflation during their lifetimes, higher $\bar{\pi}_t$, ceteris paribus expect higher future inflation, whatever cue they face.

The other terms reflect the interaction between cues and the database: covariances are in fact computed using the features of the cue and the distribution of experiences in the database. The first two covariances $\beta_1 \cdot cov[(s/a)^2, \pi_{t-s}]$ and $-\beta_2 \cdot cov(s/a, \pi_{t-s})$ 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 compared to people with the same average experience but who lived above average inflation later in life (the former people have higher $cov[(s/a_t)^2, \pi_{t-s}]$). By the second term, a person whose above average inflation experiences occurred recently expects higher inflation compared to a person whose above average inflation experiences occurred when she was middle aged (the former people have lower $cov(s/a_t, \pi_{t-s})$).

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 learning models (Marcet and Sargent 1989, Sargent 1999, Evans and Honkapohja 2001) and in time-decaying experience-based learning models

(Malmendier and Nagel 2011, 2016, Nagel and Xu 2022). In our model, these two forces act at the same time and pull beliefs in different directions. Ceteris paribus, recency dominates 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 remaining covariances reflect numerical similarity, and their strength is modulated by $\sigma > 0$. They imply that – for a given database Π_t – a surge in current inflation π_t tends to boost expectations by prompting selective retrieval of high inflation experiences compared to low inflation ones. Critically, this effect is cohort-specific. The second covariance term implies that – holding average prior experiences constant – higher current inflation π_t especially boosts the belief of a person whose above average inflation experiences are similar to π_t compared to a person whose such experiences are different from it (the former person has lower $cov[\pi_{t-s}, (\pi_{t-s} - \pi_t)^2]$). The first covariance term captures changes in the database. If the inflation surge is persistent so that the average experience $\overline{\pi}_t$ increases, inflation expectations also increase, especially for people whose above average experiences are similar to $\overline{\pi}_t$ (for them $cov[\pi_{t-s}, (\pi_{t-s} - \overline{\pi}_t)^2]$ is lower).

Numerical similarity thus 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*. Pointing to the richness of memory effects, this heterogeneity is time varying: during an upward trend in inflation, the expectations of "low inflation" cohorts quickly catch up because their database gets filled with high inflation as they live it, sharply boosting their recall by similarity. As we will show, these forces allow our model to quantitatively account for the key patterns in Figure 1: the faster de-anchoring by the elderly and the subsequent catch up by the young.

A large body of work shows the importance of inflation, stock market, and other experiences for belief formation in macro-finance. What are the mechanisms and consequences? A cognitive approach based on human memory highlights the importance of similarity and cues. If memory only works through the average record of experiences (the first term), older people should exhibit a relatively muted reaction to an inflation surge because their average database $\overline{\pi}_t$ is affected by recent events less than the database of the younger cohorts, and differences eventually fade with temporal discounting/recency effects.

Well established regularities in *selective* recall run against this force. On the one hand, primacy effects imply that belief differences between older and younger people tend to persist if these cohorts lived their above average inflation experiences in different phases of their lives (early vs middle aged). Numerical similarity in turn creates sharp state and cohort dependence in belief updating. The beliefs of the elderly change faster than those of the young, despite the elderly's slow-moving database, when high inflation cues the elderly to recall a temporally remote yet numerically similar high inflation episode, which remained "dormant" – due to dissimilarity – during low-inflation times. This prediction of selective memory can be tested using Equation (5).

Cohort-specific state dependence can be generated by a Bayesian model in which people allow for "switching" across the inflation regimes they experienced in life. In Figure 1, upon seeing high inflation, the elderly sharply revise up the probability of switching to the "high inflation" regime they experienced in their youth, while the young react less because they do not have this regime in the set of models they entertain. This account has three problems. First, it cannot explain the quick catch up by the young unless one implausibly assumes that they form a "high inflation" model right after seeing a few months of high inflation. Second, a Bayesian account cannot explain primacy effects. Third, and crucially, it cannot explain the inconsistency between density and point forecasts, which we investigate next.

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 these finer events, assume for simplicity that peoples' databases are concentrated at the inflation ranges' midpoints

π_j for $j = 1,..,10$ (we later test empirical robustness of this). Cohort differences are then captured by the experienced frequencies of different ranges. When assessing the probability of range j, the respondent is cued by the corresponding event, $\bar{\pi}_{t,E_j} = \pi_j$, and by current realized 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:*

$$\frac{\Pr(\pi_j|\pi_j,\pi_t)}{\Pr(\pi_b|\pi_b,\pi_t)} \approx \frac{n_j}{n_b} + \beta_1 \cdot \frac{n_j}{n_b} \cdot \left(\bar{s}_j^2 - \bar{s}_b^2\right)/a_t^2 - \beta_2 \cdot \frac{n_j}{n_b} \cdot \left(\bar{s}_j - \bar{s}_b\right)/a_t$$

$$-\sigma \cdot q \cdot \frac{n_j}{n_b} \cdot \left[\left(\pi_j - \pi_t\right)^2 - (\pi_b - \pi_t)^2\right]. \quad (6)$$

The same memory forces affecting point forecasts influence the estimated relative probability of different ranges. The first term in Equation (6) captures a pure database effect: the relative probability attached to range *j* relative to range b increases in its relative experienced frequency n_j/n_b. The other terms capture the interaction between time varying cues and the database, which produce cohort specific belief instability. There is a primacy effect: when $\beta_1 > 0$, range *j* is deemed more likely than range b if it is experienced on average more remotely than the latter, $\bar{s}_j^2 > \bar{s}_b^2$. There is also a counterbalancing recency effect: when $\beta_2 > 0$ range j is deemed more likely compared to b if it was experienced more recently compared to the latter $\bar{s}_j < \bar{s}_b$. Critically, the strength of primacy and recency effects are mediated by the database: they 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 compared to range b, the more so if range *j* experiences were more frequent relative to range b, 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-dependent in the same way 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). This occurs because, when people estimate an explicitly described range E_j, they are directly cued to think about the inflation state π_j corresponding to it, even if it was rarely experienced (namely, even if it is different from $\bar{\pi}_t$). Thus, the forecast density $\Pr\left(E_j|\pi_{t,E_j}\right)$ in Equation (4) differs systematically from the implicit belief $\Pr\left(E_j|\pi_{t,\mathbb{R}}\right)$ over the same ranges formed implicitly when making point expectations.

Empirical work on surveys has documented several "anomalies" associated with density forecasts for inflation and other outcomes. These anomalies include smearing of probabilities across events or outsized probability attached to events elicited before the others, and they are typically explained using "frictions" such as rounding of probabilities (Binder 2018), order effects (Tversky and Kahneman 1974, Hogarth and Einhorn 1992), and the 1/n heuristic (Benartzi and Thaler 2001). Compared to these findings, we rely on a structured memory mechanism which offers precise predictions on how cues and a person's database interact in order to shape density forecasts and their discrepancy with point forecasts. To see this, note that Equations (3) and (4) imply:

$$\mathbb{E}\left(\pi_{t+1}|\pi_{t,\mathbb{R}}\right) = \sum\nolimits_j w_{j,t} \cdot \Pr\left(E_j|\pi_{t,E_j}\right) \cdot \pi_j . \tag{7}$$

That is, memory-based point expectations are given by a *weighted* sum of ranges' expected values, where the weight on range *j* identifies the ratio between the implicit estimate of E_j used for making the point forecast and the directly elicited estimate for the same range, $w_{j,t} = \frac{\Pr\left(E_j|\pi_{t,\mathbb{R}}\right)}{\Pr\left(E_j|\pi_{t,E_j}\right)}$.

If the two estimates are consistent, which should be the case in any rational model, then $w_{j,t} = 1$. A respondent's point expectation should then be equal to the average inflation computed using her separately elicited forecast density. This is not the case with selective memory. Rarely experienced ranges are unlikely to be retrieved when forming point expectations and so $w_{j,t} < 1$. For instance, if people rarely experienced deflation, the lowest ranges elicited in the SCE, then when forming a point forecast they will underweight deflation scenarios compared to when estimating forecast densities, because in the latter case deflation ranges are cued. The opposite occurs if people rarely experience high inflation.

Critically, our model predicts that this inconsistency between point and density-based forecasts can be systematically tied to changing current inflation π_t and the average experience $\overline{\pi}_t$.

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

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

Point and density-based expectations differ only if numerical similarity matters, $\sigma > 0$. If so, the point expectation is higher than her density-based one whenever high inflation ranges are relatively more similar to her average experience than deflation ones (i.e. $d_{j,t}$ is below average at positive inflation levels $\pi_j > 0$). People who experienced lots of high inflation will insufficiently account for deflation scenarios when forming point expectations, even though they partially correct themselves when assessing deflation ranges. These people will then exhibit a positive gap between point and density-based expectations.

Critically, memory implies that the belief inconsistency should be time varying. When inflation rises sharply, both the point and the density-based forecasts will increase. However, the point forecast $\mathbb{E}(\pi_{t+1}|\pi_{t,\mathbb{R}})$ will increase less in proportion to the density-based one $\mathbb{E}(\pi_{t+1}|\mathrm{DF})$. Intuitively, observing high inflation triggers a sharp upward revision of high inflation ranges and a sharp downward revision of deflation ranges in the density forecast (while the point expectation remains more anchored to the slow-moving average experience $\overline{\pi}_t$ compared to the density based one). This state-dependent discrepancy between point and density-based expectations is a clear test of memory and can have important real-world implications. If different consumption and investment decisions are made under the influence of different cues that make inflation or some of its realizations more or less salient, beliefs and decisions will change across contexts. 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. The role of experiences is mediated by ambient cues.

3. Testing the Model's Predictions for Point Expectations

In this section we examine point expectations in Equation (5) using the Michigan Survey of Consumers, MSC, and the New York Fed's SCE.

3.1 Data

The MSC is a rotating survey panel conducted at the monthly frequency by the University of Michigan starting from January 1978. Six months after the interview, about 40% of the sample is interviewed again, and each respondent could be interviewed up to three times. The MSC collects several socio-demographics and expectations about a range of economic 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 1th percentiles at -7% and 30% expected inflation. Before 1978, the survey was delivered quarterly, respondents were fewer, and the questions were slightly different. For this reason, we focus on the post-1978 period until June 2022.

The New York Fed's SCE is also a rotating panel. It comprises about 1,300 nationally representative US respondents 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 June 2022. 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 of 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 $a_t =$ (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.[5] 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:

$$\pi_{i,t}^{e} = \gamma_0 + \gamma_1 \cdot \overline{\pi}_{t-1} + \gamma_2 \cdot cov[(s/a)^2, \pi_{t-s}] + \gamma_3 \cdot cov[(s/a), \pi_{t-s}]$$

$$+\gamma_4 \cdot cov[\pi_{t-s}, (\pi_{t-s} - \overline{\pi}_t)^2] + \gamma_5 \cdot cov[\pi_{t-s}, (\pi_{t-s} - \pi_t)^2]$$

$$+\gamma_6 \cdot \pi_{SPF,t}^{e} + \boldsymbol{\delta}_1' \boldsymbol{X}_i + \boldsymbol{\delta}_2' \boldsymbol{Z}_t + u_{it},$$

where $\pi_{i,t}^{e}$ is the point expectations at time t by respondent i, $\boldsymbol{X}_i$ controls for i's gender, education, income brackets, and marital status, and $\boldsymbol{Z}_t$ captures year dummies, which are included in most specifications to control for common shocks and to assess the ability of memory related regressors to account for cross cohort variation in beliefs. In some specifications we include the SPF forecast $\pi_{SPF,t}^{e}$, because professional inflation forecasts are prominent in the media, so the respondent may combine them with her memory-based estimate (see Bordalo et al. 2025a).

The key parameters linked to Equation (5) are γ_1, which should be positive if experiences matter, γ_2 and γ_3, which jointly determine the temporal context-driven primacy ($\gamma_2 > 0$) and recency ($\gamma_3 < 0$) effects, with the former dominating the latter when $\gamma_2 + \gamma_3 > 0$, and γ_4 and γ_5, which should be negative if numerical similarity matters. Table 1 reports the regression estimates for the MSC (Panel A) and the SCE

[5] 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.

(Panel B). We include different memory effects in progression from columns (1) to (4). In column (5) we exclude year dummies to assess the explanatory power of memory alone, without accounting for unobservable time varying factors.

Column (1) confirms that respondents who experienced higher average inflation report higher inflation expectations compared to the others, $\gamma_1 > 0$. Holding the average $\overline{\pi}_t$ 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 are directionally consistent but not statistically significant.

In Column (3) we include numerical similarity, running the full-fledged specification of Equation (5). Consistent with selective memory, the estimated coefficients on numerical similarity are negative, $\gamma_4 < 0$ and $\gamma_5 < 0$: holding average experience constant, the respondent overweighs her above average inflation experiences when these are more similar to current inflation as well as to the average inflation experienced during her lifetime, which both act as cues. Now primacy and recency effects become robust predictors of beliefs, and show up significantly also in the MSC. We thus find strong evidence for the three leading memory effects: primacy, recency, and numerical similarity. These effects are robust to adding the SPF forecast, Column (4), and to dropping year dummies, Column (5). In fact, year dummies have a fairly small impact on the R^2, showing the ability of memory to account for cohort and time variation in beliefs. As we shall see in Section 5, standard models with time dependent weights, including experience-based learning (Malmendier and Nagel 2016) cannot account for these patterns.

Table 1. Inflation Expectations, Experience and Selective Recall

	One-Year-Ahead Inflation Expectation				
	(1)	(2)	(3)	(4)	(5)
Panel A. MSC					
Average Experienced Inflation: $\overline{\pi}_{t-1}$:	0.280***	0.324***	0.554***	0.562***	0.319***
	(0.027)	(0.062)	(0.069)	(0.064)	(0.058)
Temporal Context Quadratic Component : $Cov(s^2,\pi_{t-s}) / a^2$		-0.056	2.255***	1.947***	1.814***
		(0.526)	(0.589)	(0.518)	(0.527)
Temporal Context Linear Component: $Cov(s,\pi_{t-s})/a$		-0.202	-3.095***	-2.617***	-1.769***
		(0.699)	(0.775)	(0.696)	(0.644)
Dissimilarity average inflation: $Cov((\pi_{t-s}-\overline{\pi}_{it-1})^2,\pi_{t-s})$			-0.003***	-0.002**	-0.002*
			(0.001)	(0.001)	(0.001)
Dissimilarity current inflation: $Cov((\pi_{t-s}- \pi_t)^2,\pi_{t-s})$			-0.002***	-0.004***	-0.006***
			(0.001)	(0.000)	(0.001)
SPF inflation forecast				-0.041	0.234***
				(0.102)	(0.062)
Constant	3.019***	2.849***	2.145***	2.111***	2.321***
	(0.122)	(0.248)	(0.256)	(0.360)	(0.104)
Observations	229,495	229,495	229,495	217,818	217,818
R-squared	0.091	0.091	0.093	0.060	0.044
Panel B. SCE					
Average Experienced Inflation: $\overline{\pi}_{t-1}$:	0.212***	0.464*	1.046***	0.931**	2.175***
	(0.074)	(0.242)	(0.392)	(0.395)	(0.374)
Temporal Context Quadratic Component : $Cov(s^2,\pi_{t-s}) / a^2$		5.292**	7.218**	6.371**	19.083***
		(2.555)	(2.853)	(2.835)	(2.790)
Temporal Context Linear Component: $Cov(s,\pi_{t-s})/a$		-6.543*	-9.608**	-8.351**	-26.657***
		(3.564)	(4.061)	(4.040)	(3.942)
Dissimilarity average inflation: $Cov((\pi_{t-s}-\overline{\pi}_{it-1})^2,\pi_{t-s})$			-0.010	-0.009	-0.001
			(0.007)	(0.007)	(0.007)
Dissimilarity current inflation: $Cov((\pi_{t-s}- \pi_t)^2,\pi_{t-s})$			-0.002***	-0.002***	-0.008***
			(0.001)	(0.001)	(0.001)
SPF inflation forecast				0.646*	0.937***
				(0.354)	(0.306)
Constant	5.699***	5.263***	3.810***	2.639**	-0.163
	(0.216)	(0.452)	(0.884)	(1.061)	(0.959)
Observations	139,583	139,583	139,583	139,583	139,583
R-squared	0.114	0.115	0.115	0.115	0.104
Demographic Characteristics	YES	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES	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, given by the regression specification $\pi^e_{i,t} = \gamma_0 + \gamma_1 \cdot \overline{\pi}_{t-1} + \gamma_2 \cdot cov[(s/a)^2, \pi_{t-s}] + \gamma_3 \cdot cov[(s/a), \pi_{t-s}] + \gamma_4 \cdot cov[\pi_{t-s}, (\pi_{t-s} - \overline{\pi}_{t-1})^2] + \gamma_5 \cdot cov[\pi_{t-s}, (\pi_{t-s} - \pi_t)^2] + \gamma_6 \cdot \pi^e_{SPF,t} + \boldsymbol{\delta}_1^{'} \boldsymbol{X}_i + \boldsymbol{\delta}_2^{'} \boldsymbol{Z}_t + u_{it}$. 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.

Estimated coefficients are economically meaningful. Consider temporal context first. As Appendix Table A2 shows for the MSC, in our preferred specification (Table 1, Column 4) a one-standard deviation increase in the first covariance term (second row) implies a 0.82 percentage point increase in inflation expectations while the second covariance term (third row) is associated with -1.04 percentage points decrease. This suggests that frequency is marginally stronger but comparable to primacy (they are statistically indistinguishable, in fact). Based on point estimates, the temporally harder experiences to recall – those for which temporal distance $\beta(s/a_t)$ is maximized – are those occurring at $s/a = \beta_2/2\beta_1 = 0.685$, which is approximately one third into a person's effective age.

Consider numerical similarity next. The effect of this force is not only present but strong, which is needed to explain de-anchoring. A one-standard deviation increase in the dissimilarity of experienced above average inflation episodes to average inflation (fourth row), and to current inflation (fifth row), is associated with decreases of 0.11 and 0.29 percentage points, respectively.

Similar conclusions apply to the SCE (Appendix Table A3). Here, a one-standard deviation increase in the primacy term (second row) leads to an increase in inflation expectations by 1.42 percentage points while a one-standard deviation change in the recency term (third row) is associated with a decrease in inflation expectations of 1.66 percentage points. Similarly to the MSC, the peak of temporal distance is reached at $s/a = 0.655$. 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.

We assess robustness to using 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, 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, buttressing the explanatory power of selective memory, with one interesting nuance: for longer term expectations similarity to the experienced mean inflation rate is more important than similarity to the current inflation rate, which is 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 A1) or if we define inflation experiences annually rather than quarterly (Appendix Table A5).

Overall, selective memory holds significant explanatory power for point expectations. Well established 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 proves crucial to accounting for the swift de-anchoring by the elderly as well as for the 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, in which people hold a coherent belief system which they use for different elicitation and allows us to test additional predictions of memory.

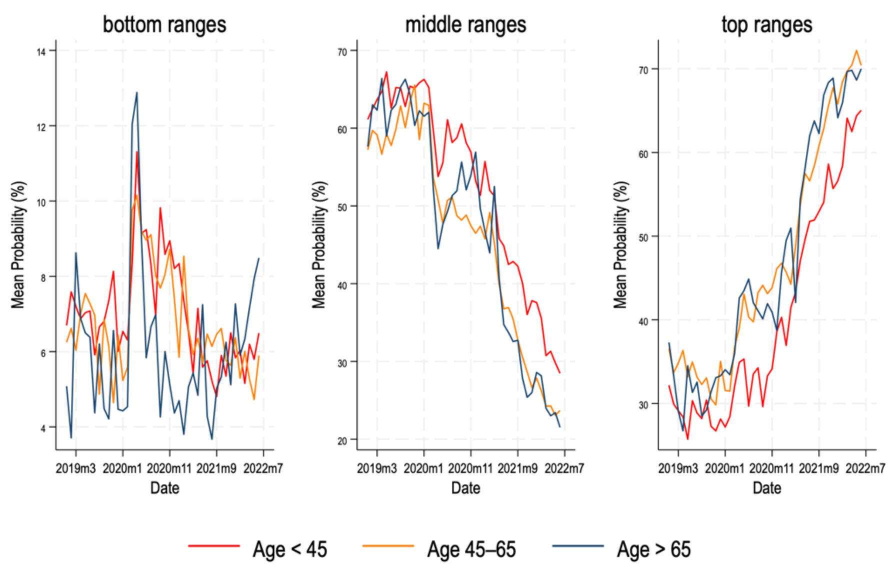
4. The Model's Predictions for Forecast Densities and Belief Inconsistency

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

Recall that the forecast density elicitation in the SCE asks households to report their probability estimates of inflation falling into each of 10 ranges: 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%. Consider the average estimates of young (<45, red), middle-aged (45-65, orange), and older (>65, blue) cohorts, aggregated over the lowest (π_{t+1}< -4%), middle ($\pi_{t+1} \in [-4,4\%]$), and top (π_{t+1} > 4%) ranges. Figure 3 reports their evolution between 2019 and 2022, the same window as our motivating Figure 1.

Figure 3 Cohort Specific State-Dependence in Range Estimation



Notes: This figure shows the mean probability that respondents assign in the NY 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.

Consistent with Figure 1, upon seeing the inflation surge older respondents increase the probability of the top ranges (π_{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 lowest range (π_{t+1} < - 4%) is much smaller and economically quite similar across cohorts: The young place a probability of 7.16% on this deflationary range, the middle-aged 6.5% and the older 6.76%.

This evidence is consistent 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 estimate probability $\Pr(\pi_{t+1} > 4\%)$ due to their higher frequency n_j/n_b compared to the young, who did not experience many such episodes. Over time, much action in forecast densities comes from middle and high inflation ranges; The probability attached to deflation is statistically different than zero but moves much less than the other ranges. This is again consistent with an interaction between cues and databases: changes in the inflation cue π_t affects 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:

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

$$\theta_4 \cdot \frac{n_{j,i,t}}{n_{b,i,t}} \cdot \left[\left(\pi_j - \pi_t\right)^2 - (\pi_b - \pi_t)^2\right] + \boldsymbol{\omega}_1' \boldsymbol{R_j} \times \boldsymbol{X}_i + \boldsymbol{\omega}_2' \boldsymbol{R_j} \times \boldsymbol{Z}_t + \boldsymbol{\omega}_3 \pi_{SPF,t}^e + v_{ijt},$$

where the left-hand side are the odds of a range j over a baseline range $b \neq j$, selected for each respondent as the range with the lowest non-zero probability assessment. On the right hand side, $n_{j,it}/n_{b,it}$ captures the corresponding relative experience frequency, $\left(\bar{s}_{j\,i,t}^{\,2} - \bar{s}_{b\,i,t}^{\,2}\right)/a_t^2$ and $\left(\bar{s}_{j\,i,t} - \bar{s}_{b\,i,t}\right)/a_t$ the corresponding relative recency, $\left[\left(\pi_j - \pi_t\right)^2 - (\pi_b - \pi_t)^2\right]$ the corresponding relative dissimilarity, $\boldsymbol{X}_i$ contains demographic fixed effects to account for individual-specific characteristics, $\boldsymbol{Z}_t$ captures year dummies, $\pi_{SPF,t}^e$ the SPF inflation forecast, and $\boldsymbol{R}_j$ contains indicators for range *j* which we interact with $\boldsymbol{X}_i$ and $\boldsymbol{Z}_t$. 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 aggregating 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.

Results from the estimation, shown in Table 2, confirm the importance of selective memory. First, a pure database effect is at work, as shown by the positive coefficient on "frequency ratio" in the first row. 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 have experienced it less frequently, under any given temporal or numerical cue.

Second, cues also matter. Temporally, we see a recency effect: the [2%,4%] range is deemed as relatively more likely if it was experienced recently, captured by the negative coefficient on "time delay." We also see a primacy effect: the same [2%,4%] range is also deemed relatively more likely by a cohort that experienced it early in life, as captured by the positive coefficient on "time delay squared". These effects interact with the database: a temporal cue favoring a range is particularly strong if the range was experienced relatively frequently in the past. An occasional [2%,4%] episode is forgotten even if it occurred recently or early in life. These temporal effects are consistent with the evidence from point estimates and inconsistent with Bayesian or adaptive models (primacy, in particular).

Crucially, 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. This is the key force behind the cohort specific state dependent de-anchoring in Figure 3: 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. This is memory-driven instability, shaped by the interaction between the database and cues. Regularities in selective recall shed light on both point and density forecasts.

Table 2. Memory and Range Probabilities

	Odds Ratio				
	(1)	(2)	(3)	(4)	(5)
Frequency Ratio	0.0162***	0.0230***	0.0242***	0.0230***	0.0242***
	(0.000682)	(0.00131)	(0.00131)	(0.00131)	(0.00132)
Relative Frequency Ratio x Relative Time Delay Squared	0.104***	0.0251***	0.0350***	0.0251***	0.0350***
	(0.00464)	(0.00728)	(0.00755)	(0.00728)	(0.00755)
Relative Frequency Ratio x Relative Time Delay	-0.106***	-0.0731***	-0.0866***	-0.0731***	-0.0866***
	(0.00412)	(0.00629)	(0.00687)	(0.00629)	(0.00687)
Relative Frequency Ratio x Relative Dissimilarity	-2.26e-05***	-8.20e-06**	-1.06e-05***	-8.23e-06**	-1.06e-05***
	(2.38e-06)	(3.43e-06)	(3.87e-06)	(3.42e-06)	(3.87e-06)
SPF				0.000858	0.00814
				(0.00615)	(0.00521)
Constant	0.0453***	0.171***	0.173***	0.171***	0.173***
	(0.00251)	(0.00293)	(0.00280)	(0.00305)	(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 $\frac{\widehat{\pi_j}_{i,t}}{\widehat{\pi_b}_{i,t}} = \theta_0 + \theta_1 \cdot \frac{n_{j,it}}{n_{b,it}} + \theta_2 \cdot \frac{n_{j,it}}{n_{b,it}} \cdot \left(\overline{s}_{j\,i,t}^{\,2} - \overline{s}_{b\,i,t}^{\,2}\right)/a^2 + \theta_3 \cdot \frac{n_{j,it}}{n_{b,it}} \cdot \left(\overline{s}_{j\,i,t} - \overline{s}_{b\,i,t}\right)/a + \theta_4 \cdot \frac{n_{j,it}}{n_{b,it}} \cdot \left[\left(\pi_j - \pi_t\right)^2 - (\pi_b - \pi_t)^2\right] + \boldsymbol{\omega}_1' \boldsymbol{R_j} \times \boldsymbol{X}_i + \boldsymbol{\omega}_2' \boldsymbol{R_j} \times \boldsymbol{Z}_t + \boldsymbol{\omega}_3\, \pi_{SPF,t}^e + v_{ijt}$ where the data come from the New York Fed SCE. Columns 2 and 3 include interactions of inflation range indicators R_j with demographic fixed effects X_i as well as year fixed effects Z_t, while Columns 4 and 5 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.

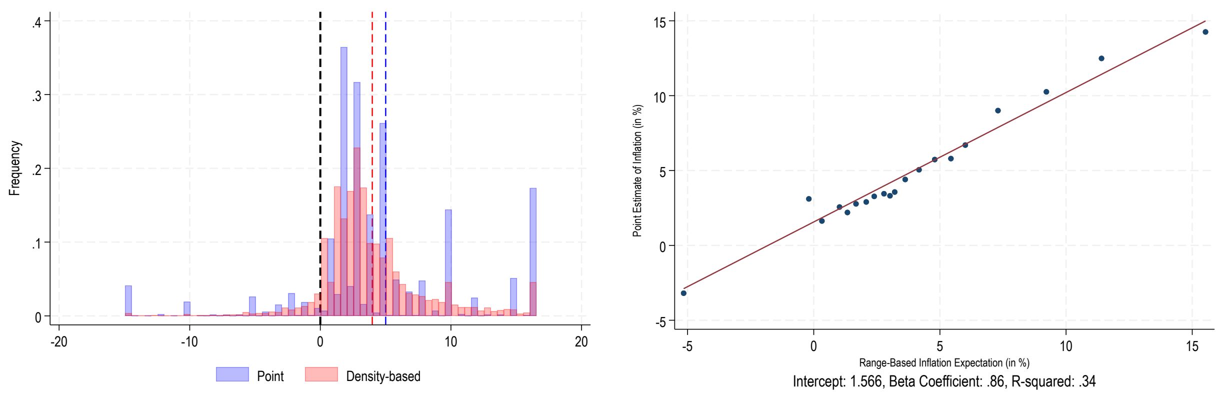
4.2 The Inconsistency between Point Expectations and Forecast Densities

A rational respondent would use her prior and the data to derive a probability density over future inflation rates. She would then use this density both to estimate the probabilities of various ranges and to form a point forecast. Average inflation computed using the respondent's density forecast would then be equal to her point expectation. This is not the case under selective memory: the elicitation of ranges cues recall of rarely experienced ranges that are neglected when thinking about a point forecast. By affecting the cue, different estimation tasks create belief inconsistencies across elicitations. We next show that this property of memory has empirical bite: there is a systematic inconsistency between the beliefs formed under point and density forecast elicitations, also reported in Bruine de Bruin et al. (2011), which varies over time in line with the interaction between cues and databases.

For each household i and time period t, we compute the density-based inflation estimate $\pi^{e}_{i,t,\mathrm{DF}}$ using the reported range probabilities by household i at time t and the 1931-2020 historical average experienced inflation rate in each range. The latter choice addresses the difficulty of assigning a numerical value to unbounded ranges >12% and <-12%, resulting in estimates of 16.19% and in -14.95%. The choices for the other ranges at the same time align quite well with range midpoints and are also consistent with how we assign values at the tails. We assign 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. In order to not mechanically create a gap between reported point and density-based expectations, we also winsorize reported point estimates at the same choices for the upper and lower ranges, at 16.19% and -14.95%. Our results are robust to using average personal experiences over ranges (complemented with midpoints or population averages if the respondent has zero experiences with a range).

Figure 4 reports in Panel A (left) the distribution of point and density-based expectations in the SCE and in Panel B (right) the binned scatterplot of a univariate regression of a respondent's point expectation on her density-based expectation. In Panel A we see a systematic discrepancy between the two measures: the distribution of density-based expectations is shifted to the left compared 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.

Figure 4: Systematic State-Dependent Discrepancy



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 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 regression of point expectations on density-based expectations in Panel B confirms that point expectations elicit higher expected inflation than forecast densities: there is a positive intercept of 1.6 percentage points. In addition, Panel B shows that point expectations exhibit stunted sensitivity to density-based ones. 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. This result is robust to controlling for respondent and time fixed effects, so it neither reflects a constant bias of specific respondents nor an anomaly of specific time periods.

Panel B shows that the discrepancy between point and density forecasts is state-dependent. A unit increase in density forecasts results in a (1-0.86) = 0.14 closing of their gap with point forecasts. Put differently, density-based forecasts appear to be more sensitive to the time-varying inflation state than point expectations. When inflation increases, people attach a sharply higher weight to high inflation ranges (as in Figure 4) and density-based expectations increase. Point expectations also increase, but less in proportion to density-based ones. As a result, the gap between the two narrows. This is consistent with a memory mechanism, which anchors point expectations to the slow-moving average experience $\overline{\pi}_t$.

Methodological work on surveys documents various distortions in density elicitations. These distortions are typically explained by "frictions" such as: i) the order effect, whereby the first elicited ranges are overestimated, ii) rounding of probabilities, whereby the density is imprecisely "discretized", or ii) the 1/n heuristic, whereby the probability of ranges is smeared toward 1/n. These mechanisms may play a role but cannot explain Figures 3 and 4. With order effects, people should systematically overestimate top ranges, which are elicited first, compared to point expectations, in which no order is present. This, however, counterfactually implies that density-based expectations should be higher than point expectations. Rounding of probabilities or smearing should create attenuation in density forecasts. This mechanism does not however explain why point expectations are systematically higher and more sluggish than density-based ones. It also fails to explain the cohort specific state-dependence in Figure 3.

Our model describes a different mechanism. Both elicitations are cued by current inflation π_t, but they yield different answers for a given π_t because density forecasts cue the possibility of all ranges, including infrequently experienced ones, while point forecasts cue a person's average experience $\overline{\pi}_{i,t}$, causing neglect of infrequent experiences (which are far from $\overline{\pi}_{i,t}$).

This logic explains why point expectations are systematically above density-based ones. Density elicitations explicitly cue the possibility of deflation, which is rarely experienced, and hence neglected when making point forecasts. Such relative overweighting of deflation, then, systematically reduces the density-based expectation below the point expectation. Looking at respondents' databases we indeed see both that deflation is experienced rarely, and that the average inflation experienced by respondents is far from it: In January 2020, just before COVID and the recent inflation surge, 89.7% of the population inflation experiences are positive, a share that increases from the young (83.6%) to the middle-aged (90.4%) to the old (92.5%). Slightly negative inflation rates just below 0% account for much of the importance of deflation as Figure A1 in the Appendix illustrates. Moreover, no respondent in the data has a negative lifetime average inflation experience while the experienced lifetime average inflation is distributed bi-modally, at slightly above 2% and slightly below 4%. Figure A2 illustrates this distribution. Under selective memory, these patterns are consistent with higher point compared to density-based expectations, and also with the difference between scenario-based and density-based inflation expectations documented in Boctor et al. (2024).

To directly test the memory mechanism, we regress a respondent's point expectation on the elicited probability $\Pr\left(E_j|\pi_{t,E_j}\right)$ she attaches to different inflation ranges E_j. In a rational model, as evident from Equation (7), the regression coefficient on each such probability should equal to expected inflation π_j conditional on the range. With selective memory, by contrast, the regression coefficient also reflects imperfect retrieval, as captured by weights $w_{j,t}$ in Equation (7). Ranges that are "neglected" or "forgotten" when making point expectations will see their estimated coefficient shrunk toward zero compared to the normative benchmark, while ranges that are recalled when making point expectations will see their regression coefficient increase in magnitude compared to the normative benchmark.

Table 3 reports the estimated coefficient from regressing point expectations on the elicited probabilities of the ten ranges. The pattern of coefficients is consistent with the memory model. The coefficients on deflation are generally not statistically significant or in some cases are even positive. This means that, even if a household estimates a higher probability of a deflation range, this is not reflected in a lower point expectation (the point expectation is elicited before the density forecast).

Table 3. Inflation Point Expectations and Range Probabilities

	Inflation Expectations Point Estimate	
	(1)	(2)
Inflation > 12%	0.196***	0.198***
	(0.009)	(0.010)
8% < Inflation < 12%	0.144***	0.156***
	(0.009)	(0.010)
4% < Inflation < 8%	0.088***	0.114***
	(0.009)	(0.010)
2% < Inflation < 4%	0.060***	0.091***
	(0.009)	(0.009)
0% < Inflation < 2%	0.048***	0.080***
	(0.009)	(0.009)
-2% < Inflation < 0%	0.021**	0.054***
	(0.009)	(0.009)
-4% < Inflation < -2%	0.014	0.038***
	(0.010)	(0.010)
-8% < Inflation < -4%	0.005	0.012
	(0.011)	(0.010)
-12% < Inflation < -8%	0.002	-0.025*
	(0.012)	(0.013)
Constant	-2.879***	-5.165***
	(0.918)	(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.

Consequently, we see that - when forming point expectations - households overweigh the positive inflation ranges, especially the frequently experienced intermediate ranges with $\pi \in [0,2\%] \cup [2\%, 4\%]$. In these cases, the estimated coefficients lie substantially above the highest possible inflation in the range, indicating overweighting. This is consistent with the memory model, where point expectations tend to be anchored to the average inflation experience $\overline{\pi}_{i,t}$, which for many respondents is close to the $[0,2\%] - [2\%, 4\%]$ ranges and certainly far from deflation.

Memory explains why point expectations are systematically above density-based ones, the first anomaly in Figure 4, Panel A. We next show that memory also explains why the discrepancy between point and density-based expectations shrinks as the latter increase, the second anomaly in Figure 4 Panel B. The mechanism comes from the model prediction embedded in Equation (8). When current inflation π_t increases, similarity prompts households to sharply increase the probability of high inflation ranges, as shown in Figure 3 for 2021. This in turn sharply increases density-based expectations. Point expectations also increase when current inflation increases, but less so, because they remain anchored to slow moving average experiences $\overline{\pi}_{i,t}$. Thus, the proportion between the two measures gets closer to one. To test for this mechanism, embedded in Equation (9), we estimate the following specification:

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

where the left-hand side is the point estimate by respondent i, $\boldsymbol{Z}_i$ denote respondent demographic characteristics and $\boldsymbol{Z}_t$ year dummies. The first regressor, $\pi_{i,t,B}^{e}$, is the range-based point expectation. The second regressor, $[\pi \cdot d]_{i,t,\mathrm{DF}}^{e}$, is a measure of the relative similarity of high inflation ranges to the respondent's database of experiences up to the previous quarter. It is computed by implementing the formula in Equation (8). If the database $\overline{\pi}_{i,t}$ 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 regression estimates, including first separately and then jointly, the different 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.

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***	1.078***	0.981***	0.919***
	(0.024)	(0.029)	(0.024)	(0.024)
Similarity of high inflation ranges to personal experiences	0.001***	0.001***	0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
(Similarity of high inflation ranges to personal experiences)^2		0.000***		-0.000***
		(0.000)		(0.000)
(Similarity of high inflation ranges to personal experiences)^3		-0.000		0.000***
		(0.000)		(0.000)
Constant	0.873***	0.858***	1.258***	1.455***
	(0.102)	(0.111)	(0.090)	(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 $\pi^e_{i,t} = \mu_0 + \mu_1 \cdot \pi^e_{i,t,B} + \mu_2 \cdot [\pi \cdot d]^e_{i,t,B} + \boldsymbol{\varphi}_1'\boldsymbol{Z}_i + \boldsymbol{\varphi}_2'\boldsymbol{Z}_t + e_{i,t}$. 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 the predictions of 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 $\overline{\pi}_{it}$ 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 drops. 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 4 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). As we introduce quadratic and squared similarity terms, we see convexity. Point expectations increase sharply as people attach higher probabilities to moderately high inflation ranges close to $\overline{\pi}_{it}$. The results are robust to controlling for time fixed effects, so they are not due to particular periods. They are also robust to controlling for respondent fixed effects. Inconsistencies in survey responses are not due to some respondents who are 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 terms[6], the economic importance of the similarity term is large: a one-standard deviation increase in range-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

We saw that selective memory deepens our understanding of the role of past experiences in belief formation by recognizing the centrality of similarity, which drives recall based on temporal and numerical

[6] In Column (1), the adjusted R2 is 34.58% relative to 33.98% in the specification without the linear similarity term in Figure 3. Going to a higher cubic order raises the adjusted R2 to 34.70%.

context. Going back to our motivating facts in Figures 1 and 2, we next show that these forces offer a good quantitative account for the broad "de-anchoring" of point inflation expectations in April 2021 and the especially strong de-anchoring by the elderly. We then show that the very same model can account, out of sample, for the re-anchoring of point expectations following the post-pandemic monetary tightening and the associated fall in inflation. To showcase the importance of selective memory, we explicitly compare our model to experience-based learning (Malmendier and Nagel 2016), in which agents optimally estimate the long run mean and persistence of an AR(1) inflation process using their personally experienced inflation history rather than all potentially available data.

We evaluate our model using the specification in Column 5 of Table 1. We thus focus on MSC expectations and include as belief predictors a person's experienced average inflation, her temporal and numerical context covariances, as well as demographic controls. We use neither the SPF forecast nor time dummies as belief predictors because we want to isolate the role of a person's past inflation experiences – mediated by cued recall – in generating meaningful time variation in beliefs.

We compare these predictions from our model to those from the learning-from-experience model described by Equations (1) and (2) in Malmendier and Nagel (2016). We again focus on MSC expectations and nonlinearly estimate their gain parameter θ using these data. Our estimation of θ starts in June 2013, the date when SCE data also become available. This choice of timeframe allows us to provide a comparison across datasets in which no differences are due to inconsistent timeframes. The appendix additionally includes with Figure A3 a model comparison based on the full timeframe of the MSC, which shows full robustness of the results. Our analysis in all cases includes survey respondents of all ages, lifting the restriction to ages 25 to 75 in Malmendier and Nagel (2016).[7] The estimation yields an estimate of θ equal to 0.93. For each respondent i and time t we thus obtain a learning-from-experiences π_{it}^{e} proxy. Unlike

[7] The results of the estimation are invariant to inclusion of these respondents.

the predictions from our model, this proxy does not allow for forgetting and selective retrieval based on changing temporal and numerical cues. To assess de-anchoring, we normalize the initial predictions of all cohorts and across models.[8]

Results of this model comparison show that our state-dependent selective-retrieval model can reproduce the patterns of Figures 1 and 2 while experience-based learning cannot. Panel A of Figure 5 shows our model's predictions, and Panel B those from experience-based learning—both for the cohorts also displayed in Figures 1 and 2. Panel A reveals that 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 fails to capture these dynamics. With experience-based learning, the elderly are somewhat more sensitive to changes than the young, because they experience and hence estimate a higher inflation persistence. But such sensitivity is too small to yield a meaningful de-anchoring. Due to many experiences with stable inflation, the beliefs of older cohorts are too rigid, and barely move from the starting point. The beliefs of the young are also rigid (their cohort only experienced stable inflation), and fail to eventually de-anchor as we see in Figures 1 and 2. Experience based learning can capture level differences in expectations across cohorts, which are not shown in the figure, but does not deliver meaningful experience-based instability. By combining slowly evolving databases with time varying cues, selective retrieval can produce level differences as well as instability in beliefs.

As a second test, we consider the performance of the two models in accounting for the post-2021 behavior of expectations out of sample. To do so, we perform an out-of-sample nowcasting exercise in which we use the coefficient estimates of the two models in our first quantification exercise, estimated in the MSC sample, to predict inflation expectations until February 2024. In this exercise we predict the

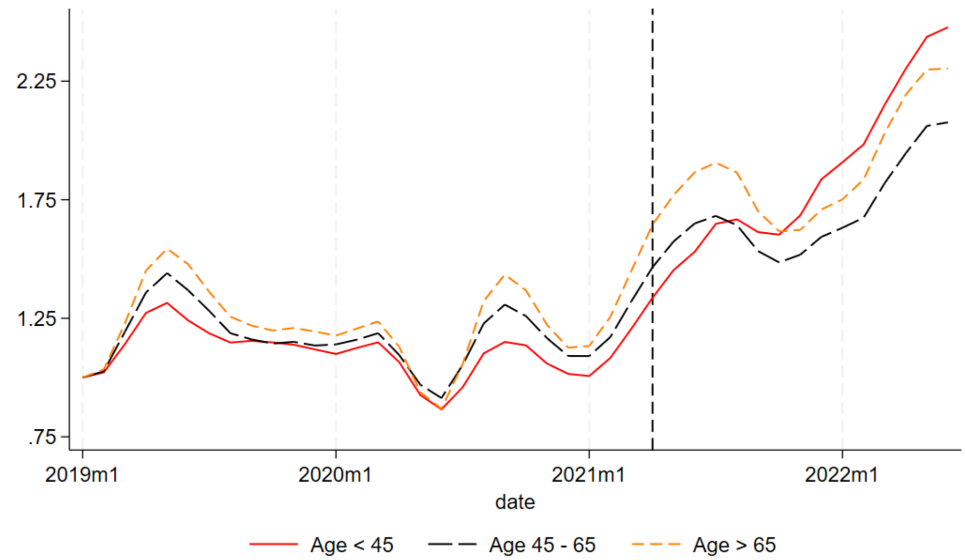
[8] Here we report the learning-from-experience proxy π_{it}^{e} directly. This choice restricts predicted expectations from the experience-based model to have a unit loading on π_{it}^{e}. Allowing measured expectations to load on π_{it}^{e} with a freely estimated coefficient affects the results little: the experience-based model fails to capture meaningful de-anchoring and re-anchoring of expectations.

beliefs of the average respondent in the MSC because our model does not make clear predictions on cohort differences in re-anchoring (because both the young and the elderly have experienced many recent low-inflation periods), and neither does the experience-based learning model.[9] We then compare model predictions with the average inflation expectation observed in the MSC throughout the period, whose values in the nowcasting subperiods have not influenced model estimations.[10]

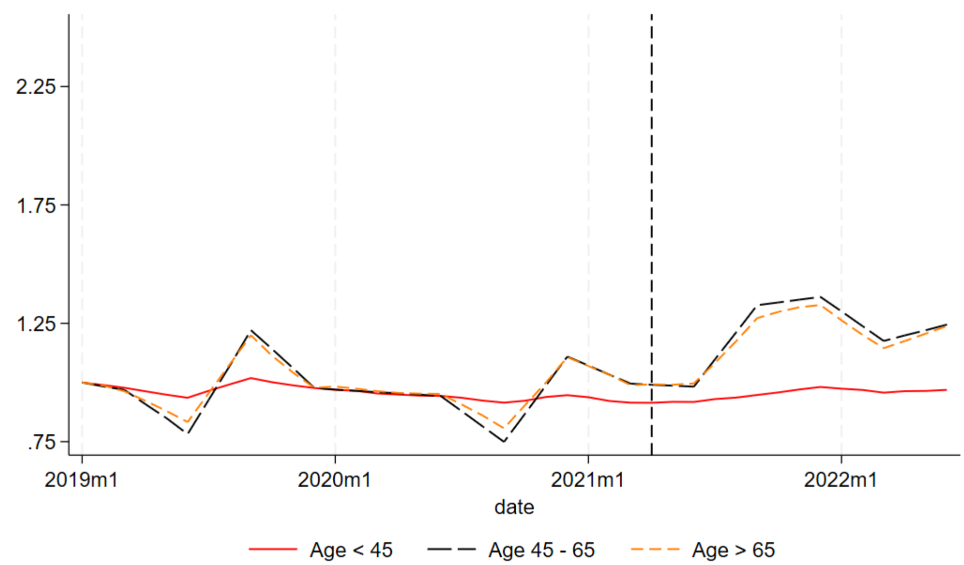
[9] In fact, there are no clear cohort differences in re-anchoring in the data.

[10] The SCE data is released only with a lag so the same nowcasting exercise is not feasible in this dataset.

Figure 5. De-Anchoring of Inflation Expectations and the Importance of Similarity



Panel A: Selective Memory Model



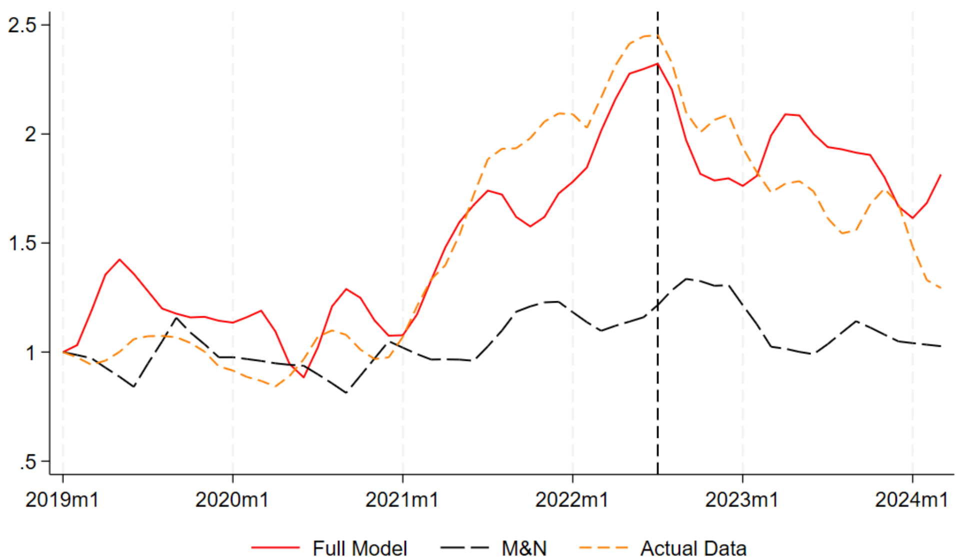
Panel B*:* Malmendier and Nagel Model

Notes: The top panel (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 5 of Table 1 but 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. In order to maintain comparability, the model is calibrated on the SCE timeframe (June 2013 – June 2022). The actual forecast and the predictions are expressed as a fraction of their value in January 2019. The dashed vertical line marks April 2021.

The results of this second exercise confirm the importance of selective memory in accounting for the data and are reported in Figure 6. First, just like Figure 5 shows, the predicted aggregate inflation expectations under the memory model (black line) are a good match to the actual evolution of inflation expectations in the data (blue line). We already saw that, due to similarity, the model generates a rise of aggregate inflation expectations in the face of surging inflation. Critically, 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 6. 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 produces stability in inflation expectations.

On the other hand, the experience-based learning model cannot produce realistic anchoring and re-anchoring. This is again due to the fact that 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 an 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 cognitive mechanism whereby experiences affect beliefs: selective memory.

Figure 6. 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 5 of Table 1 but 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. In order to maintain comparability, the model is calibrated on the SCE timeframe (June 2013 – June 2022). 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.

6. Conclusion

Memory models, with their emphasis on similarity, frequency and interference, appear to be a promising way to study household inflation expectations. The role of past experiences for belief formation has long been documented in social science (see, e.g. Weinstein 1989). In economics, Malmendier and Nagel (2011, 2016) showed the importance of inflation or stock market experiences for belief formation in these markets. For understanding the world, 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, they allow us to capture realistic state and cohort dependence in belief formation, as well as a time varying inconsistency across different belief elicitations. These features cannot be explained by full Bayesian learning or learning from experiences models. Recent evidence such as Cenzon (2025) or Butera et al. (2024) 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 (2025) and Bonaglia et al. (2025) show that this mechanism endogenizes observed forms of 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 focuses on memory. Selective attention may also play an important role. In a thought-provoking paper, Link et al. (2025) show that German households and firm managers who experienced high inflation tend to attend to inflation more and increase more their attention to inflation during the 2021-2 inflation surge, thereby revising up their expected inflation more strongly compared to 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. (2025). Studying the joint roles of memory and attention for belief formation is a promising avenue for future work, both theoretical and empirical, given the growing availability of measurement of recall (Jiang et al. 2025) and attention (Haaland et al. 2025) together with beliefs.

Our approach may also be relevant at a macroeconomic level, for the theory of monetary policy. Interest rate policies or announcements that are normatively optimal under rationality may be suboptimal under associative memory, for instance because they may cue episodes of market instability, destabilizing investor beliefs. 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 may be replicated to obtain real-time inflation expectations exactly when no real-time expectations measurements are available, but desirable to have. All that is needed, as we illustrated, 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, 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.

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APPENDIX

Proofs.

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

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

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

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

and first derivatives:

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

$$=\frac{-\left[\sum_{s=1,\dots,a}\left(\frac{s}{a}\right)\cdot\pi_{t-s}\right]}{a}+\frac{\left[\sum_{s=1,\dots,a}\pi_{t-s}\right]\left[\sum_{s=1,\dots,a}\frac{s}{a}\right]}{a^2}$$

$$=-\overline{\left(\frac{s}{a}\right)\cdot\pi_{t-s}}+\overline{\pi_{t-s}}\cdot\overline{\left(\frac{s}{a}\right)}=-cov\left(\frac{s}{a},\pi_{t-s}\right)$$

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

$$=\frac{\left[\sum_{s=1,\dots,a}\left(\frac{s}{a}\right)^2\cdot\pi_{t-s}\right]}{a}-\frac{\left[\sum_{s=1,\dots,a}\pi_{t-s}\right]\left[\sum_{s=1,\dots,a}\left(\frac{s}{a}\right)^2\right]}{a^2}$$

$$=\overline{\left(\frac{s}{a}\right)^2\cdot\pi_{t-s}}-\overline{\pi_{t-s}}\cdot\overline{\left(\frac{s}{a}\right)^2}=cov\left(\left(\frac{s}{a}\right)^2,\pi_{t-s}\right)$$

where upper bars denote arithmetic averages, and

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

$$+\frac{\left[\sum_{s=1,\dots,a}\pi_{t-s}\right]\left[\sum_{s=1,\dots,a}q\cdot(\pi_{t-s}-\pi_t)^2+(1-q)\cdot(\pi_{t-s}-\overline{\pi}_{t-1})^2\right]}{a^2}$$

$$=-q\cdot cov[\pi_{t-s},(\pi_{t-s}-\pi_t)^2]-(1-q)\cdot cov[\pi_{t-s},(\pi_{t-s}-\overline{\pi}_{t-1})^2],$$

which yields the desired result.

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

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

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

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

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

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

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

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

and

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

which yields the desired result.

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

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

$$\left. \cdot \frac{\sum_u \sum_{\pi_{t-s}=\pi_u} e^{\beta_1\left(\frac{s}{a}\right)^2 - \beta_2\left(\frac{s}{a}\right) - \sigma\cdot q\cdot(\pi_u - \pi_t)^2}}{\sum_u \sum_{\pi_{t-s}=\pi_u} e^{\beta_1\left(\frac{s}{a}\right)^2 - \beta_2\left(\frac{s}{a}\right) - \sigma\cdot q(\pi_u - \pi_t)^2 - \sigma\cdot q\cdot(\pi_u - \overline{\pi}_{t-1})^2}} \right] \cdot \Pr\left(F_j|\pi_{t,E_j}\right) \cdot \pi_j$$

$$= \sum\nolimits_j \left[\frac{e^{-\sigma\cdot q\cdot\left(\pi_j - \overline{\pi}_{t-1}\right)^2} \sum_u \sum_{\pi_{t-s}=\pi_u} e^{\beta_1\left(\frac{s}{a}\right)^2 - \beta_2\left(\frac{s}{a}\right) - \sigma\cdot q\cdot(\pi_u - \pi_t)^2}}{\sum_u e^{-\sigma\cdot q\cdot(\pi_u - \overline{\pi}_{t-1})^2} \sum_{\pi_{t-s}=\pi_u} e^{\beta_1\left(\frac{s}{a}\right)^2 - \beta_2\left(\frac{s}{a}\right) - \sigma\cdot q\cdot(\pi_u - \pi_t)^2}} \right] \cdot \Pr\left(E_j|\pi_{t,E_j}\right) \cdot \pi_j.$$

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

$$\mathbb{E}(\pi_{t+1}|\pi_{t,\mathbb{R}}) = \sum\nolimits_j \Pr\left(E_j|\pi_{t,E_j}\right) \cdot \pi_j = \mathbb{E}(\pi_{t+1}|\mathrm{DF}),$$

and first derivatives:

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

and

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

which yields the desired result:

$$\mathbb{E}(\pi_{t+1}|\pi_{t,\mathbb{R}}) \approx \mathbb{E}(\pi_{t+1}|\mathrm{DF}) + \sigma \cdot q \cdot \sum\nolimits_j \left[\overline{(\pi_u - \overline{\pi}_{t-1})^2} - \left(\pi_j - \overline{\pi}_{t-1}\right)^2 \right] \cdot \Pr\left(E_j|\pi_{t,E_j}\right) \cdot \pi_j$$

$$= \mathbb{E}(\pi_{t+1}|\mathrm{DF}) + \sigma \cdot q \cdot \mathbb{E}\left[\pi_{t+1} \cdot \left(\overline{d_{j,t}} - d_{t+1,t}\right)|\mathrm{DF}\right].$$

Tables and Figures

Table A1. Robustness: Huber Robust Regressions

	(1)	(2)	(3)	(4)	(5)
	One-year ahead Infl. Exp.				
Panel A. MSC					
Average Experienced Inflation	0.205***	0.276***	0.444***	0.419***	0.154***
	(0.015)	(0.033)	(0.036)	(0.034)	(0.028)
$Cov(s^2,\pi_{t-s}) /a^2$		0.128	1.460***	1.141***	-0.405
		(0.273)	(0.307)	(0.289)	(0.286)
$Cov(s,\pi_{t-s})/a$		-0.481	-2.194***	-1.715***	0.713**
		(0.360)	(0.400)	(0.382)	(0.353)
$Cov((\pi_{t-s}-\overline{\pi}_{it-1})^2,\pi_{t-s})$			-0.001	-0.000	0.001**
			(0.000)	(0.001)	(0.001)
$Cov((\pi_{t-s}- \pi_t)^2,\pi_{t-s})$			-0.002***	-0.002***	-0.004***
			(0.000)	(0.000)	(0.000)
SPF				0.533***	0.139***
				(0.069)	(0.032)
Constant	2.453***	2.190***	1.649***	0.035	2.205***
	(0.065)	(0.128)	(0.132)	(0.227)	(0.054)
Observations	224,223	224,238	224,203	213,299	213,271
R-squared	0.101	0.101	0.104	0.054	0.030
Panel B. SCE					
Average Experienced Inflation	0.451***	0.726***	1.098***	0.895***	2.066***
	(0.027)	(0.088)	(0.142)	(0.126)	(0.124)
$Cov(s^2,\pi_{t-s}) /a^2$		1.330	2.923***	1.432	10.155***
		(0.984)	(1.055)	(0.949)	(1.072)
$Cov(s,\pi_{t-s})/a$		-2.640*	-5.100***	-2.881**	-15.993***
		(1.345)	(1.480)	(1.316)	(1.524)
$Cov((\pi_{t-s}-\overline{\pi}_{it-1})^2,\pi_{t-s})$			-0.003	-0.002	-0.006**
			(0.003)	(0.003)	(0.002)
$Cov((\pi_{t-s}- \pi_t)^2,\pi_{t-s})$			-0.002***	-0.002***	-0.005***
			(0.000)	(0.000)	(0.000)
SPF				1.153***	1.426***
				(0.190)	(0.109)
Constant	2.219***	1.748***	0.881***	-1.203**	-4.132***
	(0.074)	(0.164)	(0.328)	(0.528)	(0.347)
Observations	126,595	126,543	126,577	126,580	126,676
R-squared	0.135	0.136	0.138	0.141	0.121
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 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 A2. Quantification Table, MSC

	Effect SD Increase	Average	SD
Average Experienced Inflation	0.72	4.04	1.31
$Cov(s^2,\pi_{t-s})/a^2$	0.82	0.07	0.40
$Cov(s,\pi_{t-s})/a$	-1.04	0.08	0.37
$Cov((\pi_{t-s}-\overline{\pi}_{it-1})^2,\pi_{t-s})$	-0.11	24.37	38.33
$Cov((\pi_{t-s}-\pi_t)^2,\pi_{t-s})$	-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 A3. Quantification Table, SCE

	Effect SD Increase	Average	SD
Average Experienced Inflation	0.74	3.00	0.80
$Cov(s^2,\pi_{t-s})/a^2$	1.42	0.28	0.22
$Cov(s,\pi_{t-s})/a$	-1.66	0.27	0.20
$Cov((\pi_{t-s}-\overline{\pi}_{it-1})^2,\pi_{t-s})$	-0.18	-3.71	20.29
$Cov((\pi_{t-s}-\pi_t)^2,\pi_{t-s})$	-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 A4. Medium-Term Inflation Expectations, Experience and Selective Recall

	(1)	(2)	(3)	(4)	(5)
	Medium-Term Inflation Expectations (t+24, t+36)				
Average Experienced Inflation: $\overline{\pi}_{t-1}$:	0.148*	0.259	0.945**	0.940**	1.707***
	(0.082)	(0.253)	(0.359)	(0.377)	(0.352)
Temporal Context Quadratic Component : $Cov(s^2,\pi_{t-s}) /a^2$		0.406	0.585*	0.581	1.397***
		(0.334)	(0.347)	(0.362)	(0.333)
Temporal Context Linear Component: $Cov(s,\pi_{t-s})/a$		-1.443	-2.375	-2.355	-5.926***
		(1.368)	(1.431)	(1.501)	(1.389)
Dissimilarity average inflation: $Cov((\pi_{t-s}-\overline{\pi}_{it-1})^2,\pi_{t-s})$			-0.018***	-0.018***	-0.017**
			(0.007)	(0.007)	(0.006)
Dissimilarity current inflation: $Cov((\pi_{t-s}- \pi_t)^2,\pi_{t-s})$			-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

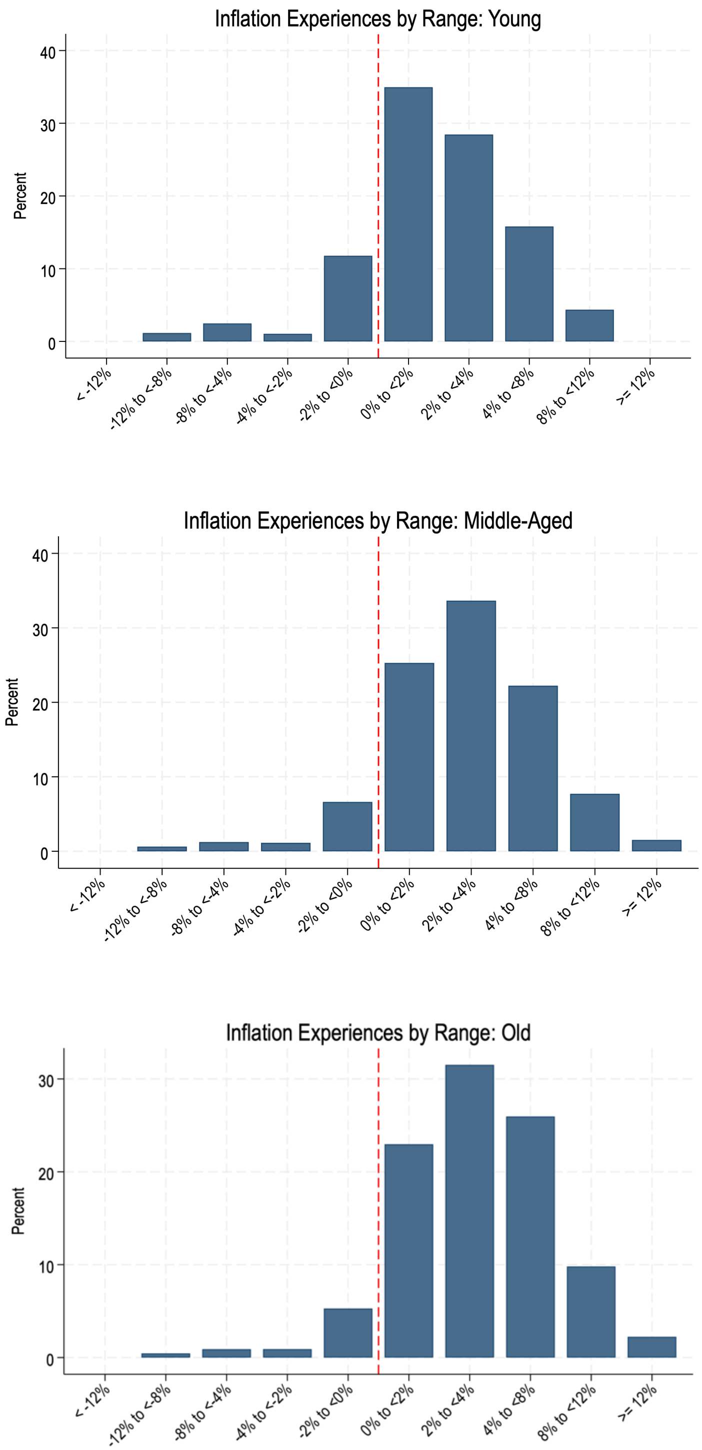
Notes: The table reports the estimates of the first-order linear approximation of a learning from experience model, augmented with similarity and a quadratic recency term. Demographic characteristics include sex, education, income quintile and marital status. The database of inflation experiences includes 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 A5. Robustness: Annually Recorded Inflation Experiences

	(1)	(2)	(3)	(4)	(5)
	One-year ahead Infl. Exp.				
Panel A. MSC					
Average Experienced Inflation	0.282***	0.334***	0.555***	0.535***	0.299***
	(0.027)	(0.062)	(0.071)	(0.067)	(0.052)
$Cov(s^2,\pi_{t-s})/a^2$		0.012	2.261***	1.822***	1.154**
		(0.534)	(0.606)	(0.542)	(0.481)
$Cov(s,\pi_{t-s})/a$		-0.309	-3.126***	-2.495***	-1.052*
		(0.711)	(0.800)	(0.726)	(0.601)
$Cov((\pi_{t-s}-\overline{\pi}_{it-1})^2,\pi_{t-s})$			-0.003***	-0.003**	-0.002*
			(0.001)	(0.001)	(0.001)
$Cov((\pi_{t-s}-\pi_t)^2,\pi_{t-s})$			-0.002***	-0.003***	-0.005***
			(0.001)	(0.000)	(0.001)
SPF				0.679***	0.261***
				(0.136)	(0.056)
Constant	0.282***	0.334***	0.555***	0.535***	0.299***
	(0.027)	(0.062)	(0.071)	(0.067)	(0.052)
Observations	238,617	238,620	238,593	226,642	226,607
R-squared	0.108	0.108	0.111	0.054	0.030
Panel B. SCE					
Average Experienced Inflation	0.209***	0.041	0.361	0.264	2.058***
	(0.075)	(0.370)	(0.402)	(0.394)	(0.363)
$Cov(s^2,\pi_{t-s})/a^2$		0.082	0.173	0.053	2.444***
		(0.465)	(0.457)	(0.445)	(0.447)
$Cov(s,\pi_{t-s})/a$		-0.013	-0.384	0.128	-10.016***
		(1.986)	(1.946)	(1.895)	(1.868)
$Cov((\pi_{t-s}-\overline{\pi}_{it-1})^2,\pi_{t-s})$			-0.011	-0.011	0.000
			(0.010)	(0.010)	(0.010)
$Cov((\pi_{t-s}-\pi_t)^2,\pi_{t-s})$			-0.002	-0.002	-0.010***
			(0.001)	(0.001)	(0.002)
SPF				0.932**	1.946***
				(0.384)	(0.327)
Constant	5.705***	6.033***	5.359***	3.482***	-1.547
	(0.219)	(0.604)	(0.706)	(1.079)	(0.983)
Observations	139,555	139,555	139,555	139,555	139,555
R-squared	0.115	0.115	0.115	0.115	0.102
Demographic Fixed Effects	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	NO

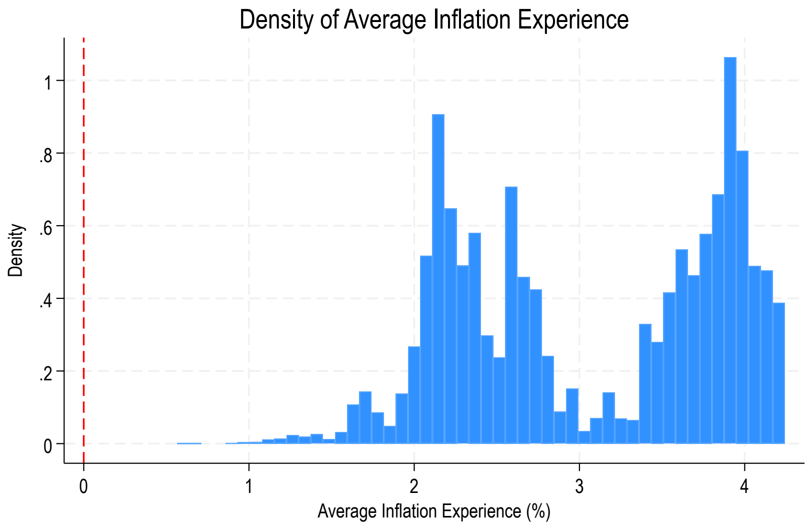
Notes: The table reports the estimates of the first-order approximation of learning from experience model, augmented with similarity and a quadratic recency term. Demographic characteristics include sex, education, income quintile and marital status. The database of inflation experiences includes the 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.

Figure A1. Inflation Experiences by Age



Notes: This figure presents distributions of annualized US quarterly CPI inflation rates across inflation ranges January 2020 for different age groups. Bars in each range show the share of total population experiences that falls into the respective range, weighted in each age group using respondent survey-weights. The young are of age <45, the middle-age of age 45-65 and the old of age >65.

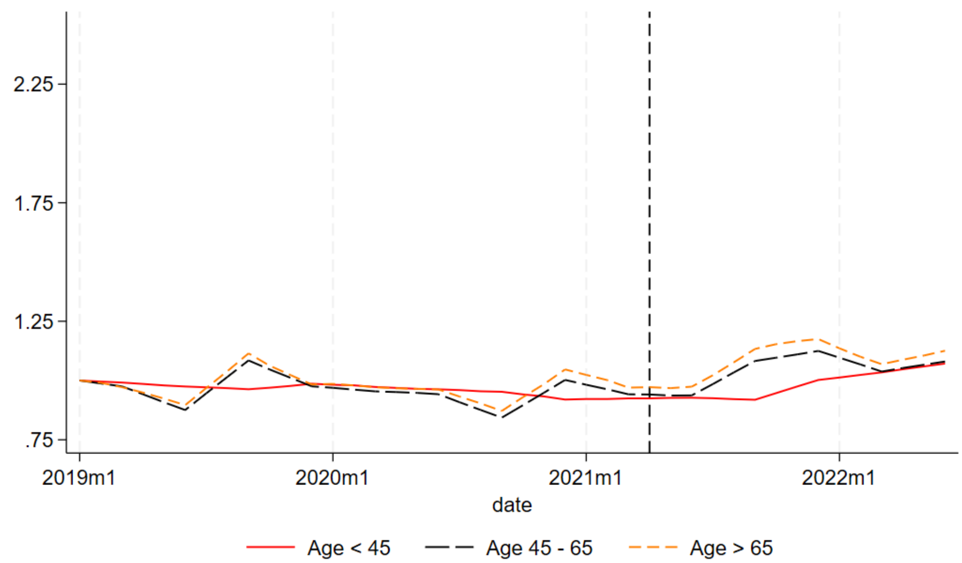
Figure A2: Average Inflation Experiences



Notes: This figure shows the average lifetime inflation experience in the population for January 2020. Inflation is measured by annualized US quarterly CPI inflation rates. The vertical red dashed line denotes 0% inflation.

Figure A3: 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 5 of Table 1 but 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 1978-2022 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.