Seemingly Anchored Inflation Expectations *

Ulrike Malmendier†
UC Berkeley ,
NBER, Brookings, CEPR, and CESifo

Stefan Nagel‡
University of Chicago,
NBER, CEPR, and CESifo

June 13, 2026

Abstract

Empirical evidence commonly cited as indicating that inflation expectations have become better anchored includes the declining sensitivity of expectations to inflation surprises over time, particularly around the adoption of inflation targeting. These patterns are typically attributed to the influence of explicit or implicit inflation targets on inflation expectations. We show that this evidence is consistent with a model of experience-based learning in which individuals learn solely from their life-time history of realized inflation, without anchoring their expectations to an announced inflation target. In this model, the prolonged experience of low short-run inflation persistence in the pre-COVID decades renders long-run expectations insensitive to inflation surprises, matching the patterns observed in empirical anchoring tests. A unique prediction of the experience-based learning model is also borne out in the data: the decline in surprise sensitivity since the 1980s is strongest among younger individuals. The memory of low inflation persistence experiences further explains why long-run inflation expectations remained stable in the face of the post-COVID inflation surge. At the same time, simulations indicate that the sensitivity of long-run expectations to inflation surprises would rise sharply if individuals were to experience another sustained episode of highly persistent inflation. Overall, long-run inflation expectations may be less firmly anchored than commonly believed.

Keywords: Inflation Expectations; Anchoring; Monetary Policy; Learning from Experience

*We are grateful for comments to Larry Ball, Yuriy Gorodnichenko, Ina Hajdini, Lubos Pastor, seminar participants at the University of Chicago, Harvard, University of Iowa, and participants at the NBER *Inflation: Frontiers or Research and Policy* conference.

†Department of Economics and Haas School of Business, University of California, Berkeley, CA 94720; e-mail: ulrike@econ.berkeley.edu

‡University of Chicago, Booth School of Business, 5807 South Woodlawn Avenue, Chicago, IL 60637, e-mail: stefan.nagel@chicagobooth.edu

1 Introduction

The surge in inflation following the COVID-19 pandemic has reignited the debate over whether inflation expectations remain well anchored. If long-term expectations are well-anchored they tend to remain close to the inflation target regardless of short-run inflation developments, reflecting the credibility of the central bank's commitment to low inflation [e.g., Bernanke and Blanchard (2025); Bundick et al. (2024)].[1] Many observers have thus drawn reassurance from the stability of long-run inflation expectations during the post-COVID inflation episode despite the sharp increase in realized inflation and in marked contrast to the unanchored expectations during the Great Inflation of the 1970s [e.g., Williams (2023)]. This interpretation also underpins the belief that long-run expectations would remain close to the Federal Reserve's inflation target even in the face of further inflationary shocks in the near future.[2]

In this paper, we offer an alternative interpretation of empirical evidence on (seemingly) anchored expectations, with rather different implications for monetary policy. We argue that the empirical patterns often cited as evidence for enhanced Federal Reserve credibility anchoring long-run inflation expectations—namely, (1) the declining sensitivity of long-term expectations to inflation surprises over the four decades following the 1970s, (2) the further decline in sensitivity after the adoption of an explicit inflation target in 2012, and (3) the stability of long-run expectations during the post-COVID inflation surge—are also consistent with individuals forming expectations based on their own past inflation experiences, without attention to central bank targets or policy commitments. Unlike conventional anchoring models, this *experience-based learning* framework also accounts for the empirically observed heterogeneity across age groups in their sensitivity to inflation surprises. From a monetary policy perspective, the key implication is that long-run inflation expectations are never truly anchored under experience-based learning. Periods of apparent stability arise only temporarily, reflecting accumulated experience with low inflation persistence, and can unravel as new experiences accrue. Consistent with this mechanism, we show that inflation

[1] Williams (2022) defines well-anchored expectations as those that (i) exhibit little sensitivity to economic shocks; (ii) remain close in level to the central bank's long-run inflation target; and (iii) exhibit uncertainty that rises less than linearly with the forecast horizon.

[2] The FOMC's Statement on Longer-Run Goals and Monetary Policy Strategy states: "The Committee judges that longer-term inflation expectations that are well anchored at 2 percent [...] enhance the Committee's ability to promote maximum employment in the face of significant economic disturbances." See `www.federalreserve.gov/monetarypolicy/files/fomc_longerrungoals.pdf`.

expectations could move rapidly away from the Federal Reserve's inflation target if individuals were to experience another sustained surge in inflation following the post-COVID episode.

Our analysis proceeds in four steps. First, we adapt the Malmendier and Nagel (2016) (MN) model of experience-based learning from inflation experiences to the formation of long-term inflation expectations and we update the empirical evidence with out-of-sample data. Second, we show that learning from experience naturally generates a decline in the sensitivity of long-run inflation expectations to inflation surprises in the decades following the 1980s, driven by a reduction in the short-run persistence of inflation experienced by individuals. Third, we document systematic heterogeneity in inflation surprise sensitivity across age groups, consistent with differences in experienced inflation histories. Fourth, we use simulations to illustrate how future inflationary episodes would affect long-run expectations under experience-based learning.

Under the MN model of experience effects, individuals update their beliefs about future inflation based on inflation outcomes realized during their lifetimes. Specifically, individuals approximate the inflation process with a perceived AR(1) law of motion and revise their estimates of both the long-run mean and the short-run persistence of inflation as they are experiencing new inflation realizations, placing greater weight on more recent observations.[3] These updated parameter estimates then form the basis for individuals' forecasts of future inflation.

In this model, learning is perpetual in the sense that long-run inflation expectations remain continuously responsive to inflation surprises and are thus never truly well anchored. The degree of responsiveness depends on individuals' perceived short-run persistence of inflation: the higher the perceived persistence, the stronger the adjustment of long-run expectations in response to a surprise. Conversely, when perceived persistence declines, as it did over the decades following 1980, experience-based expectations become less sensitive to news and thus appear more firmly anchored. However, this seeming anchoring does not reflect credible central bank targets or policy commitments. Instead, it arises results mechanically from the inflation realizations individuals have experienced. If individuals were to experience a new period of persistent inflation rates, the sensitivity of long-run expectations to inflation surprises would rise once again.

To quantify this argument, and probe the alternative, experience-based interpretation of the

[3]This adaptive learning mechanism allows for substantial time variation in individuals' perceived AR(1) parameters, in contrast to adaptive expectations models, which generate forecasts as a fixed function of past realizations.

historical patterns in long-term inflation expectations, we take the model to the data. We begin by extending MN's empirical analysis of (one-year) inflation expectations in the Michigan Survey of Consumers (MSC) beyond the original sample period that ended in 2009. We find that the experience-based learning model continues to exhibit strong out-of-sample explanatory power in more recent data, with estimated parameters for the learning gain and the pass-through from experience-based to survey expectations closely matching those in the original sample. Overall, the model goes a long way in explaining observed age-related differences in inflation expectations: for example, it accounts for why younger individuals (under age 40) held one-year inflation expectations roughly three percentage points higher than older individuals (over age 60) around 1981, following the Great Inflation of the 1970s, and why the pattern reversed in the two decades preceding the COVID-19 pandemic, with older individuals expecting higher inflation than the young.

Given the robust replication results, we turn from one-year expectations to longer-horizon expectations, which are the focus of this paper and are central to the debate on anchoring. Under learning from experience, long-horizon expectations are influenced more strongly than short-run expectations by the average level of inflation individuals have experienced. Using the same learning gain, we find that the experience-based learning model fits these longer-horizon expectations about as well as it does one-year expectations, and the pass-through from experience-based to survey expectations is close to one-for-one. This new evidence that links long-term expectations to differences in cohorts experienced history runs challenges the notion that expectations are firmly anchored. Anchoring to the central bank's inflation target should have removed such cohort-specific history-dependence, yet in the years before the COVID pandemic, older cohorts' annualized long-term inflation expectations exceeded that of younger cohorts by 20-30 basis points, consistent with older cohorts' memory of the high-inflation years of the 1970s still playing a role in shaping their expectations.

We then turn to tests of the macroeconomic news-sensitivity of long-run inflation expectations. Existing empirical tests of anchoring often rely on the notion that if expectations are truly well anchored, they should respond little to news, including unexpected inflation. It is a well-established stylized fact that the news-sensitivity of long-term inflation expectations has declined markedly since the late 1990s (Carvalho et al., 2023; IMF, 2016). This decline in news sensitivity is often interpreted as evidence of enhanced central bank credibility and the success of inflation targeting. We show, however, that an equally pronounced decline in the responsiveness of long-run expectations arises in our experience-based learning framework, even though individuals in the model neither observe nor respond to central bank targets and instead rely solely on their personal histories of realized inflation. In the model, the declining sensitivity of long-run expectations to inflation surprises follows from a reduction in perceived short-run inflation persistence. When individuals estimate the mean of an AR(1) process, recursive updating becomes less responsive to new data as the perceived persistence declines. As realized inflation became substantially less persistent in the decades following the 1980s, individuals revised down their estimates of short-run persistence, which in turn dampened the response of long-run inflation expectations to new inflation surprises. Thus, the experience-based learning model attributes the observed decline in news sensitivity not to increased attention to central bank targets or greater policy credibility, but to changes in the statistical properties of the inflation process that individuals learned about from their own experienced inflation histories.

The experience-based model also provides an alternative interpretation of empirical tests that have focused on differences in the properties of inflation expectations around the adoption of an explicit numerical inflation target by the Federal Reserve in 2012. Using forward breakeven inflation rates extracted from Treasury Inflation Protected Security (TIPS) yields as proxy for long-run inflation expectations, Bundick and Smith (2025) document a decline in the responsiveness of expectations to inflation surprises following the introduction of the target.[4] We observe a similar decline in the responsiveness of 5- to 10-year inflation expectations in the MSC. However, we also find that artificial long-run expectations generated by the experience-based model exhibit a comparable drop in responsiveness. This drop is part of the longer-term reduction in responsiveness tied to the decline in perceived short-run persistence of inflation, a trend that spans the 2012 adoption of the inflation target. This casts doubt on the notion that the drop is the effect of improved policy credibility on expectations due to the target adoption.

The experience-based model is also consistent with the stability of long-run inflation expectations in the wake of the post-COVID inflation surge documented in Bundick et al. (2024) and

[4]See, also, Gurkaynak et al. (2007), Gürkaynak et al. (2010) and Beechey et al. (2011) for related evidence.

Hajdini et al. (2025). A common interpretation of this stability is that it reflects the effectiveness of the Federal Reserve's commitment to an explicit inflation target (Hajdini et al., 2025). Analysis of the expectations implied by the experience-based model suggests caution in this interpretation. We find that the expectations of individuals learning purely from experience have been stable as well, even without any anchoring of expectations to an inflation target. After experiencing several decades of inflation with relatively low short-run persistence, the level of perceived persistence was low at the onset of the post-COVID inflation surge, leading to a low sensitivity of long-run expectations to inflation surprises. Therefore, in this inflation episode, the experience-based expectations model is observationally equivalent to one in which inflation expectations are strongly anchored to an inflation target.

While the two approaches are observationally equivalent along these aggregate time-series dimensions, examining heterogeneity across age groups reveals empirical patterns predicted by the experience-based learning model but not by conventional models of anchoring. Most importantly, we find that the sensitivity of inflation expectations to inflation surprises is highest for younger individuals entering the 1990s, consistent with their experience being dominated by the high-persistence inflation of the 1970s. This sensitivity then declines more so than for older cohorts until very recently, reflecting the fact that younger individuals' subsequent experiences were shaped primarily by a low-persistence inflation environment.

The models also differ drastically in how the inflation expectations could evolve in the future, depending on the path of realized inflation in the coming years. The post-COVID inflation surge invites comparisons to the Great Inflation of the 1970s, a period during which long-run inflation expectations became far more severely unanchored. However, it is not yet clear that the post-COVID behavior of long-run expectations differs meaningfully from the early stages of that earlier episode. The Great Inflation unfolded in three distinct waves: 1968-71, 1973-76, and 1978-81. While the post-COVID inflation surge resembles the first wave, the absence (so far) of subsequent waves makes it far more modest relative to the Great Inflation. Any comparison of the stability of long-term expectations across the two periods must take this into account.

To illustrate this point, we simulate experience-based expectations under a counterfactual scenario in which inflation from early 2026 onward mirrors the paths observed during the second and third waves of the 1970s. In this scenario, 10-year experience-based inflation expectations rise sharply, reaching more than 7% annually. This increase is to a substantial extent driven by a rise in perceived short-run persistence, which amplifies the sensitivity of long-run expectations to inflation surprises. In contrast, extrapolating the empirical relationship between inflation surprises and long-run expectations observed during the years preceding the pandemic, without allowing for a rise in the sensitivity to surprises, yields long-run expectations that remain stable.

Overall, the comparison with experience-based expectations demonstrates that the empirical case for anchoring of long-run inflation expectations is less compelling as it may seem. It may have been the Federal Reserve's monetary policy *actions*—interest rates responses that successfully reduced the level and short-run persistence of inflation—that played the predominant role in lowering and stabilizing long-run inflation expectations. By shaping the inflation outcomes that individuals observe and learn from, these actions may have had a greater impact than the Fed Reserve's *words* in its public statements and commitments regarding the inflation target. The target may still have served an important role by making the Federal Reserve's actions on interest rates responsive to deviations from the target, but the case for a direct effect on expectations is less strong than it may have seemed.

Our paper is related to recent work by Carvalho et al. (2023). Our experience-based expectations framework and their model share the assumption that people learn only from realized inflation rates about the properties of the inflation process. In their setting, long-run inflation expectations become more sensitive to inflation surprises during the Great Inflation of the 1970s because, after observing a sequence of persistent forecaster errors, forecasters switch models from decreasing-gain learning to learning with a high constant gain. In our setting, the learning gain remains constant, but the surprise-sensitivity still rises because of the rise in the perceived short-run persistence of inflation.

Our skeptical perspective on the extent to which long-run inflation expectations are truly anchored aligns with several other recent papers. Using inflation options data, Hilscher et al. (2025) document a sharp rise in the perceived probability of a long-run inflation disaster, measured at a 5-year-5-year forward horizon, during 2021-22, a pattern inconsistent with firmly anchored expectations. Kumar et al. (2015), Reis (2022), Binder et al. (2023) and Coibion and Gorodnichenko (2026) forecaster disagreement and uncertainty, challenging the notion of well-anchored expectations. The age-related heterogeneity we study in the experience-based expectations framework reflects one dimension of this disagreement. Gennaioli et al. (2024) argue that inflation expectations are unstable because inflation realizations lead to selective recall of past experiences.

Evidence in Jacome et al. (2025) suggests that central bankers do not appear to place much confidence in firm anchoring. They find that central banks in countries with histories of high inflation continue to respond aggressively to deviations of inflation expectations from target, even many years after adopting an inflation target and after medium-term inflation expectations have become less sensitive to shocks. Bocola et al. (2025) provide a theory of this pattern.

The rest of the paper is organized as follows. Section 2 provides updated estimates of the experience-based learning model, including new results on long-term expectations. Section 3 shows examines the anchoring properties of long-run expectations in the experience-based learning model. Section 4 presents the empirical anchoring tests. Section 5 looks at age-related heterogeneity in anchoring. Section 6 presents simulations of the path of long-term expectations in a future inflationary scenario.

2 Learning Inflation Experiences: Out-of-Sample Update

We start by revisiting the empirical evidence on learning-from-experience in inflation expectations, extending MN's analysis out-of-sample and to long-run expectations.

Following MN, individuals perceive the law of motion of inflation as an AR(1) process

$$\pi_{t+1} = a + \rho\pi_t + \varepsilon_{t+1}, \tag{1}$$

and they use inflation observed during their life-times to estimate the parameters $\boldsymbol{b} \equiv (a, \rho)'$ of this process. An individual in a cohort born at time s uses the recursive updating rule

$$\boldsymbol{b}_{t,s} = \boldsymbol{b}_{t-1,s} + \phi_{t,s}\boldsymbol{R}_{t,s}^{-1}\boldsymbol{x}_{t-1}(\pi_t - \boldsymbol{b}'_{t-1,s}\boldsymbol{x}_{t-1}), \tag{2}$$

$$\boldsymbol{R}_{t,s} = \boldsymbol{R}_{t-1,s} + \phi_{t,s}(\boldsymbol{x}_{t-1}\boldsymbol{x}'_{t-1} - \boldsymbol{R}_{t-1,s}), \tag{3}$$

where $\boldsymbol{x}_t \equiv (1, \pi_t)'$. Different from standard versions of adaptive learning (see, e.g., Evans and

Honkapohja (2001)), where the gain $\phi_{t,s}$ is either constant or a decreasing function of just t, here the gain also has a subscript s to indicate that the gain is heterogeneous between cohorts at each point in time. More precisely, the gain changes as people age:

$$\phi_{t,s} = \begin{cases} \frac{\theta}{t-s} & \text{if } t-s \geq \theta \\ 1 & \text{if } t-s < \theta, \end{cases} \tag{4}$$

The parameter θ determines the shape of the implied function of weights on past inflation experiences. In their baseline specification, MN estimate a value of $\theta = 3.044$ for quarterly data. The recursion starts with $\phi_{t,s} = 1$ for $t - s < \theta$, which implies that data before shortly after birth is ignored. After birth, the gain is decreasing with age. A value of $\theta = 1$ would imply that data experienced after birth is weighted equally, and hence individuals' AR(1) parameter estimates at each point in time are simple OLS estimates on the experienced life-time data. With $\theta = 3.044$, as estimated by MN, memory of past inflation fades away over time as an individual ages.

Before analyzing the anchoring question, we first provide an update on MN's estimates to see whether their results still hold in an extended sample from the MSC that includes the years after 2009 when their sample ended (see Appendix A for more detail on the data). Table 1 presents regressions of inflation expectations, aggregated to mean expectations at birth-year cohort level, on the cohort-level forecast implied by the learning-from-experience model. Panel A uses one-year expectations; Panel B uses 5- to 10-year expectations. All regressions include time dummies, which means that identification is based purely on cross-sectional differences between cohorts in their experiences and expectations and variation of these cross-sectional differences over time. Time-varying components of expectations that are common to all cohorts, including homogeneous forward-looking responses to monetary and fiscal policy changes or macroeconomic shocks, are absorbed by the time fixed effects.

In Panel A, column (1) reports the estimates from the original MN sample using quarterly inflation measured with the seasonally-adjusted CPI-U and with experience-based forecasts calculated with MN's estimate of $\theta = 3.044$.[5] Column (2) extends the sample all the way to 2025Q4. As in

[5] The slope coefficient reported here (0.63) is very similar to the estimate in MN (0.67), but the R^2 is slightly higher (65% instead of 64%). The reason is that we implemented a minor improvement in the treatment of survey

Table 1
Learning-from-Experience Model: Update of MN(2016) Estimates

Each cohort born at time s is assumed to recursively estimate an AR(1) model of inflation, with the decreasing gain $\phi_{t,s} = \theta/(t-s)$. The table reports the results of OLS regressions of 1-year survey inflation expectations (Panel A) and 5- to 10-year survey inflation expectations (Panel B) in quarter t (cohort means) on the forecasts implied by the learning-from-experience model using inflation data up to the quarter prior to the survey quarter. Standard errors shown in parentheses are two-way clustered by time and cohort.

	(1)	(2)	(3)	(4)	(5)
			Panel A: 1-year Inflation Expectations		
Experience-based forecast	0.63	0.62	0.60	0.60	0.56
	(0.07)	(0.07)	(0.06)	(0.06)	(0.07)
Exp.-based forecast $\times I_{\text{year}>2009}$					0.29
					(0.14)
#Obs.	8,215	11,415	11,415	11,415	11,415
Adj. R^2	0.65	0.63	0.63	0.63	0.63
θ	3.044	3.044	3.044	3.051	3.051
Sample	1953 - 2009	1953 - 2025	1953 - 2025	1953 - 2025	1953 - 2025
Time FE	Yes	Yes	Yes	Yes	Yes
Age FE	No	No	Yes	Yes	Yes
			Panel B: 5- to 10-year Inflation Expectations		
Experience-based forecast		0.81	0.98	0.98	0.90
		(0.13)	(0.11)	(0.11)	(0.12)
Exp.-based forecast $\times I_{\text{year}>2009}$					0.37
					(0.13)
#Obs.		9,351	9,351	9,351	9,351
Adj. R^2		0.47	0.50	0.50	0.50
θ		3.044	3.044	3.051	3.051
Sample		1953 - 2025	1953 - 2025	1953 - 2025	1953 - 2025
Time FE		Yes	Yes	Yes	Yes
Age FE		No	Yes	Yes	Yes

the MN sample, there is a strong positive relationship between the learning-from-experience forecast and inflation expectations. A one percentage point higher learning-from-experience forecast implies a 0.62 percentage point higher inflation expectation. In column (3) we add age fixed effects to make sure the inflation experience variable is not picking up constant age effects.[6] The slope coefficient is only slightly lower (0.60), which shows that the expectations heterogeneity generated by experience effects is very different from constant age effects. In column (4) we re-estimate θ, using the same nonlinear least squares approach as in MN, but here with the full sample until 2025Q4. The estimate of 3.051 is virtually identical to MN's estimate of 3.044.[7] In column (5), fixing $\theta = 3.051$, we allow the slope coefficient to be different in the out-of-sample period after the end of MN's sample. The point estimate of 0.29 for the coefficient on the interaction with the post-2009 dummy suggests a somewhat higher coefficient in the out-of-sample period. This estimate should be interpreted with caution, however, because identification comes from changes over time in differences in inflation expectations between age groups. These differences are slow-moving, and less than two decades of post-2009 data provide limited variation with which to pin them down.

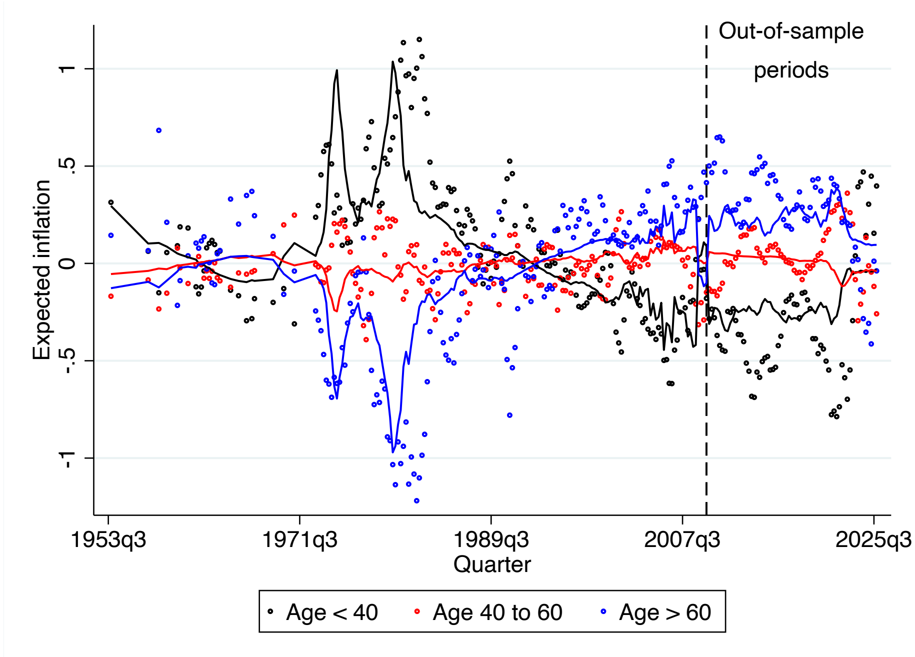
Figure 1 illustrates the fit with plots of the expectations data from the survey and the fitted values from column (4) in both panels of Table 1. The series shown in this figure are aggregated by taking means within three broad age groups, removing time and age fixed effects, and forming four-quarter moving averages. Panel (A) in this figure shows that the learning-from-experience updating scheme continues to explain well the persistent differences in one-year inflation expectations between younger and older individuals in the out-of-sample periods after 2009. Until just before the very end of the sample, when inflation rises sharply, older individuals had higher inflation expectations than younger individuals. The learning-from-experience model explains this with older individuals still carrying memory of the high average inflation rates in the 1970s and early 1980s. Interestingly, at the very end of the sample, following several post-COVID quarters with high inflation, young and old again switched sides. Now the young again have higher inflation expectations than older people.

responses in which the respondent provided a categorical response of "up" ("down") about expected inflation, but not a percentage response. MN use a procedure recommended in Curtin (1996) that draws percentage responses from the empirical distribution of percentage responses of those in the same age who gave the same categorical response of "up" ("down") in the same survey period. In MN, the imputed responses were drawn from a sample that includes missing responses. Here, we draw only from the sample of responses that excludes missing values.

[6]Bryan and Venkatu (2001), Bruine de Bruin et al. (2010), and D'Acunto et al. (2025) find substantial age effects in regression specifications without experience-based inflation expectations variable.

[7]The standard error of the θ estimate is 0.20 and hence very small relative to the magnitude of the parameter.

(A) 1-year expected inflation



(B) 5- to 10-year expected inflation

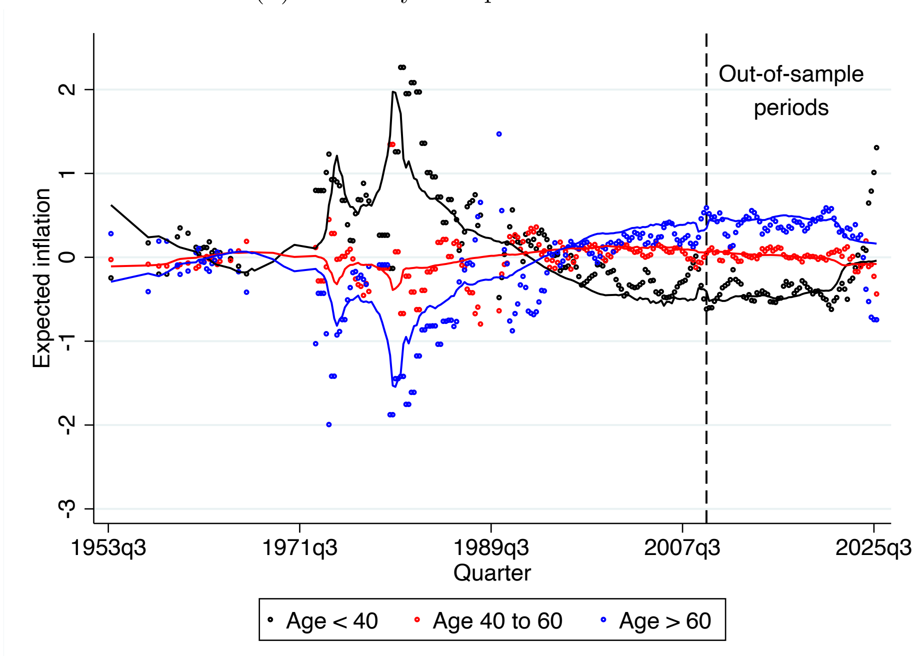


FIGURE 1
Comparison of Learning-from-Experience Forecasts with Inflation Expectations from the Michigan Survey of Consumers

Four-quarter moving averages for three age groups, shown as deviations from time and age fixed effects. Actual survey expectations shown as circles. The lines show fitted values, in panel (A) based on estimates from column (4) in the top panel of Table 1, in panel (B) based on column (4) in the bottom panel. The dashed line indicates the end of the sample in MN's data set.

The forecasts implied by the learning-from-experience model have also come close to switching signs. Thus, the learning-from-experience model also helps explain how expectations of people of different age react heterogeneously to the most recent burst of inflation.

In our analysis of anchoring below, we focus on long-run expectations. For this reason, we now extend MN's analysis to 5- to 10-year inflation expectations from the MSC. Panel B in Table 1 shows a regression of the average annual inflation rate over the next 5 to 10 years expected by survey respondents on the 7.5-year forecast implied by the learning-from-experience model. Similar to the one-year expectations, there is a strong positive relationship between survey expectations and expectations implied by the learning-from-experience model. In columns (2) and (3), we calculate experience-based expectations with the value of $\theta = 3.044$ estimated by MN. With age fixed effects in column (3), we find that a one percentage point higher learning-from-experience forecast translates almost exactly one-for-one to into observed inflation expectation in the survey. As column (4) shows, switching to $\theta = 3.051$, as estimated from the full sample in column (4) of Panel A, makes little difference: the estimated slope coefficient is identical. In column (5) we check whether the slope coefficient is different in the out-of-sample period after 2009. As in Panel A, we find a somewhat higher coefficient in the out-of-sample period.

Panel (B) of Figure 1 illustrates the fit based on the estimates from column (4) of Table 1, Panel B. Broadly speaking, the fit is similar to that in the figure's Panel (A). Thus, the learning-from-experience model explains a large share of the time-varying age-related heterogeneity not only in short-run inflation expectations, but also in long-run expectations.

In the remainder of the analysis, we focus on these long-run expectations and explore the implications of experience-based learning for the (mis-)identification of anchored inflation expectations. Since the analysis of anchoring focuses on changes in inflation expectations around shifts in macro regimes or in monetary policy, such as the adoption of inflation targets by the central bank, we briefly discuss how such changes play out in our model.

Differently from existing models, the adoption of an inflation target and other regime changes affect experience-based beliefs only to the extent that they cause changes in the properties of the inflation process and the resulting inflation realizations: The corresponding updates of the parameter values a and ρ of the perceived AR(1) process will adapt through the updating rule in

(3). For example, if there was a regime-switch that drastically lowered the persistence of inflation, individuals' estimates of the autocorrelation parameter in their AR(1) perceived law of motion would adapt and eventually reflect this reduced persistence.

Another plausible channel for regime changes to affect belief formation would be changes in the gain parameter θ. However, unlike in Kalman filtering, where statistical optimality considerations pin down the gain, in the experience-based framework θ reflects the fading of individuals' memories as they age and accumulate new experiences. Conceptually, therefore, θ need not vary over time, even if allowing for time variation in θ would improve forecast accuracy. Empirically, it seems plausible that time variation in the properties of individuals' inflation expectations in the MSC primarily reflects changes in perceived AR(1) parameters rather than changes in θ. One reason is that the experience-based model with fixed θ fits the time-varying dispersion of expectations across age groups in Figure 1. Another reason is that adding 16 years of data virtually leaves the estimate of θ in Table 1 unchanged.

That said, this interpretation should be viewed in light of the U.S. inflation environment studied here, which does not include drastic regime changes such as hyperinflations and their aftermath. Faced with such extreme changes in regime, individuals might well alter the weights they place on past data.

3 Expectations Anchoring under Learning from Experience

We now turn to the implications of experience-based expectations formation for the anchoring of long-run inflation expectations. This means we seek to understand how sensitive experience-based long-run inflation expectations are to inflation surprises. For this purpose, we work with three simplifications.

First, in the analysis in this section, as well as in the first part of the empirical work that follows, we focus on the time-series dynamics of cross-sectionally averaged expectations, abstracting from heterogeneity between individuals of different age. Most studies of anchoring focus on the properties of consensus expectations, typically measured as the mean or median of survey respondents' forecasts and therefore abstracting from underlying heterogeneity. We therefore follow this approach as well. In both the survey data and the expectations generated by the learning-from-experience model, we construct consensus expectations by aggregating across individuals of different ages at each point in time. The time-varying, age-related heterogeneity implied by experience-based learning is useful for identifying experience effects and the learning gain parameter, θ, in survey data. However, the experience-based framework also delivers predictions for the time-series dynamics of these cross-sectionally averaged expectations.

Second, and only for illustration here in this section, but not in the empirical analysis, we approximate the time-series dynamics of cross-sectionally averaged experience-based expectations with a constant-gain learning scheme, i.e., learning with the same recursion as in (3), but with constant gain. MN have shown that this approximation is highly accurate for average beliefs. The reason is that even though all individuals learn with decreasing gain, the cross-sectional average gain is constant due to generational turnover. There are always young people who learn with high gain and older people who learn with lower gain. MN's estimate of $\theta = 3.044$ implies average belief dynamics approximate those of learning with constant gain of $\gamma = 0.018$ for quarterly data; the updated estimate of $\theta = 3.051$ we reported in the previous section implies approximately the same gain of $\gamma = 0.018$ quarterly. Let $\widetilde{\mathbb{E}}_t[.]$ now denote the consensus expectations resulting from constant-gain learning.

Third, and again only for illustration in this section, we focus on changes in long-run inflation expectations, keeping fixed the perceived autocorrelation, $\hat{\rho}$, of inflation. Since estimates of ρ change only slowly, this approximation is innocuous. At the same time, it makes the updating of beliefs about long-run inflation much more transparent.

3.1 Properties of Long-Run Inflation Expectations

Let $\widetilde{\mathbb{E}}_t \pi_{t+\infty} = \lim_{h\to\infty} \pi_{t+h}$ denote the long-run inflation expectation. With constant gain γ and fixed $\hat{\rho}$, the update for the intercept parameter in the AR(1) law of motion in (1) is

$$\hat{a}_t = \hat{a}_{t-1} + \gamma(\pi_t - \hat{\rho}\pi_{t-1} - \hat{a}_{t-1}). \tag{5}$$

Based on this estimate, the long-run inflation expectation is the estimated unconditional mean inflation rate, which is

$$\widetilde{\mathbb{E}}_t \pi_{t+\infty} = \frac{\hat{a}_t}{1-\hat{\rho}}, \tag{6}$$

and from (5) the update relative to the previous period is

$$\widetilde{\mathbb{E}}_t \pi_{t+\infty} - \widetilde{\mathbb{E}}_{t-1} \pi_{t+\infty} = \underbrace{\frac{\gamma}{1-\hat{\rho}}}_{=\delta} (\pi_t - \widetilde{\mathbb{E}}_{t-1} \pi_t), \tag{7}$$

where $\pi_t - \widetilde{\mathbb{E}}_{t-1}\pi_t = \pi_t - \hat{\rho}\pi_{t-1} - \hat{a}_{t-1}$. This expression is key for understanding the properties of long-run inflation expectations under learning from experience. It shows that the sensitivity of *long-run* expectations is increasing in the perceived *short-run* persistence of inflation. When $\hat{\rho}$ is high, the response of long-run inflation expectations to an inflation surprise is much bigger than when $\hat{\rho}$ is low. Time-variation in $\hat{\rho}$ generates time-variation in time-variation in the strength of the response of long-run inflation expectations to inflation surprises.

Because this mechanism plays a central role in the analysis that follows, it is useful to elaborate on the intuition underlying the connection between short-run inflation persistence and the sensitivity of long-run inflation expectations to inflation surprises. The logic is most transparent if we approximate $\hat{\rho} \approx \rho$. Under this approximation, the inflation surprise in period t can be written as

$$\begin{aligned} \pi_t - \widetilde{\mathbb{E}}_{t-1}\pi_t &= \pi_t - \rho\pi_{t-1} - \hat{a}_{t-1} \\ &= \varepsilon_t + a - \hat{a}_{t-1}. \end{aligned} \tag{8}$$

Because the surprise is constructed by removing the predictable component $\rho\pi_{t-1}$ from observed inflation, the surprise becomes a noisy signal of the gap between the true intercept a and its perceived value $\hat{a}_{t-1}$ based on information in the previous period. Dividing this signal by $1-\rho$, as in (7), converts it into an unbiased signal about the gap between the true unconditional mean inflation rate $a/(1-\rho)$ and its perceived value $\hat{a}/(1-\rho)$. Consequently, updating beliefs about the AR(1) process parameters with gain γ implies that long-run inflation expectations adjust by $\gamma/(1-\rho)$ times the inflation surprise.[8]

[8] In Appendix B, we show that, in the case of known ρ and known variance of ε_t, a Bayesian forecaster with

The fact that the sensitivity of long-run inflation expectations to an inflation surprise increases with $\hat{\rho}$ is a robust property that does not depend on the specific estimator individuals use to form long-run inflation forecasts. For example, under constant-gain learning, one alternative approach to constructing $\widetilde{\mathbb{E}}_t\pi_{t+\infty}$ is to ignore the AR(1) structure altogether and instead simply estimate the unconditional mean inflation rate using an exponentially weighted average of past inflation realizations. In recursive updating form, this estimator can be written as

$$\bar{\pi}_t = \bar{\pi}_{t-1} + \gamma(\pi_t - \bar{\pi}_{t-1}). \tag{9}$$

This procedure yields a slightly different estimate of expected long-run inflation than (6). Iterating (5) shows that $\hat{a}_t$ is an exponentially weighted average of the quasi-differenced series $\pi_t - \hat{\rho}\pi_{t-1}$, whereas (9) instead averages raw inflation rates. Nevertheless, the sensitivity of $\bar{\pi}_t$ to surprise inflation is virtually identical to that of $\widetilde{\mathbb{E}}_t\pi_{t+\infty}$ in (7); the only difference is that, under (9), the adjustment is distributed more gradually over time.

To illustrate this timing difference, consider a one-time positive unit shock at time t to the parameter a, which the agent assumes to be constant. This shock raises the long-run mean by $1/(1-\rho)$ and generates a unit inflation surprise as defined in (8). Under the updating rule in (7), the inflation surprise is multiplied by $1/(1-\rho)$. As a result, if the gain were $\gamma = 1$, long-run expectations would adjust fully and immediately to the new level, with no further predictable revisions thereafter. By contrast, under the updating rule in (9), a gain of $\gamma = 1$ implies that the immediate response at time t to the unit increase in π_t is only a one-unit change in long-run expectations. However, because inflation is persistent and the updating rule in (9) does not filter out the persistent component, this initial adjustment is followed by predictable additional revisions of size ρ, ρ^2, and so on in subsequent periods. These incremental updates eventually cumulate to a total change of $1/(1-\rho)$. Thus, when $\rho \approx \hat{\rho}$, the long-run adjustment implied by (9) coincides

fading memory, modeled via a discounted likelihood as in Nagel and Xu (2022), Ibrahim and Chen (2000), and Zellner (2002), updates long-run expectations exactly according to (7). That said, we interpret the experience-based expectations model, and its constant-gain approximation for aggregated expectations, as a framework in which individuals form expectations using simple regression point estimates, rather than as one that presumes adherence to fully Bayesian learning and the knowledge of distributions needed for Bayesian learning. The connection to Bayesian learning explored in Appendix B is therefore relevant only insofar as it demonstrates that experience-based expectation formation lies close to Bayesian updating, without requiring individuals to follow it exactly.

with that of (7), but it unfolds gradually rather than instantaneously. For example, if $\rho = 0.5$, half of the total adjustment occurs immediately and more than 90% is complete after four quarters.

3.2 The Fragility of Anchoring under Learning from Experience

The fact that the sensitivity of long-run inflation expectations to inflation surprises can vary substantially with the perceived short-run persistence of inflation has important consequences for anchoring of inflation expectations. The sensitivity coefficient δ in (7), which is increasing in $\hat{\rho}$, is a measure of the degree of anchoring of long-run inflation expectations. It directly maps into the sensitivity estimated in empirical tests of anchoring. Gürkaynak et al. (2010), Bundick and Smith (2025) and Bundick et al. (2024) estimate the degree of anchoring with a regression specification of the form

$$\widetilde{\mathbb{E}}_t \pi_{t+h} - \widetilde{\mathbb{E}}_{t-1} \pi_{t-1+h} = \delta_0 + \delta(\pi_t - \widetilde{\mathbb{E}}_{t-1}\pi_t) + e_t. \tag{10}$$

Under learning from experience, and for long-run expectations ($h \to \infty$), the slope coefficient δ in this regression is equal to the coefficient δ in (7). A value of $\delta = 0$ implies perfectly anchored inflation expectations, as long-run expectations are insensitive to inflation surprises, and $\delta > 0$ implies imperfect anchoring, as long-run expectations respond to inflation surprises.

From our analysis so far we can conclude that anchoring is fragile under learning from experience. Even if long-run inflation expectations currently look well-anchored, this can easily change in the future.

First, under learning from experience, long-run expected inflation can never be perfectly anchored. Long-run expectations respond to an inflation surprise with at least with γ times the surprise (assuming $0 \leq \rho < 1$). This is due to a combination of two effects. First, in this model, individuals are not influenced by central bank communication about policy targets; they only look at realized inflation data. Second, generational turnover and down-weighting of data experienced earlier in life leads to a loss of memory and perpetual learning, which means that updating about long-run expectations in response to inflation surprises is perpetual as well. Long-term inflation expectations therefore never settle down to be perfectly anchored.

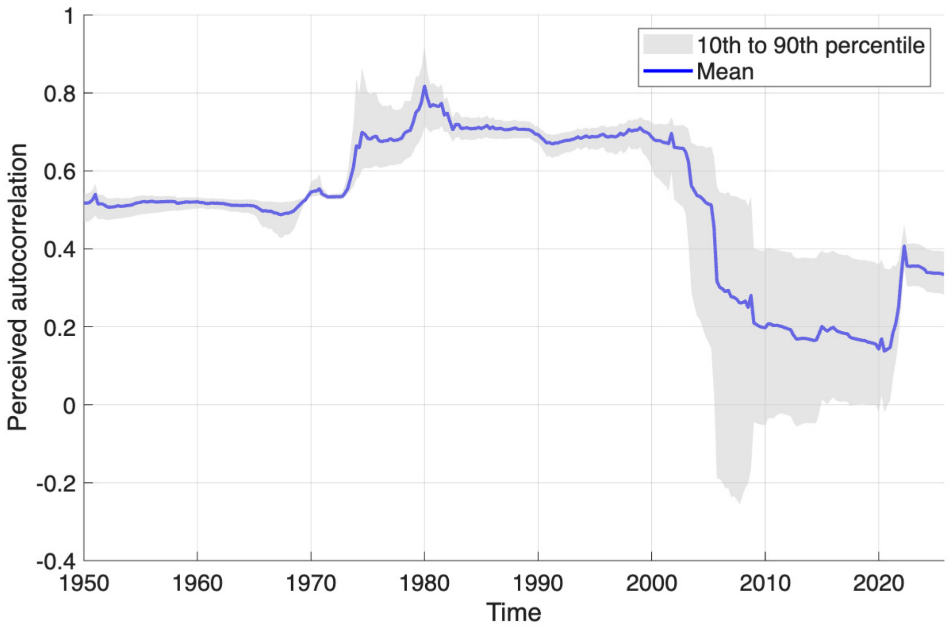
Second, the degree of anchoring as measured by δ changes over time with changes in the perceived short-run persistence of inflation. Such a change may have nothing to do with credible central bank communication of an inflation target, but can be simply a consequence of a change in the short-run persistence of inflation that the public has experienced in past data. In particular, if $\hat{\rho}$ falls at the same time when central banks adopt measures meant to enhance their credibility, it may look like the adoption of these measures improved the anchoring of inflation long-run expectations when, in fact, the cause of the change in the expectations dynamics is that people experienced inflation with low persistence.

As Figure 2a shows, $\hat{\rho}$ has dropped dramatically in the decades following the Great Inflation in the 1970s. The figure shows $\hat{\rho}$ according to the learning-from-experience model applied to realized CPI inflation, and averaged at each point in time across all active cohorts (age 25 to 74). The perceived $\hat{\rho}$ dropped from a peak around 0.8 in 1980 to around 0.2 in 2020, albeit with substantial dispersion between cohorts, as indicated by the large spread between the 10th and 90th percentile. Following (7), this drop in average $\hat{\rho}$ implies that the sensitivity of experience-based long-run inflation expectations to inflation surprises must have dropped drastically over this period. Importantly, however, this drop in sensitivity is purely a consequence of the experienced properties of realized inflation, and not a direct reflection of individuals putting weight on central bank announcements about policy targets when they form expectations.

Figure 2b shows long-run expectations from the learning-from-experience model. We calculate these from the panel of cohort-level experience-based expectations, averaged across active cohorts. The figure shows expectations over horizons of 7.5-year, 10-year, and for the 1-year period ending in 10 years (1-year, 9-year forward). The 1-year, 9-year forward expectation is virtually equal to $\widetilde{\mathbb{E}}_t \pi_{t+\infty}$. Examining the time-series of 1-year, 9-year forward expectations, it is apparent that these long-term expectations were more volatile in times when the perceived autocorrelation was higher in Figure 2a. This is consistent with the relationship between the surprise sensitivity and short-run persistence in (7), although it could also result from changing volatility of inflation surprises. The empirical tests in the next section isolate the effect of changing short-run persistence.

Given the large low-frequency movements in experience-based long-run expectations shown in this figure, it is clear that measuring the degree of anchoring by the (lack) of deviation from an inflation target, as in Bems et al. (2021) and Kumar et al. (2015), would produce the result of that expectations are not well anchored during most of the sample period. In our empirical analysis in

(A) Perceived Autocorrelation of Inflation Averaged Across Cohorts in Each Period



(B) Long-Horizon Experience-Based Inflation Expectations Averaged Across Cohorts in Each Period

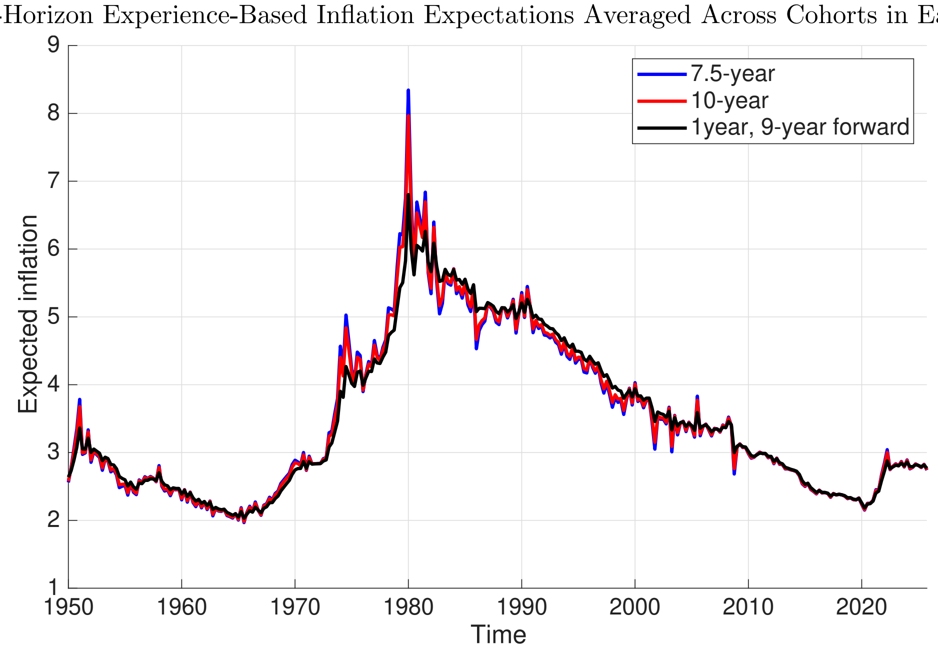


FIGURE 2
Dynamics of Average Experience-Based Inflation Expectations

the next section, we focus on more subtle tests of anchoring based on reaction to inflation surprises, such as regressions as in (10).

The figure also shows that experience-based long-run inflation expectations moved up by less than one percentage point after the COVID pandemic in 2020. This stability seemingly looks like expectations are fairly well anchored. However, by construction, this low responsiveness of experience-based long-run expectations to the inflation surprises observed at the time is due to the relatively low levels of perceived short-run persistence following the experience of many years of low-persistence inflation, and not due to anchoring to the central bank's announced inflation target. This already hints at the fact that one does not need to invoke inflation target credibility to explain the stability of long-run inflation expectations in the post-COVID years.

4 Empirical Tests of Anchoring

We now ask how estimates of the anchoring of long-run inflation expectations would have evolved over postwar U.S. history if the data were generated by learning from experience. To this end, we generate artificial data for birth-year cohorts, with each cohort updating according to the learning-from-experience rule with $\theta = 3.051$, using observed quarterly CPI inflation. In each quarter, we compute experience-based expectations for each cohort at several forecast horizons. We then construct a panel by retaining cohorts whose members are at least 25 and younger than 75, and define the consensus expectation as the average expectation across these age bins. Finally, we apply anchoring tests to this time series of artificial experience-based consensus expectations and compare the results with analogous tests applied to actual expectations data from surveys and market prices.

4.1 Anchoring Tests in First Differences

Our first set of tests relates changes in long-run inflation expectations to inflation surprises. This means that we empirically implement regressions like (10) that we discussed in the previous section. We first show estimates of δ from rolling regressions, and then we examine changes in δ around the Federal Reserve's adoption of an explicit inflation target and around the COVID pandemic.

For the rolling regressions, we set the window length 40 quarters to estimate the parameter δ

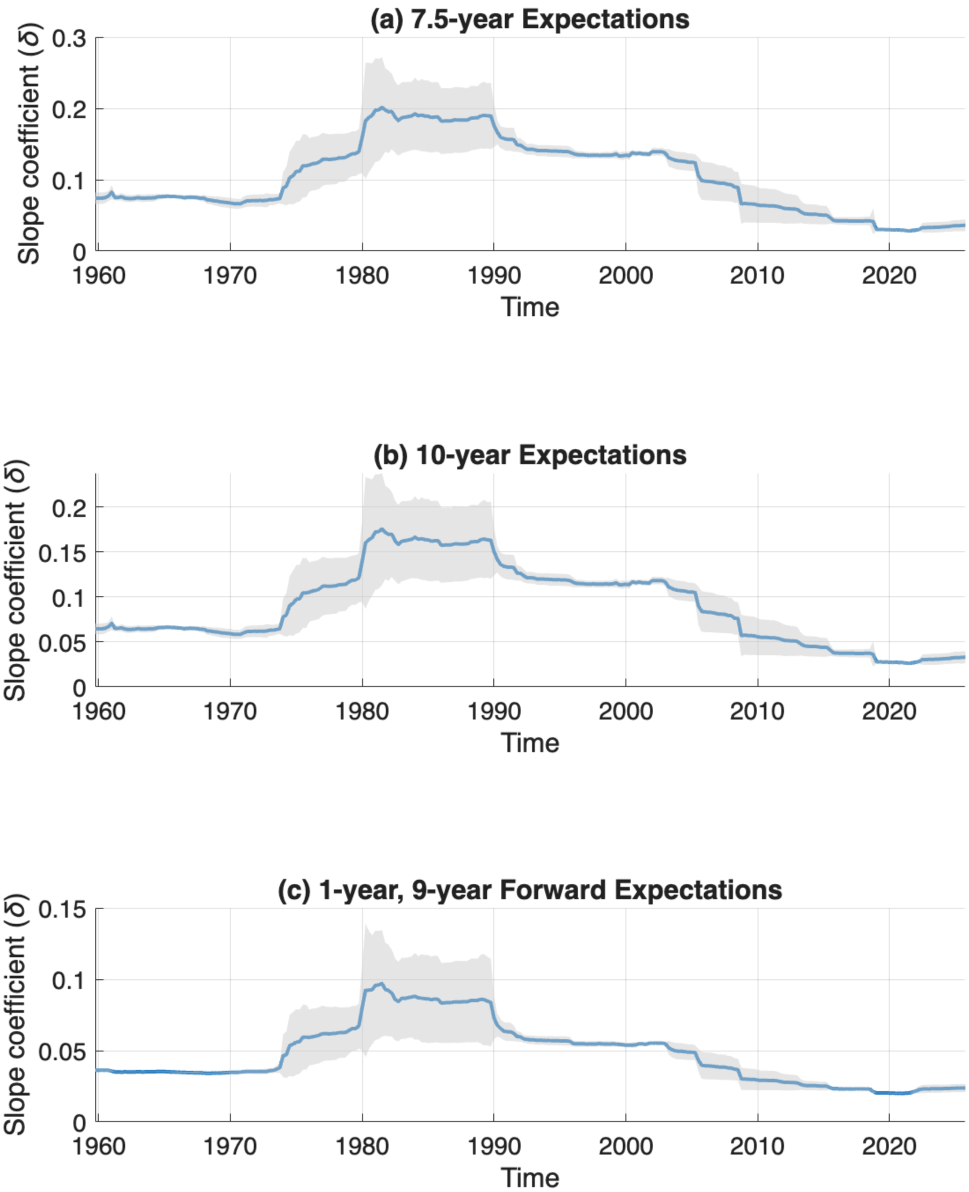


FIGURE 3

Anchoring Tests Using Experience-Based Inflation Expectations and Rolling Regressions

Rolling regressions of changes in experience-based inflation forecasts at 7.5-year, 10-year, or the 1-year, 9-year forward horizon on the contemporaneous inflation surprise relative to the previous quarter's experience-based inflation forecast for that quarter. The length of the rolling windows is 40 quarters. The shaded areas shows 95% confidence intervals based on Newey-West standard errors (4 lags).

in (10), i.e.,

$$\widetilde{\mathbb{E}}_t \pi_{t+h} - \widetilde{\mathbb{E}}_{t-1} \pi_{t-1+h} = \delta_0 + \delta(\pi_t - \widetilde{\mathbb{E}}_{t-1} \pi_t) + e_t \tag{11}$$

where the expectations $\widetilde{\mathbb{E}}_t[.]$ are generated by the learning-from-experience model with $\theta = 3.051$.

Figure 3 reports the rolling regression estimates of δ for expectations at different horizons h with 95% confidence intervals shown as shaded areas. The dates on the horizontal axis refer to the end of the rolling regression windows. For expectations at all three horizons, 7.5-year, 10-year and the 1-year period 9 years forward, the estimates of δ increase substantially in the early part of the sample. They peak in the regression windows that include the late 1970s and early 1980s. The estimates then decline over multiple decades to reach lows in the years after the Great Financial Crisis (GFC).

Thus, we observe a substantial decline in the estimated value of δ, a pattern that might be tempting to interpret as evidence of improved credibility of the Federal Reserve's implicit—and, after 2012, explicit—inflation target. However, the artificial expectations generated by the learning-from-experience model, by construction, place no weight on policy targets or central bank communication. The decline in the estimated δ instead reflects only the evolving perception of the inflation process parameters as inferred from individuals' historical experiences. To the extent that Federal Reserve policy shaped these perceptions, it did so indirectly through actions that influenced realized inflation outcomes rather than through announcements intended to reset or anchor expectations.

For comparison, Figure 4 presents rolling regression results using survey- and market-based expectations. Panel (a) shows results based on expectations over a 5- to 10-year horizon from the MSC. We use the interpolated median of individual responses, as in the standard consensus expectations series provided by the MSC.[9] Panel (b) uses 10-year median expectations from the Survey of Professional Forecasters, supplemented before 1991Q4 with data from the Livingston Survey and the BlueChip Survey, as provided by the Federal Reserve Bank of Philadelphia. Panel (c) uses quarterly averages of daily 10-year inflation swap rates.

For all three expectations series, we use the quarterly real-time forecast errors provided by the

[9] According to MSC administrators, the mean is not the "preferred measure of inflation expectations due to its sensitivity to extremely high responses," a problem that has been magnified recently in the transition from a phone- to web-based survey. See `https://data.sca.isr.umich.edu/fetchdoc.php?docid=76082`.

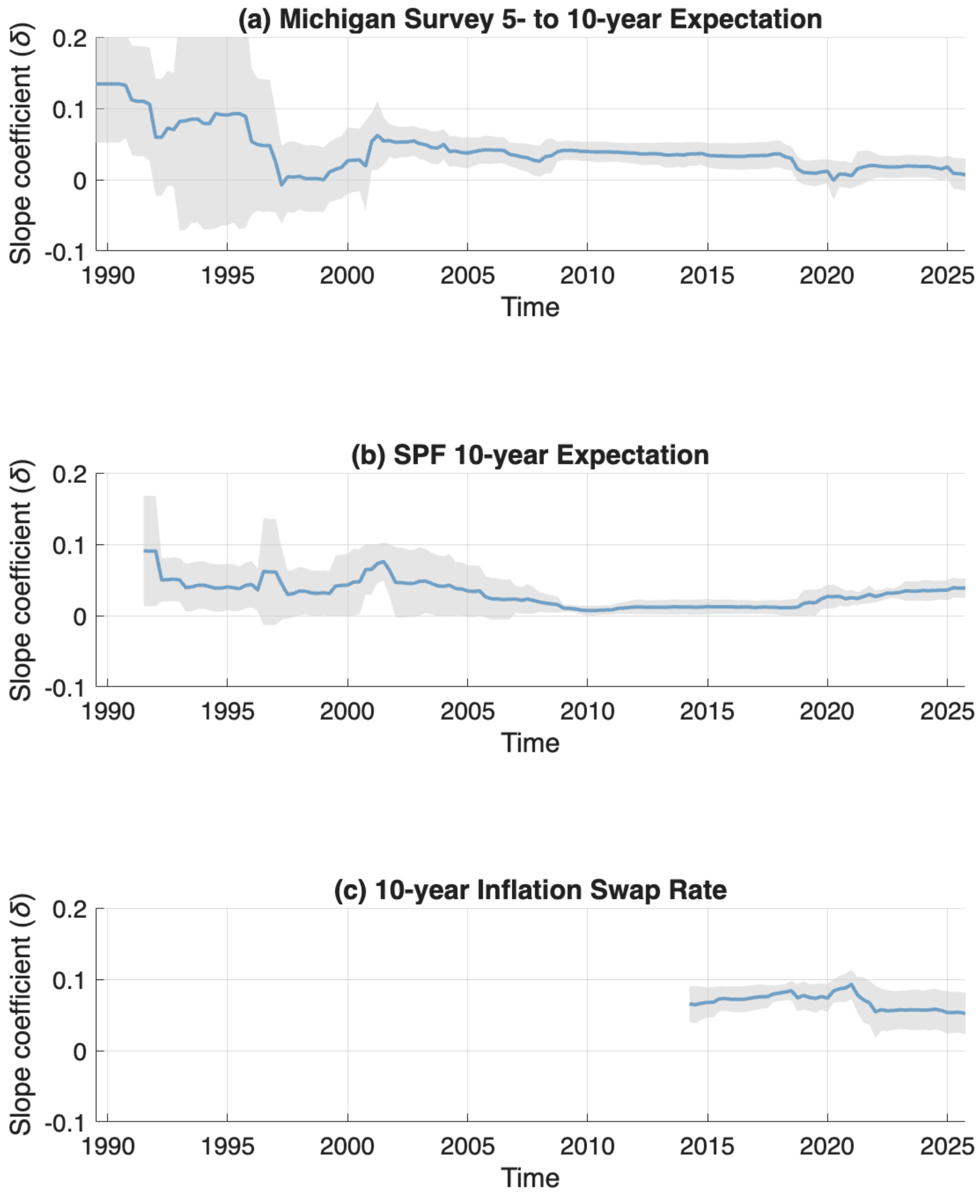


Figure 4

Anchoring Tests Using Inflation Expectations from the Michigan Survey, SPF, and Inflation Swap Rates

Rolling regressions of changes in inflation forecasts on the contemporaneous inflation surprise relative to relative to the previous quarter's inflation forecast from the SPF. The length of the rolling windows is 40 quarters. The shaded areas shows 95% confidence intervals based on Newey-West standard errors (4 lags).

Federal Reserve Bank of Philadelphia as the surprise variable. When available, we use forecast errors based on the first release of the CPI; otherwise, we use the final revised value. We use this same forecast-error series in the analysis of the other expectations measures because the SPF is the only survey that provides one-quarter-ahead forecasts and therefore the only source that allows us to construct a quarterly inflation-surprise series.

Aligning the change in expectations on the right-hand side of (11) with the timing of the surprise is not entirely straightforward. For the SPF, we calculate the change in expectations as the two-quarter change from quarter $t-1$ to $t+1$ around the forecast error quarter t to make sure forecasters have had time to take into account the information revealed in the surprise in quarter t. Before 1991Q4, the SPF did not collect 10-year expectations and the dataset from the Federal Reserve Bank of Philadelphia supplements the SPF with 10-year expectations from the BlueChip and Livingston Surveys, which are mostly available only in the first and fourth quarter of each year. In these early periods, we then add one or two more leads, as necessary, if expectations data in quarter $t+1$ is not available. For the MSC, the matching of the survey forecast with the SPF forecast error is less precise. The SPF forecast error is measured using the CPI from mid-quarter to mid-quarter. To align this forecast error as best as possible with the monthly MSC series, we match the SPF forecast error in quarter t with the change of the MSC forecast from the last month of quarter $t-1$ and the first two months of quarter t to the average of the last month of quarter t and the first two months of quarter $t+1$. Finally, swap rates should reflect news quickly and anticipate some of the CPI data before release. For this reason, the best alignment results from matching the quarter t SPF forecast error with the change in average daily swap rates from the first month of quarter $t-1$ to first month of quarter t.

Panel (a) of Figure 4 shows that the estimates with MSC data look very similar to the ones based on the artificial data in Panel (a) and (b) of Figure 3 (note that the plots in Figure 4 starts in 1990, which is close to the middle of the plots in Figure 3). The estimated δ declines strongly from 1990 to 2020. The magnitude of the estimated δ is a little lower than in Figure 3, but part of this is due to attenuation caused by measurement errors. In the artificial data, we have an exact match, in terms of timing, of the surprise measure and the expectations series. In contrast, for the actual expectations, the timing of the survey is not perfectly aligned with the CPI information release. Moreover, for MSC, the SPF forecast error series is based on SPF expectations, not MSC expectations.

The δ estimates based on the SPF expectations in Panel (b) follow a time path similar to those based on the artificial 10-year expectations in Figure 3, but their magnitude is smaller, at roughly half the size of the estimates from the artificial experience-based expectations data. This is consistent with SPF forecasters putting more weight on the Federal Reserve's (first implicit, then explicit) inflation target than respondents in the MSC. However, this appears not to be a permanent feature. During the post-COVID inflation episode, the surprise sensitivity of SPF expectations rose to levels comparable to those for experience-based expectations in Figure 3.

For inflation swaps in Panel (c), we only have a short sample. Perhaps surprisingly, in the short sample that is available, the sensitivity of inflation swap rates to SPF inflation surprises is stronger than the sensitivity of the survey expectations in Panels (a) and (b) and also stronger than the sensitivity of the experience-based expectations in Figure 3 during the same periods.

We now zoom in on the periods around the Federal Reserve's adoption of an explicit inflation target in 2012. Bundick and Smith (2025) test for changes in δ around the target adoption, comparing the January 1999 to December 2011 period with January 2012 to December 2019 following the policy change. Using market-based inflation expectations extracted from prices of inflation-protected bonds, they find that δ dropped substantially, and they interpret this as the effect of the inflation target adoption. However, as the analysis above makes clear, a drop in δ can also arise with experience-based expectations, without any attention to announced policy targets, if individuals' perception of the degree of short-run persistence changes. For this reason, we now run similar anchoring tests on the artificial expectations data generated by the learning-from-experience model.

Columns (1) to (3) in Panel A of Table 2 presents the results from regressions of changes in expectations at various horizons on inflation surprises and their interaction with a dummy for the January 2012 to December 2019 post-adoption period. Similar to the results in Bundick and Smith (2025), we find that the estimated δ dropped dramatically from pre- to post-adoption. In all three specifications, the point estimates of the interaction coefficient are more than two standard errors below zero. Their magnitude implies that the δ coefficient fell by between 33% to 55% of its

Table 2
Anchoring Tests Using Experience-Based Inflation Expectations

The dependent variable in columns (1) to (3) is the quarterly change in the experience-based inflation expectation based over a 7.5-year, 10-year, or the 1-year, 9-year forward horizon. The dependent variable in columns (4) to (6) are two-quarter changes in actual expectations. The main explanatory is the contemporaneous inflation surprise relative to the previous period's inflation forecast for that quarter. We use the SPF surprise in columns (4) to (6). As in Bundick and Smith (2025), the sample in Panel A runs from January 1999 to December 2019 (due to data availability it starts in July 2004 in column (7)) and the dummy variable I_{post} takes a value of zero until the end of 2011, prior to the adoption of inflation targeting by the Federal Reserve, and a value of one afterwards. In Panel B, the sample runs from January 2012 to December 2025 and the dummy variable I_{post} takes a value of zero until the end fourth quarter of 2020, prior to the post-COVID inflation episode, and a value of one afterwards. Newey-West standard errors (4 lags) are shown in parentheses.

	Experience-based			MSC	SPF	Swap
	(1)	(2)	(3)	(4)	(5)	(6)
	7.5y	10y	1y, 9y fwd.	5-10y	10y	10y
Panel A: Around 2012 Inflation Targeting Adoption						
Intercept	0.012	0.008	-0.005	-0.014	-0.007	-0.051
(s.e.)	(0.009)	(0.007)	(0.003)	(0.012)	(0.009)	(0.037)
$\pi_t - \widetilde{\mathbb{E}}_{t-1}\pi_t$	0.065	0.057	0.030	0.039	0.012	0.069
(s.e.)	(0.013)	(0.010)	(0.004)	(0.007)	(0.005)	(0.010)
I_{post}	-0.009	-0.007	0.000	-0.011	-0.001	0.069
(s.e.)	(0.010)	(0.008)	(0.003)	(0.019)	(0.018)	(0.046)
$I_{\text{post}} \times (\pi_t - \widetilde{\mathbb{E}}_{t-1}\pi_t)$	-0.035	-0.029	-0.010	-0.037	0.004	0.012
(s.e.)	(0.013)	(0.010)	(0.004)	(0.012)	(0.008)	(0.017)
Adj. R^2	79.2%	81.0%	90.2%	38.3%	9.0%	43.5%
Obs.	84	84	84	84	84	62
Panel B: Around the COVID Pandemic						
Intercept	0.003	0.001	-0.005	-0.013	-0.012	0.032
(s.e.)	(0.002)	(0.002)	(0.000)	(0.017)	(0.013)	(0.021)
$\pi_t - \widetilde{\mathbb{E}}_{t-1}\pi_t$	0.030	0.027	0.020	0.002	0.017	0.094
(s.e.)	(0.001)	(0.001)	(0.000)	(0.010)	(0.004)	(0.010)
I_{post}	-0.024	-0.017	0.003	0.189	-0.051	-0.073
(s.e.)	(0.012)	(0.009)	(0.001)	(0.141)	(0.064)	(0.042)
$I_{\text{post}} \times (\pi_t - \widetilde{\mathbb{E}}_{t-1}\pi_t)$	0.010	0.009	0.005	-0.012	0.037	-0.056
(s.e.)	(0.005)	(0.004)	(0.002)	(0.029)	(0.014)	(0.013)
Adj. R^2	91.1%	93.2%	98.3%	10.6%	34.1%	44.3%
Obs.	56	56	56	56	56	56

pre-2012 value.

This analysis demonstrates that, using this type of test, one could mistakenly infer that individuals have anchored their long-run inflation expectations to the Federal Reserve's explicit inflation target, when in fact the decline in δ simply reflects changes in the perceived short-run persistence of inflation. These changes arise from the gradual updating of individuals' beliefs based on the evolving statistical properties of realized inflation, not from any direct anchoring to the announced target.

Column (4) runs similar tests with changes in MSC 5- to 10-year expectations as the dependent variable. The estimates are quite similar to those we obtain with 5- and 10-year experience-based expectations. Columns (5) and (6) use changes in SPF expectations and changes in market-based expectations extracted from Bloomberg 10-year inflation swap rates at the dependent variable, respectively. For these expectations, we do not find a drop of δ around the inflation target adoption to begin with. The interaction coefficient is positive, rather than negative, and, statistically, not significantly different from zero.

Bundick et al. (2024) use similar types of tests to examine changes in the degree of anchoring around the COVID pandemic.[10] For the United States, they find a small positive, and statistically insignificant increase in δ. As we noted in the introduction, other observers have pointed informally to the apparent stability of long-run inflation expectations in surveys and in market-based measures as suggestive of well-anchored expectations.

However, as Panel B of Table 2 shows, given the path of realized inflation that individuals had lived through until the post-COVID pandemic, experience-based expectations generate similarly stable long-run expectations. Columns (1) to (3) in Panel B use changes in experience-based expectations as the dependent variable. The sample runs from January 2012 to December 2025 and the dummy variable I_{post} takes a value of zero until the end fourth quarter of 2020, prior to the post-COVID inflation episode, and a value of one afterwards. All three specifications show a statistically significant increase in δ after 2020. However, the magnitude of the increase is small. The post-COVID coefficients, obtained by adding the coefficient on the inflation surprise and the coefficient on its interaction with I_{post}, remain far below the peak values of δ observed during the

[10]See Hajdini et al. (2025) for updated tests with a longer sample.

1980s in Figure 3. Thus, the learning-from-experience model is fully consistent with the relative stability of long-run inflation expectations after the COVID pandemic.

As columns (4) to (6) show, the picture for expectations from the MSC, SPF, and inflation swaps is mixed. Long-run expectations from the SPF actually registered the strongest increase in sensitivity to inflation surprises. However, for the MSC and inflation swaps we find a decrease in sensitivity. Overall, there is no clear pattern of deviation from the properties of experience-based inflation expectations in columns (1) to (3). The lack of clarity is presumably partly due to the relatively short post-COVID sample.

4.2 Anchoring Tests in Levels

The advantage of tests that based on differenced expectations is that they relatively cleanly isolate the reaction to surprise information. A disadvantage is that measurement problems due misalignment in the timing of expectations measurement and the inflation realization entering the surprise variable may distort the results. Delayed reaction to information can lead to distortions as well. An alternative is to run tests in levels. Tests in levels are less sensitive to these measurement problems.

Following Bernanke and Blanchard (2025) (BB), we examine regressions of the form

$$\widetilde{\mathbb{E}}_t \pi_{t+h} = \alpha_0 + \sum_{j=1}^{4} \alpha_j \widetilde{\mathbb{E}}_{t-j} \pi_{t-j+h} + \sum_{j=0}^{4} \beta_j \pi_{t-j} + e_t. \tag{12}$$

The idea underlying this regression is that well-anchored expectations should not be sensitive to realized inflation, which means that the sum of the β_j coefficients,

$$\bar{\beta} = \sum_{j=0}^{4} \beta_j, \tag{13}$$

should be small.

BB impose the restriction that the α_j and β_j coefficients jointly add up to unity, but they also note that an unrestricted specification yields almost identical estimates. They also impose $\alpha_0 = 0$. We leave the coefficients unconstrained, and, in particular, we do not impose $\alpha_0 = 0$ because doing

Table 3
Bernanke-Blanchard Anchoring Tests

The dependent variable is the level of long-term inflation expectations as implied by learning from experience (10-year horizon), or as measured in the Michigan Survey (5- to 10-year horizon) and the Survey of Professional Forecasters (10-year horizon) at quarterly frequency. The main explanatory variables are four lags of the dependent variable, as well as the contemporaneous realization and four quarterly lags of the CPI inflation rate. The sum of coefficients reported in the table is the sum of the estimated slope coefficients on the five CPI inflation realization variables. The sample runs from 1991Q4 to 2019Q4 in columns (1) to (3) and until 2025Q4 in columns (4) to (6). Newey-West standard errors (4 lags) are shown in parentheses.

	Pre-Covid			Full Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
	Exp.-based	MSC	SPF	Exp.-based	MSC	SPF
	10y	5-10y	10y	10y	5-10y	10y
Sum of coefficients lagged exp.	0.954	0.867	0.898	0.958	0.895	0.896
(s.e.)	(0.007)	(0.034)	(0.028)	(0.007)	(0.039)	(0.029)
Sum of coefficients realized infl.	0.046	0.045	0.027	0.045	0.020	0.024
(s.e.)	(0.006)	(0.012)	(0.009)	(0.005)	(0.010)	(0.010)
Adj. R^2	99.2%	90.5%	96.3%	99.2%	79.4%	94.1%
Obs.	109	109	109	133	133	133

so would effectively hardwire a high autocorrelation of inflation expectations.[11]

BB estimate the regression with pre-COVID data and in a full sample that includes the post-COVID inflation episode. Using the long-term inflation expectations series provided by the Federal Reserve Bank of Cleveland (which are based on an estimated affine term structure model that takes market prices and survey data as inputs), BB find essentially identical estimates of the sensitivity of long-term expectations to realized inflation in the pre-COVID sample as in the full sample.

In columns (1) and (4) of Table 3 we present estimates from running these tests on artificial experience-based expectations. Column (1) uses the pre-COVID sample 1991Q4 to 2019Q4, as in BB, and column (4) uses the full sample ending in 2025Q4, the same endpoint as in the post-COVID sample in Panel B of Table 2. With experience-based expectations, we find that our estimate of $\bar{\beta}$, the sum of the coefficients on realized inflation is actually slightly lower in the full sample than in the pre-COVID sample, but the magnitude is almost identical. Thus, we basically obtain a very similar result as what BB find based on actual inflation expectations. Therefore, these tests in levels lead to a similar conclusion as our earlier tests in differences: the stability of long-run

[11]To see this, consider the case of an IID random variable $y_t = \mu + \varepsilon_t$ where ε_t is IID with variance σ^2 and μ is a constant. In this case, the slope coefficient in a regression of y_t on its own lag, without intercept, is $\mathbb{E}[y_t y_{t+1}]/\mathbb{E}[y_t^2] = \mu^2/(\mu^2 + \sigma^2)$ which is greater than zero and different from the true autocorrelation of zero.

inflation expectations in response to the post-COVID inflation episode is consistent with a model of experience-based inflation expectations formation.

Considering the associated standard errors, the point estimates of $\bar{\beta}$ using actual expectations data in columns (2) and (3) as well as (5) and (6) are broadly in the same range as the estimates using artificial experience-based expectations. Both for the MSC and the SPF we obtain lower point estimates in the full sample than in the pre-COVID sample.

5 Experience-Based Heterogeneity in Anchoring

Thus far, we have shown that the empirical evidence from standard anchoring tests is broadly consistent with a model of experience-based inflation expectation formation in which individuals place zero weight on the central bank's explicit or implicit inflation targets. To move beyond this observational equivalence, we now examine predictions that are unique to the experience-based learning framework. These predictions center on systematic heterogeneity in the sensitivity of long-run inflation expectations to inflation surprises.

The experience-based expectations model implies that two key dimensions of heterogeneity shape the sensitivity of long-run inflation expectations to inflation surprises. First, individuals of different ages update beliefs with heterogeneous gains. Younger individuals have accumulated shorter experience histories and therefore learn with higher gain, whereas older individuals learn with lower gain. All else equal, a higher gain implies greater responsiveness of inflation expectations to inflation surprises. Second, individuals of different ages are heterogeneous in their perceived autocorrelation of inflation. As discussed in Section 3, higher perceived inflation persistence implies greater sensitivity of long-run inflation expectations to inflation surprises. Which age group exhibits greater sensitivity of long-run expectations to inflation surprises therefore depends on the inflation history that each cohort has experienced.

By contrast, models that attribute anchoring to credibility of the central bank's implicit or explicit inflation target do not generate age-based heterogeneity in long-run inflation expectations, nor do they predict that any such heterogeneity should vary systematically with individuals' experienced inflation histories.

We start in Figure 5 with rolling regressions as in Figures 3 and 4, but now with the sample

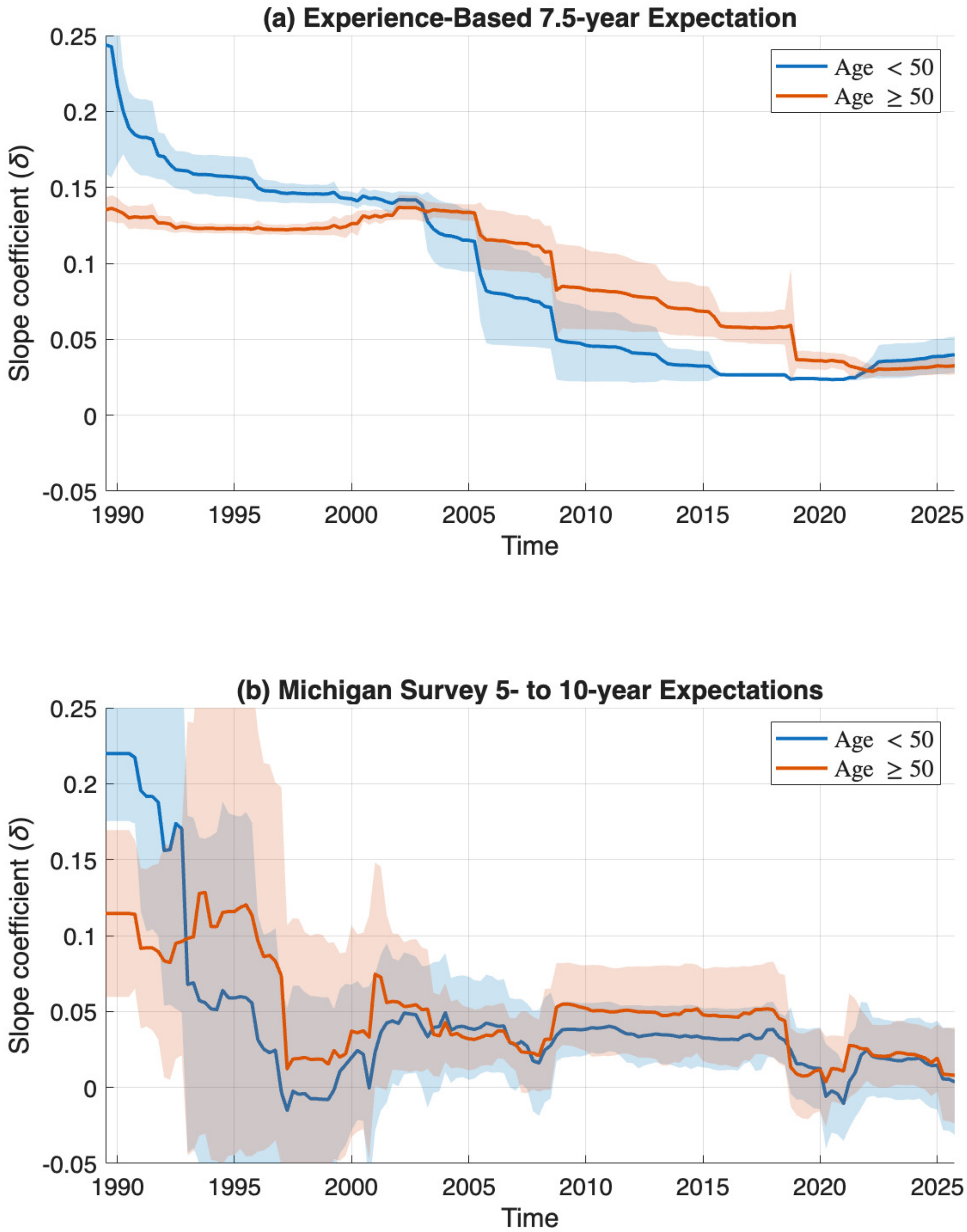


Figure 5
Anchoring Tests Using Experience-Based Inflation Expectations and Data from the Michigan Survey: Heterogeneity by Age

Rolling regressions of changes in inflation forecasts on the contemporaneous inflation surprise relative to relative to the previous quarter's inflation forecast from the SPF. The length of the rolling windows is 40 quarters. The shaded areas shows 95% confidence intervals based on Newey-West standard errors (4 lags).

split into two age groups: age < 50 and age ≥ 50. Panel (a) shows estimates of the sensitivity of experience-based expectations (7.5-year horizon) to inflation surprises, and Panel (b) reports results for actual expectations from the MSC (5- to 10-year horizon). As before, we average across age bins for experience-based expectations and we use the interpolated median of individual responses in the MSC, but now within the two age groups.

We restrict the analysis to two age groups because statistical power is limited. Period-by-period measures of inflation expectations in the MSC are noisy, and estimates of their sensitivity to inflation surprises are therefore subject to substantial estimation error. Subdividing the sample by age further amplifies this noise. Using two age groups strikes a balance: it limits estimation error while still capturing the main dimensions of heterogeneity predicted by the model.

The results in Figure 5 show that, despite substantial statistical uncertainty in estimating sensitivity, Panels (a) and (b) exhibit strikingly similar broad patterns. First, over the full sample, both experience-based expectations and MSC expectations display a much larger decline in sensitivity to inflation surprises for younger individuals than for older individuals. Second, in both panels, the sensitivity of younger individuals eventually falls below that of older individuals. This crossover occurs somewhat later for experience-based expectations (around 2003) than for observed expectations (around 1997). However, given the large estimation error for observed expectations, which is clearly visible in the confidence bands in Panel (b), precise alignment in timing is not expected, even if the underlying expectation formation process is well captured by the experience-based learning model. Third, toward the end of the sample, sensitivities converge and become very similar across the two age groups in both panels.

We also provide formal statistical tests along the lines of the anchoring tests in Table 2, but here focused on heterogeneity between age groups with the difference between changes of the inflation expectations of younger individuals (age < 50) minus changes of the inflation expectations of older individuals (age ≥ 50) as the dependent variable. In a regression of this dependent variable on interactions of subperiod dummy variables and the inflation surprise, we look for heterogeneity in changes of the inflation surprise sensitivity around three breakpoints. The first is the beginning of 1994 when the Federal Reserve started explaining policy actions by issuing a press statement (Poole and Rasche, 2003). The second and third are the breakpoints at the adoption of an inflation

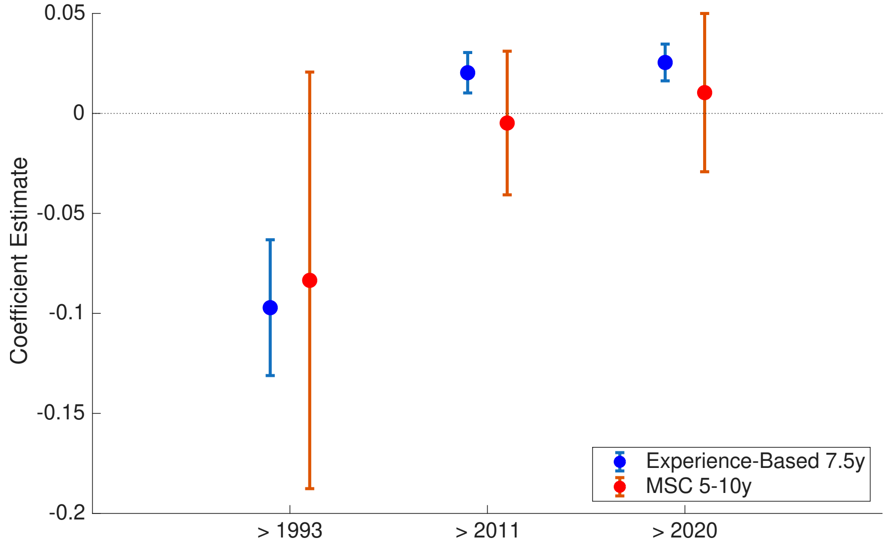


FIGURE 6

Differences (Between Subperiods) in Differences (Age < 50 Minus Age ≥ 50) in Inflation Surprise Sensitivity of Experience-Based and Actual Expectations

Estimated slope coefficients on subperiod dummy variable interactions with inflation surprises in regressions where the dependent variable is the difference between changes of the inflation expectations of younger individuals (age < 50) minus changes of the inflation expectations of older individuals (age ≥ 50). The error bars show 95% confidence intervals based on Newey-West standard errors (4 lags).

target at the beginning of 2012 and at the start of the post-COVID inflation in 2021 as in Table 2.

In these regressions, the three interactions between subperiod dummy variables and the inflation surprise capture how changes in the estimated degree of anchoring across subperiods differ between age groups. Figure 6 provides a visual summary of the estimated slope coefficients on the three interaction terms, along with their associated 95% confidence intervals, for both experience-based expectations and actual expectations from the MSC. Table A.I in Appendix C shows the full regression results.

The coefficient on the $I_{>1993}$ dummy interacted with the inflation surprise measure in Figure 6 shows that the experience-based expectations model predicts a substantially stronger decline in the inflation-surprise sensitivity post-1993 for younger individuals than for older individuals. The point estimate from the MSC is close to this prediction. Although the point estimates are very similar, the difference in sensitivity between younger and older individuals in the MSC is estimated imprecisely. A key source of this limited precision is the small number of observations prior to 1994. During the 1980s, 5- to 10-year inflation expectations were not elicited in every survey wave, resulting in substantial gaps in the series.

For the $I_{>2011}$ and $I_{>2020}$ dummy interactions with the inflation surprise, the experience-based expectations model predicts that the inflation surprise sensitivity of the young to increase relative to the inflation surprise sensitivity of older individuals, but by a small magnitude. The estimates from the MSC are close to these predictions.

Conventional models of inflation-expectations anchoring do not predict such age-based heterogeneity in sensitivity to inflation surprises. This provides further reason to question whether anchoring to central bank inflation targets is the primary mechanism behind the stabilization of long-run expectations in recent decades.

6 Repeating the Experience of the 1970s: How Would Long-Run Inflation Expectations Respond?

We have argued that it may be premature to attribute the declining sensitivity of long-run inflation expectations to inflation surprises to improved anchoring around the Federal Reserve's inflation target. Expectations formed purely through learning from realized inflation exhibit a similar decline in sensitivity, even in the absence of any anchoring to an inflation target. By the same token, the stability of long-run expectations during the post-COVID inflation surge is consistent with experience-based expectations shaped by the pre-COVID history of weakly persistent inflation—conditions that, as we have shown, produce low sensitivity of long-run expectations to new surprises.

Which of these alternatives—true anchoring to the target or low perceived persistence inferred from experience—is correct has crucial implications for the path ahead. Bernanke and Blanchard (2025), for example, emphasize that the stability of long-run inflation expectations during the post-COVID episode stands in stark contrast to the 1970s, when expectations shifted far more dramatically. In making this comparison, however, it is important to recall that the Great Inflation unfolded in three distinct waves: 1968-71, 1973-76, and 1978-81. The post-COVID episode resembles the first of these waves. The key question is: would long-run expectations remain as stable as they have been if the economy were to experience two additional inflation waves similar to those of 1973-76 and 1978-81?

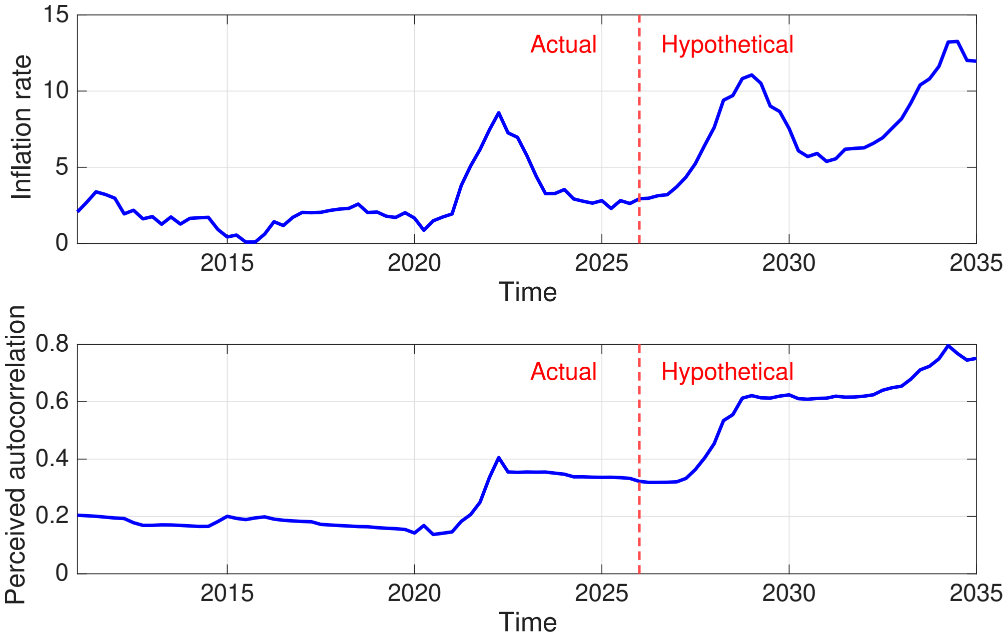


Figure 7
Repeating the Experience of the 1970s:
Hypothetical Path of Inflation and Perceived Autocorrelation

In this section, we ask the hypothetical question of how long-run expectations would change if the economy were to experience two additional waves of inflation similar to those of 1973-76 and 1978-81. That is, we take realized inflation rates until 2026Q1 and append the inflation rates from 1972Q1 to 1980Q4. Panel (A) of Figure 7 shows the resulting path of inflation. Coincidentally, the level of the inflation rate in 1972Q1 was almost exactly the same as in 2026Q1, so there is virtually no jump at the boundary to the hypothetical sample. We then calculate experience-based expectations in this hypothetical sample after 2026Q1.

As we discussed earlier, the perceived short-run persistence of inflation is key to the sensitivity of long-run inflation expectations to inflation surprises under the AR(1) perceived law of motion in the experience-based model. Panel (B) of Figure 7 shows the resulting path of the perceived first order autocorrelation of quarterly inflation rates if the hypothetical path of future inflation were to realize. Starting from less than 0.4 after 2026Q1, it would reach approximately 0.8 by the mid-2030s, the same level as in 1980 (as we have shown in Figure 2a). In other words, as our earlier analysis in equation (7) implied, the sensitivity of long-run inflation expectations to inflation surprises would rise dramatically.

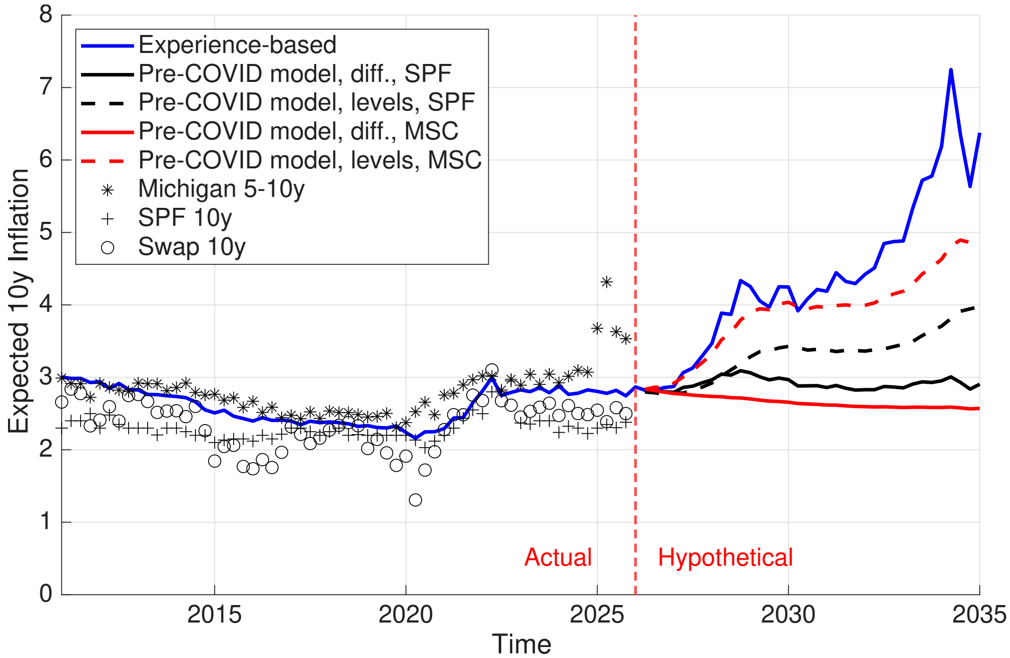


FIGURE 8

Repeating the Experience of the 1970s: Path of Long-Run Inflation Expectations

Figure 8 shows the path of experience-based long-run inflation expectations at a 10-year forecast horizon implied by the hypothetical inflation path after 2026Q1. As the blue line shows, long-run expected inflation would rise to around 7%, which is nearly the level reached around 1980 (see Figure 2b). Thus, under learning from experience, the absence of anchoring to the central bank's inflation target and the path-dependent sensitivity of expectations to inflation surprises imply that living through two additional inflation waves would bring back long-run inflation expectations with properties similar to those observed in the early 1980s.

In contrast, if long-run inflation expectations retained the sensitivity to inflation surprises that they had in the years prior to the COVID pandemic, consistent with a high degree of anchoring to the Federal Reserve's inflation target, the path of long-run inflation expectations would look very different. The solid black and solid red lines shows inflation expectations calculated with the model in Bundick and Smith (2025),

$$\widetilde{\mathbb{E}}_t \pi_{t+\infty} = \rho \widetilde{\mathbb{E}}_{t-1} \pi_{t+\infty} + (1-\rho)\pi^* + \delta(\pi_t - \widetilde{\mathbb{E}}_{t-1}\pi_t), \tag{14}$$

where we set $\rho = 0.93$ for quarterly data, as calibrated by Bundick and Smith to match empirical properties of the Philipps curve, $\pi^* = 2.5\%$ (reflecting a 2% inflation target for the PCE inflation rate, plus a 0.5% addition for the typical gap between CPI and PCE inflation). We use inflation surprises from the experience-based expectations model as proxy for $\pi_t - \widetilde{\mathbb{E}}_{t-1}\pi_t$. For the black solid line we use the estimate of $\delta = 0.017$ for the SPF in Table 2, Panel B, column (5). Based on these parameter values, the model features a low sensitivity to inflation surprises and a modest tendency to pull long-run expectations back to the inflation target. As shown in Figure 8, this results in a minor rise in long-run inflation expectations in response to the two additional waves of inflation after 2026Q1. For the red solid line, we use the estimate of $\delta = 0.002$ for the MSC in column (4) of Panel B of Table 2, which implies long-run expectations that are almost insensitive to inflation surprises, as is evident in the figure. This is a prototypical well-anchored long-run inflation expectations scenario.

The dashed black and dashed red lines in Figure 8 show inflation expectations based on similar calculations with the levels model of Bernanke and Blanchard (2025),

$$\widetilde{\mathbb{E}}_t\pi_{t+h} = \alpha_0 + \sum_{j=1}^{4}\alpha_j\widetilde{\mathbb{E}}_{t-j}\pi_{t-j+h} + \sum_{j=0}^{4}\beta_j\pi_{t-j}. \tag{15}$$

We use the SPF estimates from column (3) in Table 3 for the black dashed line, and the MSC estimates from column (2) of Table 3 for the red dashed line. Based on this levels model with pre-COVID estimates, the sensitivity of long-run inflation expectations is a bit stronger than based on the differences model, especially with the MSC parameter estimates. Even so, at the peak, there is still a gap of more than 2 percentage to experience-based expectations.

Hence, when individuals learn from experience, extrapolating the statistical relationship between long-run inflation expectations and realized inflation from a period shaped by decades of low and weakly persistent inflation will understate how strongly expectations may respond in future inflationary episodes. In this setting, applying pre-COVID estimates going forward would mistakenly interpret the temporarily low sensitivity of long-run expectations to inflation surprises as a permanent tendency to be well-anchored.

In summary, given how well the overall empirical evidence fits a model in which individuals place zero weight on announced inflation targets, the impact of further inflation waves on expectations could be much more severe than implied by models that assume substantial anchoring to an inflation target. We also note that even the experience-based expectations model may still be too optimistic about the stability of long-run expectations. Under experience-based learning, realized inflation is the only source of news that moves expectations. In practice, individuals also respond to other information that shapes their views about future inflation. The MSC expectations in 2025 in Figure 8, provide an example. During this period, survey expectations moved substantially away from the predictions of the experience-based model, presumably in response to news about tariffs from the U.S. government. More generally, the experience-based model leaves some variation in observed expectations unexplained. For example, in Panel B of Table 1, the R^2 is about 50%. At the aggregate time-series level, the R^2 from using average experience-based 7.5-year expectations to explain 5- to 10-year Michigan survey expectations is about 60%. While some of this unexplained variation will be measurement error, some of it likely reflects the fact that individuals use information beyond realized inflation rates when forming views about future inflation. Responses to such news provide an additional source of potential instability in long-run expectations.

7 Conclusion

The empirical behavior of long-run inflation expectations in the years prior to the COVID pandemic and their stability during the post-COVID inflation episode looks suggestive of a substantial degree of anchoring to the Federal Reserve's inflation target. However, similar empirical patterns are to be expected if individuals form expectations based on experiences of realized inflation, without attention to an announced inflation target. Since inflation in the decades before the pandemic was characterized by low persistence, experience-based learners would naturally hold long-run expectations that are relatively insensitive to inflation surprises. Yet, their low sensitivity is temporary. Under experience-based learning, episodes of persistent inflation can raise perceived persistence and, in turn, increase the responsiveness of long-run expectations, even when the central bank is committed to an inflation target. For this reason, it may be premature to infer from the recent stability of long-run expectations that they would remain stable if the economy were to experience additional inflationary shocks.

Empirical support for the experience-based model comes not only from its ability to match time-series patterns in aggregate consensus expectations, but also from its implications for expectations heterogeneity. In the two decades before the pandemic, older individuals regularly reported substantially higher long-run inflation expectations than younger individuals, consistent with the older generation's lingering memory of the high inflation of the 1970s, which is difficult to reconcile with the notion of strongly anchored long-run expectations. We also find that the inflation surprise sensitivity of younger individuals' long-run expectations declined much more in the decades following the 1980s than for older individuals, which is not explained by models that attribute anchoring primarily to central bank inflation targets.

Overall, the evidence suggests that the mechanism underpinning the stability of long-run inflation expectations in recent decades differs from that emphasized in the anchoring literature. In the experience-based learning model, central bank actions affect expectations through their influence on individuals' realized inflation histories, rather than through communication about long-run policy targets. By the same logic, the future stability of inflation expectations depends critically on maintaining low and weakly persistent realized inflation.

The implication for monetary policy is that announcements of inflation targets, or other statements about policy objectives, may by themselves do little to stabilize long-run inflation expectations. If beliefs are shaped by experience, policy must generate the realized inflation outcomes that lead individuals to update their beliefs toward the target. This requires interest-rate policy that responds forcefully enough to deviations of inflation from target. In this sense, credibility is built through the realized inflation history that the public observes. Policy communication still matters, but its main role may be to transmit information about the policy stance, including the future path of short-term interest rates, to financial markets, rather than to exert a direct effect on long-run inflation expectations.

Even with effective policy response to deviations from target inflation, some degree of expectations instability is unavoidable. As older inflation experiences receive declining weight, new inflation outcomes continue to reshape beliefs, implying that expectations can never be permanently anchored in the strong sense of becoming unresponsive to realized inflation. One might ask whether policy could achieve greater stability by reducing individuals' reliance on past inflation data and increasing their attention to central bank targets and communication. Evidence from information experiments and surveys in Coibion and Gorodnichenko (2026) and Coibion et al. (2023) suggests that this may be difficult to accomplish. Moreover, our prior research on experience effects among FOMC members (Malmendier et al., 2021) shows that even highly informed central bankers fail to shake off the influence of past experiences. A plausible interpretation of experience-based learning is therefore that experiences dynamically "rewire" the brain in ways that cannot easily be undone by acquiring more abstract, theoretical knowledge about policy targets.

Thus, to the extent that households (and central bankers) continue to place substantial weight on experienced inflation, the most reliable way to preserve stable long-run inflation expectations is to maintain a realized inflation record consistent with the target.

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Appendix

A Data

A.1 Michigan Survey of Consumers

The survey data on inflation expectations from the Survey Research Center at the University of Michigan is from Malmendier and Nagel (2016), supplemented with data until the end of 2025, and with a small methodological adjustment in the imputation of missing percentage responses from categorical responses, as explained below. Survey data is available since 1953, initially three times per year, then quarterly (1960-1977), and monthly since 1978 (see Curtin (1982)). The files up to 1977 are available from the Inter-University Consortium for Political and Social Research ($ICPSR$) at the University of Michigan. As in MN, the sample is restricted to respondents aged 25 to 74.

MN follow Curtin (1996) in making several adjustments to the raw data to correct known deficiencies. These adjustments are similar to the those used by the Survey Research Center in processing the data to construct its indices (e.g., the consumer sentiment index). Two of these adjustments only concern the early part of the data: imputing missing percentage responses for a small number of respondents expecting prices to decline (in data prior to February 1980) and adjustment of responses that prices will stay the same that reflected misunderstanding (in data prior to March 1982). The third adjustment involves imputing percentage responses when respondents provided only a categorical response of "up" ("down") by drawing from the empirical distribution of percentage responses of those with the same birth year who gave the same categorical response of "up" ("down") in the same survey period (Curtin's original method draws from the empirical distribution in the same period, without breaking up the sample by age). In MN, the imputed responses were drawn from a sample that includes the missing percentage responses. Here, we draw, with replacement, only from the sample of responses that excludes missing values.

In some of the survey waves prior to 1978, the survey only asks about the expected direction of future price changes ("up," "same," or "down"), but not about the expected percentage of price changes. MN impute average percentage expectations at the cohort-level by estimating the relationship between average percentage responses and the proportion of "up" and "down" responses in periods when both categorical and percentage expectations are available. Importantly, this imputation procedure is only designed to impute cross-sectional differences in expected inflation between cohorts, not the cross-sectional average of expectations each period. For this reason, we use the imputed data only in the cohort-level analysis in Section 2, but not in the calculation of the time series of aggregate consensus expectations in subsequent sections.

For the cohort-level analysis in Section 2 we follow MN and aggregate the inflation expectations by taking the averages, weighted using survey weights, within birth-year cohort each month. To get quarterly data, we then average monthly data within each quarter.

A.2 Survey of Professional Forecasters

We obtain quarterly 10-year expectations of CPI inflation in the SPF from the Federal Reserve Bank of Philadelphia. The series starts in 1991Q4. We supplement this series with the series of "Additional 10-Year-Ahead Inflation Forecasts from Other Sources," also provided by the Federal Reserve Bank of Philadelphia. These additional forecasts are from the BlueChip Survey and the Livingston Survey and they start in 1979Q4, and data is available in most years only in the first and fourth quarter.

A.3 Inflation Swaps

Data on 10-year inflation swap rates is from Bloomberg (USSWIT10), starting in July 2004, at daily frequency.

B Bayesian Updating with Fading Memory

With known ρ, the quasi-differenced series $\pi_t - \rho\pi_{t-1} = a + \varepsilon_t$ is IID. Hence, if starting with a diffuse prior and learning with constant gain γ, the steady-state posterior mean at time $t-1$ is

$$\hat{a}_{t-1} = \gamma \sum_{j=1}^{\infty} (\pi_{t-j} - \rho\pi_{t-1-j})(1-\gamma)^{j-1}, \tag{A.1}$$

and the posterior precision at $t-1$, which is equal to the prior precision coming into period t, is a weighted sum of the precision of individual observations in the past:

$$\frac{1}{\sigma^2} \sum_{j=1}^{\infty} (1-\gamma)^{j-1} = \frac{1}{\gamma\sigma^2}. \tag{A.2}$$

Consequently, the prior mean of $\mu = a/(1-\rho)$ is $\hat{a}_{t-1}/(1-\rho)$ with prior variance $\gamma\sigma^2/(1-\rho)^2$.

We now show that a weighted likelihood, or power prior, that discounts the prior by the factor $1-\gamma$, as in Nagel and Xu (2022), Ibrahim and Chen (2000), and Zellner (2002), leads to Bayesian updating that confirms these constant-gain updating relationships. The discounting of the prior by the the factor $1-\gamma$ is equivalent to boosting the prior variance by the factor $(1-\gamma)^{-1}$. With the posterior mean being a precision-weighted average of prior mean and observation $\pi_t - \rho\pi_{t-1}$, this yields a posterior mean at t of

$$\begin{aligned} \hat{a}_t &= \frac{\gamma\sigma^2(1-\gamma)^{-1}}{\gamma\sigma^2(1-\gamma)^{-1} + \sigma^2}(\pi_t - \rho\pi_{t-1}) + \frac{\sigma^2}{\gamma\sigma^2(1-\gamma)^{-1} + \sigma^2}\hat{a}_{t-1} \\ &= \frac{\gamma}{\gamma + 1 - \gamma}(\pi_t - \rho\pi_{t-1}) + \frac{1-\gamma}{\gamma + 1 - \gamma}\hat{a}_{t-1} \\ &= \gamma(\pi_t - \rho\pi_{t-1}) + (1-\gamma)\hat{a}_{t-1} \\ &= \gamma(\pi_t - \rho\pi_{t-1} - \hat{a}_{t-1}) + \hat{a}_{t-1}, \end{aligned} \tag{A.3}$$

which confirms the constant-gain calculation of the posterior mean as in (A.1) that we started out with and it is the same updating scheme as in (5) in the main text, but here with known ρ. The posterior mean of μ is $\hat{a}_t/(1-\rho)$, which leads to the updating of long-run expectations as in (7), but again here with known ρ.

If ρ is uncertain, similar calculations with the posterior mean $\hat{\rho}$ instead of the true ρ still provide a good approximation of the posterior mean of μ as long as $|\rho|$ is substantially smaller than 1 and the uncertainty about ρ is small.

C Anchoring Tests Allowing for Heterogeneity by Age

Table A.I
Anchoring Tests: Heterogeneity by Age

The dependent variable in columns (1) to (2) is the quarterly change in the experience-based inflation expectation (7.5-year horizon) for individuals below and above age 50, and in column (3) it is their difference. Columns (4) to (6) use actual inflation expectations from the Michigan Survey of consumers (5- to 10-year horizon) for the same age groups. The main explanatory is the contemporaneous inflation surprise relative to the previous period's inflation forecast. In columns (1) to (3) the surprise is measured as realized inflation relative to the experienced-based expectation for that quarter. We use the SPF surprise in columns (4) to (6). The number of observations in columns (4) to (6) in this panel is lower than in columns (1) to (3) because there are gaps in the Michigan Survey 5- to 10-year expectations until 1991. Newey-West standard errors (4 lags) are shown in parentheses.

	Experience-based			MSC		
	(1)	(2)	(3)	(4)	(5)	(6)
	Age < 50	Age >= 50	Diff.	Age < 50	Age >= 50	Diff.
Intercept	-0.014	-0.001	-0.013	-0.090	-0.095	0.005
(s.e.)	(0.020)	(0.009)	(0.013)	(0.035)	(0.051)	(0.069)
$I_{>1993}$	0.012	0.024	-0.012	0.058	0.072	-0.014
(s.e.)	(0.022)	(0.013)	(0.015)	(0.040)	(0.052)	(0.071)
$I_{>2011}$	0.001	-0.016	0.017	0.006	0.006	0.001
(s.e.)	(0.008)	(0.011)	(0.010)	(0.026)	(0.023)	(0.030)
$I_{>2020}$	-0.015	-0.032	0.017	0.245	0.192	0.053
(s.e.)	(0.011)	(0.013)	(0.006)	(0.143)	(0.151)	(0.049)
$\pi_t - \widetilde{\mathbb{E}}_{t-1}\pi_t$	0.154	0.090	0.064	0.178	0.105	0.073
(s.e.)	(0.023)	(0.009)	(0.017)	(0.048)	(0.030)	(0.052)
$I_{>1993} \times (\pi_t - \widetilde{\mathbb{E}}_{t-1}\pi_t)$	-0.102	-0.005	-0.097	-0.139	-0.056	-0.083
(s.e.)	(0.027)	(0.016)	(0.017)	(0.048)	(0.033)	(0.053)
$I_{>2011} \times (\pi_t - \widetilde{\mathbb{E}}_{t-1}\pi_t)$	-0.028	-0.048	0.020	-0.049	-0.044	-0.005
(s.e.)	(0.013)	(0.013)	(0.005)	(0.015)	(0.019)	(0.018)
$I_{>2020} \times (\pi_t - \widetilde{\mathbb{E}}_{t-1}\pi_t)$	0.023	-0.003	0.025	-0.004	-0.014	0.010
(s.e.)	(0.006)	(0.004)	(0.005)	(0.034)	(0.036)	(0.020)
Adj. R^2	63.5%	83.5%	35.1%	31.2%	24.4%	2.7%
Obs.	304	304	304	185	185	185