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Nicola Gennaioli
Marta Leva
Raphael Schoenle
Andrei Shleifer

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ABSTRACT

In a model of memory and selective recall, household inflation expectations remain rigid when inflation is anchored but exhibit sharp instability during inflation surges, as similarity prompts retrieval of forgotten high-inflation experiences. Using data from the New York Fed's Survey of Consumer Expectations and the University of Michigan's Consumer Survey, we show that similarity can quantitatively account for the sharp post-pandemic rise in inflation expectations, particularly among the elderly. The memory-based model also accounts for how people estimate future inflation ranges and why they neglect infrequent experiences when forming point expectations. These predictions are likewise supported by the data.

Nicola Gennaioli
Department of Finance
Università Bocconi
Via Roentgen 1
20136 Milan, Italy
nicola.gennaioli@unibocconi.it

Marta Leva
Università Bocconi
marta.leva@studbocconi.it

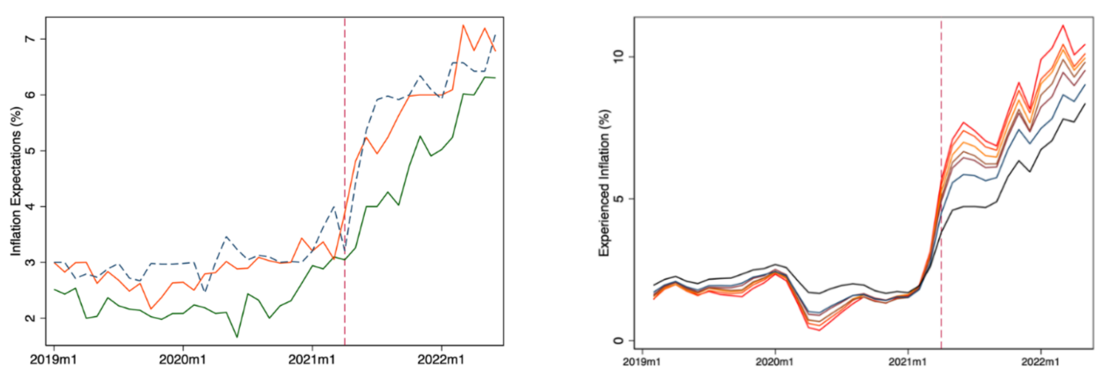
Raphael Schoenle
Brandeis University
Department of Economics
415 South Street
Waltham, MA 02454
and CEPR
schoenle@brandeis.edu

Andrei Shleifer
Department of Economics
Harvard University
Littauer Center M-9
Cambridge, MA 02138
and NBER
ashleifer@harvard.edu

1. Introduction

Following the post-pandemic surge in inflation, there is a growing interest in understanding how households form their expectations about inflation. In macroeconomic models, these expectations play an important role in wage setting, durable good consumption, investment decisions, and in the setting of monetary policy. The conventional wisdom is that households' inflation expectations are sticky, anchored to past experiences. Malmendier and Nagel (2011, 2016, 2021) show that such expectations depend on a time-discounted average of lifetime inflation experiences, which of course only gradually adjusts to recent events. Other papers show that household inflation expectations anchor also to recent prices of groceries and gasoline (e.g. d'Acunto et al. (2022, 2023, 2024), Cavallo et al. (2017), Coibion and Gorodnichenko (2015), Gelman et al. (2016), Binder (2018)). Due to such idiosyncratic experiences, expectations are more volatile, also in the cross section, but remain fundamentally backward looking.

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



Panel A (left) shows the 12-month ahead median inflation expectations in the New York Fed's Survey of Consumer Expectations for respondents 45 years old or younger (lower-envelope green line), 45-65 years old (orange line) or 65+ years old (dashed blue 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 green to red.

Yet the evidence from the recent inflation surge does not support stickiness, nor does it align with a simple effect of past or recent experiences. Figure 1, Panel A, reports the evolution of inflation expectations from 2019 to 2023 in the Survey of Consumer Expectations by the New York Fed. Around April 2021, inflation expectations in the US sharply 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 occurs for all age groups, but the elderly (dashed blue line) react faster and more strongly than the young (lower-envelope green line). This is surprising: in standard accounts, the elderly should exhibit higher inflation expectations than the young due to higher lifetime inflation experiences. But they should react to recent events *less* than the young: a recent experience has less impact on the elderly's 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.

What explains such sharp belief updating, especially by the elderly? We argue that selective memory, in particular the hitherto neglected role of memory cues, can answer this question. Intuitively, high inflation today cues people to recall their similarly high inflation experiences. As the elderly see high inflation, they are reminded of high inflation they saw in the past. They then sharply revise their beliefs upward because they automatically *select* high inflation experiences from their database. The effect of course also accounts for eventual de-anchoring by the young: as their database is filled with high inflation experiences, they also recall those selectively, provided inflation stays high, revising their beliefs upwards. Similarity-based recall can yield sharp movements in expectations from changing cues.

Building on this intuition, we present a memory-based model of inflation expectations and use it to analyze these effects in the data. The model builds on three regularities of human recall. First, recall of an experienced inflation level increases in its past experienced frequency. Second, recall is associative: it increases in similarity between the inflation experience and the inflation event the agent is assessing. Third, different experiences interfere with each other in recall, so that a more similar or frequent inflation level inhibits recollection of less similar or frequent levels.

Following memory research (Kahana 2012), similarity depends on both the context and the numerical inflation level. Context yields well-established primacy and recency effects. *Ceteris paribus*, recent inflation is easier to retrieve because its temporal context is similar to the present. Early inflation experiences are easier to retrieve because they have been rehearsed more often, so they spontaneously come to mind when imagining inflation. Due to these effects, the probability of recalling an inflation experience should be inverse U-shaped in its distance from the present. The second driver of recall, numerical similarity, increases the recollection of past inflation rates that are closer to those the agent is thinking about. When current inflation is 3%, inflation rates close to 3% more easily come to mind.

This model generates inflation expectations via several channels. In line with existing work, it allows for recency effects (Nagel and Malmendier (2011, 2016); Nagel and Xu (2022)), but it also allows for primacy effects, which cause persistent belief differences across cohorts. Numerical similarity yields state-dependence, and hence memory based de-anchoring: as people see a jump in inflation, say from 2% to 10%, they start selectively recalling inflation levels around 10%. This effect is especially strong for people who have more 10% experiences (the elderly), even if these experiences reside in the remote past. A second implication of numerical similarity is that measured beliefs depend on whether a person is asked to report her point expectation or the probabilities of different inflation ranges. When forming her point expectation, she may neglect ranges she infrequently experienced. Yet, when prompted to think about these ranges, she may selectively recall experiences of them. The principle is again that, as numerical cues change, so do retrieval and beliefs.

We test these predictions using 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) and find supportive evidence for recency, primacy, and numerical similarity, pointing to the crucial role of selective memory for household expectation formation in macroeconomic contexts. The central finding is that numerical similarity is quantitatively needed to account for de-anchoring of expectations around April

2021. Recency effects cannot explain all of: i) the stability of expectations in the pre-2021 period, ii) their sharp rise in April 2021, and iii) the strong de-anchoring by the elderly. Selective recall explains why inflation expectations are neither always rigid nor always volatile. When inflation is low and anchored, expectations are rigid because dissimilar experiences of high and unstable inflation are not retrieved. But the same expectations quickly de-anchor when inflation rises sharply.

The literature on household inflation expectations is large and points not only to the role of experiences, but also of demographics (Manski (2004, 2018); d'Acunto et al. (2021a, 2021b), Bruine de Bruin et al. (2010) and Armantier et al. (2013)).[1] Hajdini et al. (2024) confirm the role of experiences in recent and also international data while Goldfayn and Wohlfart (2020), Braggion et al. (2024), and Salle et al. (2024) provide evidence for the importance of historical experiences for inflation or disinflationary expectations. Andre et al. (2022) stress mental models in recall which Zuellig (2022) quantifies in the inflation expectations context. D'Acunto and Weber (2022) highlight the role of memory based on detailed data on grocery shopping behavior and prices. Another approach, used also for professional forecasters, emphasizes inattention due to processing costs (Sims 2003, Woodford 2009), which also gives rigidity in belief updating (Carroll (2003), Carroll et al. (2020) or Bracha and Tang (2022)).

Our innovation is to build, following Bordalo et al. (2022), a model of selective recall based on the cognitive structure of cues and similarity, and to quantify its effects. This approach differs from the more reduced-form approach to belief overreaction in Bordalo et al. (2018), Maxted (2024), L'Huillier et al. (2023), or Bianchi et al. (2024a, 2024b). Selective memory allows us to reconcile pre-pandemic rigidity with the volatility in 2021, and to study the inconsistency between point expectations and beliefs about inflation ranges (beliefs are often measured using these ranges), finding support in the data.

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

2. The Model

2.1 The Memory Database, the Cue, and Similarity

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

The Database, the Cue and Similarity. The database $\Pi_t = (\pi_{t-s})_{s=1,\ldots,a}$ collects the inflation levels observed by the agent in the past, starting from a periods ago. a is the agent's "effective age" (i.e. the age of her personal inflation records). The inflation cue is a salient signal prompting retrieval from Π_t. Cues play a central role in selective recall (see Kahana 2012). When asked to recall the event "white things in the kitchen", people may recall "plates" but forget "yogurt." Yogurt may however come to mind if the task is to recall the event "white things in the fridge", for yogurt is associated with the fridge location. Here the cue is the question\event (e.g. kitchen, fridge) that must be assessed, which prompts retrieval of similar experiences (e.g., plates, yogurt).

For our purposes, the cue is the future inflation scenario the agent is evaluating at time t, denoted by $\pi_{t,t+1}$, which ignites selective retrieval of past inflation experiences π_{t-s} based on similarity. We formalize similarity as shaped by the cue's numerical value and temporal context (Kahana 2012). Numerical similarity is intuitive: if the agent assesses the probability of inflation at 10%, experiences close to 10% are more similar to the cue and hence easier to recall. The temporal context in which the evaluation takes place also matters, for two reasons. First, because the current realized inflation level π_t is top of mind. This effect also works numerically and fosters retrieval of inflation levels similar to current inflation regardless of the future event the agent is evaluating. Second, temporal context captures broader aggregate or subjective conditions, which influence similarity and hence recall along the time dimension. Such temporal context effects are the foundation for the well-established recency and primacy effects (Kahana 2012). When recalling words from a list, the first (primacy) and last (recency) studied words are recalled best. The last word shares temporal context with the present, thus being more similar to the current cue. The first word studied is often rehearsed, so it persistently taints the "word list" context. As a result, it is similar to almost any cue about it.

In our domain, when thinking today about future inflation, the agent on the one hand more easily recalls last year's inflation (recency) due to similar temporal context (e.g. aggregate or personal states). At the same time, she also ceteris paribus more easily recalls early-life inflation experiences (primacy), compared to, say, inflation four years ago, because she had more opportunities to rehearse and re-live early inflation experiences during her lifetime, strengthening their memories.

Formally, we model similarity as decreasing in a measure of discrepancy $d\left(\pi_{t-s}, \pi_{t,t+1}\right)$ between the past experience π_{t-s} and the cue $\pi_{t,t+1}$ along numerical and temporal context. Specifically, we assume the functional form:

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

The first term $\sigma_1 \cdot \left(\pi_{t-s} - \pi_{t,t+1}\right)^2$ captures numerical dissimilarity between the experienced inflation π_{t-s} and the future event $\pi_{t,t+1}$ the agent is evaluating. If the agent is thinking about the possibility that future inflation is $\pi_{t,t+1} = 6\%$, experienced inflation levels closer to 6% are more similar, and thus ceteris paribus easier to recall. Parameter $\sigma_1 \geq 0$ captures the importance of this force.

The next two terms concern the broader temporal context. Term $\sigma_2 \cdot (\pi_{t-s} - \pi_t)^2$ captures the current inflation context. If current inflation is $\pi_t = 3\%$, experienced inflation levels closer to 3% are more similar to the current inflation context being thus ceteris paribus easier to retrieve. 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 current inflation vs the future event cues, and σ the strength of numerical similarity. The term containing the function $\beta(s/a)$ captures primacy and recency effects, which depend on the delay s between the experience and the current cue, expressed as a share of the agent's effective age. To account for both effects, we assume that $\beta(s/a)$ is inverse U-shaped in s, taking the quadratic form $\beta(x) = -\beta_1 \cdot x^2 + \beta_2 \cdot x$ with parameters $\beta_1 \geq 0$ and $\beta_2 \geq 0$.

Recall. The agent forms her expectation by recalling past experiences based on their similarity to the cue. As is common in many memory models, we assume that similarity decreases exponentially with the discrepancy function, $S(\pi_{t-s}, \pi_{t,t+1}) = e^{-d(\pi_{t-s}, \pi_{t,t+1})}$. The probability of recalling past experience π_{t-s} is then proportional to its similarity with $\pi_{t,t+1}$:

$$\Pr(\pi_{t-s}|\pi_{t,t+1}) \propto S(\pi_{t-s}, \pi_{t,t+1}), \tag{2}$$

where the normalization constant ensures that probabilities add to one in the database Π_t. Normalization captures interference. From the cue-stimulus, different experiences compete in recall. Ceteris paribus, it is easier to retrieve a specific experienced inflation level, say $\pi = 10\%$, compared to another, say $\pi' = 2\%$, if the former is relatively more similar to the cue $\pi_{t,t+1}$ both numerically and in temporal context, and if it has occurred more frequently, as in being repeated more often in Π_t.

To form beliefs, the agent samples her database Π_t sufficiently many times that the distribution of retrieved inflation levels can be approximated by (2). This distribution is then used to form beliefs about future inflation. In particular, the believed probability of an inflation event $E \subset \mathbb{R}$, such as $E = [0\%, 2\%]$ over the next 12 months, is given by:

$$\Pr(E|\pi_{t,E}) = \sum_{\pi_{t-s} \in E \cap \Pi_t} \Pr(\pi_{t-s}|\pi_{t,E}), \tag{3}$$

where $\pi_{t,E}$ is the cue corresponding to E. Point expectations are given by the average retrieved value:

$$\mathbb{E}(\pi_{t+1}|\pi_{t,\mathbb{R}}) = \sum_{\pi_{t-s} \in \Pi_t} \Pr(\pi_{t-s}|\pi_{t,\mathbb{R}}) \cdot \pi_{t-s}, \tag{4}$$

where we assume that, when forming point expectations, the agent is cued by the entire range of possible inflation levels, $E = \mathbb{R}$. Equations (3) and (4) are the key objects that we match to survey data.

2.2 Model Predictions

The model's testable predictions rely on two objects. The first is the database of experiences Π_t, which varies across respondents with different ages a, and over time due to changes in realized inflation π_t. This database is observable from historical data. The second is the cue, $\pi_{t,E}$, which depends on the inflation range the agent is thinking about, because this range covers different scenarios. Variation in inflation and survey questions is observable, but the exact value of the cue is not. To make progress, we assume that if the agent is thinking about event $E \subset \mathbb{R}$, say $E = [0\%, 2\%]$, the numerical cue is her average past experience in this same range E. This implies that distance (1) becomes:

$$d(\pi_{t-s}; E, \pi_t) = \sigma \cdot (1-q) \cdot \left(\pi_{t-s} - \bar{\pi}_{E,t-1}\right)^2 + \sigma \cdot q \cdot (\pi_{t-s} - \pi_t)^2 - \beta_1 \cdot (s/a)^2 + \beta_2 \cdot (s/a), \quad (5)$$

where $\bar{\pi}_{E,t-1} = \frac{\sum_{E \cap \Pi_{t-1}} \pi_{t-s}}{|E \cap \Pi_{t-1}|}$ is average experiences with the event E in the question up to $t-1$.[2]

Point Expectations. 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), is a respondent's point expectation about inflation at a future time (e.g. 12 months ahead). This question concerns the full inflation support, $E = \mathbb{R}$, so that $\bar{\pi}_{E,t-1} = \bar{\pi}_{t-1}$, which is the agent's average experienced inflation up to $t-1$. Our model then makes the following prediction.

[2] The specification of distance in Equation (6) can also be interpreted as capturing the idea that the similarity of experience to the question E and the current inflation state π_t is given by the weighted product of its similarity to them. Little changes if we alternatively specify the cue as the convex combination $\pi_{t,t+1} = (1-q)\bar{\pi}_{E,t-1} + q\pi_t$.

Proposition 1 *The linear approximation of a respondent's point inflation expectations with respect to* β_1*,* β_2 *and* σ *around* $\beta_1 = \beta_2 = \sigma = 0$*, is given by:*

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

$$-\sigma \cdot (1-q) \cdot cov[\pi_{t-s}, (\pi_{t-s} - \overline{\pi}_{t-1})^2] - \sigma \cdot q \cdot cov[\pi_{t-s}, (\pi_{t-s} - \pi_t)^2]. \quad (6)$$

Our analysis estimates this equation using point expectations data. The first determinant of expectations is a respondent's average experienced inflation $\overline{\pi}_{t-1}$. People who have experienced higher inflation during their lifetimes, higher $\overline{\pi}_{t-1}$, ceteris paribus expect higher inflation in the future. From the viewpoint of memory, this effect captures the first order influence of the database Π_t.

The second determinant of recall is the primacy or recency of experiences, respectively captured by $\beta_1 \cdot cov[(s/a)^2, \pi_{t-s}]$ and $-\beta_2 \cdot cov(s/a, \pi_{t-s})$. To see whether primacy or recency dominates, one needs to compute the relative extremum of the function. If this point lies above 0.5, which occurs when $\beta_2 > \beta_1$, then recency dominates, as the very last episodes have higher weight than the very first. The opposite happens if this point lies below 0.5, in which case one would conclude that primacy has a stronger effect. Unlike similarity, this retrieval mechanism is not sensitive to the value of current inflation π_t. It captures weighting experiences according to the date when they occurred.

The third determinant of expectations is numerical similarity to the inflation cue. If $\sigma > 0$ periods of high inflation cause overweighting of a person's higher inflation experiences compared to her lower ones. A persistent surge of inflation may then cause a sharp upward revision of expectations, but especially by people whose high inflation experiences are similar to actual inflation π_t (capturing similarity to the current inflation context) and to the average cue $\overline{\pi}_{t-1}$ (capturing similarity to the future event people are thinking about). Numerical similar triggers sharp and heterogeneous updating. This is why similarity may prompt recall of high inflation experiences, *regardless of how remote they are in the past*.

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 cognitively realistic memory perspective stresses 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 $\overline{\pi}_{t-1}$ is barely affected by recent events. Temporal context (the second term) enriches the picture. If recency dominates, a person's expectations tend to overweight recent events, as in Malmendier and Nagel (2011, 2016) or Nagel and Xu (2022), which strengthens the reactivity of beliefs. Dominance of primacy, on the contrary, enhances rigidity. Although it is a priori unclear whether primacy or recency dominate, both forces imply that expectations should be less reactive to news for the elderly than for the young, because they cause overweighting of specific time-stamped experiences in a database that for the elderly is very slow moving.

Numerical similarity to cues (the third and fourth terms) changes matters sharply, introducing a state-dependent element into the formation of inflation expectations. That is, numerical similarity can cause a strong reaction to recent news, because it leads individuals to selectively sample similar experiences in their past. This may superficially appear like a recency effect but it is not. As already argued, it can cause a strong belief change by the elderly, despite their slow-moving database, by cueing recall of high inflation experiences that were previously "dormant" – due to dissimilarity – in low-inflation times. This prediction of selective memory can be tested using Equation (6).

Inflation events. The model can also be applied to study the judged probability of inflation events $E \subset \mathbb{R}$. As described in Data Section 3.1, 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 $j = 1,..,10$. Differences in memory databases are then captured by the experienced frequencies of different ranges. When assessing the probability of range j, the respondent is cued by the corresponding inflation event π_j, and by current realized inflation π_t.

Proposition 2 *Let n_j be the frequency of π_j. The linear approximation of a respondent's estimate for the odds of π_j versus a base π_b with respect to β_1, β_2 and σ around $\beta_1 = \beta_2 = \sigma = 0$, is given by:*

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

$$-\sigma \cdot q \cdot \frac{n_j}{n_b} \cdot \left[\left(\pi_j - \pi_t\right)^2 - (\pi_b - \pi_t)^2\right]. \tag{7}$$

The relative probability attached to range $j \neq b$ increases in its relative experienced frequency n_j/n_b, a pure database effect, but also in similarity. For a given frequency, when $\beta_1 > 0$, range j is deemed more likely if it is experienced more remotely than range b, $\bar{s}_j > \bar{s}_b$. The converse is true, due to recency, when $\beta_2 > 0$. These effects capture temporal context. When $\sigma > 0$ numerical similarity also matters: range j is deemed more likely if current inflation is closer to it compared to range b, the more so if it was more frequently experienced, that is, if n_j/n_b is higher. If inflation increases from 2% to 10%, the judged probability of the 10% range should go up for everybody, but especially so for people having lived more 10% inflation experiences. Beliefs about ranges are similarly state-dependent.

One important question for both survey design and for understanding the world concerns the consistency between elicited point expectations and elicited range probabilities. If beliefs obey the laws of probability, which include rational expectations, the two methods should be consistent because both beliefs are formed using the same probability space. This is not so with selective memory: when ranges are elicited, the survey question is about each event $E = \pi_j$, so it cues the range itself. When point expectations are elicited, the question is instead about the entire support $E = \mathbb{R}$, not about any specific range. In this latter case, then, each range π_j is less salient as a retrieval cue, so certain ranges may be downplayed, causing inconsistency between different elicitations.

A famous inconsistency in psychology, well documented in the lab, is the so-called "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 whether this inconsistency is present in the important field context of household inflation expectations. Our model allows us to analyze inconsistencies in different survey answers. To see this, note that Equations (3) and (4) imply:

$$\mathbb{E}(\pi_{t+1}|\mathbb{R},\pi_t) = \sum_j w_{jt} \cdot \Pr(\pi_j|\pi_j,\pi_t) \cdot \pi_j. \tag{8}$$

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 π_j used for making the point forecast and the directly elicited estimate for the same range, $w_{jt} = \frac{\Pr(\pi_j|\mathbb{R},\pi_t)}{\Pr(\pi_j|\pi_j,\pi_t)}$.

If the two estimates are consistent, which should be the case under any rational model, $w_{jt} = 1$. Point expectations should then be equal to the average inflation computed using range probabilities. This is not so with selective memory, in particular due to the numerical similarity cue, $\sigma > 0$.

Proposition 3 *Let* $\mathbb{E}(X_k|B) = \sum_k Pr(\pi_k|\pi_k,\pi_t) \cdot X_k$ *be the expectation of random variable* X_k *based on observed range estimates. Let* $d_{j,t} = \left(\pi_j - \overline{\pi}_{t-1}\right)^2$ *be the distance between range j and average inflation experiences. A linear approximation of* w_{jt} *with respect* β_1, β_2 *and* σ *around* $\beta_1 = \beta_2 = \sigma = 0$ *yields:*

$$\mathbb{E}(\pi_{t+1}|\mathbb{R},\pi_t) \approx \mathbb{E}(\pi_{t+1}|B) + \sigma \cdot q \cdot \mathbb{E}\left[\pi_j \cdot (\overline{d} - d_j)|B\right]. \tag{9}$$

Point and range-based expectations differ only if $\sigma > 0$. If so, the agent has higher point expectations compared to her range-based expectations whenever high inflation ranges are relatively more similar to her average experiences than low inflation ones, namely when d_j is lower than average at high inflation levels π_j. This implies that people who experienced lots of high inflation will insufficiently account for low inflation scenarios when forming point expectations, even though they partially correct themselves when explicitly assessing low inflation ranges. It also implies that during rising inflation, when the average experience $\overline{\pi}_{t-1}$ grows for many people, point-expected inflation will be high because everybody tends to exhibit higher neglect of experiences with low inflation ranges. In high inflation periods point expectations de-anchor also due to neglect of the possibility of low inflation scenarios.

The discrepancy between point and bin-based expectations is a clear test of the power of memory cues. It rejects any rational model, including models in which people may be learning in a Bayesian way (e.g. Markov-switching inflation regimes models). It can also 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 listening to a podcast on the risk of high inflation, but at the same time prefer a cheaper to a more expensive car because the car dealer's context does not cue high inflation risk. The role of experiences is mediated by memory cues.

3. Testing the Model's Predictions

Our empirical analysis first estimates the point expectations Equation (6) using the Michigan Survey of Consumers, MCS, and the New York Fed's SCE. We then move to beliefs about ranges, estimating Equations (7) and (9).

3.1 Data

The MCS 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 MCS 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 likewise based on a rotating panel and runs at a monthly frequency. The SCE consists of approximately 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. We exploit both point expectations and individual-level forecast densities. 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. The forecast density question asks respondents to report their probability assessments 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%. To facilitate subsequent estimations of range-related Equations (7) and (9), we apply appropriate adjustments to these ranges and the winsorization points, which we highlight for each estimation below.

Current and experienced realized inflation comes from the Shiller database (Shiller, 2005), which reports the monthly CPI back to 1871. We measure experiences at a quarterly frequency, using the annualized quarterly growth rate of the CPI. At 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 $a =$ (actual years of age $-16) * 4$. 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 consider alternative horizons for robustness. We also use data on professional CPI inflation forecasts from the Survey of Professional Forecasters (SPF).

3.2 Cues and Point Expectations

Our analysis gauges the importance of the different channels of the formation of inflation point expectations in the model as embodied in Equation (6) by estimating the following specification:

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

$$+\gamma_4 \cdot cov[\pi_{t-s}, (\pi_{t-s} - \overline{\pi}_{t-1})^2] + \gamma_5 \cdot cov[\pi_{t-s}, (\pi_{t-s} - \pi_t)^2]$$

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

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. We include the SPF inflation forecast $\pi_{SPF,t}^{e}$, because professional forecasts are prominent in the media, so the respondent's reported expectation likely combines her memory estimate with an aggregate signal (see Bordalo et al. 2024).

The key parameters linked to Equation (6) are γ_1, which should be positive if experiences matter, γ_2 and γ_3, which jointly determine existence of a temporal context effect and dominance of recency or primacy, and γ_4 and γ_5, which should be negative if numerical similarity matters. Table 1 reports the regression estimates for the MCS (Panel A) and the SCE (Panel B). We include different memory effects in progression from columns (1) to (4). In column (5) we exclude year dummies in order to assess the explanatory power of memory alone, without accounting for unobservable time varying factors.

Column (1) confirms experience effects: respondents who experienced higher average inflation report higher inflation expectations compared to the others. Is this effect mediated by selective retrieval? Column (2) assesses temporal context. There are different patterns in the MCS and SCE: in the MCS there is no significant effect of temporal context alone, while the latter is impactful and statistically significant in the SCE, with evidence supporting the coexistence of primacy and recency effects, with the predicted U-shaped pattern of expected inflation if high inflation experiences are either early or recent.

In Column (3) we include numerical similarity, running the full-fledged specification suggested by our model in Equation (6). Consistent with the predictions of selective memory, the estimated coefficients on numerical similarity are negative, so that people overweight their own high inflation experiences when these are more similar to current inflation as well as to the average experienced inflation in the course of their lifetime, which both act as cues. Now primacy and recency effects become more robust, and show up significantly also in the MSC. We thus find consistent strong evidence for the three leading memory effects: primacy, recency, and numerical similarity.

The memory effects remain strong and robust to including the SPF forecast, Column (4), and to dropping year dummies, Column (5). In fact, dropping year dummies has a fairly small effect on the explanatory power of the specification, its R^2, testifying to the ability of the selective memory model to account for variation in beliefs.

Table 1. Inflation Expectations, Experience and Selective Recall

	(1)	(2)	(3)	(4)	(5)
	One-year ahead Infl. Exp.				
Panel A. MCS					
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,π_{t-s}) /a^2		0.012	2.261***	1.822***	1.154**
		(0.534)	(0.606)	(0.542)	(0.481)
Cov(s,π_{t-s})/a		-0.309	-3.126***	-2.495***	-1.052*
		(0.711)	(0.800)	(0.726)	(0.601)
Cov((π_{t-s}-$\overline{\pi}_{it-1}$)^2,π_{t-s})			-0.003***	-0.003**	-0.002*
			(0.001)	(0.001)	(0.001)
Cov((π_{t-s}- π_t)^2,π_{t-s})			-0.002***	-0.003***	-0.005***
			(0.001)	(0.000)	(0.001)
SPF				0.679***	0.261***
				(0.136)	(0.056)
Constant	2.973***	2.772***	2.101***	-0.029	2.227***
	(0.122)	(0.250)	(0.264)	(0.463)	(0.102)
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	0.212***	0.464*	1.046***	0.931**	2.175***
	(0.074)	(0.242)	(0.392)	(0.395)	(0.374)
Cov(s^2,π_{t-s}) /a^2		5.292**	7.218**	6.371**	19.083***
		(2.555)	(2.853)	(2.835)	(2.790)
Cov(s,π_{t-s})/a		-6.543*	-9.608**	-8.351**	-26.657***
		(3.564)	(4.061)	(4.040)	(3.942)
Cov((π_{t-s}-$\overline{\pi}_{it-1}$)^2,π_{t-s})			-0.010	-0.009	-0.001
			(0.007)	(0.007)	(0.007)
Cov((π_{t-s}- π_t)^2,π_{t-s})			-0.002***	-0.002***	-0.008***
			(0.001)	(0.001)	(0.001)
SPF				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.

What is the economic importance of the estimated coefficients? Consider temporal context first.

As Appendix Table A2 shows for the MCS, in our preferred specification (Column 4, Table 1) a one-standard deviation increase in the first covariance term (second row) implies 0.82 percentage point increase in inflation expectations while the second covariance term (third row) is associated with -1.04 percentage points lower inflation expectations. This suggests that frequency is marginally stronger than primacy, but the two coefficients are not statistically distinguishable. Using the previous logic, the temporally harder experiences to recall – those for which the temporal distance $\beta(x)$ 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. The overall effect of temporal context reflects the conflict between primacy and recency effects.

Consider numerical similarity next. A key finding of our analysis is the strong effect of this force, which proves critical to account for de-anchoring. A one-standard deviation increase in the dissimilarity of experienced inflation episodes relative to the average experienced inflation (fourth row), as well as relative to the current-inflation memory cue (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 term that captures quadratic temporal context (second row) leads to an increase in inflation expectations by 1.42 percentage points while a one-standard deviation change in the linear term (third row) is associated with a decrease in inflation expectations of 1.66 percentage points. Moreover, as in the case of MCS, recency slightly dominates primacy (again the difference is not statistically distinguishable) with the peak reached at $s/a = 0.655$, and the last episode being more easily remembered for every $a \geq 4$. Looking instead at the effect of similarity, a one-standard deviation increases in the similarity measures result in decreases in inflation expectations by 0.18 and 0.20 percentage points, respectively.

We perform robustness analysis 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. The exercise is useful because longer term expectations are highly relevant for individual decisions as well as for the steering the course of monetary policy. Our results on temporal context and numerical similarity carry over to longer term expectations, 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 expectations. This intuitively suggests that long-term expectations are shaped by longer-term experiences, indicating that different cohorts have different long-run inflation anchors. We also perform robustness with respect to changing the estimation, in particular by applying robust regression methods (Appendix Table A1) and also by defining inflation experiences based on an annual rather than a quarterly horizon (Appendix Table A5).

3.3 Cues and Estimated Probability of Ranges

We next demonstrate the ability of the model to account for the estimated probability of different inflation ranges using the SCE in which respondents report their probability estimates $\widehat{\pi}_{j_{i,t}}$ specific to each range *j*, such as the probability that inflation will be 2% and 4% over the next 12 months. Based on Equation (7) we estimate several variants of the following regression specification:

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

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

where the left-hand side are the odds of a range *j* over a baseline range $b \neq j$, which for each respondent we select as the range with the lowest non-zero probability assessment, $\frac{n_{j,it}}{n_{b,it}}$ captures the corresponding relative experience frequency, $\left(\bar{s}_{j\,i,t}^{\;2}-\bar{s}_{b\,i,t}^{\;2}\right)/a^2$ and $\left(\bar{s}_{j\,i,t}-\bar{s}_{b\,i,t}\right)/a$ the corresponding relative recency, $\left[\left(\pi_j-\pi_t\right)^2-\left(\pi_b-\pi_t\right)^2\right]$ the corresponding relative dissimilarity, $\boldsymbol{X}_i$ contains individual-level fixed effects to account for individual-specific characteristics, $\boldsymbol{Z}_t$ captures year dummies, $\pi^e_{SPF,t}$ 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 experience-driven differences in the assessment of a specific range across cohorts. To avoid creating fat tails in the ratios and allow for the use of Huber-robust weights, our estimation smooths out any zero experience counts and range probabilities by recombining ranges suitably at the tails to >8%, 4% to 8%, 2% to 4%, 0% to 2%, -2% to 0%, -4% to -2%, and <-4% and excluding single-valued density forecasts.

We estimate the above specification by adding, successively, respondent range-specific demographic characteristics, then range-specific year fixed effects and last an SPF indicator that accounts for systematic differences in the impact of the SPF across partitions of the forecast density. We apply Huber-robust survey weights to account for any remaining potential regression outliers. Key parameters in the specifications include θ_1, which should be positive if the relative experience 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 relatively more likely, and θ_4 which should be negative if the higher relative similarity of the target range j to the current inflation cue boosts its estimated odds.

Results from the estimation, shown in Table 2, confirm the importance of selective memory mechanisms across specifications. First, a pure database effect is a work, as shown by the first row. The relative odds of the target range increase in the relative experience frequency of this range compared to the base one. Second, the range's relative frequency exerts a stronger effect if experiences with it occur early in life, so there is primacy at work, or if they are highly recent, so that also recency is at play, consistent with the evidence from point estimates. Crucially, the results in column (4) also show the importance of numerical cues: a higher relative frequency of the target range exerts a weaker role if the range is relatively more dissimilar from current inflation. Thus, the same selective memory forces of the database, temporal context and numerical similarity all affect both point expectations and the estimated probabilities of different inflation events.

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 Recency 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 Recency	-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 $\frac{\widehat{\pi_j}_{i,t}}{\widehat{\pi_b}_{i,t}} = \theta_0 + \theta_1 \cdot \frac{n_{j,it}}{n_{b,it}} + \theta_2 \cdot \frac{n_{j,it}}{n_{b,it}} \cdot \left(\bar{s}_{j\,i,t}^{\,2} - \bar{s}_{b\,i,t}^{\,2}\right)/a^2 + \theta_3 \cdot \frac{n_{j,it}}{n_{b,it}} \cdot \left(\bar{s}_{j\,i,t} - \bar{s}_{b\,i,t}\right)/a + \theta_4 \cdot \frac{n_{j,it}}{n_{b,it}} \cdot \left[\left(\pi_j - \pi_t\right)^2 - (\pi_b - \pi_t)^2\right] + \boldsymbol{\omega}_1'\boldsymbol{R_j} \times \boldsymbol{X}_i + \boldsymbol{\omega}_2'\boldsymbol{R_j} \times \boldsymbol{Z}_t + \boldsymbol{\omega}_3\, \pi_{SPF,t}^{e} + v_{ijt}$ 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.

3.4 Point Expectations vs. Ranges

We conclude the regression analysis by testing the model’s prediction for the relationship between range beliefs and point expectations, which is another test for the role of cues in shaping beliefs through selective memory. This analysis tests for a sharp departure from rationality, based on respondent's systematic inconsistency across different survey questions. We test Equation (9) by estimating the following specification:

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

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, $\pi^e_{i,t,B}$, is the range-based point expectation, which we compute for each individual *i* as the average of the midpoints in the forecast density (assigning +/- 13% to the respective ranges in the tail), weighted by the elicited probabilities for each range. In order to not mechanically create a wedge between reported point expectations and the density-based expectations, this estimation consistently winsorizes reported inflation expectations also at +/- 13%. The second regressor, $[\pi \cdot d]^e_{i,t,B}$, 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 (9).

Key parameters in this specification are μ_1, which should be positive and equal to one if point expectations and range beliefs are formed using the same database of experiences, and μ_2, which should be positive if similarity is at play. A positive μ_2 means that selective memory prompts respondents to overweight – when forming their point expectations – inflation ranges that are more similar to their own accumulated life experiences. Table 3 reports the regression estimates, including first separately and then jointly, the different fixed effects.

These results support the selective memory model. The positive sign in the first regressor shows that there is a strong positive correlation between point expectations and range-based expectations. The coefficient is indistinguishable from one, as predicted by the theory, in line with the notion that both point expectations and range estimation are formed using the same memory database, so the two exhibit a form of consistency. Consistency however, is not full and its limits are in line with the prediction of the model: point expectations appear to overweight ranges that the respondents are more familiar with, in the sense of being more similar to their average inflation experiences, and underweight ranges which respondents are less familiar with, compared to assessing these ranges separately and explicitly. Inconsistencies in survey responses by the same person are not due to inattention or laziness, but the role of memory cues and experiences.

Table 3. Inflation Point Expectations vs. Ranges

	(1)	(2)	(3)
VARIABLES	Inflation Expectations Point Estimate		
Density-based Inflation Expectation	1.066***	1.044***	1.019***
	(0.0150)	(0.0171)	(0.0184)
Similarity of High Inflation Ranges to Personal Experiences	0.00206***	0.00218***	0.00208***
	(0.000197)	(0.000215)	(0.000216)
Constant	0.466***	0.857***	0.947***
	(0.0594)	(0.0786)	(0.0719)
Observations	140,435	138,973	138,973
R-squared	0.404	0.370	0.373
Demographic Fixed Effects	No	Yes	Yes
Year Fixed Effects	No	No	Yes

Notes: This table reports estimated coefficients and standard errors from estimating $\pi_{i,t}^{e} = \mu_0 + \mu_1 \cdot \pi_{i,t,B}^{e} + \mu_2 \cdot [\pi \cdot d]_{i,t,B}^{e} + \boldsymbol{\varphi}_1' \boldsymbol{Z}_i + \boldsymbol{\varphi}_2' \boldsymbol{Z}_t + e_{i,t}$. The data come from the New York Fed SCE. Regressions use survey weights and standard errors are clustered at the cohort-year level.

This finding implies that different respondents may exhibit a differential degree of inconsistency at the same point in time due to their different experience databases. It also implies that as inflation trends change the experience database for many people changes in the same direction. In particular, increasing average inflation experiences for many people at the same time could trigger a systematic gap, in our case a systematic overshooting of point expectations compared to a more careful analysis of individual inflation scenarios. Quantitatively, these results also support the memory model. A one-standard deviation increase in range-based inflation expectations increases reported inflation point forecasts by 2.45 pp. But a one-standard deviation increase in the similarity of high-inflation ranges is also associated with a 0.57 pp. increase in point inflation forecasts. Respondents substantially overweight ranges they are more familiar with and underweight those they are less familiar with.

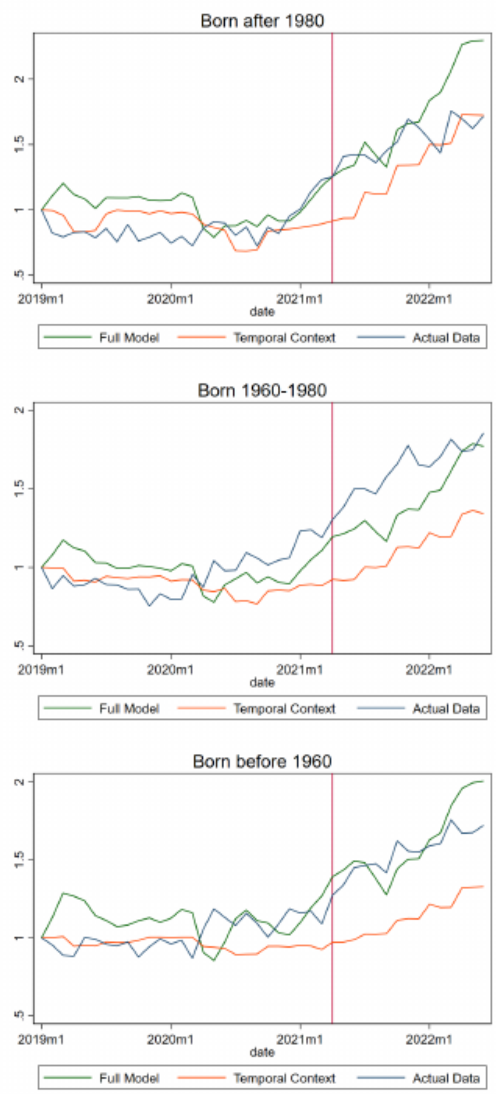
3.5 How Inflation Expectations De-Anchor (and Re-Anchor)

As seen above, selective memory can deepen our understanding of belief formation and the role of experiences in it, by introducing key concepts of selective retrieval: similarity based on temporal context, but crucially also based on state-dependent cues. We now go back to the initial motivation of the paper: can selective memory explain de-anchoring captured in Figure 1? Our answer obtained from quantifying the predictions of the model is yes. Moreover, the power of the model also becomes apparent in a now-casting exercise: The model can likewise account for the re-anchoring of inflation expectations following the post-pandemic monetary tightening and the associated fall in inflation.

Our analysis shows these results based on two quantification exercises, focused on point forecasts. First, we compute inflation expectations implied by our model, both using the full specification and setting similarity to zero. We call "temporal context" the model with zero numerical similarity.

Second, we compare the predicted expectations to the actual evolution of beliefs in the data. Using the estimates in Column (5) of Table 1 based on the New York Fed's SCE data, this exercise compares these evolutions for three cohorts that have different memories of high inflation: the young (born after 1980), the middle-aged (born 1960-1980), and the elderly (born before 1960). Third, we also perform an out-of-sample nowcasting exercise for the recent period of falling inflation expectations, or re-anchoring. To do so, we use the coefficient estimates of our first model based on point estimates (Column (5), Table 1) for the period from January 2013 to June 2022 in the MCS. We then predict inflation expectations by nowcasting them until February 2024, both using the full specification and setting similarity to zero, and we compare the nowcasts to the inflation expectations data which is available in the MCS for this period, but has not influenced the estimation.[3]

Figure 2. De-Anchoring of Inflation Expectations and the Importance of Similarity



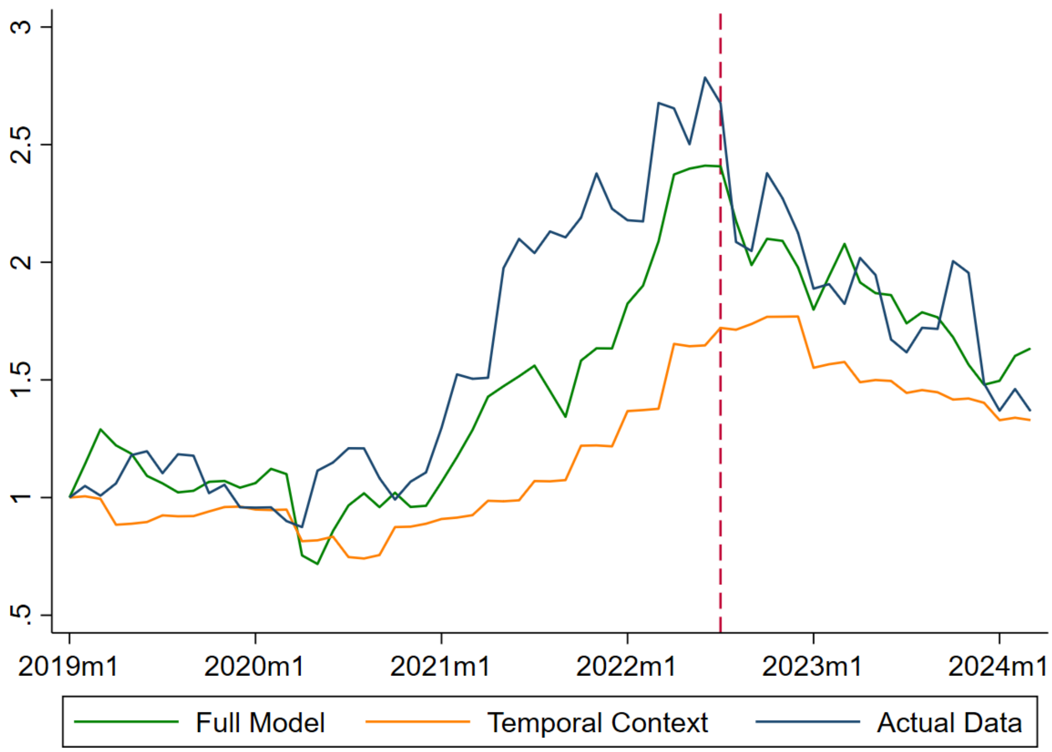
Notes: The figure shows actual inflation expectations, prediction of the model when we exclude the similarity terms by setting them to zero and the prediction of the model when we include them, averaged within each cohort group. The specification used is the one in Column 5 of Table 1. Data come from the New York Fed's SCE. The actual forecast and the predictions are expressed as a fraction of their value in January 2019. The red line marks April 2021.

According to both exercises, the model accounts for de-anchoring and re-anchoring patterns observed in the data. As Figure 2, corresponding to the first exercise, shows, de-anchoring needs

[3] The SCE data is released only with a lag so the same now-casting exercise is not feasible in this dataset.

similarity: In all panels, inflation expectations predicted by the model trend up when actual inflation expectations go up. At the same time, similarity does not hinder the model performance before 2021, because when inflation is stable, similarity produces the observed stability of inflation expectations. By contrast, not allowing for numerical similarity underpredicts the quantitative evolution of beliefs in the data, across cohorts. In contrast, the full specification that includes similarity captures the rapid increase in inflation beliefs. As we show in Appendix Figure A1, constructing a yearly database implies an even stronger effect for the elderly because it averages out high-frequency inflation movements.

Figure 3. Nowcasting: Re-Anchoring of Inflation Expectations



Notes: The figure shows actual inflation expectations, prediction of the model when we exclude the similarity by setting its terms to zero and prediction of the model when we include them, averaged in the full sample. Data come from the Michigan Consumer Survey. In order to maintain comparability, the model is calibrated on the SCE timeframe (January 2013 – June 2022). The actual forecast and the predictions are expressed as a fraction of their value in January 2019. The red line marks June 2022, which is the end of our estimation period and the beginning of the nowcasting period.

The mirror image of the rise in inflation expectations during the post-pandemic recovery is the fall of inflation expectations during the subsequent monetary tightening and fall in inflation. As the second exercise shows, we find that memory again plays a central role in explaining such dynamics: As Figure 3 shows, a model with both similarity and recency predicts the persistent and sharp increase in inflation expectations until mid 2022 and their gradual decline until 2024. The temporal context specification which sets similarity to zero exhibits instead excessive rigidity, failing to match the observed boom-bust pattern of beliefs. Selective memory by making beliefs relatively more state-dependent produces both the pre-2021 rigidity of beliefs and their sharp post-covid changes.

4. Conclusion

We present a model of inflation expectations based on the approach in Bordalo et al. (2022) and evaluate its predictions using micro data on individual inflation expectations 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 model predicts sharp belief instability due to selective recall of past experiences, which is confirmed in the quantitative assessment of inflation expectations in 2021. In particular, the model can explain why inflation expectations of the elderly rose more sharply than those of the young during the post-pandemic rise of inflation. Likewise, the model makes predictions for the full distribution of ranges of inflation forecasts, which we also test and confirm.

Memory models, with their emphasis on similarity, frequency and interference, appear to be a promising way to study belief formation, including macroeconomic expectations. We view the current analysis as a first step toward developing a cognitively founded model of expectation formation applicable to macroeconomics and finance. Going forward, one important open issue is the connection between memory and learning. In rational models, people store experiences in their prior and consistently update the latter based on data, optimally using all past information. With selective memory, the accumulation of experiences fills the database realizations of the data generating process, but then the agent retrieves information selectively, based on similarity to salient cues and interference. The resulting beliefs may be unstable but still follow a distorted version of the DGP, similarly to models of Diagnostic Expectations (Bordalo et al. 2018). The explicit memory foundation, though, may produce a richer pattern of behavior, accounting also for belief rigidity, of which some rich patterns have emerged in this paper, as well as endogenize different beliefs distortions based on measurable features of the data generating process.

Our approach may be relevant 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 US consumers, and a theory embedding regularities in 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:

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

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

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

and first derivatives:

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

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

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

where upper bar evidently denotes arithmetic average, and

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

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

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

which yields the desired result.

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

$$\Pr\left(\pi_j|\pi_{t,t+1}\right) \propto \sum\nolimits_{\pi_{t-s}=\pi_j} e^{-\beta\cdot s-\sigma\cdot q\cdot\left(\pi_j-\pi_t\right)^2},$$

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

$$\frac{\Pr\left(\pi_j|\pi_{t,t+1}\right)}{\Pr\left(\pi_b|\pi_{t,t+1}\right)} = \frac{\sum_{\pi_{t-s}=\pi_j} e^{-\beta\cdot s-\sigma\cdot q\cdot\left(\pi_j-\pi_t\right)^2}}{\sum_{\pi_{t-s}=\pi_b} e^{-\beta\cdot s-\sigma\cdot q\cdot(\pi_b-\pi_t)^2}},$$

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

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

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

$$\frac{\partial}{\partial\beta}\frac{\Pr\left(\pi_j|\pi_{t,t+1}\right)}{\Pr\left(\pi_b|\pi_{t,t+1}\right)} = -\frac{n_j}{n_b}\cdot\left(\bar{s}_j-\bar{s}_b\right),$$

and

$$\frac{\partial}{\partial\sigma}\frac{\Pr\left(\pi_j|\pi_{t,t+1}\right)}{\Pr\left(\pi_b|\pi_{t,t+1}\right)} = -q\cdot\frac{n_j}{n_b}\cdot\left[\left(\pi_j-\pi_t\right)^2-(\pi_b-\pi_t)^2\right],$$

which yields the desired result.

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

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

$$\left.\cdot\frac{\sum_u\sum_{\pi_{t-s}=\pi_u} e^{-\beta\cdot s-\sigma\cdot q\cdot(\pi_u-\pi_t)^2}}{\sum_u\sum_{\pi_{t-s}=\pi_u} e^{-\beta\cdot s-\sigma\cdot q(\pi_u-\pi_t)^2-\sigma\cdot q\cdot(\pi_u-\bar{\pi}_{t-1})^2}}\right]\cdot\Pr\left(\pi_j|\pi_{t,j}\right)\cdot\pi_j$$

$$= \sum_j \left[\frac{e^{-\sigma \cdot q \cdot \left(\pi_j - \overline{\pi}_{t-1}\right)^2} \sum_u \sum_{\pi_{t-s}=\pi_u} e^{-\beta \cdot s - \sigma \cdot q \cdot (\pi_u - \pi_t)^2}}{\sum_u e^{-\sigma \cdot q \cdot (\pi_u - \overline{\pi}_{t-1})^2} \sum_{\pi_{t-s}=\pi_u} e^{-\beta \cdot s - \sigma \cdot q \cdot (\pi_u - \pi_t)^2}} \right] \cdot \Pr\left(\pi_j | \pi_{t,j}\right) \cdot \pi_j.$$

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

$$\mathbb{E}(\pi_{t+1} | \mathbb{R}, \pi_t) = \sum_j \Pr\left(\pi_j | \pi_j, \pi_t\right) \cdot \pi_j = \mathbb{E}(\pi_{t+1} | B),$$

and first derivatives:

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

and

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

which yields the desired result:

$$\mathbb{E}(\pi_{t+1} | \mathbb{R}, \pi_t) \approx \mathbb{E}(\pi_{t+1} | B) + \sigma \cdot q \cdot \sum_j \left[\overline{(\pi_u - \overline{\pi}_{t-1})^2} - \left(\pi_j - \overline{\pi}_{t-1}\right)^2 \right] \cdot \Pr\left(\pi_j | \pi_{t,j}\right) \cdot \pi_j$$

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

Tables and Figures

Table A1. Robustness: Huber Robust Regressions

	(1)	(2)	(3)	(4)	(5)
	One-year ahead Infl. Exp.				
Panel A. MCS					
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,π_{t-s}) /a^2		0.128	1.460***	1.141***	-0.405
		(0.273)	(0.307)	(0.289)	(0.286)
Cov(s,π_{t-s})/a		-0.481	-2.194***	-1.715***	0.713**
		(0.360)	(0.400)	(0.382)	(0.353)
Cov((π_{t-s}-$\overline{\pi}_{it-1}$)^2,π_{t-s})			-0.001	-0.000	0.001**
			(0.000)	(0.001)	(0.001)
Cov((π_{t-s}- π_t)^2,π_{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,π_{t-s}) /a^2		1.330	2.923***	1.432	10.155***
		(0.984)	(1.055)	(0.949)	(1.072)
Cov(s,π_{t-s})/a		-2.640*	-5.100***	-2.881**	-15.993***
		(1.345)	(1.480)	(1.316)	(1.524)
Cov((π_{t-s}-$\overline{\pi}_{it-1}$)^2,π_{t-s})			-0.003	-0.002	-0.006**
			(0.003)	(0.003)	(0.002)
Cov((π_{t-s}- π_t)^2,π_{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, MCS

	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	0.148*	0.259	0.945**	0.940**	1.707***
	(0.082)	(0.253)	(0.359)	(0.377)	(0.352)
$Cov(s^2,\pi_{t-s})/a^2$		0.406	0.585*	0.581	1.397***
		(0.334)	(0.347)	(0.362)	(0.333)
$Cov(s,\pi_{t-s})/a$		-1.443	-2.375	-2.355	-5.926***
		(1.368)	(1.431)	(1.501)	(1.389)
$Cov((\pi_{t-s}-\overline{\pi}_{it-1})^2,\pi_{t-s})$			-0.018***	-0.018***	-0.017**
			(0.007)	(0.007)	(0.006)
$Cov((\pi_{t-s}-\pi_t)^2,\pi_{t-s})$			-0.000	-0.000	-0.002**
			(0.001)	(0.001)	(0.001)
SPF				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

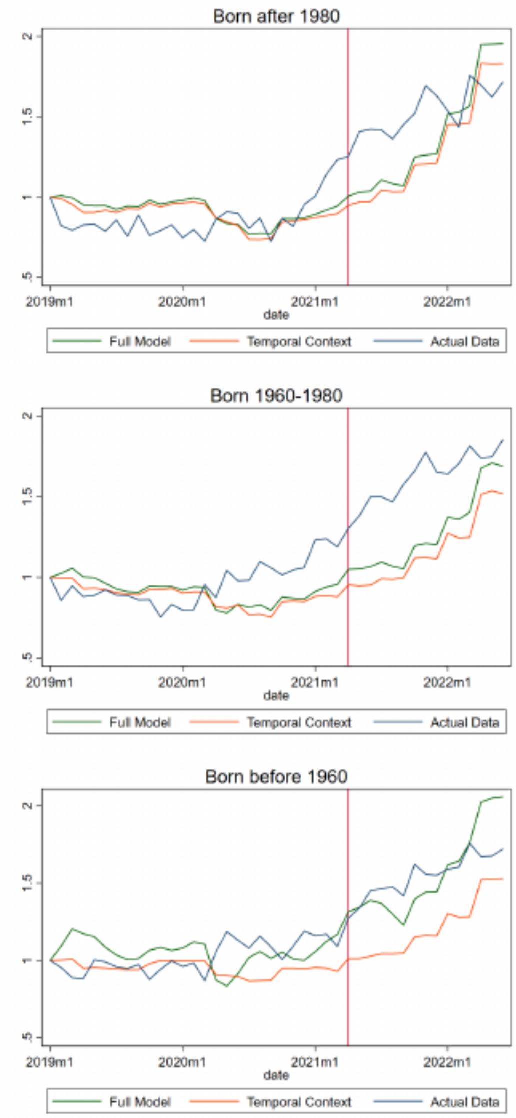
Notes: The table reports the estimates of the first-order linear approximation of a learning from experience model, augmented with similarity and a quadratic recency term. Demographic characteristics include sex, education, income quintile and marital status. The database of inflation experiences includes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



Notes: The figure shows actual inflation expectations, prediction of the model when we exclude the similarity terms by setting them to zero and prediction of the model when we include them, averaged within each cohort group. The specification used is the one in Column 5 of Table A5. Data come from the SCE. The actual forecast and the predictions are expressed as a fraction of their value in January 2019. The red line marks April 2021.