Seemingly Anchored Inflation Expectations *

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Empirical evidence suggestive of better anchoring of inflation expectations—such as the declining sensitivity to inflation surprises over time or around the adoption of inflation targeting—is commonly attributed to the influence of explicit or implicit inflation targets. We show, however, 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 and the fact that the decline in surprise sensitivity since the 1980s is strongest among younger individuals. The memory of low inflation persistence experiences also 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.

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I. 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, Smith, and Van der Meer (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

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`.

can unravel as new experiences accrue. Consistent with this mechanism, we show that inflation 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.

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.

To quantify this argument, and probe the alternative, experience-based interpretation of the 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. We find that the experience-based learning model fits these longer-horizon expectations about as well as it does one-year expectations, with comparable estimates for both the learning gain and the pass-through from experience-based to survey expectations. 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.

We then turn to tests of the news-sensitivity of long-run inflation expectations. We next examine the sensitivity of long-run inflation expectations to macroeconomic news. 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,

Eusepi, Moench, and Preston 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 as learned from individuals' own 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 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 (Bundick, Smith, and Van der Meer 2024). A

4. See, also, Gurkaynak, Levin, Marder, and Swanson (2007), Gürkaynak, Levin, and Swanson (2010) and Beechey, Johannsen, and Levin (2011) for related evidence.

common interpretation of this stability is that it reflects the effectiveness of the Federal Reserve's commitment to an explicit inflation target (Hajdini, Shapiro, Smith, and Villar (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 2025 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 6% 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 two decades preceding the pandemic—without allowing for a rise in the sensitivity to surprises—yields a far more moderate increase, with long-run expectations rising only to about 4%.

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*—those 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.

Our paper is related to recent work by Carvalho, Eusepi, Moench, and Preston (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, Raviv, and Reis (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, Afrouzi, Coibion, and Gorodnichenko (2015), Reis (2022), Binder, Janson, and Verbrugge (2023) and Coibion and Gorodnichenko (2025) 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, Leva, Schoenle, and Shleifer (2024) argue that inflation expectations are unstable because inflation realizations lead to selective recall of past experiences.

Evidence in Jacome, Magud, Pienknagura, and Uribe (2025) suggests that central bankers also do not appear to place a lot of trust in firm anchoring. They find that central banks in countries with high inflation histories continue to adjust their policy rate aggressively to deviations of inflation expectations from the target inflation rate many years after adopting an inflation target and after medium-term inflation expectations have become less sensitive to shocks.

II. 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:

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

TABLE I
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 one-year survey inflation expectations in quarter t (cohort means) on the one-year 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)
Experience-based forecast	0.68	0.66	0.63	0.63	0.60
	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)
Exp.-based forecast $\times I_{\text{year}> 2009}$					0.19
					(0.13)
#Obs.	8,215	11,215	11,215	11,215	11,215
Adj. R^2	0.59	0.58	0.58	0.58	0.58
θ	3.044	3.044	3.044	2.960	2.960
Sample	1953 - 2009	1953 - 2024	1953 - 2024	1953 - 2024	1953 - 2024
Time FE	Yes	Yes	Yes	Yes	Yes
Age FE	No	No	Yes	Yes	Yes

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 I presents regressions of one-year inflation expectations, aggregated to mean expectations at birth-year cohort level, on the cohort-level forecast implied by the learning-from-experience model. 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.

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 2024Q4. As in 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 0.66 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 (0.63), 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 2024Q4. The estimate of 2.960 is slightly lower than MN's estimate of 3.044, but the weighting of past data and the experience-based forecasts implied by this new estimate are almost identical to those implied by MN's estimate.[7] In column (5), fixing $\theta = 2.960$, we allow the slope coefficient to be different in the out-of-sample period after the end of MN's sample. The point estimate suggests a somewhat higher coefficient in the out-of-sample period, but the difference is not statistically significant.

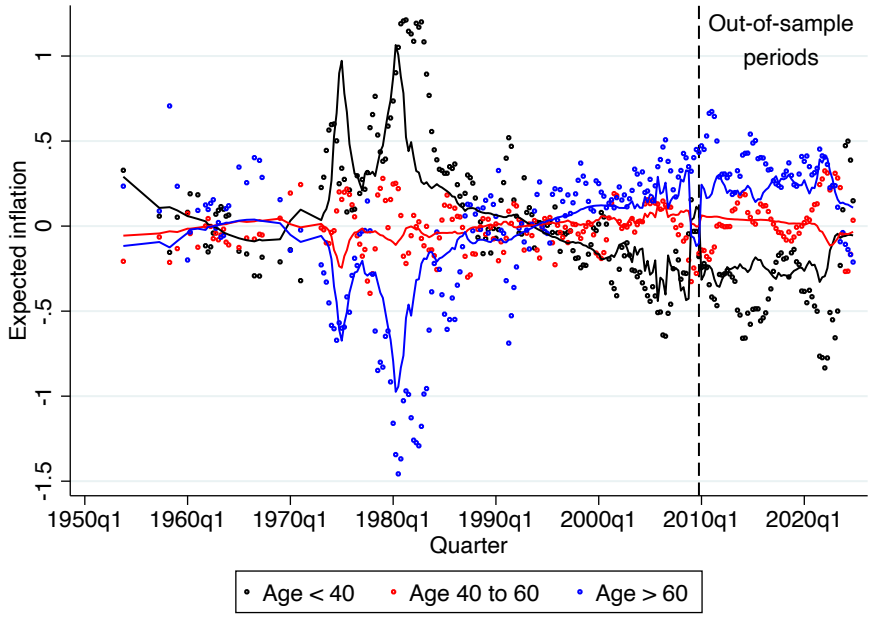
Figure I, panel (A), illustrates the fit with expectations data from the survey and the fitted values from column (4) in Table I. The series shown in this figure are aggregated by taking means within three broad age groups, removing time and age fixed effects, and forming four-quarter moving averages. The figure reveals that the learning-from-experience updating scheme continues to explain well the persistent differences 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

5. The slope coefficient reported here (0.68) is the virtually the same as in MN (0.67), but the R^2 is slightly lower (59% instead of 64%). The reason is that we implemented a minor improvement in the treatment of survey responses who 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, Vanderklaauw, Downs, Fischhoff, Topa, and Armantier (2010), and D'Acunto, De Fiore, Sandri, and Weber (2025) find substantial age effects in regression specifications without experience-based inflation expectations variable.

7. The standard error of the θ estimate is 0.19 and hence very small relative to the magnitude of the parameter.

(A) 1-year expected inflation



(B) 5- to 10-year expected inflation

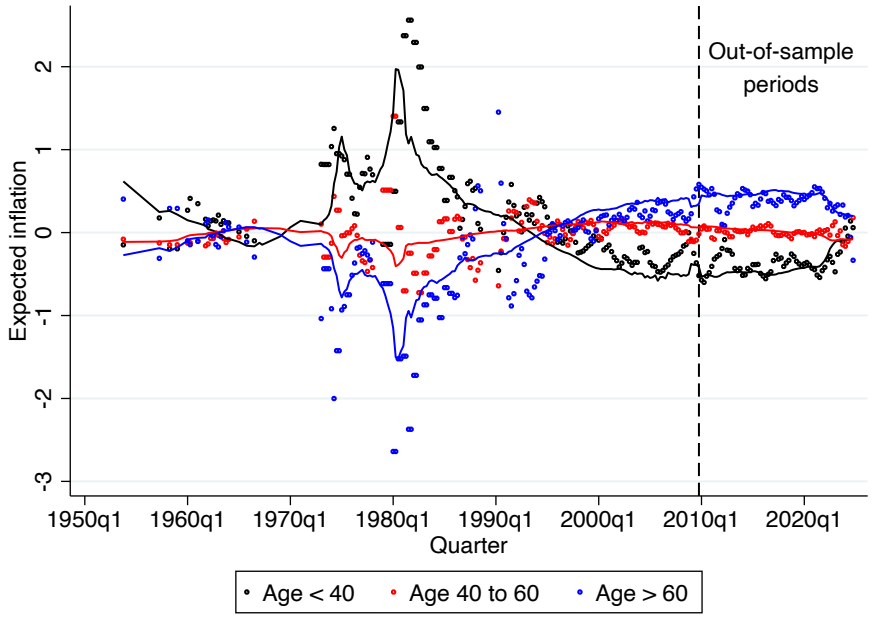


FIGURE I
Comparison of Learning-from-Experience Forecasts with Inflation Expectations from the Michigan Survey of Consumers

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 Table I, in panel (B) based on column (2) in Table II. The dashed line indicates the end of the sample in MN's data set.

TABLE II
Learning-from-Experience Model: 5- to 10-year Inflation Expectations

Each cohort born at time s is assumed to recursively estimate an AR(1) model of inflation, with the decreasing gain $\phi_{t,s} = \theta/(t-s)$ and using quarterly annualized inflation rate data up to the end of quarter $t-1$. The table reports the results of OLS regressions of 5- to 10-year survey inflation expectations in quarter t (cohort means) on the 7.5-year forecasts implied by the learning-from-experience model. Standard errors shown in parentheses are two-way clustered by time and cohort.

	(1)	(2)	(3)	(4)
Experience-based forecast	0.84	1.00	1.00	0.95
	(0.13)	(0.10)	(0.10)	(0.11)
Exp.-based forecast $\times I_{\text{year}> 2009}$				0.21
				(0.11)
#Obs.	9,151	9,151	9,151	9,151
Adj. R^2	0.42	0.44	0.44	0.44
θ	3.044	3.044	2.960	2.960
Sample	1953 - 2024	1953 - 2024	1953 - 2024	1953 - 2024
Time FE	Yes	Yes	Yes	Yes
Age FE	No	Yes	Yes	Yes

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. 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 to the most recent burst of inflation.

In our analysis of anchoring, 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. Table II 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. All specifications in this table in include time and age fixed effects.

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 (1) and (2), we calculate experience-based expectations with the value of $\theta = 3.044$ estimated by MN. With age fixed effects in column (2), 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 (3) shows, switching to $\theta = 2.960$ from column (4) in Table I makes little difference; the estimated slope coefficient is almost identical. In column (4) we check whether the slope coefficient is different in the out-of-sample period after 2009. We find a slightly higher coefficient in the out-of-sample period, but the difference is smaller than two standard errors.

Panel (B) of Figure I illustrates the fit based on the estimates from column (2) of Table II. Broadly speaking, the fit is similar as in panel (A). The learning-from-experience model explains a large share of the time-varying age-related heterogeneity in long-run expectations as well, not only short-run expectations. In the remainder of our analysis, we focus on these long-run expectations.

III. 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 averaging 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. 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 $\theta = 2.960$ 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.

III.A. 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 unconditional mean inflation rate $a/(1-\rho)$. 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]

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

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

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

This procedure yields a slightly different estimate of 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 with that of (7), but it unfolds gradually rather than instantaneously. For example, if $\rho = 0.5$, roughly half of the total adjustment is complete after four quarters.

III.B. 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, Levin, and Swanson (2010), Bundick and Smith (2025) and Bundick, Smith, and Van der Meer (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 $|\hat{\rho}| < 1$). 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 II 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. Following (7), this suggests 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

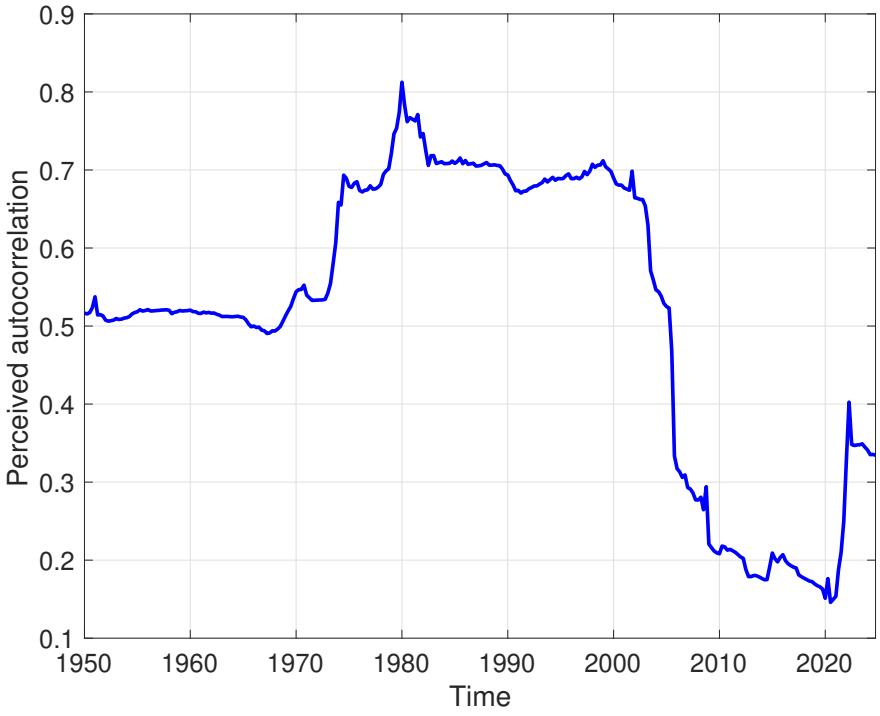


FIGURE II
Perceived Autocorrelation of Inflation Averaged Across Cohorts in Each Period

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.

Figure III 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 9 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 II. 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, Caselli, Grigoli, and Gruss (2021) and Kumar, Afrouzi, Coibion, and Gorodnichenko (2015), would produce the result of that expectations are not well anchored during

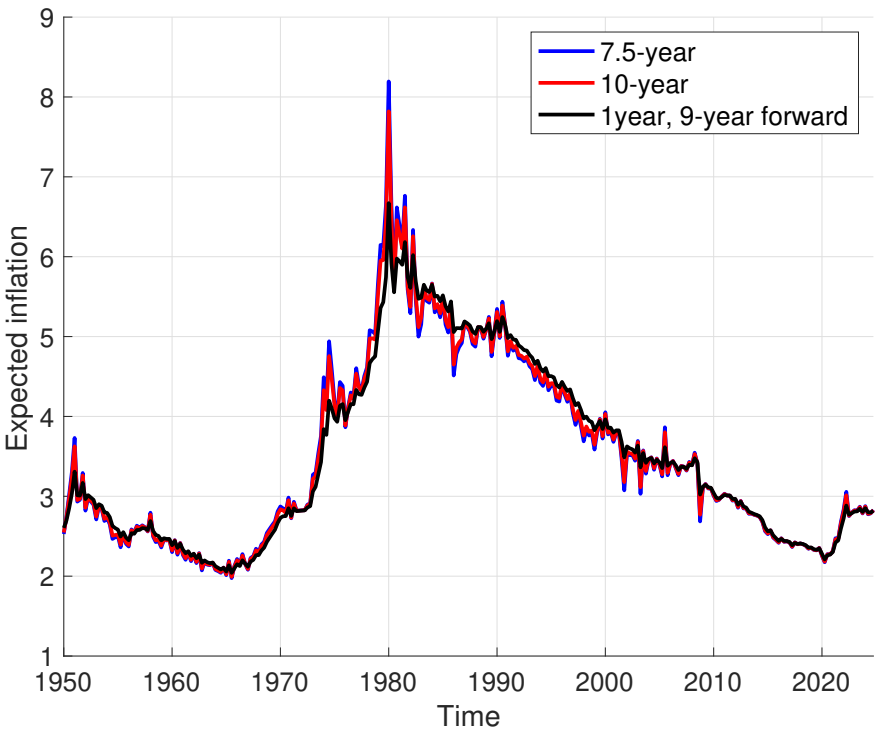


FIGURE III
Long-Horizon Experience-Based Inflation Expectations Averaged Across Cohorts in Each Period

most of the sample period. In our empirical analysis in 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.

IV. Empirical Tests of Anchoring

We now investigate how estimates of degree of long-run inflation expectations anchoring would have looked like over the post-World War II history, if the data was generated by learning from

experience. For this purpose, we generate artificial data for birth-year cohorts, where each cohorts learns according to the learning-from-experience updating scheme with $\theta = 2.960$ from observed data on quarterly CPI inflation. Each quarter, we calculate experience-based expectations for each cohort over various forecast horizons. We then construct panel data by keeping observations for cohorts whose members are of age 25 or older and below age 75 and we take the mean of these expectation across these age bins as consensus expectation. We then apply anchoring tests to this time series of artificial experience-based consensus expectations and compare the results to anchoring tests applied to time-series of actual expectations data from surveys and market prices.

IV.A. 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 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 $\theta = 2.960$.

Figure IV 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 com-

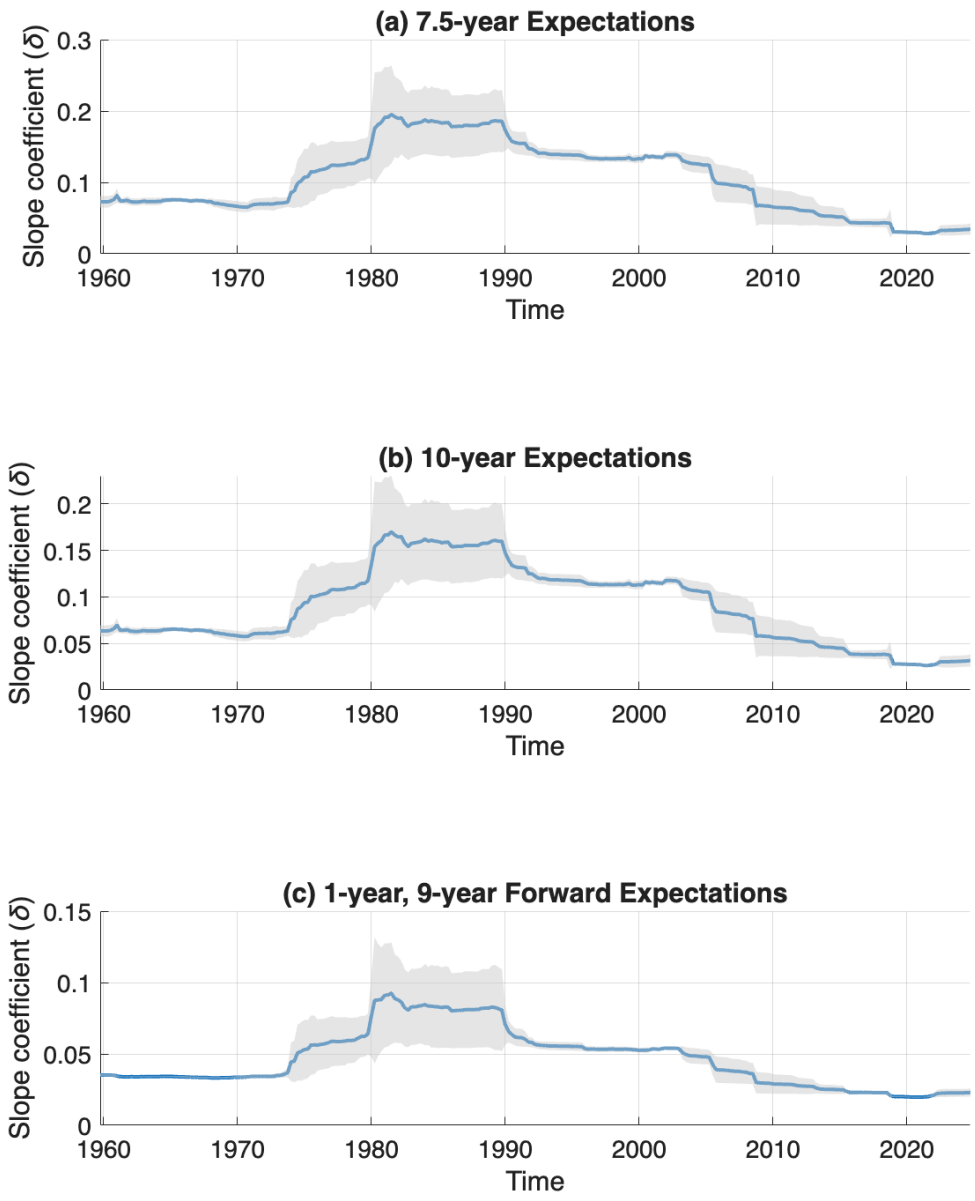


FIGURE IV

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).

munication. 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 IX 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 Michigan Survey of Consumers. We use the interpolated median of individual responses, as in the standard consensus expectations series provided by the MSC. 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 as a surprise variable the quarterly real-time forecast errors provided by the Federal Reserve Bank of Philadelphia. When available, we use the forecast error based on the first release of the CPI, otherwise we use the final revised number. We use this forecast error series also for the analysis with the other expectations series because the SPF is the only survey that offers forecasts at a one-quarter horizon and is hence the only one that allows us to construct a quarterly surprise series.

Aligning the change in expectations on the right-hand side of (11) with the timing surprise is not entirely straightforward. For the SPF, we calculate it 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 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

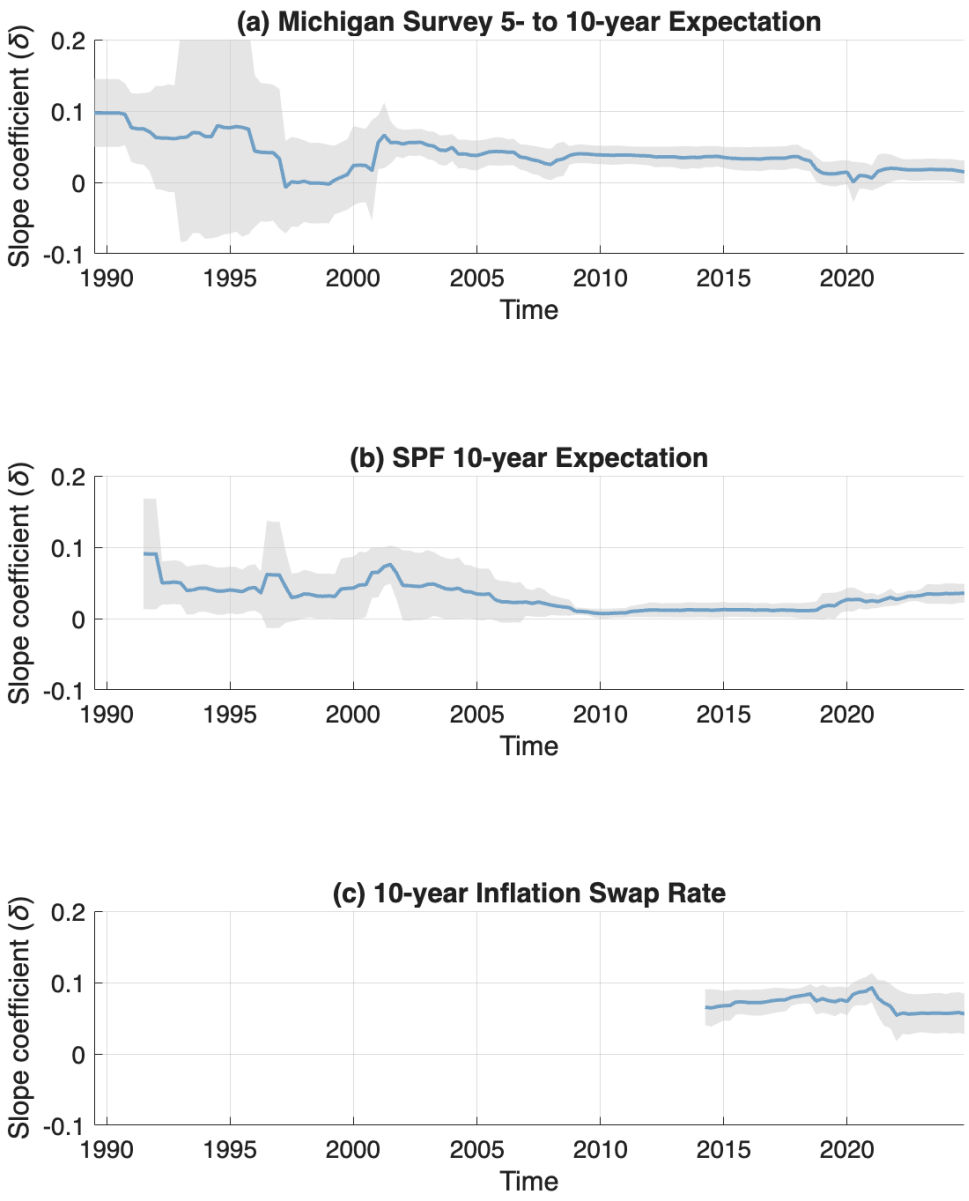


FIGURE V

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).

t with the change of the average MSC forecasts 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 $t+1$. Swap rates should reflect news quickly and anticipate some of the released CPI data. 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 IX shows that the estimates with Michigan Survey data look very similar to the ones based on the artificial data in Panel (a) and (b) of Figure IV (note that the plots in Figure IX starts in 1990, which is close to the middle of the plots in Figure IV). The estimated δ declines strongly from 1990 to 2020. The magnitude of the estimated δ is a little lower than in Figure IX, 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 similar time path as those based on the artificial 10-year expectations in Figure IV, but the magnitude is smaller at about half compared with those in the artificial experience-based expectations data. This is consistent with SPF forecasters putting more weight on the Federal Reserves (first implicit, then explicit) inflation target than the respondents in the MSC. However, this seems to be far from a permanent state of affairs. During the post-COVID inflation episode, the surprise-sensitivity of SPF expectations rose to levels that match those for experience-based expectations in Figure IV.

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 IV 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-

TABLE III

Anchoring Tests Using Experience-Based Inflation Expectations around 2012 Inflation Targeting Adoption

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 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. 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
Intercept	0.013	0.009	-0.005	-0.009	-0.007	-0.051
(s.e.)	(0.009)	(0.007)	(0.002)	(0.012)	(0.009)	(0.037)
$\pi_t - \widetilde{\mathbb{E}}_{t-1}\pi_t$	0.066	0.057	0.029	0.027	0.012	0.069
(s.e.)	(0.012)	(0.010)	(0.004)	(0.004)	(0.005)	(0.010)
I_{post}	-0.010	-0.007	0.000	-0.014	-0.001	0.069
(s.e.)	(0.010)	(0.008)	(0.002)	(0.020)	(0.018)	(0.046)
$I_{\text{post}} \times (\pi_t - \widetilde{\mathbb{E}}_{t-1}\pi_t)$	-0.036	-0.029	-0.010	-0.020	0.004	0.012
(s.e.)	(0.013)	(0.010)	(0.004)	(0.008)	(0.008)	(0.017)
Adj. R^2	80.0%	81.6%	90.5%	19.1%	9.0%	43.5%
Obs.	84	84	84	84	84	62

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 Table III 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. The point estimate of the coefficient on the interaction is more than three standard errors from zero and its magnitude indicates that the δ coefficient dropped to between 1/3 to 2/3 of its pre-2012 magnitude.

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 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 SPF expectations and changes in market-based expectations extracted from Bloomberg 10-year inflation swap rates at the dependent variable. 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, Smith, and Van der Meer (2024) use similar types of tests to examine changes in the degree of anchoring around the COVID pandemic. 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.

TABLE IV

Anchoring Tests Using Experience-Based Inflation Expectations around the COVID Pandemic

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). The sample runs from January 2012 to December 2023 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
Intercept	0.003	0.001	-0.005	-0.018	-0.012	0.032
(s.e.)	(0.002)	(0.002)	(0.000)	(0.015)	(0.013)	(0.021)
$\pi_t - \widetilde{\mathbb{E}}_{t-1}\pi_t$	0.030	0.028	0.020	-0.007	0.017	0.094
(s.e.)	(0.001)	(0.001)	(0.000)	(0.012)	(0.004)	(0.010)
I_{post}	-0.044	-0.033	0.001	0.083	-0.095	-0.067
(s.e.)	(0.017)	(0.013)	(0.002)	(0.036)	(0.098)	(0.074)
$I_{\text{post}} \times (\pi_t - \widetilde{\mathbb{E}}_{t-1}\pi_t)$	0.011	0.010	0.005	0.009	0.045	-0.058
(s.e.)	(0.005)	(0.004)	(0.002)	(0.012)	(0.019)	(0.017)
Adj. R^2	92.5%	94.2%	98.3%	8.9%	36.5%	44.0%
Obs.	48	48	48	48	48	48

However, as Table IV 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 Table IV use changes in experience-based expectations as the dependent variable. The sample runs from January 2012 to December 2023 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. The change in δ captured by the interaction effect is strongest for the 5-year expectations in column (1), but this result to some extent just reflects the rise in short-run inflation expectations after the COVID pandemic. For the longer-run expectations in columns (2) and (3), we obtain smaller coefficients. At all three horizons, the post-COVID coefficients, obtained by adding the coefficient on the inflation surprise with the interaction coefficient, are still far from the peak values δ during the 1980s in Figure IV. Thus, the learning-from-experience model is very much 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 none of them the sensitivity in the post-COVID period (again summing coefficient on the inflation surprise with the interaction coefficient, which yields 0.016, 0.062, and 0.036) is hugely different from the sensitivity of the 10-year experienced-based expectations (0.038), taking into account the relatively large standard errors, due to the short post-COVID sample, in columns (4) to (6).

IV.B. 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

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

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 so would effectively hardwire a high autocorrelation of inflation expectations.[9]

9. 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.

TABLE V
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 2023Q4 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.	0.956	0.871	0.898	0.960	0.877	0.895
(s.e.)	(0.007)	(0.032)	(0.028)	(0.007)	(0.029)	(0.029)
Sum of coefficients realized infl.	0.045	0.044	0.027	0.044	0.024	0.025
(s.e.)	(0.006)	(0.009)	(0.009)	(0.005)	(0.009)	(0.010)
Adj. R^2	99.2%	92.1%	96.3%	99.2%	90.9%	94.2%
Obs.	109	109	109	125	125	125

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 and the full sample.

In columns (1) and (4) of Table V we present estimates when these tests are run 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 2023Q4, the same endpoint as in the post-COVID sample in Table IV. 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 inflation expectations in response to the post-COVID inflation episode is consistent with a model of experience-based inflation expectations formation.

The estimates of $\bar{\beta}$ using actual expectations data, considering the standard errors of the esti-

mates, 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.

V. 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 different 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 differ in their perceived autocorrelation of inflation. As discussed in Section III, 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 central bank credibility, through implicit or explicit inflation targets, 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 VI with rolling regressions as in Figures IV and IX, but now with the sample 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

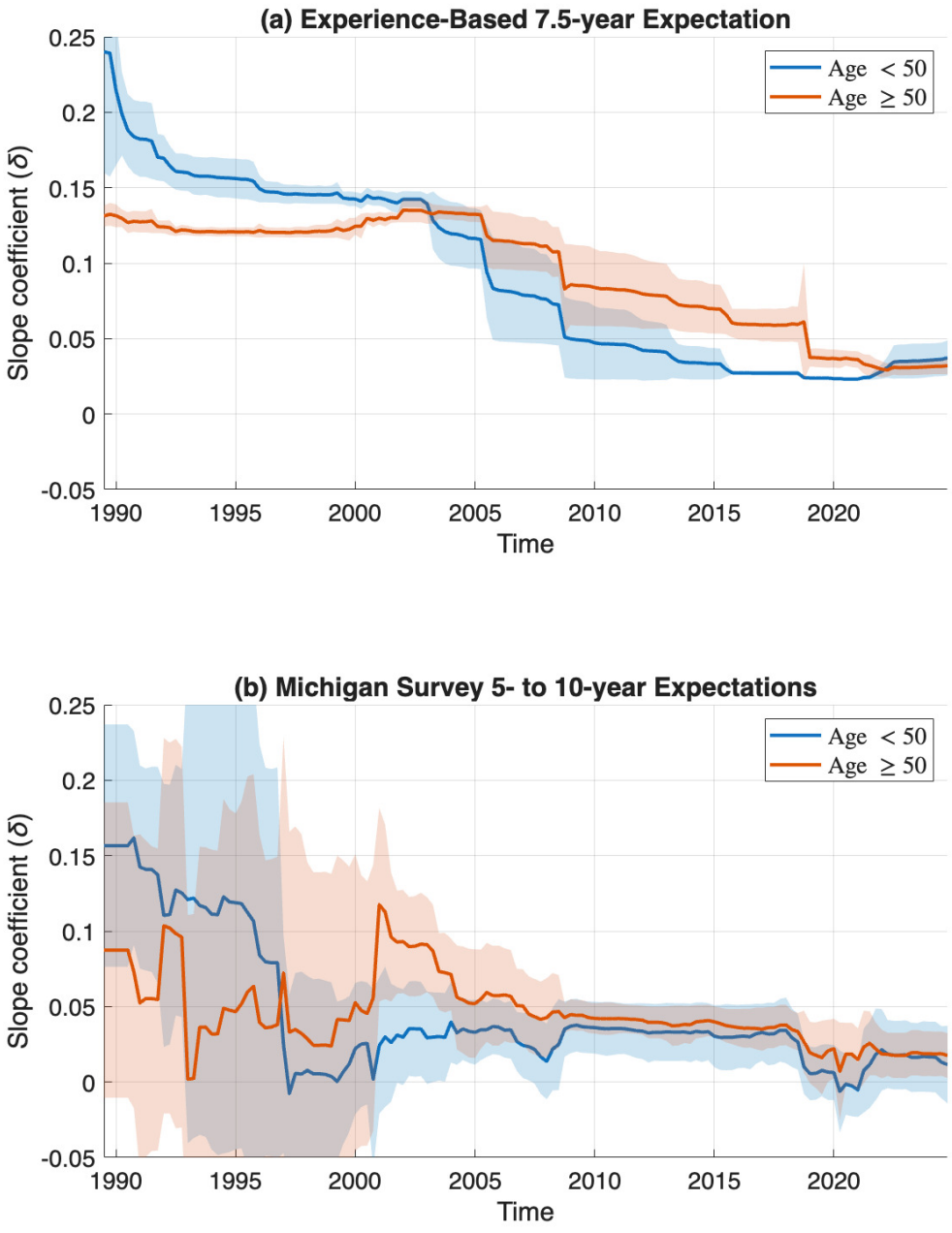


FIGURE VI
Anchoring Tests Using Experience-Based Inflation Expectations and Data from the Michigan Survey: Heterogeneity by Age

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).

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 VI 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 observed 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.

Table VI provides formal statistical tests along the lines of the anchoring tests in Tables III and Tables IV, but here focused on heterogeneity between age groups. We look at changes in the inflation surprise sensitivity heterogeneity between age groups 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 target at the beginning of 2012 as in Table III and the begin of the post-COVID inflation at the start of 2021 as in IV.

The three interactions between subperiod dummy variables and the inflation surprise capture changes in the estimated degree of anchoring across subperiods. For example, the coefficient on the $I_{>1993}$ dummy interacted with the inflation surprise measures the change in sensitivity from the pre-1994 period to the post-1993 period. As shown in columns (1) and (2), the experience-

TABLE VI
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	-0.015	-0.002	-0.013	-0.085	-0.017	-0.068
(s.e.)	(0.020)	(0.009)	(0.013)	(0.035)	(0.071)	(0.084)
$I_{>1993}$	0.013	0.026	-0.012	0.055	-0.001	0.055
(s.e.)	(0.021)	(0.013)	(0.015)	(0.039)	(0.072)	(0.086)
$I_{>2011}$	-0.000	-0.016	0.016	0.005	0.019	-0.014
(s.e.)	(0.008)	(0.011)	(0.010)	(0.020)	(0.026)	(0.025)
$I_{>2020}$	-0.019	-0.041	0.022	0.089	-0.014	0.103
(s.e.)	(0.014)	(0.017)	(0.008)	(0.039)	(0.030)	(0.047)
$\pi_t - \widetilde{\mathbb{E}}_{t-1}\pi_t$	0.150	0.087	0.063	0.134	0.060	0.074
(s.e.)	(0.022)	(0.009)	(0.016)	(0.034)	(0.046)	(0.061)
$I_{>1993} \times (\pi_t - \widetilde{\mathbb{E}}_{t-1}\pi_t)$	-0.098	-0.002	-0.096	-0.099	-0.014	-0.085
(s.e.)	(0.026)	(0.015)	(0.017)	(0.035)	(0.047)	(0.061)
$I_{>2011} \times (\pi_t - \widetilde{\mathbb{E}}_{t-1}\pi_t)$	-0.029	-0.048	0.019	-0.045	-0.032	-0.012
(s.e.)	(0.014)	(0.013)	(0.005)	(0.012)	(0.013)	(0.012)
$I_{>2020} \times (\pi_t - \widetilde{\mathbb{E}}_{t-1}\pi_t)$	0.022	-0.002	0.024	0.026	0.008	0.017
(s.e.)	(0.007)	(0.004)	(0.005)	(0.016)	(0.013)	(0.017)
Adj. R^2	64.2%	83.8%	36.1%	29.9%	11.9%	5.9%
Obs.	300	300	300	181	181	181

based expectations model predicts a substantial decline in inflation-surprise sensitivity for younger individuals (-0.098), while the sensitivity of older individuals remains essentially unchanged (-0.002). Columns (4) and (5) show that the sensitivity of actual 5- to 10-year inflation expectations from the MSC changes by magnitudes (-0.096 and -0.014) that closely match the model's predictions. Although the point estimates are very similar, column (6) indicates that the difference in sensitivity between younger and older individuals in the MSC is estimated imprecisely: the point estimate of -0.085 is accompanied by a standard error of 0.061. 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.

The coefficients for the $I_{>2011}$ dummy interaction with the inflation surprise are all negative and quite close to zero for both experience-based expectations in columns (1) and (2) and the MSC expectations in columns (4) and (5), although the signs of the young minus old differences in columns (3) and (4) do not agree. The magnitudes of the differences are small, though. The experience-based model predicts that both young and older individuals should have experienced a small drop in inflation surprise sensitivity and this is broadly consistent with what we see in actual expectations.

Going into the post-COVID inflation period, for the $I_{>2020}$ dummy interaction with the inflation surprise, the experience-based model predicts only a small rise in the inflation surprise sensitivity and only for the young. This is also what we find for MSC expectations.

Figure VII 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. While the MSC estimates for the interaction between the inflation surprise and the $I_{>1993}$ dummy are imprecisely estimated, the pattern and magnitude of the coefficients implied by the experience-based model are broadly consistent with those observed in the MSC data.

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. As we show next, the two approaches also yield markedly

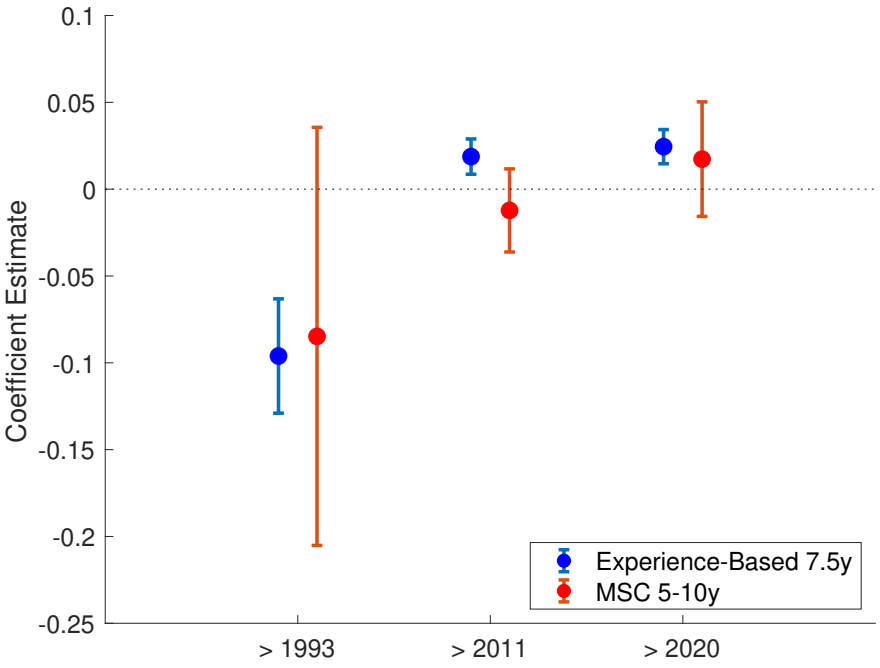


FIGURE VII

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

Estimated slope coefficients on subperiod dummy variable interactions with inflation surprises from Table VI columns (3) and (6). The error bars show 95% confidence intervals based on Newey-West standard errors (4 lags).

different predictions about the future evolution of inflation expectations.

VI. 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 since the 1970s 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 the 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. Yet in this comparison one must keep in mind 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, but would long-run expectations remain as stable as they have been if the economy were to experience two additional waves of inflation similar to those of 1973-76 and 1978-81?

In this section, we ask the hypothetical question of how long-run expectations would change if the economy experienced two additional waves of inflation similar to those of 1973-76 and 1978-81. We take realized inflation rates until 2025Q3 and append the inflation rates from 1972Q1 to 1980Q4. Panel (A) of Figure VIII shows the resulting path of inflation. Coincidentally, the level of inflation in 1972Q1 was almost exactly the same as in 2025Q3, so there is virtually no jump at the boundary to the hypothetical sample. We then calculate experience-based expectations in this hypothetical sample after 2025Q3.

As we discussed earlier, the perceived short-run persistence of inflation is key to the sensitivity

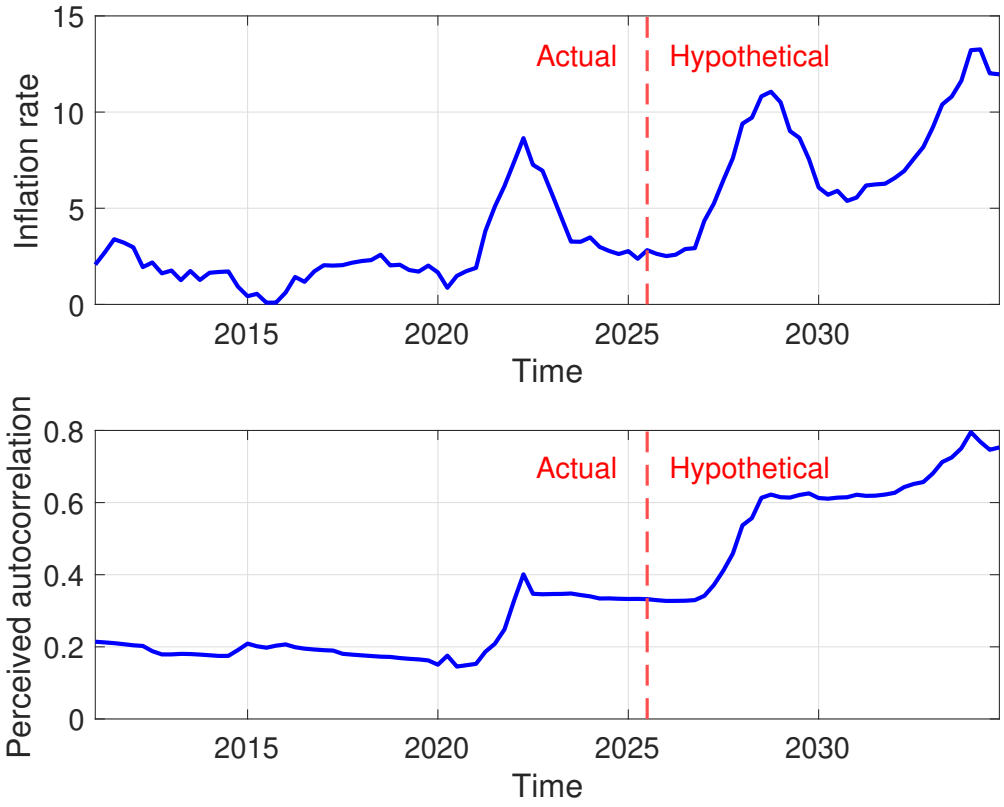


FIGURE VIII
Repeating the Experience of the 1970s: Hypothetical Path of Inflation and Perceived Autocorrelation

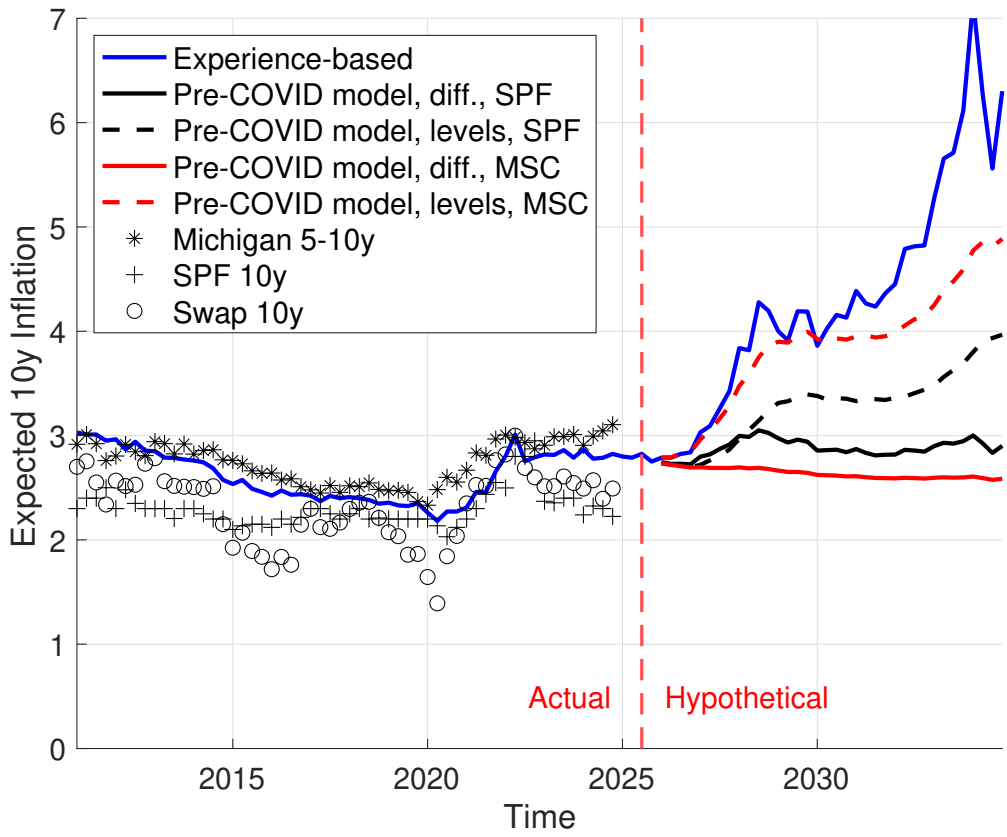


FIGURE IX
Repeating the Experience of the 1970s: Path of Long-Run Inflation Expectations

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 VIII shows the resulting path of the perceived first order autocorrelation of quarterly inflation rates if the hypothetical path of future inflation were to realize. By the mid-2030s, it would reach approximately 0.8, the same level as in 1980, as shown in Figure II. As a consequence, as our earlier analysis in equation (7) tells us, the sensitivity of long-run inflation expectations to inflation surprises would rise dramatically.

Figure IX shows the path of experience-based long-run inflation expectations at a 10-year forecast horizon that would result from the hypothetical inflation path after 2025Q3. Long-run expected inflation would reach levels around 6%, which is a little lower, but not much, than the levels reached around 1980 in Figure III. Thus, under learning-from-experience, given the lack of anchoring to the central bank's inflation target and the path-dependent sensitivity of inflation expectations to inflation surprises, living through these two additional waves of inflation would bring back inflation expectations with similar properties as those 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, the path of long-run inflation expectations would look very different. The black and red solid 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 IV, 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 IX, this results in a minor rise in long-run inflation expectations in response to the two additional waves of inflation after 2025Q3. For the red solid line, we use the estimate of $\delta = 0.003$ for the MSC in column (4) of Table IV, 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.

For the dashed lines in Figure IX, we do similar calculations with the levels model of Bernanke and Blanchard (2025),

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

using the estimates for the SPF in column (3) in Table V for the black dashed line, and the MSC estimates in column (2) of Table V 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, when experience-based long-run inflation expectations are at their 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 be-

tween 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.

Which of these paths going forward would be more likely to materialize, conditional on the hypothetical inflationary scenario taking place? We do not know. However, given how well the empirical evidence overall fits with a model in which individuals place zero weight on announced inflation targets, there is little reason to be confident that a model that implies substantial anchoring to an inflation target is the appropriate one.

VII. 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. The inflation history of the decades before the pandemic, characterized by low inflation persistence, would naturally lead experience-based learners to hold long-run expectations that are relatively insensitive to inflation surprises. Yet, in this experience-based model, this low sensitivity is temporary. Episodes of persistent inflation can raise perceived persistence and, in turn, increase the responsiveness of long-run expectations. 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 and difficult to reconcile with the notion of strongly anchored long-run expectations. We also find that the inflation surprise sen-

sitivity 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. Policy targets cannot ensure stable expectations.

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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 2024, 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 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 II, but not in the calculation of the time series of aggregate consensus expectations in subsequent sections.

For the cohort-level analysis in Section II 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 $\pi_t - \rho\pi_{t-1} = \varepsilon_t - a$ 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

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

The posterior variance at $t-1$, which is equal to the prior variance coming into period t, is equal to

$$\text{var}(\varepsilon_t)\gamma^2(1 + (1-\gamma) + (1-\gamma)^2 + \ldots) = \gamma\sigma^2. \tag{A.2}$$

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