LEARNING FROM INFLATION EXPERIENCES*

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How do individuals form expectations about future inflation? We propose that individuals overweight inflation experienced during their lifetimes. This approach modifies existing adaptive learning models to allow for age-dependent updating of expectations in response to inflation surprises. Young individuals update their expectations more strongly than older individuals since recent experiences account for a greater share of their accumulated lifetime history. We find support for these predictions using 57 years of microdata on inflation expectations from the Reuters/Michigan Survey of Consumers. Differences in experiences strongly predict differences in expectations, including the substantial disagreement between young and old individuals in periods of highly volatile inflation, such as the 1970s. It also explains household borrowing and lending behavior, including the choice of mortgages. *JEL* Codes: E03, G02, D03, E31, E37, D84, D83, D14.

I. INTRODUCTION

How do individuals form expectations about future inflation? The answer to this question is of central importance for both monetary policy and individual financial decisions. Policy makers would like to better understand the formation of inflation expectations to improve their inflation forecasts and resulting policy choices (Bernanke 2007). Individuals' perception of inflation persistence is likely to influence actual persistence (Roberts 1997; Orphanides and Williams 2005a; Milani 2007). Inflation expectations influence the real interest rates perceived by individuals, which in turn affects financial decisions (e.g., in the housing market), real expenditure decisions, and macroeconomic outcomes (Woodford 2003).

Despite a large volume of research, there is still little convergence on the best approach to model the dynamics of individuals' inflation expectations (see Mankiw, Reis, and Wolfers 2003; Blanchflower and Kelly 2008). In particular, the empirical

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heterogeneity in expectations remains hard to reconcile with existing models. Consider the time series of inflation expectations from the Reuters/Michigan Survey of Consumers in Figure I.[1] The figure plots the expectations of young (age below 40), middle-aged (age 40–60), and older individuals (age above 60) as deviations from the cross-sectional mean in each period. It reveals that the dispersion in beliefs can be large, reaching almost 3 percentage points during the high-inflation years of the 1970s and early 1980s. We also see repeated reversals in relative beliefs, with the young expecting higher inflation than the old following those years of high inflation, but having lower expectations in the late 1960s, mid-1990s, and late 2000s. These patterns are unexplained in existing models.

In this article, we argue that personal experiences play an important role in shaping expectations. Individuals put more weight on realizations experienced during their lifetimes than on other available historical data. In the words of the Chairman of the Federal Reserve Paul Volcker during the high inflation of the late 1970s: "An entire generation of young adults has grown up since the mid-1960s knowing only inflation, indeed an inflation that has seemed to accelerate inexorably. In the circumstances, it is hardly surprising that many citizens have begun to wonder whether it is realistic to anticipate a return to general price stability, and have begun to change their behavior accordingly."[2]

We formalize this idea by building on existing adaptive learning algorithms in the macroeconomics literature in which agents estimate forecasting rules from historical data.[3] We modify these algorithms to allow for learning from experience, by which we mean the possibility that agents are influenced more strongly by inflation realizations observed during their lifetimes than by other historical data. Specifically, we assume that individuals use experienced inflation rates to recursively estimate an AR(1) model of inflation. The key difference to standard adaptive learning models is that we allow the gain, that is, the strength of updating in response to surprise inflation, to depend on age.

1. We discuss the data and the figure in detail in Section III.A.

2. See Volcker (1979, p. 888), quoted in Orphanides and Williams (2005b).

3. See Marcet and Sargent (1989); also Bray (1982), Sargent (1993), and Evans and Honkapohja (2001). In these models, agents use adaptive-learning algorithms as rules of thumb because of cognitive and computational constraints.

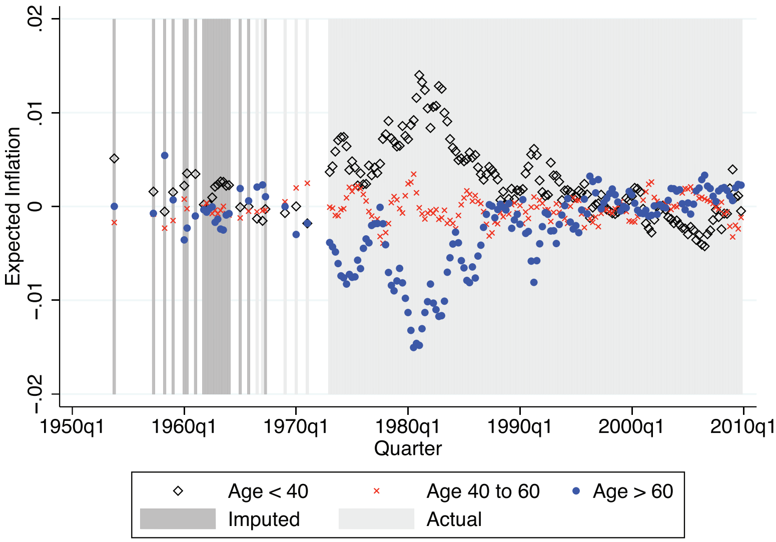


FIGURE I

Inflation Expectations by Age Group Relative to Cross-Sectional Mean

Four-quarter moving averages of mean one-year inflation expectations of young individuals (below 40), mid-aged individuals (between 40 and 60), and old individuals (above 60), shown as deviations from the cross-sectional mean expectation. Percentage forecasts are available from the survey in periods shaded in light gray; they are imputed from categorical responses in the periods shaded in dark gray; and they are unavailable in unshaded periods.

Young individuals react more strongly to an inflation surprise than do older individuals, who already have a longer data series accumulated in their lifetime histories. As a result, different generations disagree about the outlook for inflation. Moreover, learning dynamics are perpetual. Beliefs keep fluctuating and do not converge in the long-run, as attention to distant historical data diminishes when old generations disappear and new generations emerge.

We estimate our model using 57 years of microdata on inflation expectations from the Reuters/Michigan Survey of Consumers (MSC). To identify the model parameters, we exploit the fact that learning from experience generates cross-sectional differences in expectations that vary over time depending on the evolution of each cohort's inflation experiences. This identification from cross-sectional variation eliminates omitted macroeconomic variables or other unobserved common effects that could otherwise bias the estimation results. Furthermore, by focusing on cross-sectional differences, we can isolate the incremental explanatory power of individuals' lifetime experiences over and above any common time-specific factors that individuals may pay attention to, such as published forecasts of professional forecasters. This is a key distinction from standard adaptive learning models that are typically fit to aggregate time-series of (mean or median) expectations.

Our estimation results show that past experiences have an economically important effect on inflation expectations. Individuals of different ages disagree significantly in their expectations of future inflation, and this heterogeneity is well explained by differences in their lifetime experiences of inflation persistence and the mean rate of inflation. The heterogeneity is particularly pronounced following periods of highly volatile inflation.

We also link the effect of experiences on beliefs to households' financial decisions in the Survey of Consumer Finances. Disagreement about future inflation implies disagreement about real interest rates. Consistent with this effect, households with higher experience-induced inflation expectations tilt their exposure toward liabilities (but not assets) with nominally fixed rates.[4] The effects are economically large. For instance, a 1 percentage point difference in the learning-from-experience forecast of one-year inflation affects the mortgage balance by as much as a 1 standard deviation change in log income. Our findings complement the evidence in Piazzesi and Schneider (2012) that disagreement about future inflation between younger and older households in the late 1970s, as measured in the survey data, helps one understand household borrowing and lending, portfolio choices, and prices of real assets. Our findings identify the source of this disagreement between generations, namely differences in their experiences.

Finally, we link learning from experience to aggregate expectations. We show that the cross-sectional averages of the experience-based forecasts closely match the time-series of the average survey expectations at each point in time. Furthermore, the

4. Relatedly, Inoue, Kilian, and Kiraz (2009) relate inflation to consumption decisions. Their emphasis is different, though. They use consumption behavior to calculate implicit inflation expectations.

average learning-from-experience forecast can be approximated quite closely by constant-gain learning with a gain parameter that is almost identical to the estimates that Orphanides and Williams (2005a) and Milani (2007) obtained by fitting adaptive learning models to aggregate data.[5] The similarity is remarkable because our estimation of the learning rule parameters does not utilize any information about the level of the average expectations or any aggregate data; it only uses information about cross-sectional differences between cohorts.

Learning from experience further provides a natural microfoundation for constant-gain learning. While standard implementations of constant-gain learning motivate the downweighting of past data with structural shifts and parameter drift, learning from experience offers an alternative reason: memory of macroeconomic history is lost as new generations emerge whose subjective beliefs are shaped by relatively recent experiences. Our approach builds on the psychology evidence on the role of personal experiences and availability bias (Tversky and Kahneman 1973) rather than on the stochastic properties of macroeconomic variables to explain why data in the distant past is ignored.

The learning-from-experience mechanism also sheds light on one source of the dispersion in inflation expectations that is documented in Cukierman and Wachtel (1979) and Mankiw, Reis, and Wolfers (2003). This is an alternative to sticky information (Mankiw and Reis 2002), heterogeneity based on gender and demographics (Bryan and Venkatu 2001), or dispersion as a proxy for uncertainty (Zarnowitz and Lambros 1987; Bomberger 1996; Rich and Tracy 2010; Bachmann, Elstener, and Sims 2013). In our model, dispersion arises naturally due to differences in experiences.

Overall, our article demonstrates that learning from experience plays a significant role in the formation of expectations. Our analysis builds on earlier work by Vissing-Jorgensen (2003) that points to age-related dispersion in individuals' stock return and inflation expectations. Our findings also tie in closely with the evidence in Malmendier and Nagel (2011) that past stock- and bond-market return experiences predict portfolio choices of households. Although these portfolio choice effects could arise from experience-induced changes in beliefs about asset returns or

5. Eusepi and Preston (2011) use a smaller gain to calibrate a stochastic growth model in which agents learn about wages and the return on capital.

changes in risk preferences, the expectations data that we use here allow us to isolate the beliefs channel. Interestingly, our estimates of the weighting of past inflation experiences match very closely the estimates of the weighting of past asset-return experiences in Malmendier and Nagel (2011), even though the inflation expectations data is from a completely different data set. Further evidence for experience effects in financial decisions exists for mutual fund managers during the stock market boom and bust of the late 1990s (Greenwood and Nagel 2009), for CEOs who grew up in the Great Depression (Malmendier and Tate 2005; Malmendier, Tate, and Yan 2011), and for investors participating in initial public offerings (Kaustia and Knüpfer 2008; Chiang et al. 2011). Also related is the work by Fuster, Laibson, and Mendel (2010) and Fuster, Hebert, and Laibson (2011), who propose a model of "natural expectations" and demonstrate its ability to match hump-shaped dynamics in various economic time series.

The rest of the article is organized as follows. Section II introduces our learning-from-experience framework and the estimation approach. Section III presents the data and the core results on learning from inflation experiences. Section IV shows that learning from experience also helps one understand household decisions about bond investing and mortgage borrowing. In Section V, we look at the aggregate implications of our results. Section VI concludes.

II. Learning from Experience

Consider two individuals, one born at time s, and the other at time $s+j$. At time $t > s+j$, how do they form expectations of next period's inflation, π_{t+1}? The essence of learning from experience is that they place different weights on recent and distant historical data, reflecting the different inflation histories of their lives so far. The younger individual, born at $s+j$, has experienced a shorter data set and is therefore more strongly influenced by recent data. As a result, the two individuals may produce different forecasts at the same point in time.

We model the perceived law of motion that individuals are trying to estimate as an AR(1) process, as, for example, in Orphanides and Williams (2005b):

$$\pi_{t+1} = \alpha + \phi\pi_t + \eta_{t+1}. \tag{1}$$

Individuals estimate $b \equiv (\alpha, \phi)'$ recursively from past data following

$$b_{t,s} = b_{t-1,s} + \gamma_{t,s} R_{t,s}^{-1} x_{t-1}(\pi_t - b'_{t-1,s} x_{t-1}), \tag{2}$$

$$R_{t,s} = R_{t-1,s} + \gamma_{t,s}(x_{t-1}x'_{t-1} - R_{t-1,s}), \tag{3}$$

where $x_t \equiv (1, \pi_t)'$. The recursion is started at some point in the distant past.[6] The sequence of gains $\gamma_{t,s}$ determines the degree of updating cohort s applies when faced with an inflation surprise at time t. For $\gamma_{t,s} = \frac{1}{t}$, the algorithm represents a recursive formulation of an ordinary least squares estimation that uses all available data until time t with equal weights (see Evans and Honkapohja 2001). For constant $\gamma_{t,s}$, it represents a constant-gain learning algorithm with exponentially decaying weights. Our key modification of this standard adaptive learning framework is that we let the gain γ depend on the age $t - s$ of the members of cohort s. Specifically, we consider the following decreasing-gain specification,

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

where $\theta > 0$ is a constant parameter that determines the shape of the implied function of weights on past inflation experiences. We let the recursion start with $\gamma_{t,s} = 1$ for $t - s < \theta$, which implies that data before birth are ignored.[7] This specification is the same as in Marcet and Sargent (1989) with one modification: the gain here is decreasing in age, not time. The parameterization $\frac{\theta}{t-s}$ allows experiences earlier and later in life to have a different influence. For example, the memory of past episodes of high inflation might fade away as an individual ages. Alternatively, high inflation experienced at young age,

6. We see later that our empirical estimate of the parameter that determines $\gamma_{t,s}$ implies that past data are downweighted sufficiently fast so that initial conditions do not exert any relevant influence.

7. As will become clear, our econometric specification does allow individuals to use all available historical data when forming expectations, but isolates the incremental effect of data realized during individuals' lifetimes. Also note that our results are robust to variations in the starting point for experience accumulation; see Online Appendix D.

and perhaps conveyed through the worries of parents, might leave a particularly strong and lasting impression.

Figure II illustrates the role of θ. The top graph presents the sequences of gains γ as a function of age (in quarters) for different values of θ. For any θ, gains decrease with age. This is sensible in the context of learning from experience: young individuals, who have experienced only a small set of historical data, have a higher gain than older individuals, for whom a single inflation surprise has a weaker marginal influence on expectations. The graph also illustrates that higher θ implies that gains are higher and, hence, less weight is given to the more distant past. The latter implication is further illustrated in the bottom graph, which shows the implied weights on past inflation for a 50-year-old individual. Our gain parameterization is flexible in accommodating monotonically increasing, decreasing, and flat weights. For $\theta = 1$, all observations since birth are equal-weighted. For $\theta < 1$, observations early in life receive more weight, and for $\theta > 1$ less weight, than more recent observations. With $\theta = 3$, for example, very little weight is put on observations in the first 50 quarters since birth. The parameterization also allows for weight sequences that are virtually identical to those in Malmendier and Nagel (2011) (see Online Appendix A). Hence, we can compare the weights estimated from inflation expectations with those estimated from portfolio allocations.

The different weights that young and old individuals place on past observations give rise to cross-sectional heterogeneity in expectations. Given the perceived law of motion in equation (1), these between-cohort differences can arise from two sources: from differences in the perceived mean, $\mu = \alpha(1-\phi)^{-1}$, and from differences in the perceived persistence, ϕ, of deviations of recent inflation from the perceived mean.

In addition to past inflation experiences, we allow other information to affect expectations. Let $\pi_{t+1|t,s}$ be the forecast of period $t+1$ inflation made by cohort s at time t. The experience-based component of individuals' one-step-ahead forecast is obtained from equation (2) as $\tau_{t+1|t,s} = b'_{t,s}x_t$.[8] We capture

8. In our estimation, we apply the AR(1) process in equation (1) to quarterly inflation data, while the survey data provides individuals' forecasts of inflation over a one-year (i.e., four-quarter) horizon. Correspondingly, we employ multiperiod learning-from-experience forecasts that we obtain by iterating, at time t, on the perceived law of motion in equation (1) using the time t estimates $b_{t,s}$. To economize on notation, we do not explicitly highlight the multiperiod nature of the forecasts here.

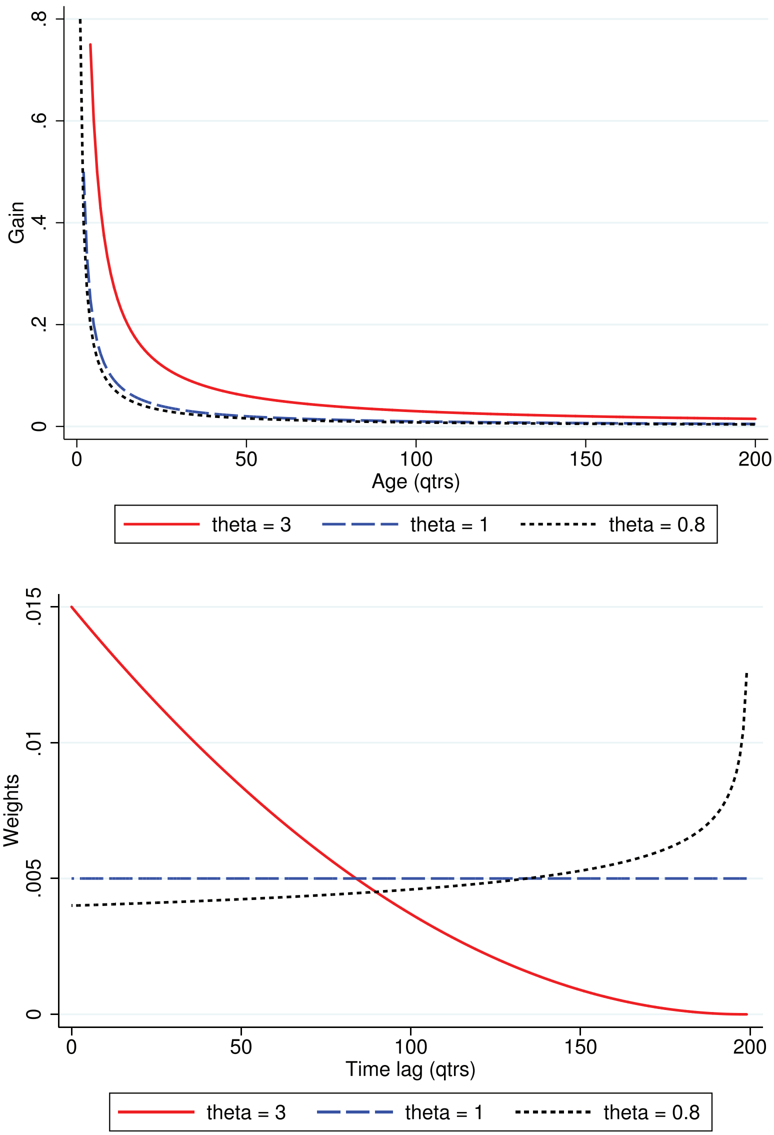


FIGURE II

Examples of Gain Sequences and Associated Implied Weighting of Past Data

The top panel shows the sequence of gains as a function of age for an individual who is 50 years (200 quarters) old. The bottom panel shows the weighting of past data implied by the gain sequence in the top panel, with the weights for most recent data to the left and weights for early life experiences to the right.

the influence of information other than experienced inflation by assuming

$$\pi_{t+1|t,s} = \beta\tau_{t+1|t,s} + (1-\beta)f_t. \tag{5}$$

That is, the subjective expectation is a weighted average of the learning-from-experience component $\tau_{t+1|t,s}$ and an unobserved common component f_t that is available to all individuals at time t. Examples are the opinion of professional forecasters, the representation of their opinions in the news media (e.g., as in Carroll 2003), or even a component that is based on all available historical data. In either case, the coefficient β captures the incremental contribution of lifetime experiences $\tau_{t+1|t,s}$ to $\pi_{t+1|t,s}$ over and above these common components. Thus, we do not assume that individuals only use data realized during their life-times, but isolate empirically the incremental effect of lifetime experiences on expectations formation.

Empirically, we first estimate the following modification of equation (5):

$$\tilde{\pi}_{t+1|t,s} = \beta\tau_{t+1|t,s} + \delta' D_t + \varepsilon_{t,s}, \tag{6}$$

where $\tilde{\pi}_{t+1|t,s}$ denotes measured inflation expectations from survey data. A vector of time dummies D_t absorbs the unobserved f_t. We also add the disturbance $\varepsilon_{t,s}$, which we assume to be uncorrelated with $\tau_{t+1|t,s}$, but which is allowed to be correlated over time within cohorts and between cohorts within the same time period. It captures, for example, measurement error in the survey data and idiosyncratic factors influencing expectations beyond those explicitly considered here. We use this specification to jointly estimate θ and β with nonlinear least squares. (Recall that $\tau_{t+1|t,s}$ is a nonlinear function of θ.)

The presence of time dummies in equation (6) implies that we identify β and θ, and hence the learning-from-experience effect, from cross-sectional differences between the subjective inflation expectations of individuals of different ages, and from the evolution of those cross-sectional differences over time. The cross-sectional identification allows us to rule out confounds that can affect the estimation of adaptive learning rules from aggregate (mean or median) time-series data. With aggregate data, it is difficult to establish whether a time-series relationship between inflation expectations and lagged inflation truly reflects adaptive learning or some other formation mechanism (e.g., rational expectations) that happens to generate expectations with similar time-series properties. In contrast, the learning-from-experience model makes a clear prediction about the cross-section: expectations should be heterogeneous by age, and for young people they should be more closely related to recent data than for older people. Moreover, we can estimate the gain parameter θ that determines the strength of updating from this cross-sectional heterogeneity. This provides a new source of identification.

III. Inflation Experiences and Inflation Expectations

We estimate the learning-from-experience effects by fitting the estimating equation (6) and the underlying AR(1) model to the MSC data on inflation expectations.

III.A. Data

We measure inflation experiences using long-term historical data on the Consumer Price Index (CPI). To capture inflation experiences during the lifetimes of even the oldest respondents, we need inflation data stretching back 74 years before the start of the MSC survey data in 1953. We obtain the time series of inflation data since 1872 (until the end of 2009) from Robert Shiller's website (see Shiller 2005) and calculate annualized quarterly log inflation rates. Figure III shows annual inflation rates from this series.

The inflation expectations microdata is from the MSC, conducted by the Survey Research Center at the University of Michigan since 1953, initially three times a year, then quarterly (1960–1977), then monthly (since 1978; see Curtin 1982). We obtain the 1953–1977 surveys from the Inter-University Consortium for Political and Social Research (ICPSR) at the University of Michigan. From 1959 to 1971, the questions of the winter-quarter Survey of Consumer Attitudes were administered as part of the Survey of Consumer Finances (SCF), also available at the ICPSR. The data from 1978 to 2009 are available from the University of Michigan Survey Research Center. Online Appendix B provides more details.

In most periods, the survey asks both about the expected direction of future price changes ("up," "same," or "down") and about the expected percentage of price changes. Because our analysis aims to make quantitative predictions, we focus on

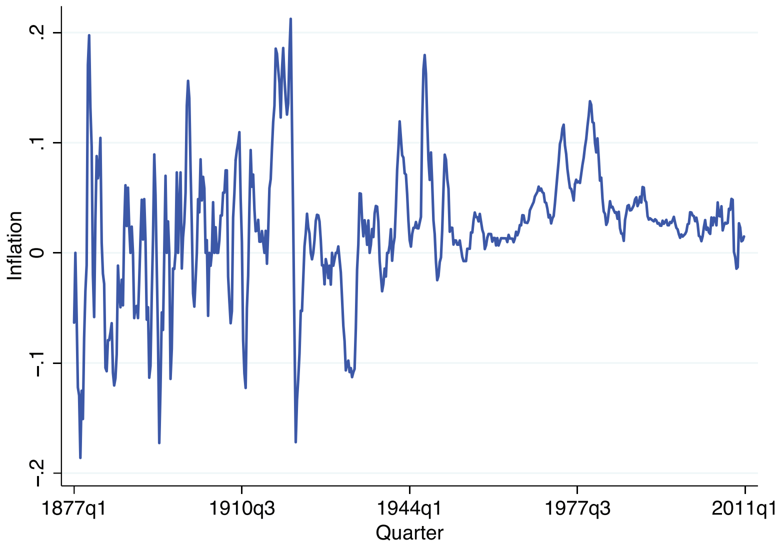


FIGURE III

Annual CPI Inflation Rates

percentage expectations. For quarters in which the survey asks only the categorical question about the expected direction (20 out of 429 surveys), we impute percentage responses from the distribution of the categorical responses. (The imputation procedure is described in Online Appendix C.) Figure I highlighted the periods in which we have percentage expectations data in light gray and the quarters in which the survey asks only the categorical questions in dark gray.

Since learning from experience predicts that inflation expectations differ by past experiences, we aggregate the data at the cohort level, that is, by birth year.[9] If multiple monthly surveys are administered within a quarter, we average the monthly means within the quarter to make the survey compatible with our quarterly inflation data. We restrict the sample to household heads aged 25–74 to ensure reasonable cohort sizes.

Figure I provided some sense of the variation in the data. It plots the average inflation expectations of young (below age 40), middle-aged (40–60), and older individuals (ages above 60),

9. The cohort aggregation also alleviates concerns about digit preferencing and extreme outlier forecasts.

expressed as deviations from the cross-sectional mean expectation each period. To better illustrate lower-frequency variation, we plot the data as four-quarter moving averages. The figure shows that the dispersion across age groups reaches almost 3 percentage points during the high-inflation years of the 1970s and early 1980s. The fact that then-young individuals expected higher inflation is consistent with learning from experience: their experience was dominated by high and persistent inflation, whereas the experience of older individuals also included the modest and less persistent inflation rates of earlier decades.

III.B. Baseline Results

We now fit the estimating equation (6) and the underlying AR(1) model using nonlinear least squares on the cohort-level aggregate data. We relate the inflation forecasts in the MSC to learning-from-experience forecasts. We assume that the data available to individuals who are surveyed (at various points) during quarter t are quarterly inflation rates until the end of quarter $t-1$. Since the survey elicits expectations about the inflation rate over the course of the next year, but the (annualized) inflation rates that serve as input to the learning-from-experience algorithm are measured at quarterly frequency, we require multiperiod forecasts from the learning-from-experience model. We obtain these forecasts by iterating on the perceived AR(1) law of motion from equation (1) at each cohort's quarter t estimates of the AR(1) parameters α and ϕ (which are based on inflation data up to the end of quarter $t-1$). Hence, the one-year forecast is the average of the AR(1) forecasts of quarter $t+1$ to quarter $t+4$ annualized inflation rates. To account for possible serial correlation of residuals within cohorts and correlation between cohorts within the same time period, we report standard errors that are robust to two-way clustering by cohort and calendar quarter.

Table I presents the estimation results. In the full sample (column (1)), we estimate a gain parameter θ of 3.044 (std. err. 0.233). Comparing this estimate of θ with the illustration in Figure II, one can see that the estimate implies weights that are declining a bit faster than linearly. The estimation results also reveal a strong relationship between the learning-from-experience forecast and measured inflation expectations. We estimate the sensitivity parameter β to be 0.672 (std. err. 0.076), implying that when two individuals differ in their

TABLE I

Learning-from-Experience Model: Estimates from Cohort Data

	(1)	(2)	(3)	(4)	(5)
	Baseline			Restricted	
Gain parameter θ	3.044	3.144	3.976	4.144	3.044
	(0.233)	(0.257)	(0.494)	(0.446)	—
Sensitivity β	0.672	0.675	0.664	0.693	0.672
	(0.076)	(0.079)	(0.084)	(0.111)	(0.093)
Time dummies	Yes	Yes	No	No	No
Imputed data included	Yes	No	No	No	No
Restrictions			$f_t = SPF_{t-1}$	$f_t = \overline{\tau}_{t+1\|t}$	$f_t = \overline{\tau}_{t+1\|t}$ $\theta = 3.044$
Adj. R^2	0.637	0.635	—	—	—
RMSE	0.0148	0.0152	0.0189	0.0191	0.0194
# Obs.	8,215	7,650	7,400	7,650	7,650

Notes. Each cohort born at time s is assumed to recursively estimate an AR(1) model of inflation, with the decreasing gain $\gamma_{t,s} = \theta/(t-s)$ and using quarterly annualized inflation rate data up to the end of quarter $t-1$. The table reports the results of nonlinear least squares regressions of one-year survey inflation expectations in quarter t (cohort means) on these learning-from-experience forecasts. Standard errors reported in parentheses are two-way clustered by time (quarter) and cohort. The sample period runs from 1953 to 2009 (with gaps).

learning-from-experience forecast by 1 percentage point, their one-year inflation expectations differ by 0.672 percentage point on average. To check whether the imputation of percentage responses from categorical responses affects our results, we rerun the estimation excluding the imputed data. As shown in column (2), the estimates remain very similar, with $\theta = 3.144$ (std. err. 0.257) and $\beta = 0.675$ (std. err. 0.079).

We have also reestimated the coefficients accounting for age-specific differences in consumption baskets. These estimations address the concern that inflation differentials between age-specific consumption baskets could be an omitted variable that happens to be correlated with the differences in age-specific learning-from-experience forecasts that we construct. In other words, individuals might form inflation expectations based on (recent) inflation rates they observe in their age-specific consumption baskets. We rerun the regressions in Table I controlling for differences in inflation between consumption baskets of the elderly and overall CPI using the experimental CPI for the elderly series (CPI-E) provided by the Bureau of Labor Statistics. As reported in Online Appendix E, our results are unaffected. We also report a similar analysis with a gasoline price series to check whether age-specific sensitivity to gasoline price inflation drives the results. We find that this extension does not add explanatory power either, nor does it significantly affect our learning-rule parameter estimates. Hence, the cross-sectional differences that we attribute to learning-from-experience effects are not explained by differences in age-specific inflation rates.

The presence of the time dummies in these regressions is important. It rules out that the estimates pick up time-specific effects unrelated to learning from experience. If individual expectations were unaffected by heterogeneity in inflation experiences—for example, if all individuals learned from the same historical data applying the same forecasting rules—then β would be zero. The effect of historical inflation rates, including "experienced" inflation rates, on current forecasts would be picked up by the time dummies. The fact that β is significantly different from zero is direct evidence that differences in experienced-inflation histories are correlated with differences in expectations. The significant β-estimate also implies that recent observations exert a stronger influence on expectations of the young since the set of historical inflation rates experienced by the young that enters into the construction of the learning-from-experience forecast comprises only relatively few observations.

Consider again the strong divergence in expectations between younger and older cohorts during the late 1970s and early 1980s displayed in Figure I. The higher expectations of younger individuals are consistent with their experience being dominated by the high-inflation years of the 1970s, whereas older individuals also experienced the low-inflation years of the 1950s and 1960s. The discrepancy faded away only slowly by the 1990s, after many years of moderate inflation. Our model explains this difference as the result of younger individuals perceiving inflation to be (i) higher on average and (ii) more persistent when inflation rates were high until the early 1980s, but less persistent when inflation rates dropped subsequently. Our estimates of the gain parameter further imply that when individuals weight their accumulated lifetime experiences, recent data receive higher weight than experiences earlier in life, though experiences from 20 to 30 years ago still have some measurable long-run effects.

Figure IV illustrates the extent to which learning-from-experience effects explain cross-sectional differences in inflation

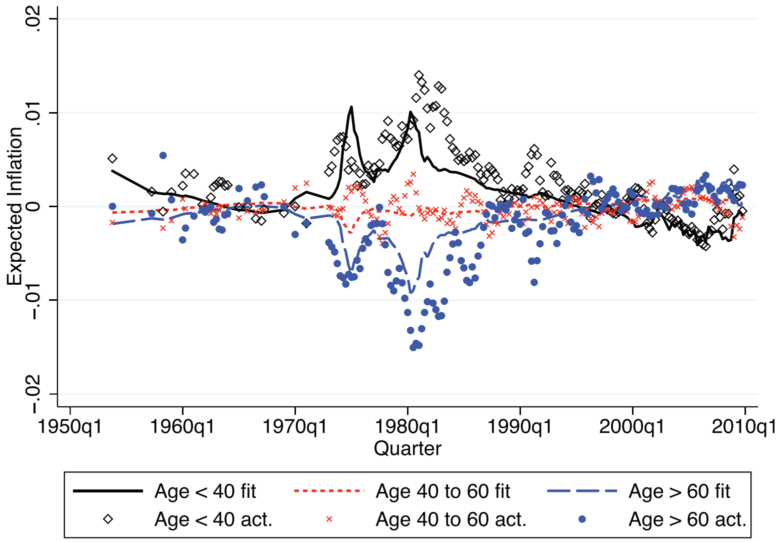


FIGURE IV

Comparison of Actual and Fitted One-Year Inflation Expectations by Age Group Relative to Cross-Sectional Mean

Four-quarter moving averages for individuals below age of 40, between 40 and 60, and above 60, shown as deviations from the cross-sectional mean expectation. The fitted values correspond to column (1) in Table I.

expectations. The figure shows the raw survey data and the fitted values based on the estimates in column (1) of Table I. For the purpose of these plots, we average inflation expectations and the fitted values within the same categories of the young (age < 40), middle-aged (40–60) and old (> 60) that we used in Figure I, expressed as deviations from the cross-sectional mean expectation in each period (since our baseline estimation with time dummies focuses on cross-sectional differences.) To better illustrate lower-frequency variation, we plot the data as four-quarter moving averages. Fitted values are drawn as lines, raw inflation expectations are shown as diamonds (young), x's (middle-aged), and filled circles (old). The plot shows that the learning-from-experience model does a good job of explaining the age-related heterogeneity in inflation expectations. In particular, it accounts to a large extent for the sizable difference in expectations between young and old in the late 1970s and early 1980s, including the double spike. It also captures all of the low-frequency reversals in the expectations gap between older and younger individuals.

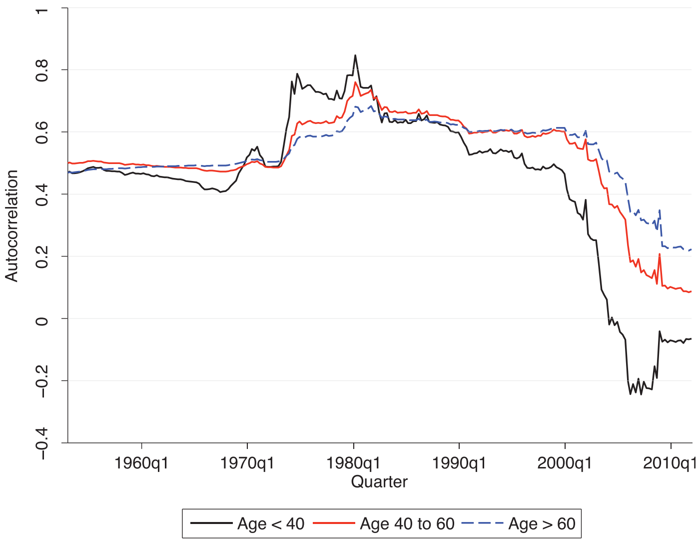
Figure V illustrates the stronger response of younger individuals to recent data. We plot the time series of the persistence and mean parameters for each age group over the course of our sample period, using the θ estimate from Table I, column (1). For the purpose of the plot, we average these perceived parameters again within the three age groups. The figure reveals that the perceived mean increased up to 1980 and then declined. The path of the perceived persistence is flatter but also increases initially and then declines dramatically after 2000. In both graphs, the assessments of younger individuals are much more volatile than those of older individuals. Our estimates also imply that at the end of the sample period, young individuals' perceived inflation persistence is close to zero. That is, the expectations of young individuals at the end of the sample period are well anchored, in the sense that they would be relatively insensitive to a short period of higher-than-expected inflation. As Mishkin (2007) and Bernanke (2007) argue, better anchoring of inflation expectations plays an important role in explaining why the dynamics of inflation have changed in recent decades. Figure V illustrates that learning-from-experience effects help one understand the source of this improved anchoring. According to our estimates, older individuals' perceived inflation persistence, however, is still substantially above zero.

One possible implication of learning from experience is that younger people always revise their expectations more strongly in response to inflation surprises. In Online Appendix F, we test and confirm this hypothesis. We caution, however, that this is not a necessary implication because of the effect of experience on the autocorrelation coefficient.[10]

To refine our understanding of the formation of inflation expectations, it would be useful to further analyze the exact transmission channel of experience effects. For example, how do

10. If the perceived law of motion were an IID process, and individuals used experienced inflation rates to simply estimate the mean, the intuition would hold: a positive (negative) inflation surprise would always lead to an upward (downward) revision of expectations, and the effect would weaken with age. In case of an AR(1) perceived law of motion, an inflation surprise also leads to a revision in the estimate of the autocorrelation coefficient, and the resulting revision of expectations need not be in the same direction as the inflation surprise. See Online Appendix F for more details.

(a) Autocorrelation ϕ



(b) Mean μ

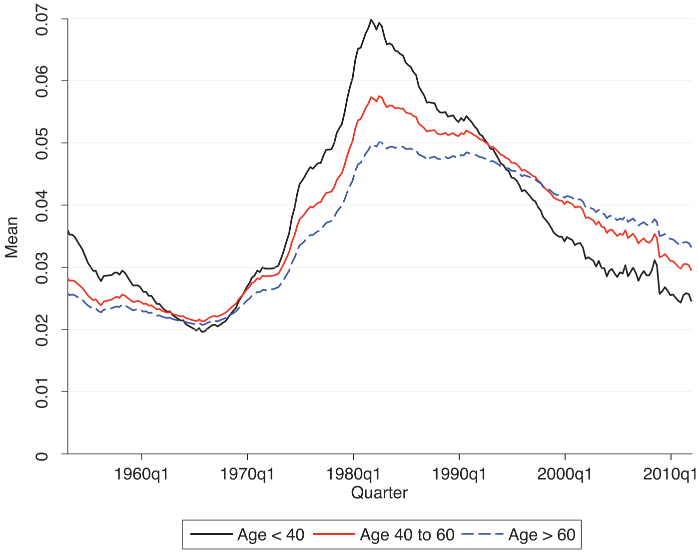


FIGURE V

Learning-from-Experience AR(1) Model Estimates

Estimates of autocorrelation (top) and mean inflation (bottom), based on with $\theta = 3.044$, for individuals below age of 40, between 40 and 60, and above 60.

experience effects depend on the cognitive ability to perceive price changes? How do they depend on the prices of items personally consumed versus the CPI? Does the strength of experience effects vary depending on macroeconomic conditions, for example, inflation during boom times versus recessions?

Our data are not rich enough to fully address these questions. At best, we can explore suggestive subsample variation. One such variation is in the starting point for personal experiences, which could be already before birth (in case of parental transmission) or after birth (when individuals start paying attention to price increases). As shown in Online Appendix Table OA.I, our findings are not sensitive to this variation. If we assume that inflation experiences start to accumulate 10 years before birth, the estimated gain parameter θ is higher, which implies a greater degree of downweighting of early experiences. As a result, the weights on prebirth experiences are very small, and the specification effectively gets back to the implied weights of the baseline estimation. Conversely, if we assume that inflation experiences start to accumulate 10 years after birth, the estimated θ is lower, which puts more weight on early experiences and gets back to the implied weights in the baseline estimation. Evidently, our specification has sufficient flexibility to adapt to different starting points for experience accumulation without resulting in much difference in the fit of the model.

We have also explored whether inflation during booms and recessions leave systematically different imprints on individuals' belief formation. In unreported results, we have divided our sample period into postwar boom, stagflation (1969Q4–1982Q4), Great Moderation (1983–2006), and Great Recession, fixing θ at the estimate of 3.044 from our main specification in Table I, column (1). We do not detect systematic differences in terms of the estimated coefficients of experience-based inflation formation. The stagflation period does generate a somewhat higher β estimate ($\beta = 0.769$); but we also find a relatively high sensitivity parameter during the postwar boom, $\beta = 0.688$.

III.C. Exploring the Common Factor

Our main estimating equation (6) includes time dummies to identify the learning-from-experience effect with a test of the null hypothesis $\beta = 0$. The specification also allows us to estimate θ purely from cross-sectional differences, removing potentially confounding unobserved common factors in expectations. We now ask whether learning-from-experience forecasts can explain not only cross-sectional differences but also the level of expectations. We also explore the nature of the common factor f_t in the underlying structural model (5), which is absorbed by the time dummies in our estimating equation (6). For both steps, we reestimate equation (6) without the time dummies and intercept, but with observable proxies for f_t.

First we consider the possibility that f_t captures individuals' tendency to rely, to some extent, on the opinions of professional forecasters that get disseminated in the media. We specify f_t as the sum of the Survey of Professional Forecasters (SPF) forecast in quarter $t-1$ and a noise term η_t that is uncorrelated with the SPF forecast and the learning-from-experience forecast. Equation (5) becomes

$$\pi_{t+1|t,s} = \beta\tau_{t+1|t,s} + (1-\beta)\mathrm{SPF}_{t-1} + (1-\beta)\eta_t. \tag{7}$$

Since this estimating equation does not include time dummies, it uses information about the levels of inflation expectations, not just cross-sectional differences. The estimation results are shown in column (3) of Table I. In the estimation, we remove the imputed data from the sample, as the imputation was only designed to capture cross-sectional differences, not levels. The number of observations is further slightly lower than in column (2) because SPF forecasts are not available in a few quarters early in the sample. As before, we work with one-year forecasts in the survey data, so we use the corresponding four-quarter, iterated version of the learning-from-experience forecast.

As column (3) shows, replacing the time dummies with the SPF has little effect on the estimate of β compared with column (2). With 3.976 (std. err. 0.612), the estimate of θ is higher, but the implied weighting of past inflation experiences remains quite similar to the weighting implied by the estimates in columns (1) and (2). The standard error of β also remains similar and the standard error of θ doubles. The noisier θ estimate reflects that the removal of the time dummies leaves the noise term η_t in equation (7) in the regression residual. This effect of the noise term can also be seen in the increase in root mean square error (RMSE) compared with columns (1) and (2).[11] Nevertheless, the fact that

11. We focus on the RMSE since this regression is run without intercept, and hence the adjusted R^2 is not a useful measure of fit.

the β estimate in column (3) is virtually identical to those in columns (1) and (2) indicates that SPF forecast captures much of the common component of f_t that could be correlated with the learning-from-experience forecast.

Another possibility is that the common component f_t in individuals' beliefs is the result of a social learning process in which individuals with different experiences of inflation histories share their opinions, and as a result, their beliefs have a tendency to converge to the average belief, as in DeGroot (1974). To explore this possibility, we represent f_t as the mean learning-from-experience forecast across all age groups, which we denote as $\overline{\tau}_{t+1|t}$, and a noise term:

$$\pi_{t+1|t,s} = \beta\tau_{t+1|t,s} + (1-\beta)\overline{\tau}_{t+1|t} + (1-\beta)\eta_t. \tag{8}$$

Column (4) of Table I reports the results. The estimates are almost identical to those in column (3). Evidently, the average learning-from-experience forecast is very close to the SPF forecast and it, too, does a good job in absorbing the component of f_t that could be correlated with the learning-from-experience forecast. As in column (3), though, θ is estimated with substantially higher standard errors than in the specifications with time dummies.

In a last estimation, shown in column (5) of Table I, we explore the fit of regression model (8) after fixing θ at its more precise estimate from column (1), $\theta = 3.044$, which was more cleanly identified due to the inclusion of time dummies. This specification allows us, on the one hand, to track both the cross-sectional and the time-series variation in inflation expectations induced by learning from experience, and, on the other hand, to eliminate the potential confounds affecting the (noisier) estimates of θ in columns (3) and (4). We find that the estimate of β is almost unchanged, and there is little deterioration in fit. The RMSE is only slightly higher than in column (4). We use this specification in Section V when we explore time variation in inflation expectations and the aggregate implications of learning from experience.

IV. Inflation Experiences and Financial Decisions

So far our results show that differences in inflation experiences generate differences in beliefs about future inflation. To what extent do these differences in beliefs affect the economic decisions of households? Since differences in inflation expectations generate disagreement about real rates of return on assets and liabilities with nominally fixed rates, households with higher experience-based inflation expectations should be more inclined to borrow and less inclined to invest at nominally fixed rates than households with lower experience-based inflation expectations. We test this prediction by estimating the regression equation

$$y_{t,s} = \beta_1 \tau_{t+1|t,s} + \beta_2' X_{t,s} + \beta_3' A_{t-s} + \beta_4' D_t + \xi_{t,s}, \tag{9}$$

where $y_{t,s}$ is a measure of either fixed-rate liabilities or fixed-rate assets held at time t by people born in year s, and $\tau_{t+1|t,s}$ denotes the learning-from-experience forecast of inflation, constructed with the θ estimate from Table I, column (1). $X_{t,s}$ is a vector of cohort characteristics, A_{t-s} a vector of age dummies, and D_t a vector of time dummies. We also add the disturbance $\xi_{t,s}$, which we allow to be correlated between cohorts within the same time period.

To estimate the effect of learning from inflation experiences on financial decisions, we turn to the SCF, which provides detailed information on households' financial situation. We rely on the data set constructed by Malmendier and Nagel (2011), which comprises both the modern triennial SCF from 1983 to 2007 and older versions of the SCF from 1960 to 1977. For comparability with our baseline estimation in Table I, we aggregate the microdata again at the cohort level.[12] In each survey wave, we construct per capita numbers of debt and bond holdings (in September 2007 dollars), as well as income and net worth, for all birth-year cohorts. We then run the estimation of log values on the resulting cohort panel. Online Appendix G provides further detail about the data set and the construction of our variables.

12. Cohort-level aggregation is common in the household finance and asset pricing literature (see, e.g., Geanakoplos, Magill, and Quinzil 2004; Venti and Wise 2004; Doepke and Schneider 2006; Piazzesi and Schneider 2012) as well as in labor economics (see, e.g., Kahn (2010) and Storesletten, Telmer, and Yaron 2004). It also serves to minimize the influence of outliers and erroneous zeros when analyzing ratios such as log(debt/income), or regressing log(debt) on log(income). For completeness, and as a robustness check, we show household-level regressions in Online Appendix H, Tables OA.IV and OA.V, with similar or even stronger results.

TABLE II

Survey of Consumer Finances: Summary Statistics of Cohort Aggregates

	(1) Log fixed-rate mortgages	(2) Log long-term bonds	(3) Log new fixed-rate mortgages	(4) Log new variable-rate mortgages	(5) Log income	(6) Log net worth
Mean	9.76	8.61	6.71	3.39	10.91	11.63
Std. dev.	1.29	1.85	3.45	3.72	0.41	0.89
p10	8.43	6.26	0.00	0.00	10.42	10.44
Median	10.05	8.73	8.21	0.00	10.93	11.62
p90	10.92	10.87	9.50	8.30	11.42	12.79
Sample	Full	Full	≥1983	≥1983	Full	Full

Notes. The SCF sample includes 19 surveys during the period from 1960 to 2007, and 18 of those have information on holdings of long-term bonds. The data on borrowing and bond holdings is aggregated to per capita numbers at the cohort level.

Table II provides summary statistics for the key variables in our analysis. Households' main fixed-rate liability is mortgage debt, shown in column (1). Prior to 1983, the SCF often provides mortgage information only for households' primary residence, not for other real estate owned by the household. To construct a measure that is consistent over time, we focus on fixed-rate mortgage balances secured by the primary residence. The mean of log per capita balances is 9.76. Note that the underlying mean of dollar per-capita balances is \$26,605, not \$17,327 ($= e^{9.76}$), since Table II shows the average of cohort-level log values (which is not equal to the log of the average).

On the asset side, we measure households' holdings of long-term bonds, shown in column (2). This variable includes holdings through mutual funds and defined contribution (DC) accounts.

We also tabulate separately the summary statistics for mortgages that are newly taken out or refinanced in the calendar year a household is surveyed. (The survey is carried out from June to September.) We split these (re)financing volumes into "new fixed-rate" and "new variable-rate" mortgages, as shown in columns (3) and (4). Note that the information about fixed versus variable rates is available only starting in 1983; however, variable-rate mortgages were largely nonexistent in the United States prior to the 1980s (see Green and Wachter 2005).

We use these alternative outcome variables when focusing on the flow rather than the level of liabilities. To understand their magnitude, we have to be careful in interpreting the numbers. For example, average new fixed-rate mortgage financing is \$5,466(and not $e^{6.71} = 820.57$). Moreover, this is the amount aggregated over the six to nine months leading up to the survey in June to September. It amounts to about \$8,000 annualized. Hence, the average new fixed-rate mortgage financing is rather high compared with the average stock of about \$35,000 in the post-1982 sample. The relatively large amount of new financing also suggests that the stickiness is not so high that looking at stock of fixed-rate mortgage balances would be uninformative.

Finally, columns (5) and (6) show family income and net worth, which we use as control variables. In the years before 1983, the coverage of household assets in the SCF is not as comprehensive as from 1983 onwards. For the sake of comparability over time, our measure of net worth uses only categories of assets and liabilities that are available in all survey waves: financial assets, defined as stocks, bonds, and cash, including mutual funds and DC accounts, plus equity in the households' primary residence.

Table III presents the estimation results. In each column we regress the log of the respective cohort-level per capita nominal position on the learning-from-experience inflation forecast, constructed using the estimate of $\theta = 3.044$ from Table I, column (1). We control for the logs of per capita income and net worth. All regressions include dummies for the survey year and for age.[13]

Column (1) shows that households' fixed-rate mortgage positions are positively related to the learning-from-experience inflation forecast. The point estimate of the coefficient is more than 4 standard errors above zero. As predicted, households whose experiences lead them to expect higher inflation and, hence, lower real interest rates take on more fixed-rate liabilities. The magnitude of the effect is large: a 1 percentage point difference in the learning-from-experience forecast corresponds to a 0.35 change in the log of the fixed-rate mortgage balance, which is between a third and a quarter of a standard deviation of the dependent

13. Including households' equity in their home as part of the wealth control might attenuate the size of the coefficient on this variable (since equity = home value minus mortgage). We check whether using nonhousing wealth affects the inflation experience estimate. We find that such variations have virtually no effect on coefficient of interest. For example, if we repeat the regression in column (1) of Table III with a wealth variable that excludes home equity, we get a coefficient of 34.17 (std. err. 8.03), almost identical to the one we report in Table III.

TABLE III
INFLATION EXPERIENCES AND HOUSEHOLD NOMINAL POSITIONS

	(1) Fixed-rate mortgages	(2) Long-term bonds	(3) Fixed-rate mortgages	(4) Long-term bonds	(5) New fixed-rate mortgages	(6) New variable-rate mortgages
Learn.-from-exp. forecast	35.27	−20.56	26.77	−9.07	132.71	−42.82
	(8.39)	(13.74)	(4.47)	(6.92)	(25.08)	(55.57)
Log income	0.92	0.45	0.60	0.02	1.23	2.60
	(0.16)	(0.25)	(0.13)	(0.13)	(1.19)	(1.29)
Log net worth	−0.10	1.09	0.18	1.18	−0.56	−1.79
	(0.15)	(0.13)	(0.06)	(0.10)	(0.69)	(0.94)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Age dummies	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full	Full	≥1983	≥1983	≥1983	≥1983
Adj. R^2	0.617	0.852	0.856	0.915	0.485	0.243
# Obs.	950	900	450	450	450	450

Notes. The SCF sample includes 19 surveys during the period from 1960 to 2007, and 18 of those have information on holdings of long-term bonds. The data are aggregated to per capita numbers at the cohort level. Each cohort is assumed to recursively estimate an AR(1) model of inflation, with $\theta = 3.044$, as in Table I, column (1). We use the resulting learning-from-experience forecast of inflation to explain log fixed-rate mortgage borrowing and log long-term bond holdings in OLS regressions. Log mortgage borrowing in columns (5) and (6) comprises only loans taken out or refinanced in the year in which the survey was carried out. Standard errors reported in parentheses are clustered by time period.

variable (see Table II). This magnitude is comparable to the variation associated with a 1 standard deviation change in log income.

In column (2), we estimate the effect of inflation experiences on households' nominal bond positions. Here, the sign of the coefficient is negative, indicating that households with higher learning-from-experience forecasts of inflation invest less in long-term bonds. The coefficient estimate is on the same order of magnitude as the coefficient in column (1), but not statistically significant. Taken together, the results in column (1) and (2) show that households with higher learning-from-experience inflation forecasts tilt their exposure to fixed-rate liabilities rather than assets. As shown in columns (3) and (4), we obtain similar results when restricting the sample period to 1983–2007, when the SCF data are of higher quality.

In columns (5) and (6), we refine the analysis in two ways. First, we focus on mortgages that have recently been taken out or refinanced, rather than the total mortgage positions of households. The flow variable addresses concerns about the "stickiness" of mortgage positions: they include loans taken out many years ago. Once a household has taken out a mortgage and bought a house, the mortgage balance cannot easily be adjusted. Although a household can take out a second mortgage, buy a bigger house, or (since the 1980s) refinance with a variable-rate mortgage, there are frictions and indivisibilities that are likely to generate substantial stickiness. In contrast, for the volume of newly taken out or refinanced mortgages, this stickiness plays less of a role. Using the more recent data on refinancing, we are also able to distinguish between fixed-rate and variable-rate mortgages. According to our hypothesis, households with higher learning-from-experience forecasts of inflation should be more likely to take out a fixed-rate mortgage and less likely to take out a variable-rate mortgage.

The results in column (5) and (6) are consistent with this prediction. We find that households with high learning-from-experience forecasts of inflation are significantly more likely to take out new fixed-rate mortgages and to refinance at fixed rates. A 1 percentage point difference in the learning-from-experience forecast corresponds roughly to a 1.33 change in the log of the fixed-rate mortgage balance, which is more than a third of a standard deviation of the dependent variable according to Table II. We also find that experience-based inflation expectations are negatively related to the volume of new variable-rate mortgages, but the estimated coefficient in column (6) is not statistically significant, and the point estimate is small—a 1 percentage point difference in the learning-from-experience forecast corresponds only to about a ninth of the standard deviation of the dependent variable.

One potential confound in the interpretation of these results are changes in lending practices during the latter part of our sample period. In the 2000s subprime lending expanded, much of it at variable rates and much of it to younger households of lower credit quality. At the same time, the change in relative expectations of young individuals—from expecting high inflation at the beginning of the 1980s to low inflation expectations toward the end of our sample period—is an important source of variation. Hence, one might worry that this expansion in credit over the sample period could contribute to the detected correlation because it induced younger people to choose variable-rate mortgages at the same time their experienced-based inflation expectations were below those of older individuals.

To address this concern, we reestimate the empirical model from Table III, column (5), on the subsample excluding post-2000 surveys (i.e., using only surveys from 1983 to 1998). We obtain a coefficient on the learning-from-experience forecast of 149.38 (std. err. 78.51). While the standard errors are substantially bigger than in the full sample, the magnitude of the point estimate is very similar to the full-sample estimate (slightly larger). Thus, the results do not seem to be driven just by the post-2000 credit expansion.

Overall, the findings in this section confirm that learning from inflation experiences affects not only the expectations of individuals but also their asset allocation to long-term bonds and their mortgage financing decisions. The latter is, for many households, among the most important financial decisions they make during their life-times.

V. Aggregate Implications

Our analysis so far has focused on using heterogeneity in inflation experiences to explain heterogeneity in expectations and financial decisions. We now explore whether learning from experience also helps explain aggregate dynamics in inflation expectations. We show that experience-based forecasts aggregate to average forecasts that closely resemble those from constant-gain algorithms in the existing literature, which have been shown to explain macroeconomic time series data. We argue that learning from experience provides a micro-underpinning for adaptive-learning models, but offers conceptual and econometric advantages in the identification of the structural parameters that pin down the learning rule.

V.A. Approximating Constant-Gain Learning

We start from the model in equation (8), which allows for social learning. Averaging across all cohorts s in each period t, and denoting cross-sectional averages with an upper bar, we get

$$\overline{\pi}_{t+1|t} = \overline{\tau}_{t+1|t} + (1-\beta)\eta_t. \tag{10}$$

Thus, apart from the noise term η_t, the mean expectation is pinned down by the mean learning-from-experience forecast across all age groups, $\overline{\tau}_{t+1|t}$. This mean learning-from-experience forecast behaves approximately as if it were generated from a constant-gain learning algorithm: while individuals update their expectations with decreasing gain (i.e., older individuals react less to a given inflation surprise than younger individuals), the average gain each period is constant (as long as the weight on each age group is constant over time). The average learning-from-experience forecast is an approximation, rather than an exact match, of a constant-gain learning forecast because the means of the surprise terms in equations (2) and (3) are not exactly identical to the surprises arising in a constant-gain learning algorithm.

Figure VI illustrates how well the approximation with a constant gain works. The figure compares the weights on past inflation implied by learning-from-experience with $\theta = 3.044$ (from Table 1, column (i)) and averaged across all age groups (solid line) with the weights implied by constant-gain learning (dashed line). We use the constant gain for which the constant-gain algorithm minimizes the squared deviations from the average learning-from-experience weights. The result is a constant gain of $\gamma = 0.0180$.

The figure shows that the weighting of past data is very similar. It is noteworthy that the deviation-minimizing constant gain $\gamma = 0.0180$ is virtually the same as the gain required to match aggregate expectations and macro time-series data. For example, Milani (2007) reports that an estimate of $\gamma = 0.0183$ provides the best fit of a dynamic stochastic general equilibrium model with constant-gain learning to macroeconomic variables. Orphanides and Williams (2005a) choose a gain of 0.02 to match the time-series of inflation forecasts from the SPF. Our estimate of γ is, instead, chosen to match the weights implied by the θ that we estimated purely from cross-sectional heterogeneity. We did not employ aggregate expectations data, and we did not try to fit future realized inflation rates. Hence, our estimates of θ from between-cohort heterogeneity provide "out-of-sample" support for values of the gain parameter around $\gamma = 0.0180$ that are necessary, according to the prior literature, to fit time-series data. We conclude that the aggregate implications of learning from experience for the formation of expectations are very similar to those of constant-gain learning algorithms, which have been used successfully to explain macroeconomic dynamics (e.g., Sargent 1999; Orphanides and Williams 2005a; Milani 2007), but with the added benefit of empirical consistency with between-cohort heterogeneity.

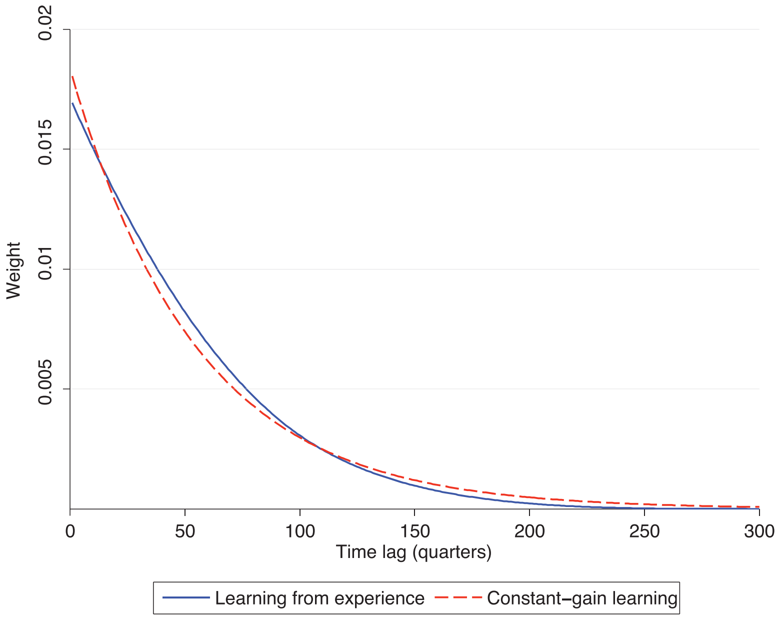


FIGURE VI

Comparison of Implied Mean Weights on Past Inflation Observations under Learning-from-Experience and Constant-Gain Learning

The learning-from-experience weights for each lag are calculated for each age at the point estimate $\theta = 3.044$ from Table I, column (1), and then averaged across all ages from 25 to 74 (equally weighted). The weights implied by constant-gain learning are calculated with gain $\gamma = 0.0180$, which minimizes squared deviations from the learning-from-experience weights shown in the figure.

V.B. *Explaining Aggregate Expectations*

We now test directly how well the learning-from-experience model matches aggregate survey expectations. Figure VII shows both the time path of averages from the raw survey data (circles) and average experience-based forecasts (solid line), as before based on $\theta = 3.044$. Since our imputation of percentage responses only targeted cross-sectional differences, but not the average level of percentage expectations, we omit all periods in which we only have categorical inflation expectations data.

It is apparent from the figure that the average learning-from-experience forecasts closely track average expectations. The good match is by no means mechanical. As discussed already, our

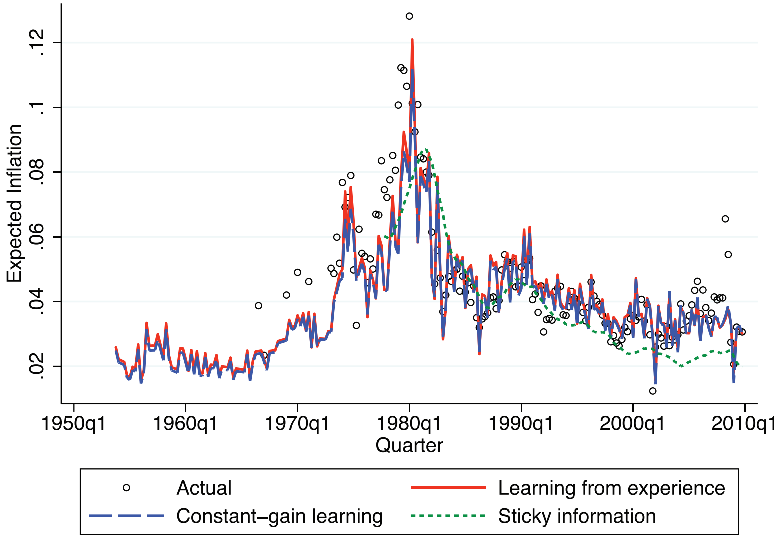


FIGURE VII

Average Survey Expectations (Actual) Compared with Average Learning-from-Experience Forecasts, Constant-Gain Forecasts, and Sticky Information Forecasts

estimation of θ uses only cross-sectional differences in expectations, but no information about the level of the average expectation. The time path for average expectations generated by the θ that best fits cross-sectional differences could easily have failed to match average expectations. As the figure shows, though, the two time paths match well.

Figure VII also shows the time path of constant-gain learning forecasts, using $\gamma = 0.0180$ from Figure VI. Not surprisingly, given that γ was chosen to minimize the distance in the implied weights, the forecasts are almost indistinguishable. This illustrates further that at the aggregate level, the learning-from-experience expectations formation mechanism can be approximated well with constant-gain learning.

Finally, we compare the average learning-from-experience forecast to a sticky information forecast. Sticky information, as in Mankiw and Reis (2002) and Carroll (2003), induces stickiness in expectations, and it is possible that our estimation of the learning-from-experience rule is picking up some of this stickiness. We calculate sticky information inflation expectations as in Carroll's model as a geometric distributed lag of current and past quarterly SPF forecasts of one-year inflation rates. Note that the sticky information model can only be estimated from 1977Q4 on, when the SPF data with all the required lags are available (129 observations, compared to 173 observations for full sample).[14] We set the weight parameter $\lambda = 0.25$ as in Mankiw and Reis (2002) (and similar to $\lambda = 0.27$ estimated in Carroll 2003). The resulting sticky-information forecast is shown as the short-dashed line in Figure VII. The graph illustrates that the learning-from-experience model helps predict actual forecast data better than the sticky information model. For example, learning-from-experience forecasts track actual forecasts more closely during the peak around 1980 and also during the 2000s, though both models fail to match a few highly positive expectations toward the end of the last decade.

We evaluate the statistical significance of this graphical impression in Table IV. We regress average survey expectations on the average forecast predicted for the same quarter under the various models. For the learning-from-experience model (column (1)), the estimated coefficient is 0.887, less than 1 standard error away from the model prediction of 1. With 56.4% the adjusted R^2 is high. This confirms the visual impression that experience-based forecasts closely track the actual average survey expectations. The constant-gain forecast in column (2) produces almost identical results, not surprisingly given its similarity with $\overline{\tau}_{t+1|t}$ when using $\gamma = 0.0180$. The sticky information coefficient in column (3) is only a bit lower and noisier, and the adjusted R^2 is slightly higher. Note, though, that the learning-from-experience model, reestimated over the shorter subsample from column (3), yields an even higher adjusted R^2, 67.2%, and a learning-from-experience coefficient of 1.039 (std. err. 0.114) that is even closer to 1. Most important, if we include both the sticky information and the experience-based forecast (column (4)), the coefficient on the experience-based forecast becomes only slightly smaller but remains large (also relative to the sticky-information coefficient) and significant. Hence, the experience-based forecast does not

14. We use the one-year inflation forecasts that the SPF constructs from median CPI inflation forecasts for each of the four quarters ahead. Before 1981Q3, when the CPI inflation forecast series is not available, we use the GDP deflator inflation forecast series.

TABLE IV
EXPLAINING MEAN INFLATION EXPECTATIONS

	(1)	(2)	(3)	(4)
Learning-from-experience forecast	0.887			0.695
	(0.120)			(0.132)
Constant-gain-learning forecast		0.931		
		(0.137)		
Sticky-information forecast			0.878	0.390
			(0.199)	(0.150)
Intercept	0.009	0.008	0.011	−0.000
	(0.005)	(0.005)	(0.006)	(0.005)
Adj. R^2	0.564	0.555	0.602	0.715
# Obs.	173	173	129	129

Notes. OLS regressions with quarterly data from 1973Q1 to 2009Q4 (with gaps). The dependent variable is the forecast of one-year inflation made during quarter t, averaged across all cohorts. Newey-West standard errors (with five lags) are shown in parentheses.

just pick up the sticky information effect of Mankiw and Reis (2002) and Carroll (2003).

VI. CONCLUSION

Our analysis shows that inflation expectations depend on the inflation experiences that people accumulate during their lives. Differences in experienced mean inflation and inflation persistence generate (time-varying) differences in inflation expectations between cohorts. The experience of younger individuals is dominated by recent observations, whereas older individuals draw on a more extended historical data set in forming their expectations.

Learning from experience can explain, for example, why young individuals forecasted much higher inflation than did older individuals following the high-inflation years of the late 1970s and early 1980s: both the mean inflation rate and inflation persistence were particularly high in the short data set experienced by young individuals at the time. For recent years, instead, toward the end of our sample, our estimates imply a perceived persistence of inflation shocks close to zero, particularly for young individuals. This suggests that unexpected movements in inflation are currently unlikely to move inflation expectations much.

To further refine the understanding of expectations formation and the impact on financial decisions, it will be important to shed more light on the exact transmission channel for experience effects. For example, does the salience of an experience depend on individuals' personal investment choices or financial constraints? Does it vary by macroeconomic conditions? These are important questions for future research.

More work is needed to ascertain whether the learning-from-experience model applies more generally to other types of macroeconomic expectations. In this regard it is interesting to note that the weights individuals put on past inflation experiences, according to our estimates, are very similar to the weights they put on past stock market return experiences when they choose asset allocations in their investment portfolios, according to the estimates in Malmendier and Nagel (2011).[15] This is remarkable because the weights we estimated here are based on a different data set and because we analyze beliefs rather than investment choices. Taken together, these findings are suggestive that individuals process different types of macroeconomic experiences in similar ways when they form expectations.

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Supplementary Material

An Online Appendix for this article can be found at QJE online (qje.oxfordjournals.org).

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15. The weighting function in Malmendier and Nagel (2011) is controlled by a parameter λ which relates to θ in this article as $\theta \approx \lambda + 1$ (see Online Appendix A), and is estimated in the range from 1.1 to 1.9.

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