



# 1 Introduction

How do individuals form expectations about future inflation? The answer to this question is of central importance both for monetary policy and for individual financial and consumption decisions. Despite a large volume of research, there is still little convergence on the best model to predict inflation expectations (see Mankiw, Reis, and Wolfers (2003); Blanchflower and Kelly (2008)). The “stickiness” of inflation rate changes (Sims (1998), Mankiw and Reis (2006)) and the empirical heterogeneity in the formation of expectations remain hard to reconcile with existing models. Similar concerns apply to the formation of macro-relevant expectations and their influence on aggregate dynamics more generally, as discussed, for example, in Fuster, Laibson, and Mendel (2010) and Fuster, Hebert, and Laibson (2011).

In this paper, we show that individuals’ personal experiences play an important role that is absent from existing models. We argue that, when forming macroeconomic expectations, individuals put a higher weight on realizations of macroeconomic data experienced during their life-times compared with other available historical data.

Such *learning from experience* carries a rich set of implications. First, expectations are history-dependent. For example, the experience of high inflation rates may shape the inflation expectations of cohorts that have lived through this period for a substantial amount of time. Second, beliefs are heterogeneous. Young individuals place more weight on recent data than older individuals since recent experiences make up a larger part of their life-times so far. As a result, different generations tend to disagree about the future. Third, learning dynamics are perpetual. Beliefs keep fluctuating and do not converge in the long-run, as weights on historical data diminish when old generations disappear and new generations emerge. Averaged across cohorts, expectations resemble those obtained from constant-gain learning algorithms commonly used in macroeconomics; but between cohorts, the speed of updating and the resulting beliefs are heterogeneous.

We test the experience-based model using 57 years of microdata on inflation expectations from the Reuters/Michigan Survey of Consumers (*MSC*). In our empirical framework, we

assume that individuals employ regression-based forecasting rules similar to those used in the adaptive learning literature, in particular Marcet and Sargent (1989), but with the twist that we allow individuals to overweight data realized during their life-times so far. Specifically, individuals use inflation rates experienced in the past to recursively estimate an AR(1) model of future inflation. The learning-from-experience mechanism is implemented by allowing the gain, i.e., the strength of updating in response to surprise inflation, to depend on age. Thus, young individuals react more strongly to an inflation surprise than older individuals who have more data accumulated in their life-time histories. A gain parameter determines how fast these gains decrease with age as more data accumulates. We estimate this gain parameter empirically by fitting the learning rule to the individual inflation expectations reported in the *MSC*.

The availability of microdata is crucial for our estimation since our identification strategy exploits time-variation in cross-sectional differences of inflation experiences and relates it to time-variation of cross-sectional differences in inflation expectations. The time-series variation in cross-sectional heterogeneity allows us to employ time dummies in our estimations and thus to separate the experience effect from time trends or any other time-specific determinants of inflation expectations. For example, when forming expectations, individuals might also draw, to some extent, on the full inflation history available at a given time, or on published forecasts of professional forecasters. With the inclusion of time dummies, the experience coefficient isolates the *incremental* explanatory power of life-time experiences. Hence, our empirical approach allows us to rule out that omitted macroeconomic variables or any other unobserved effects common to all individuals bias the estimation results. This is a key distinction from other models of belief formation, such as adaptive learning models, where parameters are fit to aggregate time-series of (mean or median) expectations.

Our estimation results show that learning from experience has an economically important effect on inflation expectations. Individuals of different ages differ significantly in their inflation expectations, and these differences are well explained by differences in their inflation

experiences. The heterogeneity is particularly pronounced following periods of high surprise inflation. For example, in the late 1970s and early 1980s, the average inflation expectation of younger individuals ( $< 40$  years of age) exceeded that of older individuals ( $> 60$  years) by several percentage points. This divergence is consistent with the experience of younger individuals being dominated by the high-inflation years of the 1970s, while 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 also imply that recent inflation experiences receive higher weight than experiences earlier in life, though experiences from 20 to 30 years ago still have some long-run effects for older individuals.

We also explore the aggregate implications of learning from experience. We show that if one averages experience-based expectations across cohorts at each point in time, the average learning-from-experience forecast matches the average survey expectations closely. The similarity is remarkable because our estimation did not utilize any information about the level of the average survey expectations, only information about cross-sectional differences between cohorts. Hence, learning from experience helps to simultaneously predict both the cross-section and the time-series of inflation expectations.

We also show that the average learning-from-experience forecast can be approximated quite closely with constant-gain learning algorithms that are popular in macroeconomics. The constant-gain parameter that best matches our estimated learning-from-experience weights,  $\gamma = 0.0180$ , turns out to be quantitatively very similar to those that Orphanides and Williams (2005) and Milani (2007) have estimated by fitting the parameters to macroeconomic data and aggregate survey expectations, 0.0183 and 0.02 respectively. As with the survey data, this similarity is remarkable because we did not calibrate the learning-from-experience rule

to match the average level of inflation expectations or any macroeconomic data.

At the same time, learning from experience and constant-gain learning differ fundamentally in their motivation for the observed down-weighting of past data: rather than reflecting the response to structural changes in macroeconomic time series, learning from experience is based on the notion that memory of past data is lost as older generations die and new ones are born. We show that the structural-change based explanation, which is usually advanced in constant-gain learning models, is hard to reconcile with the empirical evidence: both professional forecasters (in the *SPF*) and households (in the *MSC*) discount past inflation data much less than the degree of structural change in the time-series of inflation would call for. Moreover, the degree of structural change in different time series does not seem to be related much to the gains implied by survey expectations.

We also emphasize an econometric advantage of the learning-from-experience approach: The gain parameter is identified purely from cross-sectional variation. Compared with empirical work on adaptive learning that uses only aggregate time-series data, this opens up a new dimension of data that helps pin down the parameters of individuals' learning rule. This is useful in two ways. First, it helps alleviate the concern that models of boundedly rational learning involve too many degrees of freedom, rendering the model not falsifiable.<sup>1</sup> Second, empirically, the identification from cross-sectional data offers some advantage in capturing the dynamics of survey expectations. We show that estimating the gain parameter purely from cross-sectional variation without our learning-from-experience framework provides a better out-of-sample fit to mean inflation expectations than estimating a constant-gain rule from time-series data, even though the estimation within the learning-from-experience framework did use any data on the level of mean expectations at all.

Our paper connects to several strands of literature. A large macroeconomic literature analyzes the formation of expectations. While the crucial role of expectations for macroeco-

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<sup>1</sup>This is the first of three concerns expressed in Sargent (1993) that Marcat and Nicolini (2003) summarize as "... using models of boundedly rational learning would entail problems similar to those found in models of adaptive expectations of the prerational-expectations era, namely: (i) too many degrees of freedom are available to the economist, so the model is not falsifiable; ..."

conomic outcomes and asset prices is well understood at least since Keynes (1936), we know less well how economic agents form their subjective beliefs about the future. The literature on adaptive learning (see Bray (1982); Sargent (1993); Evans and Honkapohja (2001)) views individual agents as econometricians who make forecasts based on simple forecasting rules estimated on historical data. Fuster, Laibson, and Mendel (2010) and Fuster, Hebert, and Laibson (2011) propose a model of “natural expectations” and demonstrate its ability to match hump-shaped dynamics in different economic time series. Yet, there is little direct empirical evidence on the actual forecasting rules employed by individuals, even though the formation of inflation expectations, and macroeconomic expectations more generally, are of first-order importance for macroeconomic policy (Bernanke (2007)). For example, disagreement about future inflation leads to disagreement about real interest rates (given that the nominal interest rate is fixed in financial markets), which in turn influences borrowing and lending among households. Piazzesi and Schneider (2012) show that the disagreement between younger and older households in the late 1970s helps understand quantities of household borrowing and lending, shifts in household portfolios, and the prices of real assets at the time.

Conceptually, our approach is related to bounded-memory learning in Honkapohja and Mitra (2003) in that memory of past data is lost or, in our case, underweighted. However, while bounded-memory learning agents are homogeneous, the memories of agents in the experience-based model differ depending on their age. Our approach also relates to the boundedly-rational learning model in Marcet and Nicolini (2003), where agents learn differently during stable and during instable periods. Our approach pins the gain in learning to agents’ age rather than a threshold rule that is chosen to fit the data.

There is a small, but growing literature that looks at heterogeneity in expectations formation with microdata. Building on early work by Cukierman and Wachtel (1979), Mankiw, Reis, and Wolfers (2003) examine the time-variation in dispersion in inflation expectations and relate it to models of “sticky information.” Carroll (2003) further investigates the sticky-

information model, but with aggregate data on inflation expectations. Bryan and Venkatu (2001) provide evidence of gender-specific heterogeneity in inflation expectations as well as other demographics-based differences. Branch (2004), Branch (2007), and Pfajfar and Santoro (2010) estimate from survey data how individuals choose among competing forecasting models. Piazzesi and Schneider (2012) incorporate survey data on heterogeneous subjective inflation expectation into asset pricing, while Piazzesi and Schneider (2011) use data on subjective interest rate expectations and a model with adaptive learning. Shiller (1997) and Ehrmann and Tzamourani (2009) examine the relation between cross-country variation in inflation histories and the public’s attitudes towards inflation-fighting policies. Our paper contributes to this literature by demonstrating that learning from experience plays a significant role in expectations formation and produces both heterogeneity in expectations and gradually fading memory over time.

Our analysis is related to earlier empirical findings in Malmendier and Nagel (2011), who show that past stock-market and bond-market experiences predict future risk taking of individual investors. Interestingly, the weighting of past experiences implied by the learning-from-experience rules estimated in this paper matches very closely the weighting scheme estimated from a completely different data source, the Survey of Consumer Finances, in Malmendier and Nagel (2011). However, the data used in Malmendier and Nagel (2011) did not allow to determine whether these effects are driven by beliefs (e.g., experiences of high stock returns make individuals more optimistic) or by endogenous preference formation (e.g., experiences of high stock returns make individuals less risk averse or lead to other changes in “tastes” for certain asset classes). The data used in this paper measures directly individual expectations and thus identifies the beliefs channel.

Evidence consistent with learning-from-experience effects is also presented in Vissing-Jorgensen (2003) and Greenwood and Nagel (2009), who show that young investors and young mutual fund managers in the late 90s were more optimistic about stocks, and in particular technology stocks, than older investors, consistent with being more strongly influenced by

their recent good experience. Vissing-Jorgensen also points out that there is age-heterogeneity of inflation expectations in the late 1970s and early 1980s. Kaustia and Knüpfer (2008) and Chiang, Hirshleifer, Qian, and Sherman (2011) find that investors' participation and bidding strategies in initial public offerings is influenced by extrapolation from previously experienced IPO returns.

The rest of the paper is organized as follows. Section 2 introduces our experienced-based learning framework and estimation approach. Section 3 discusses the data set on inflation expectations. Section 4 presents our core set of results on learning-from-experience effects in inflation expectations. In Section 5, we look at the implications of our results at the aggregate level. Section 6 concludes.

## 2 Learning from experience

Consider two individuals, one is member of the cohort born at time  $s$ , and the other belongs to the cohort born at time  $s + j$ . How do they form expectations of next period's inflation,  $\pi_{t+1}$ , at time  $t > s + j$ ? The essence of the learning-from-experience hypothesis is that they place different weights on recent and distant historical data, reflecting the different inflation histories they have experienced in 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.

Our analytical framework builds on the forecasting rules proposed in the adaptive learning literature, in particular Marcet and Sargent (1989). (See also Sargent (1993) and Evans and Honkapohja (2001).) In this literature, agents are assumed to use relatively simple forecasting models, motivated by cognitive and computational constraints that limit individuals in their ability to make optimal forecasts. The algorithms represent "rules of thumb" that practitioners and individuals might employ. The key departure from the standard adaptive-learning models is that we allow individuals to put more weight on data experienced during their lifetimes than on other historical data. This gives rise to cross-sectional differences in



expectations between different cohorts. Our analysis also differs from much of the adaptive learning literature in that we are interested in identifying and estimating individuals' actual forecasting rules, while much of the earlier work on adaptive learning focuses on analyzing the conditions under which simple learning rules lead to convergence to rational-expectations equilibria.

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 (2004):

$$\pi_{t+1} = \alpha + \phi\pi_t + \eta_{t+1}. \quad (1)$$

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

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

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

where  $x_t \equiv (1, \pi_t)'$  and the recursion is started at some point in the distant past.<sup>2</sup> The sequence of gains  $\gamma_{t,s}$  in the recursive algorithm determines the degree of updating cohort  $s$  applies when faced with an inflation surprise. For example, with  $\gamma_{t,s} = 1/t$ , the algorithm represents a recursive formulation of an ordinary least squares estimation that uses all data available until time  $t$  with equal weights (see Evans and Honkapohja (2001)). With  $\gamma_{t,s}$  set to a constant, it represents a constant-gain learning algorithm, which weights past data with exponentially decaying weights. Our key modification of the standard learning framework is that we let the gain  $\gamma$  depend on the age  $t - s$  of the members of cohort  $s$ . As a result, individuals of different age can be heterogeneous in their forecasts and adjust their forecasts to different degrees in response to surprise inflation. Given the perceived law of motion in equation (1), these cross-sectional differences can arise from two sources: first, from differences

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<sup>2</sup>We will see below that, in our setting, past data gets downweighted sufficiently fast so that initial conditions do not exert any relevant influence.

in individuals' perception of the mean,  $\mu = \alpha(1 - \phi)^{-1}$ , and, second, from differences in the perception of persistence,  $\phi$ , of deviations of recent inflation from this perceived mean.

Specifically, we consider the following decreasing-gain specification,

$$\gamma_{t,s} = \begin{cases} \frac{\theta}{t-s} & \text{if } t - s \geq \theta \\ 1 & \text{if } t - s < \theta, \end{cases} \quad (4)$$

where  $\theta > 0$  is a constant parameter that determines the shape of the implied function of weights on past experienced inflation observations. We let the recursion start with  $\gamma_{t,s} = 1$  for  $t - s < \theta$ , which implies that data before birth is ignored. (As explained below, our econometric specification does allow for all available historical data to affect the forecast, but isolates incremental the effect of data realized during individuals' life-times on expectation formation.) This specification is the same as in Marcet and Sargent (1989) with one modification: the gain here is decreasing in age, not in time, and individuals use only data realized during their life-times. The specification allows for the possibility that experiences in the distant past have a different influence than more recent experiences. For example, the memory of past episodes of high inflation might fade away over time, as also assumed in standard models such as constant-gain learning. Alternatively, high-inflation experiences at young age, perhaps conveyed through the worries of parents, might leave a particularly strong and lasting impression on the formation of beliefs about future inflation.

Figure 1 illustrates the role of the parameter  $\theta$ . The top graph of Figure 1 presents the sequences of gains  $\gamma$  as a function of age for different values of  $\theta$ . Regardless of the value of  $\theta$ , 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, presumably have a higher gain than older individuals, who have experienced a longer data history, and for whom a single inflation surprise observation should have a weaker marginal influence. The down-weighting of past data is also consistent with the corresponding assumption in constant-gain learning models. There, the motivations for assuming such down-weighting of past data

are, for example, that individuals believe that a structural break may have occurred or that they perceive the parameters of the inflation process to be time-varying. Our model adds additional micro-foundation to that assumed pattern.

The top graph of Figure 1 also illustrates that the higher  $\theta$  is, the slower is the rate at which the gains decrease with age and, hence, the less weight is given to observations that are more distant in the past. The latter implication is further illustrated in the bottom graph of Figure 1, which shows the implied weights on past inflation observations as a function of the time lag relative to current time  $t$  for the example of 50-year (200 quarters) old individual. For  $\theta = 1$ , all historical observations since birth are weighted equally. For  $\theta > 1$ , instead, weights on earlier observations are lower than those on more recent observations. With  $\theta = 3$  very little weight is put on observations in the first 50 quarters since birth towards the right of the bottom graph.

In other words, our gain parametrization is flexible in accommodating different weighing schemes. The weights can be monotonically increasing, decreasing, or flat. An additional advantage of the decreasing-gain specification in equation (4) is that, for appropriate choices of the weighting parameters, it produces weight sequences that are virtually identical to those in Malmendier and Nagel (2011). (See Appendix A.) This allows us to compare the weights estimated from inflation expectations with those estimated from portfolio allocations in Malmendier and Nagel (2011).

In addition to past inflation experiences, we allow all other information sources to affect inflation expectations. Let  $\pi_t^h = h^{-1} \sum_{i=1}^h \pi_{t-h+i}$  denote the average annualized inflation rate over the  $h$  periods leading up to  $t$ , and let  $\pi_{t+h|t,s}^h$  be the forecast of  $\pi_{t+h}^h$  made by cohort  $s$  at time  $t$ , as indicated by the subscript  $|t, s$ . The learning-from-experience component of individuals' one-step-ahead forecast of inflation is obtained from (2) as  $\tau_{t+1|t,s}^1 = b'_{t,s} x_t$ , and the multi-period version of it,  $\tau_{t+h|t,s}^h$ , is obtained by iterating on the forecasting model at the time- $t$  estimates  $b_{t,s}$ . We capture the influence of information sources other than experienced

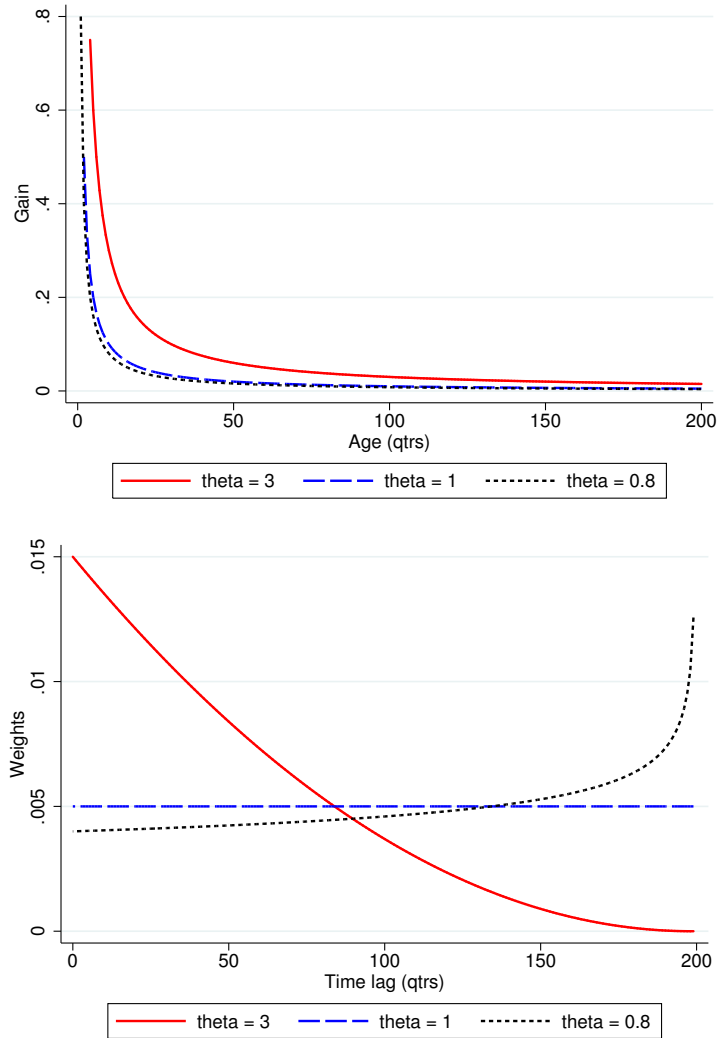


Figure 1: Examples of gain sequences (top) and associated implied weighting of past data (bottom) for a 50-year old individual. The top panel shows the sequence of gains as a function of age over the course of a 50-year individual’s life. The bottom panel shows the weighting of past data implied by the gain sequence in the top panel, with the weights for most recent data to the left and weights for early life experience to the right.

inflation by assuming

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

That is, the subjective expectation is a weighted average of the learning-from-experience component  $\tau_{t+h|t,s}^h$  and an unobserved common component  $f_t^h$  of individuals'  $h$ -period forecasts. This unobserved component  $f_t^h$  could represent any kind of forecast based on common information available to all individuals at time  $t$ , such as the opinion of professional forecasters or the representation of their opinions in the news media (e.g., as in Carroll (2003)). Alternatively,  $f_t^h$  could capture a common component of individual forecasts that is driven by all available historical data. In either case, the coefficient  $\beta$  captures the incremental contribution of life-time experiences  $\tau_{t+h|t,s}^h$  to  $\pi_{t+h|t,s}^h$  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 life-time experiences on expectations formation.

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

$$\tilde{\pi}_{t+h|t,s}^h = \beta \tau_{t+h|t,s}^h + \delta' D_t + \varepsilon_{t,s}^h, \quad (6)$$

where  $\tilde{\pi}_{t+h|t,s}^h$  denotes measured inflation expectations from survey data. In this estimating equation, we absorb the unobserved  $f_t^h$  with a vector of time dummies  $D_t$ . We also add the disturbance  $\varepsilon_{t,s}^h$ , which we assume to be uncorrelated with  $\tau_{t+h|t,s}^h$ , 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  $\theta$  and  $\beta$  with non-linear least squares. (Recall that  $\tau_{t+h|t,s}^h$  is a non-linear function of  $\theta$ .)

The presence of time dummies in equation (6) implies that we identify  $\beta$  and  $\theta$ , and hence the learning-from-experience effect on expectations, 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 to rule out confounds affecting prior work, which estimates adaptive learning rules from aggregate data, e.g., from the time-series of mean or median inflation expectations. Under the prior approach, it is hard to establish whether the time-series relationship between inflation expectations and lagged inflation truly reflects adaptive learning or, instead, some other formation mechanism (e.g., rational expectations) that happens to generate expectations that are highly correlated. In contrast, experience-based learning 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  $\theta$  that determines the learning speed from this cross-sectional heterogeneity. This provides a new source of identification for the learning speed in adaptive learning algorithms.

### 3 Data

To test whether past experiences affect expectations, we use long-term historical data on the consumer price index (CPI) from Shiller (2005). In order to fully capture experienced inflation during the lifetimes of even the oldest individuals in the expectations survey sample, we need inflation data stretching back 74 years before the start of the survey in 1953. We obtain the time series of inflation data since 1872 (until the end of 2009) from Robert Shiller's website and calculate annualized quarterly log inflation rates. Figure 2 shows annual inflation rates from this series.

The inflation expectations microdata is from the Reuters/Michigan Survey of Consumers (MSC), conducted by the Survey Research Center at the University of Michigan. These surveys were administered since 1953, initially three times per year, then quarterly from 1960 through 1977, and monthly since 1978 (see Curtin (1982)). We obtain data for surveys conducted from 1953 to 1977 from the Inter-university Consortium for Political and Social Research (*ICPSR*) at the University of Michigan. From 1959 to 1971, the questions of the

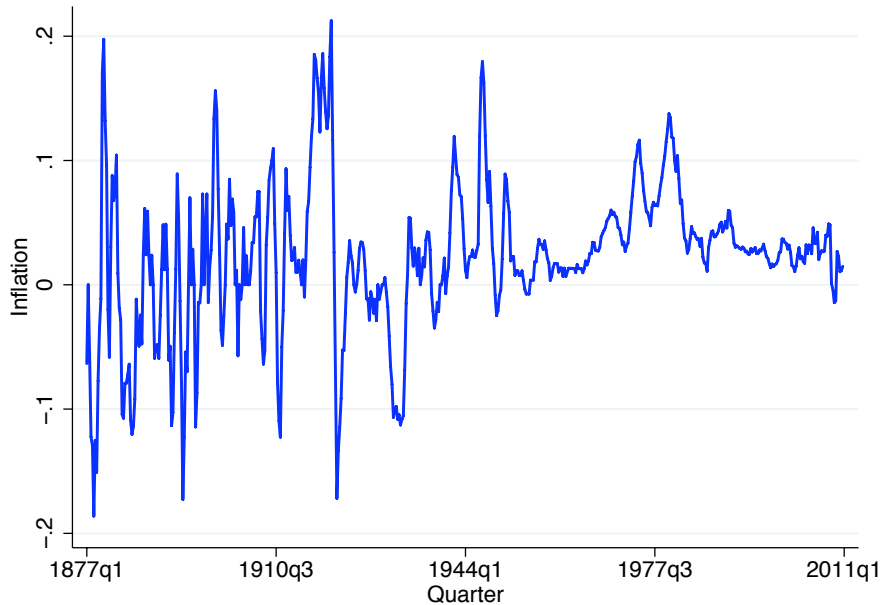


Figure 2: Annual CPI inflation rates

winter-quarter Survey of Consumer Attitudes were administered as part of the Survey of Consumer Finances (*SCF*), and so we obtain those data from the *SCF* files at *ICPSR*. The data from 1978 to 2007 is available in from the University of Michigan Survey Research Center. Appendix B provides more detail on the data.

In most periods, the survey asks two questions about expected inflation, one about the expected direction of future price changes (“up,” “same,” or “down”) and one about the expected percentage of price changes. Our analysis aims to make quantitative predictions and thus focuses on the percentage expectations. However, for quarters in which the survey asks only the categorical questions about the expected direction, we are able to impute percentage responses from the categorical responses. The imputation procedure is described in detail in Appendix C. Figure 3 highlights the periods in which we have percentage expectations data in light grey and the quarters in which the survey asks only the categorical questions in dark grey.

Since our learning-from-experience hypothesis predicts that inflation expectations should

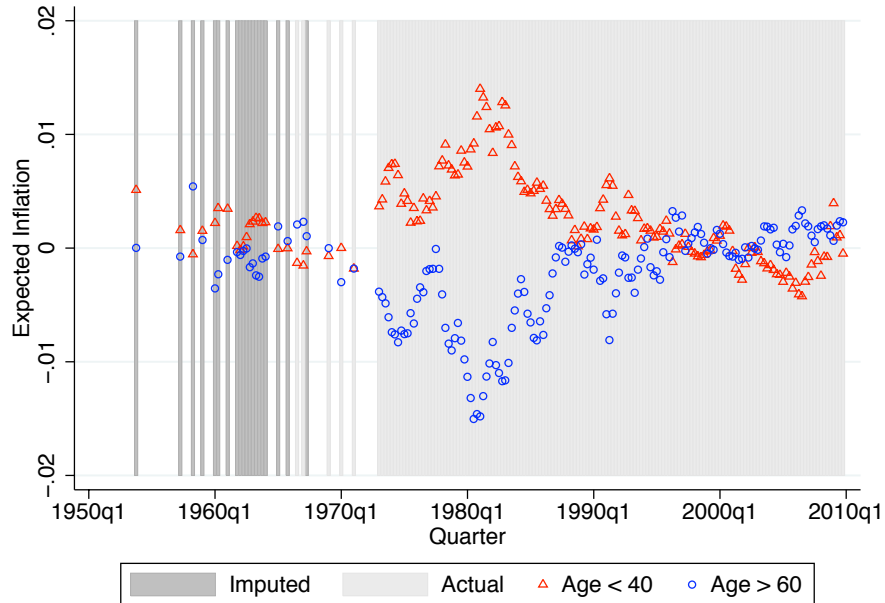


Figure 3: Four-quarter moving averages of mean one-year inflation expectations of young (age < 40) and old (age > 60) in excess of the full-sample cross-sectional mean expectation. Percentage forecasts are available from the survey in periods shaded in light grey; they are imputed from categorical responses in the periods shaded in dark grey; and they are unavailable in unshaded periods.

be heterogeneous across different age groups, we aggregate the data at the cohort level, i.e., by birth year. For each survey month and each cohort, we compute the mean inflation expectations of all members of the cohort. In the computation of this mean, we apply the sample weights provided by the MSC. If multiple monthly surveys are administered within the same quarter, we average the monthly means within each quarter to make the survey data compatible with our quarterly inflation rate series.

We restrict our sample to respondents whose age ranges from 25 to 74. This means that for each cohort we obtain a quarterly series of inflation expectations that covers the time during which members of this cohort are from 25 to 74 years old.

To provide some sense of the variation in the data, Figure 3 plots the average inflation expectations of young individuals (averaging across all cohorts that are in the age range from



25 to 39) and old individuals (averaging across cohorts that are in the age range 61 to 74), relative to the full-sample cross-sectional mean expectation at each point in time. To better illustrate lower frequency variation, we plot the data as four-quarter moving averages. The dispersion across age groups widens to almost 3 percentage points (pp) during the high inflation years of the 1970s and early 1980s. The fact that young individuals at the time expected higher inflation is consistent with the learning-from-experience story: The experience of young individuals around 1980 was dominated by the recent high-inflation years, while older individuals' experience also included the modest inflation rates of earlier decades. For younger individuals, with a smaller set of experienced-inflation data points, these recent observations exert a stronger influence on their expectations. As we show below, differences in the perceived persistence of inflation between young and old matter as well, in addition to the differences in perceived mean inflation.

## 4 Estimation of the learning-from-experience forecast model from cohort data

We now estimate the learning-from-experience effects by fitting the estimating equation (6) and the underlying AR(1) model to the MSC inflation expectations data, using nonlinear least squares on the cohort-level aggregate data. We relate survey expectations measured in quarter  $t$  to learning-from-experience forecasts  $\tau_{t+h|t,s}^h$ , where we assume that the data available to individuals in constructing  $\tau_{t+h|t,s}^h$  are quarterly inflation rates until the end of quarter  $t - 1$ . We work with survey expectations of inflation rates over the next year, so  $h = 4$ . 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 1: Learning-from-experience model: Estimates from cohort data

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 non-linear 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 and cohort. The sample period runs from 1953 to 2009 (with gaps).

	Baseline		Restricted		
	(i)	(ii)	(iii)	(iv)	(v)
Gain parameter $\theta$	3.044 (0.233)	3.144 (0.257)	3.976 (0.494)	4.144 (0.446)	3.044 -
Sensitivity $\beta$	0.672 (0.076)	0.675 (0.079)	0.664 (0.084)	0.693 (0.111)	0.672 (0.093)
Time dummies	Yes	Yes	No	No	No
Imputed data included	Yes	No	No	No	No
Restrictions			$f_t^h = SPF_{t-1}$	$f_t^h = \bar{\tau}_t^h$	$f_t^h = \bar{\tau}_t^h$ $\theta = 3.044$
Adj. $R^2$	0.637	0.635	-	-	-
RMSE	0.0148	0.0152	0.0189	0.0191	0.0194
#Obs.	8215	7650	7400	7650	7650

#### 4.1 Baseline results

Table 1 presents the estimation results. In the full sample, we estimate the gain parameter  $\theta$  to equal 3.044 (s.e. 0.233). Comparing this estimate of  $\theta$  with the illustration in Figure 1 one can see that the estimate implies weights that are declining a bit faster than linearly. The estimation results in column (i) also show that there is a strong relationship between the learning-from-experience forecast  $\tau_{t+h|t,s}^h$  and measured inflation expectations, captured by the sensitivity parameter  $\beta$ , which we estimate to be 0.672 (s.e. 0.076). The magnitude of  $\beta$  implies that, when two individuals differ in their weighted-average inflation experiences by 1 pp, their one-year inflation expectations differ by 0.672 pp on average.

To check whether the imputation of percentage responses from categorical responses has

any influence on the results, we re-run the estimation without the imputed data, using only those time periods in which percentage responses are directly available. The results are presented in column (ii). As can be seen, whether or not imputed data is used has little effect on the results. We estimate a similar gain parameter,  $\theta = 3.144$  (s.e. 0.257), and a similar sensitivity parameter  $\beta = 0.675$  (s.e. 0.079).

The presence of the time dummies in these regressions is important to rule out that the estimates pick up time-specific effects unrelated to learning from experience. If individual expectations were unaffected by inflation experiences—for example, if all individuals learned from the same historical data set in the same way, applying the same forecasting rules—then  $\beta$  would be estimated to 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  $\beta$  is not equal to zero is direct evidence that differences in experienced-inflation histories are correlated with differences in expectations. The positive  $\beta$ -estimate also implies that recent observations exert a stronger influence on expectations of the young, because their set of experienced historical inflation rates comprises only relatively few observations.

Interestingly, the weighting of past inflation experiences implied by the point estimates of  $\theta$  is similar to the weighting implied by the estimates obtained in Malmendier and Nagel (2011) by relating data on household asset allocation to experienced risky asset returns.<sup>3</sup> This is remarkable since the data on inflation expectations is drawn from a different data set, and since we look at beliefs about inflation rather than asset allocation choices. Despite those differences, the dependence on life-time macroeconomic histories in both cases seems to imply a similar weighting of experienced data. Taken together, our findings imply that a common expectations-formation mechanism may be driving both sets of results.

One possible alternative theory for these (time-varying) age-related differences in inflation expectations is that different age groups consume different consumption baskets, and that

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<sup>3</sup>The weighting function in Malmendier and Nagel (2011) is controlled by a parameter  $\lambda$  which relates to  $\theta$  as  $\theta \approx \lambda + 1$  (see Appendix A), and which is estimated to be in the range from 1.1 to 1.9, depending on the specification.

individuals form inflation expectations based on the (recent) inflation rates they observe on their age-specific consumption baskets. The concern would be that these inflation differentials between age-specific consumption baskets could be correlated with differences in age-specific learning-from-experience forecasts that we construct. In other words, inflation differentials between age-specific consumption baskets could be a correlated omitted variable. To address this issue, we re-run the regressions in Table 1 controlling for differences between inflation rates on consumption baskets of the elderly and overall CPI inflation rates. We measure the inflation rates of the elderly with the experimental CPI for the elderly series (CPI-E) provided by the Bureau of Labor Statistics. The results reported in Appendix D show that this does not affect our results. Appendix D also reports on a similar analysis with a gasoline price series to check whether age-specific sensitivity to gasoline price inflation could drive the results, but we find that this extension does not add explanatory power and does not significantly affect our learning-rule parameter estimates. The cross-sectional differences that we attribute to learning-from-experience effects are not explained by differences in age-specific inflation rates.

To get a better sense of the extent to which learning-from-experience effects explain cross-sectional differences in inflation expectations, Figure 4 presents plots of fitted values for different age groups. Panel (a) is based on the baseline estimates from column (i) in Table 1, Panel (b) reports the fitted values from the restricted model in column (iv). The fit of the restricted model in Panel (b) is shown for the estimation sample, i.e., periods in which non-imputed percentage expectations are available. For the purpose of these plots, we average inflation expectations and the fitted values within the same young (age < 40) and old (age > 60) categories that we used earlier in Figure 3. Since our baseline estimation with time dummies focuses on cross-sectional differences, we plot the inflation expectations and fitted values of these subgroups after subtracting the full-sample mean each period. Thus, the plots focus on cross-sectional differences. To eliminate high-frequency variation, we show 4-quarter moving averages for both actual and fitted values. Fitted values are drawn as lines,

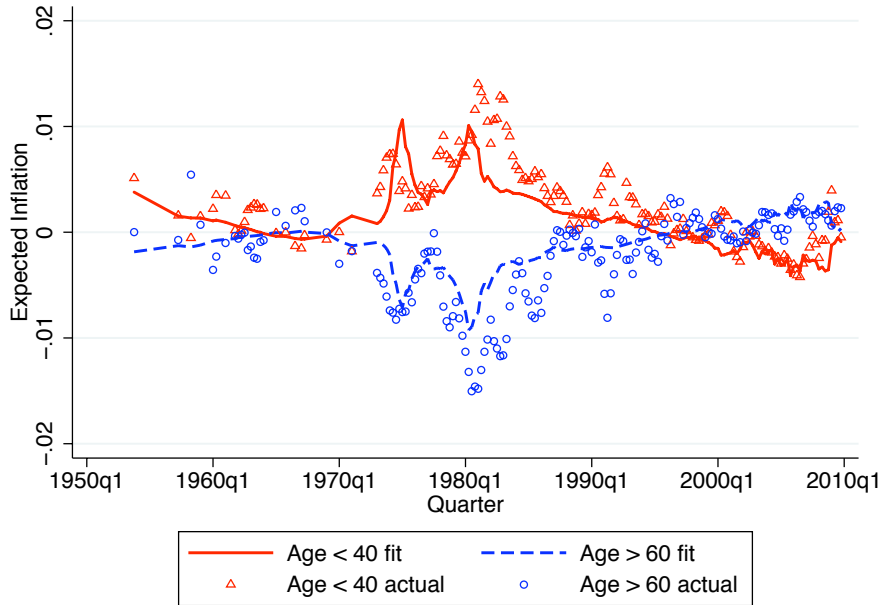


Figure 4: Comparison of 4-quarter moving averages of actual and fitted one-year inflation expectations for young and old in excess of the full-sample cross-sectional mean expectation. The fitted values corresponds to column (i) in Table 1.

raw inflation expectations are shown as triangles (young) or circles (old). The plot shows that the experience-based model does a good job of explaining the differences in inflation expectations between young and old. In particular, it accounts, to a large extent, for the large difference in expectations between young and old in the late 1970s and early 1980s.

## 4.2 Time path of perceived inflation process parameters

Figure 5 reports the persistence and unconditional mean inflation perceived by young and old over the course of the sample, as implied by the estimate of  $\theta$  from Table 1, column (i). The figure shows that there has been first an increase and then a dramatic decline in the perceived persistence and the perceived unconditional mean inflation rates. Young individuals' views about mean and persistence are much more volatile than older individuals' views, as they are more strongly influenced by recent data. For example, our estimates imply that at the end of the sample period, young individuals' inflation expectations are well anchored at

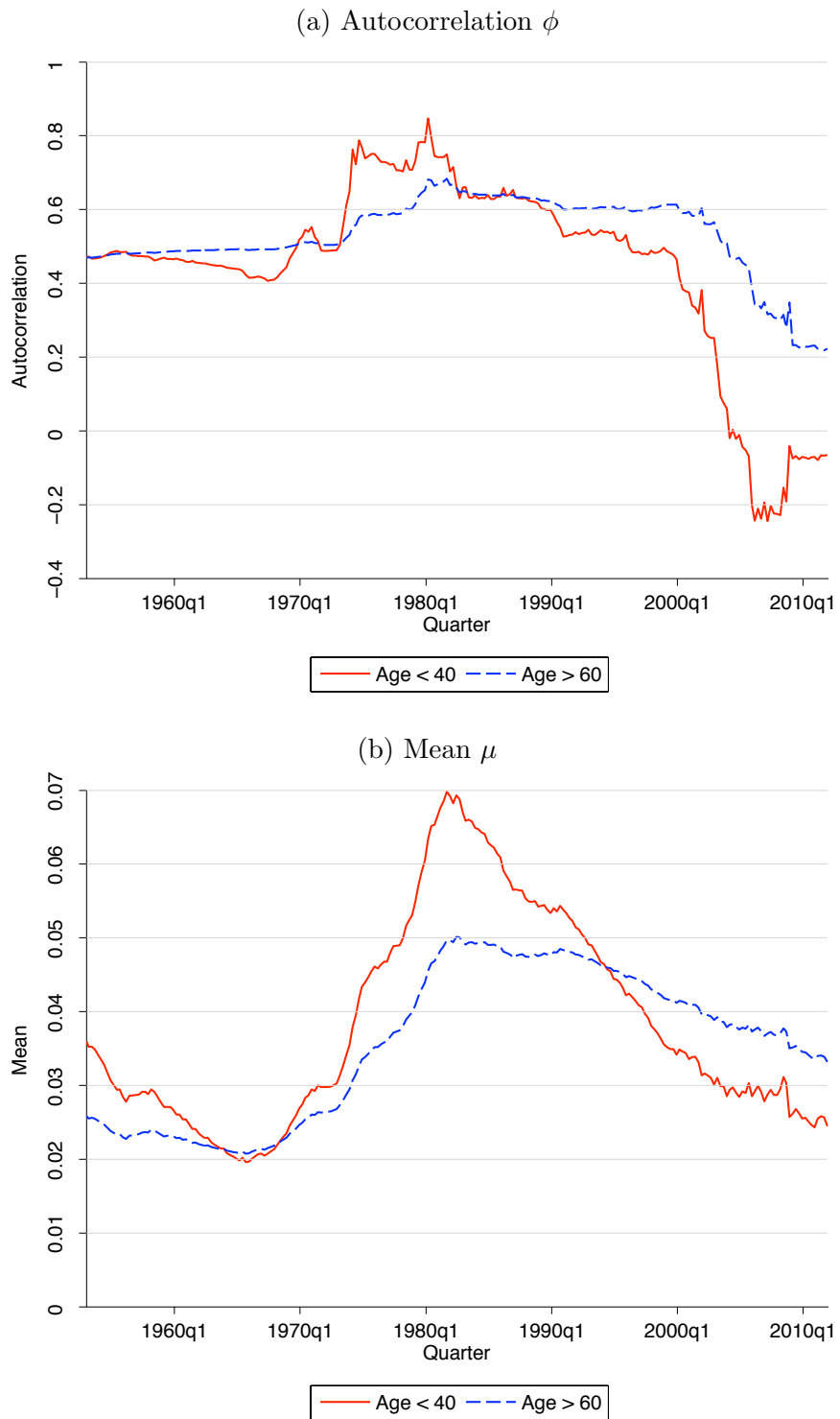


Figure 5: Learning-from-experience AR(1) model estimates (with  $\theta = 3.044$ ) of autocorrelation (top) and mean inflation (bottom) for young and old.

low expected inflation rates, as the perceived persistence is close to zero. Older individuals perceived inflation persistence, however, is still substantially above zero.

### 4.3 Exploring the common factor

The specification in (5) with time dummies is useful to cleanly demonstrate the existence of the learning-from-experience effect with a test of the null hypothesis  $\beta = 0$ . It also allows estimation of  $\theta$  purely from cross-sectional differences, removing potentially confounding unobserved factors that also affect expectations. On the other hand, it would be useful to know to what extent variation in the levels of expectations rather than just cross-sectional differences can be explained with the learning-from-experience forecasts. It would also be useful to learn more about the nature of the common factor  $f_t^h$  that is absorbed by the time dummies in (5). To explore this, columns (iii) to (v) in Table 1 consider restricted versions of the estimating equation (5) that are estimated without time dummies and intercept, but instead with observable proxies for  $f_t^h$ .

One possibility is that  $f_t^h$  captures individuals' tendency to rely to some extent, in the formation of their expectations, on the opinions of professional forecasters that get disseminated in the media. To check this, we specify  $f_t^h$  in (5) as the sum of the Survey of Professional Forecasters (*SPF*) forecast in quarter  $t - 1$  and a noise term  $\eta_t^h$  that is uncorrelated with the *SPF* forecast and  $\tau_{t+h|t,s}^h$ . Equation (5) becomes

$$\pi_{t+h|t,s}^h = \beta \tau_{t+h|t,s}^h + (1 - \beta) SPF_{t-1} + (1 - \beta) \eta_t^h. \quad (7)$$

We estimate this equation without time dummies, which means we now utilize information about levels in inflation expectations, not just cross-sectional differences, in the estimation. For this reason, we remove the imputed data from the sample, because our imputation is only designed to impute cross-sectional differences, but not levels. The number of observations in column (iii) is further slightly lower than in column (ii) because *SPF* forecasts are not available in a few quarters early in the sample.

As column (iii) shows, replacing the time dummies with the *SPF* has little effect on the estimate of  $\beta$  compared with column (ii). With 3.976 (s.e. 0.612), the estimate of  $\theta$  is higher, though, but the weighting of past inflation observations implied by this point estimate is still quite similar to the weighting implied by the estimates in columns (i) and (ii). Moreover, the point estimate is not far from those in columns (i) and (ii) in terms of standard errors. The much bigger standard error in column (iii) compared with columns (i) and (ii) reflects that the removal of the time dummies leaves the noise term  $\eta_t^h$  in (7) in the regression residual, resulting in noisier estimates. The effect of the noise term can also be seen in the increase in RMSE compared with columns (1) and (2).<sup>4</sup> Nevertheless, the fact that the  $\beta$  estimate in columns (iii) is virtually identical to those in columns (i) and (ii) indicates that *SPF* forecast captures much of the component of  $f_t$  that could be correlated with  $\tau_{t+h|t,s}^h$ .

Column (iv) explores an alternative proxy for  $f_t^h$ . The common component of individuals' inflation expectations could be the result of a social learning process in which individuals with different experienced 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  $f_t^h$  as the sum of the mean learning-from-experience forecast across all age groups, which we denote  $\bar{\tau}_t^h$ , and a noise term, and so equation (5) becomes

$$\pi_{t+h|t,s}^h = \beta \tau_{t+h|t,s}^h + (1 - \beta) \bar{\tau}_t^h + (1 - \beta) \eta_t^h. \quad (8)$$

Column (iv) reports the results for this model. The estimates are almost identical to those in column (iii). Evidently, the average learning-from-experience forecast is very close to the *SPF* forecast and it seems to be a good representation of individuals common component of inflation expectations. As in column (iii), though,  $\theta$  is estimated with substantially higher standard errors than in the specification with time dummies in columns (i) and (ii). For this reason, we also explore the fit after fixing  $\theta$  at its more precise estimate  $\theta = 3.044$  from

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<sup>4</sup>Since this regression is run without intercept, the adj.  $R^2$  is not a useful measure of fit and we focus on the RMSE.



column (i). The result is shown in column (v). In this case, the RMSE is only slightly higher than in column (iv), and the estimate of  $\beta$  is almost unchanged. Despite the slightly worse in-sample fit, there is the possibility that the specification in column (v) might actually do better out-of-sample because  $\theta$  is estimated with greater precision. We return to this point further below. For now we use model (8) with  $\theta = 3.044$  as our preferred specification.

## 5 Aggregate implications

Our focus so far was on inflation expectations at the cohort level, and on how cohort-specific experiences help explain heterogeneity in expectations. We now show that experience-based learning also helps explain the dynamics of aggregate (mean) inflation expectations.

First, we relate our approach to the existing literature on adaptive learning and show that experience-based forecasts aggregate to average forecasts that closely resemble those from constant-gain algorithms, which have been shown to explain macroeconomic time series data. We argue that learning-from-experience provides a micro-underpinning for adaptive-learning models,

We then discuss the differences between the existing approaches and learning from experience, both conceptually and econometrically. Conceptually, learning from experience builds on psychological evidence on updating biases, rather than the assumption of a boundedly rational (but otherwise optimized) choice of limited data processing, which had been hard to reconcile with the empirical evidence. Econometrically, only the experience-based learning model allows us to estimate the updating speed from cross-sectional data, which helps overcome the existing difficulties in identifying structural parameters in adaptive learning models.

Our starting point is model (8). Averaging cross-sectionally across all cohorts each period, and denoting cross-sectional averages with an upper bar, we get

$$\bar{\pi}_{t+h|t}^h = \bar{\tau}_t^h + (1 - \beta) \bar{\eta}_t^h. \quad (9)$$

Thus, apart from the noise term  $\bar{\eta}_t^h$ , the mean expectation is pinned down by the mean learning-from-experience forecast across all age groups,  $\bar{\tau}_t^h$ .

### 5.1 Approximating constant-gain learning (and its aggregate implications)

In our learning-from-experience framework, individuals update their expectations with *decreasing* gain: as individuals age, their experienced set of data expands and their expectations react less to a given inflation surprise than those of younger individuals. In contrast, the mean learning-from-experience forecast,  $\bar{\tau}_t^h$ , behaves approximately as if it was generated from a *constant-gain* learning algorithm: since the gain  $\gamma_{t,s}$  varies only by age  $t - s$ , its average 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 mean of the inflation-surprise term in (2) is not exactly identical to the surprise arising in a constant-gain learning algorithm.

We illustrate how well the approximation with a constant gain works in Figure 6. The figure compares the implied learning-from-experience weights on past inflation averaged across all age groups (solid line) with the weights implied by constant-gain learning (dashed line). We calculate the learning-from-experience weights based on our point estimate of  $\theta = 3.044$  from Table 1, column (i), averaged across all ages from 25 to 74 (equally weighted). We then calculate the constant gain for which the constant-gain algorithm minimizes the squared deviations from the above average learning-from-experience weights. The result is a constant gain of  $\gamma = 0.0180$ , with implied weights as shown by the dashed line.

The figure shows that the weighting of past data is very similar. It is particularly noteworthy that the deviation-minimizing constant gain  $\gamma = 0.0180$  is virtually the same as the gain that appears to be 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 DSGE model with constant-gain learning to macroeconomic variables. Orphanides and Williams (2005) choose a gain of 0.02 to match the time series of inflation forecasts from

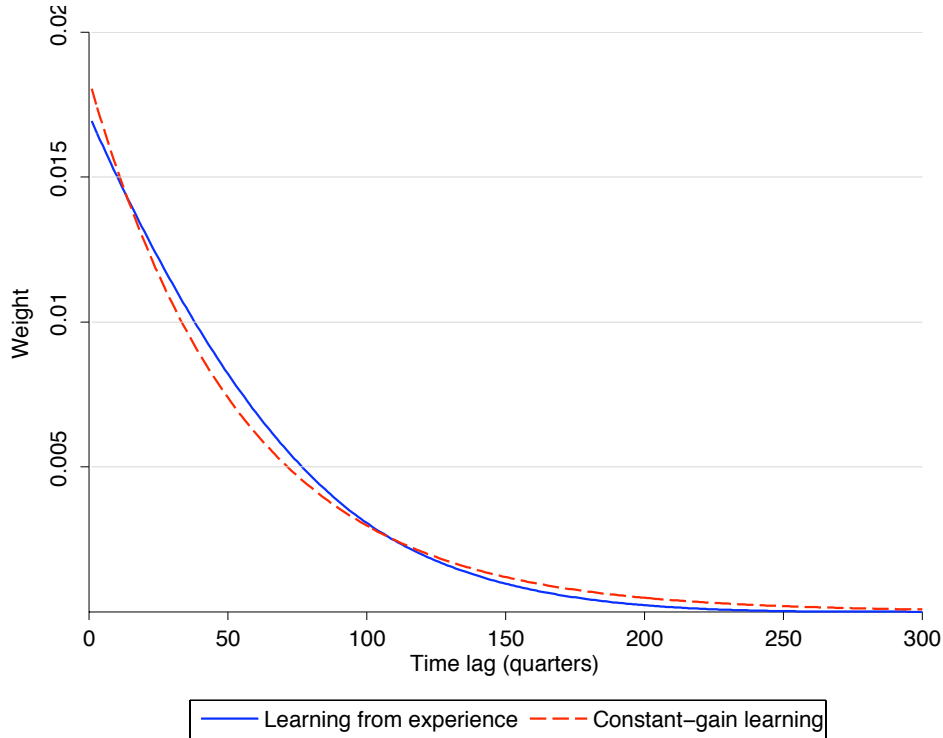


Figure 6: Comparison of implied mean weights on past inflation observations under learning-from-experience and constant-gain learning. The learning-from-experience weights for each lag are calculated for each age at the point estimate  $\theta = 3.044$  from Table 1, column (i), and then averaged across all ages. 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.

the *SPF*. Our estimate of  $\gamma$  was, instead, chosen to match the weights implied by our estimate of  $\theta$  from cross-sectional heterogeneity. We did not employ aggregate expectations and realized inflation rates in estimation of  $\theta$ . Hence, our estimates from between-cohort heterogeneity bring in new data, and their consistency with parameters chosen to fit time-series data provides “out-of-sample” support for values of the gain parameter in this range. We can conclude that the implications of learning from experience for expectations formation in aggregate are likely to be very similar to those of the constant-gain learning algorithms, which have been shown to be a good description of macroeconomic dynamics (e.g., Sargent (1999), Orphanides and Williams (2005), Milani (2007)).

## 5.2 Explaining aggregate inflation expectations

How well does the learning-from-experience model match survey expectations in aggregate? Figure 7 shows both the time path of the actual 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 learning-from-experience forecasts track the average survey expectations closely. In the interpretation of this figure, it is important to keep in mind that the good match is by no means a mechanical result. Our estimation of  $\theta$  used only cross-sectional differences in survey expectations between cohorts, but no information about the level of the average survey expectation. It could have been possible, in principle, that the  $\theta$  that fits cross-sectional differences produces a time path for average expectations that completely fails to match survey expectations. As the figure shows, though, the two time paths match well.

Figure 7 also shows the time path of constant-gain-learning forecasts, using  $\gamma = 0.0180$  as in Figure 6, which minimizes the distance in the implied weights, relative to the experience-based model. Not surprisingly, 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 also 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 might be picking up some of this stickiness in expectations. 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.<sup>5</sup> We set the weight parameter  $\lambda = 0.25$

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<sup>5</sup>We use the 1-year inflation forecasts that the *SPF* constructs from median CPI inflation forecasts for

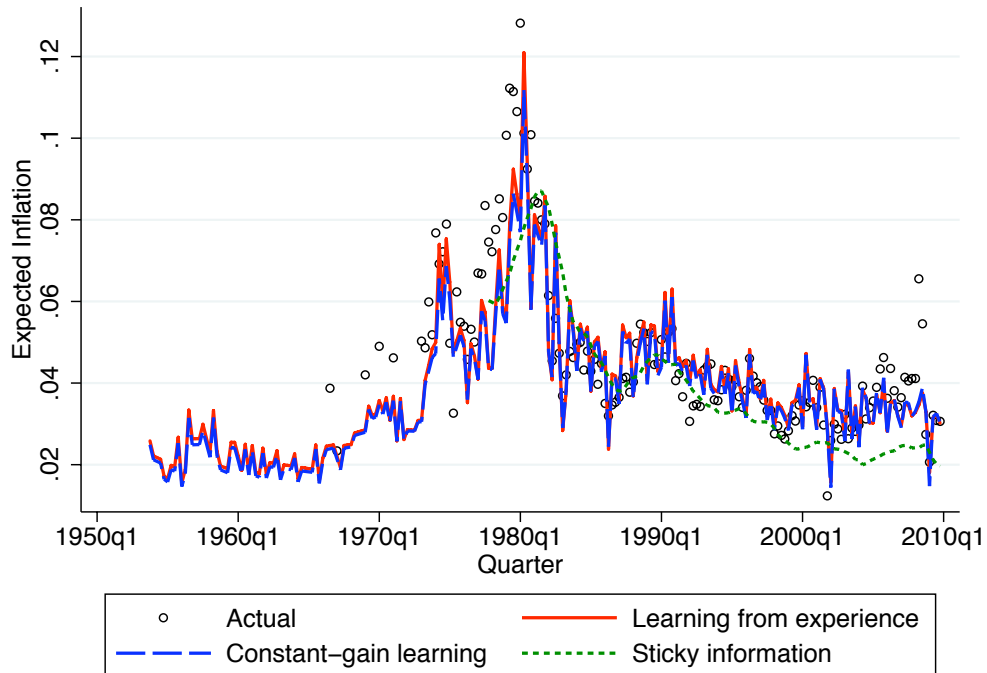


Figure 7: Average survey expectations (actual) compared with average learning-from-experience forecasts, constant-gain forecasts, and sticky-information forecasts.

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 7. The graph illustrates that the experience-based model helps to predict actual forecast data beyond the predictive power of the sticky-information model. For example, experience-based forecasts track actual forecasts more closely during the peak around 1980 and also during the 2000s (though both model fail to match the highly positive expectations towards the end of the the decade).

We evaluate the economic and statistical significance of this graphical impression in Table 2. We regress the average survey expectations in quarter  $t$  on the average forecast predicted by learning-from experience (column (i)), by constant-gain learning (column (ii)), and by the sticky-information model (column (iii)). The learning-from-experience model in (9) predicts a

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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 2: Explaining mean inflation expectations

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 5 lags) are shown in parentheses.

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

coefficient on the experience-based forecast of one, and column (i) shows that the estimated coefficient of 0.887 is close to one, and less than one standard error away from it. With 56.4% the adj.  $R^2$  is high. This confirms the informal graphical impression in Figure 7 that the learning-from-experience forecast closely tracks the actual average survey expectations. Not surprisingly, given the similarity of  $\bar{\tau}_t^h$  and constant-gain learning forecasts, using the constant-gain learning forecast as explanatory variable in column (ii) produces almost identical results. The explanatory power of the sticky-information forecast in column (iii) is also similar, only a bit lower and a bit noisier, and the adj.  $R^2$  is slightly higher.

Most importantly, we add the sticky-information forecast as an explanatory variable along with the learning-from-experience forecast in column (iv). We find that the coefficient on the learning-from-experience forecast becomes slightly smaller, but remains large (also relative to the sticky-information coefficient) and significant. Hence, we can conclude that the learning-from-experience forecast does not just pick up the sticky-information effect of Mankiw and Reis (2002) and Carroll (2003).

### 5.3 Learning from experience as foundation of perpetual learning

Despite the similarity between learning from experience and constant-gain learning at the aggregate level, the models differ in a fundamental way concerning the motivation for the down-weighting of past data and the constant gain. The standard motivation for the discounting of past data in constant-gain learning is the concern that structural changes or drifting parameters have rendered historical data in the distant past irrelevant for the estimation of the current parameters of the perceived law of motion. Learning-from-experience attributes the down-weighting to memory of past data being lost as older generations die and new ones are born. As Sargent (1999), Orphanides and Williams (2005), and Milani (2007) have emphasized, perpetual learning is important for explaining macroeconomic dynamics. It is therefore important to identify the underlying reasons that give rise to perpetual learning. Only then is it possible to make predictions about the circumstances in which economic agents are likely to update with a high or low gain.

Within the standard framework, it has been difficult to rationalize the value of the gain parameter that best explains the dynamics of survey expectations. If individuals' concerns about structural change and parameter drift motivate the down-weighting of data in the distant past, the degree of down-weighting, and hence the gain, should depend on the nature of the stochastic process that individuals are trying to estimate. Individuals should use high gains for processes that are subject to frequent structural changes and substantial parameter drift. The gain should be chosen in such a way that it minimizes the loss from forecast errors. Empirically, however, there seems to be a disconnect between these statistically optimal gains and the gains implied by observed survey expectations. Using a quadratic loss function, Branch and Evans (2006) find that the optimal gain that minimizes inflation forecast errors is substantially higher than the gain that delivers the best fit to the Survey of Professional Forecasters (*SPF*) inflation forecasts.

A similar pattern exists in the Michigan Survey data. Figure 8 presents, on top, recursive estimates of the optimal gain that minimizes the MSE in constant-gain learning forecasts

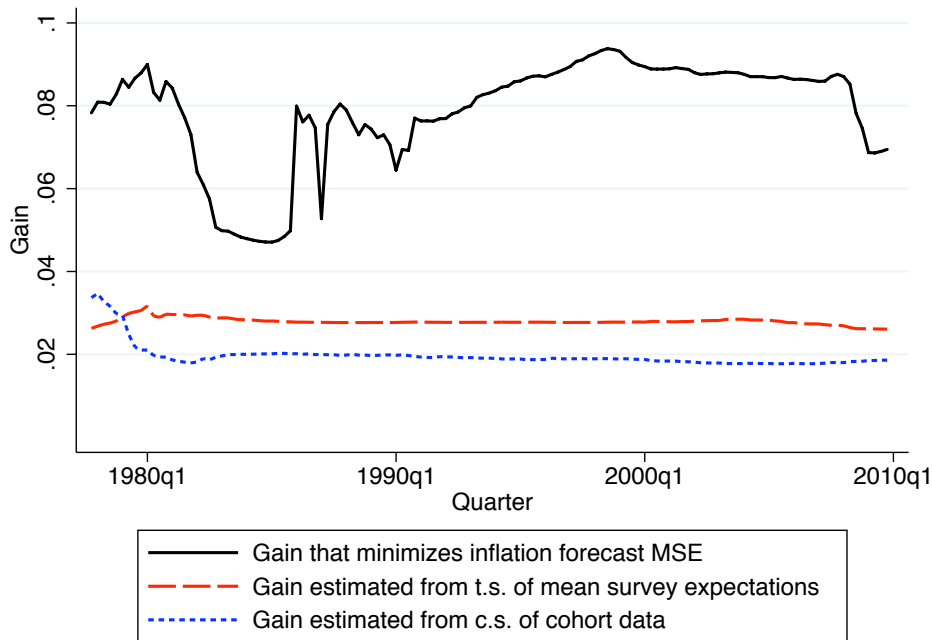


Figure 8: Recursive comparison of optimal gain with gains implied by constant-gain and learning-from-experience model estimates. The optimal gain (solid line) minimizes the MSE in one-year inflation forecasts, and it is estimated over expanding windows, where the first extends from 1953Q4 to 1977Q4. Gains implied by constant-gain (long-dashed line) and learning-from-experience (short-dashed line) models are estimated over the same windows, employing only non-imputed data, where the constant-gain model is fitted to mean expectations, while the learning-from-experience model is fitted to cohort data as in column (ii) in Table 1 and the estimate of  $\theta$  is converted to an implied gain as in Figure 6.

of one-year inflation rates. (The first estimation window extends from 1953Q4 to 1977Q4; subsequent ones expand while keeping the starting point fixed.) For the most part, the optimal gain is relatively high, around 0.08, consistent with the optimal gain calculated by Branch and Evans (2006). The gains implied by our learning-from-experience model fitted to *MSC* expectations data, instead, are much lower, consistent with the gain estimates in Branch and Evans (2006) that best fits the *SPF* inflation expectations. We calculate these implied gains by estimating  $\theta$  as in column (ii) in Table 1, but now with expanding estimation windows, and then, as in Figure 6, picking the gain in a constant-gain learning rule that most closely matches the learning-from-experience model. Figure 8 also plots the gain estimates



from fitting a constant-gain learning rule to mean inflation expectations from the *MSC*.<sup>6</sup> The estimated gains are slightly higher than the implied gains from the learning-from-experience rule, but the difference is small compared with the big gap to the statistically optimal gains.

Apparently, both professionals (in the *SPF*) and households (in the *MSC*) discount past inflation data much less than the degree of structural change in the time-series of inflation would call for. Moreover, the degree of structural change in different time series does not seem to be systematically related to the gains implied by survey expectations—at least in the relatively stable environment of post-war US data.<sup>7</sup> For example, Branch and Evans (2006) find that the statistically optimal gain for GDP forecasting is much lower than the optimal gain for inflation forecasting—indicating a lower degree of structural change in the GDP series—but the gains that each fit best the survey expectations on inflation and GDP expectations are almost identical.

This lack of connection between the degree of structural change in macroeconomic time series and the gains in survey-data estimates of learning rules suggests that alternative reasons besides structural change may account for the discounting of past observations that is evident in survey expectations data. The learning-from-experience framework provides such an alternative explanation: memory of past data is lost as older generations die and new ones are born. Thus, even if each individual used a decreasing gain that weighted all data realized during her lifetime equally, the mean expectation in the population would resemble the forecast from a constant-gain learning model. This explanation of perpetual learning is not only consistent with the time-series of aggregate inflation expectations, but also, as we have shown above, with cross-sectional heterogeneity of inflation expectations, and, as shown in Piazzesi and Schneider (2012), with heterogeneity in borrowing and lending and asset price movements that are driven by this heterogeneity in inflation expectations.

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<sup>6</sup>Since our imputation procedure is not suitable for imputation of mean expectations, only for cross-sectional differences, we can use only non-imputed data in the estimation of the constant-gain learning rule. For comparability, we therefore also use non-imputed data in the estimation of the learning-from-experience model, i.e. as in column (ii) of Table 1 rather than column (i).

<sup>7</sup>Marcet and Nicolini (2003) propose a model where individuals update their expectations with decreasing gain stable periods, but they switch to a constant gain when a large prediction error is detected

Due to the finite memory implied by the finite life span of generations, the learning-from-experience framework is consistent with approximate constant-gain learning in aggregate, but the finite life-span feature does not fully explain the level of the implied gain. We estimate  $\theta = 3.044$  in our full sample, while equally weighting each life-time observation of inflation would imply  $\theta = 1$ . Given our evidence from cross-sectional heterogeneity that individuals' forecasts are shaped by their life-time experiences, we believe that it is more natural to explain this down-weighting of experiences earlier in life implied by  $\theta > 1$  with a slow fading of experiences as time progresses (and limited absorption of experiences very early in life) rather than individuals' concerns about structural change. This perspective would also help to explain why survey respondents appear to use similar gains for macroeconomic time-series with different structural change properties, as in Branch and Evans (2006).

#### 5.4 Identification of the updating speed from cross-sectional heterogeneity

A second important difference between standard constant-gain learning and the learning-from-experience framework is that the gain parameter  $\theta$ , and hence the updating speed, can be estimated from cross-sectional data because learning from experience induces cross-sectional heterogeneity between age groups. This brings in a new dimension of data that can help pin down the learning dynamics. As Chevillon, Massmann, and Mavroeidis (2010) show, identification of structural parameters in macro models with adaptive learning is difficult, and the problems are magnified if the parameters of the learning rule are unknown and need to be estimated. Fitting the learning rule to the time path of mean or median survey expectations can help pin down the learning-rule parameters, but the estimates may be imprecise.

As we have shown earlier, we obtain the most precise estimates of the gain parameter  $\theta$  when we focus purely on cross-sectional variation by employing time dummies in Table 1. Here we show that this way of estimating the gain also yields the best pseudo-out-of-sample fit to survey expectations. Figure 9 compares the pseudo-out-of-sample fit of the learning-from-experience model with the constant-gain learning model. We estimate the gain parameters

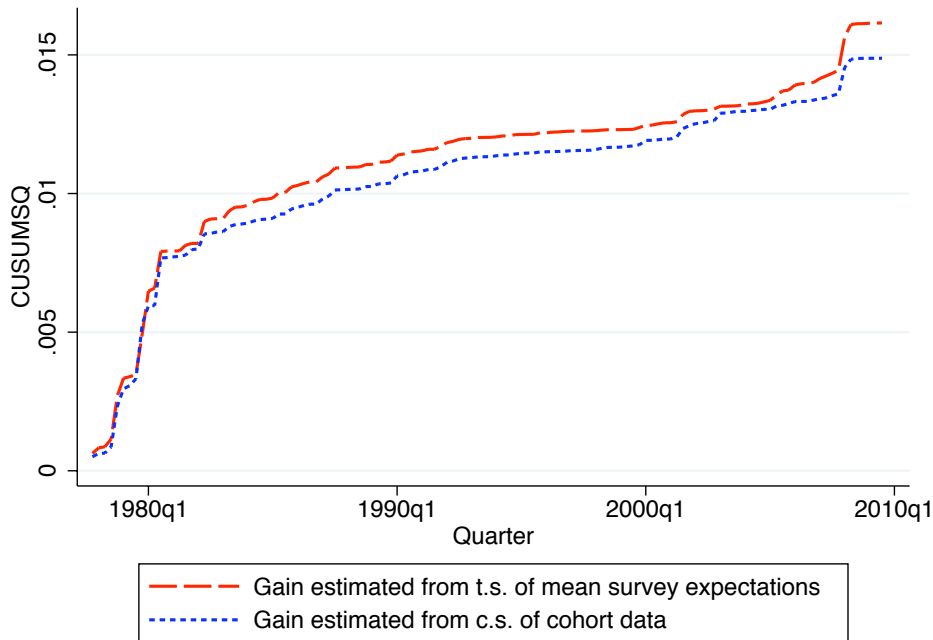


Figure 9: Pseudo-out-of-sample cumulative sum of squared errors in predicting mean inflation expectation. For the constant-gain model, the gain parameter  $\gamma$  is estimated over expanding windows, where the first extends from 1953Q4 to 1977Q4. For each window, mean expectations data until quarter  $t - 1$  is used to estimate  $\gamma$ , and this estimate of  $\gamma$  is then used to predict, based on inflation data until  $t - 1$ , the mean inflation survey expectation in quarter  $t$ . The plot cumulates the sum of squared errors from this prediction. For learning from experience, the plots are constructed in similar fashion, but based on estimates of  $\theta$  from cohort-panel expectations data as in column (ii) in Table 1.

in both models recursively, with expanding windows, where the first window extends from 1953Q4 to 1977Q4. For each window, expectations data until quarter  $t - 1$  is used to estimate the gain parameter (mean expectations in case of the constant-gain model, and cohort data as in column (ii) of Table 1 in case of the learning-from-experience model), and we then predict, based on this gain estimate and historical inflation data until  $t - 1$ , the mean inflation survey expectation in quarter  $t$ . In case of the learning-from-experience model this prediction is given by  $\bar{\pi}_t^h$  as in (9), in the case of constant-gain learning it is simply the fitted value of the constant-gain learning rule. The figure plots the cumulative sum of squared errors from these prediction from 1978Q1 to the end of the sample.

As Figure 9 shows, the learning-from-experience rule, with  $\theta$  estimated from cross-sectional heterogeneity between cohorts, has a slight advantage in terms of pseudo-out-of-sample fit compared with the constant-gain rule. It achieves this advantage even though no information on the level of mean expectations is used in the estimation of  $\theta$ , as all of it is absorbed by the time dummies. Evidently, the time dummies are helpful in absorbing common noise factors in the mean survey expectations that are otherwise obscuring the relationship between survey respondents' inflation expectations and historical inflation data.

## 6 Discussion and conclusion

Our empirical analysis shows that individuals' inflation expectations differ depending on the characteristics of the inflation process experienced during their life times. Differences in the experienced mean inflation rate and the persistence of inflation shocks generate (time-varying) differences in inflation expectations between cohorts. The experience of younger individuals is dominated by recent observations, while older individuals draw on a more extended historical data set in forming their expectations.

Such learning from experience can explain, for example, why young individuals forecasted much higher inflation than older individuals following the high inflation years of the late 1970s and early 1980s. Both the mean rate of inflation and inflation persistence were particularly high in the short data set experienced by young individuals at the time. Learning-from-experience complements the sticky information explanation put forward in Mankiw and Reis (2002) and Carroll (2003) for the same time period.

For the more recent time period towards the end of our sample in 2010, our estimates imply that the perception of the persistence of inflation shocks is close to zero, particularly for young individuals. This suggests that unexpected movements in the inflation rate are currently unlikely to move inflation expectations much. As argued in Roberts (1997), Orphanides and Williams (2005), and Milani (2007), these changes in individuals' perceptions of persistence are likely to influence, in turn, the persistence of inflation rates.

The learning-from-experience framework differs from more conventional representative-agent applications of learning in that it generates heterogeneity in inflation expectations. Nevertheless, its implications for the average level of inflation expectations are similar to those resulting from representative-agent constant-gain learning algorithms that are popular in macroeconomics (see, e.g., Orphanides and Williams (2005); Milani (2007)). There are, however, two important differences.

First, differently from constant-gain learning models, the learning-from-experience theory relies on psychology evidence and micro-data to motivate non-standard learning mechanisms. Information in the distant past is discarded not only because of structural shifts and parameter drift, but also because memory of macroeconomic history is lost as new generations emerge whose subjective beliefs are shaped by relatively recent experience. This is an additional reason why learning dynamics may be perpetual, without convergence in the long-run.

Second, in the learning-from-experience framework, the heterogeneity between cohorts can be exploited to estimate the speed of updating in response to inflation surprises. This is useful because the existing difficulties in identifying the gain parameter from macro data. In light of this, it is remarkable that our estimate of the speed of updating, averaged across cohorts, are quantitatively similar to those obtained in earlier work in macroeconomics that estimated the speed of updating to fit macroeconomic time-series or aggregate survey expectations.

The heterogeneity between young and old in their views about future inflation can also produce interesting macroeconomic effects. Disagreement about future inflation leads to disagreement about real interest rates (given that the nominal interest rate is fixed in financial markets), which in turn influences borrowing and lending among households. Piazzesi and Schneider (2012) analyze this mechanism, and they show that the disagreement between younger and older households in the late 1970s helps understand quantities of household borrowing and lending, shifts in household portfolios, and the prices of real assets at the time.

## Appendix

### A Implied weighting of past data with learning from experience

The learning-from-experience algorithm in our analysis implicitly weights past observations in almost exactly similar fashion as the (ad-hoc) weighting function in Malmendier and Nagel (2011). Moreover, the parameter  $\theta$  that controls the strength of updating in the framework here maps into the parameter that controls the weighting function in Malmendier and Nagel (2011). This makes the results easily comparable.

To see the weighting of past data implied by the learning-from-experience rule, consider an individual born in year  $s$  making an inflation forecast at time  $t$  and rewrite (2), as

$$\begin{aligned}
 R_{t,s}b_{t,s} &= R_{t,s}b_{t-1,s} + \gamma_{t,s}x_{t-1}(\pi_t - b'_{t-1,s}x_{t-1}) \\
 &= (R_{t,s} - \gamma_{t,s}x_{t-1}x'_{t-1})b_{t-1,s} + \gamma_{t,s}x_{t-1}\pi_t \\
 &= (1 - \gamma_{t,s})R_{t-1,s}b_{t-1,s} + \gamma_{t,s}x_{t-1}\pi_t \\
 &= (1 - \gamma_{t-1,s})(1 - \gamma_{t,s})R_{t-2,s}b_{t-2,s} + \gamma_{t-1,s}(1 - \gamma_{t,s})x_{t-2}\pi_{t-1} + \gamma_{t,s}x_{t-1}\pi_t, \quad (\text{A.1})
 \end{aligned}$$

where the second-to-last equality follows from (3). Now consider equation (3),

$$\begin{aligned}
 R_{t,s} &= R_{t-1,s} + \gamma_{t,s}(x_{t-1}x'_{t-1} - R_{t-1,s}) \\
 &= (1 - \gamma_{t,s})R_{t-1,s} + \gamma_{t,s}x_{t-1}x'_{t-1} \\
 &= (1 - \gamma_{t-1,s})(1 - \gamma_{t,s})R_{t-2,s} + \gamma_{t-1,s}(1 - \gamma_{t,s})x_{t-2}x'_{t-2} + \gamma_{t,s}x_{t-1}x'_{t-1}. \quad (\text{A.2})
 \end{aligned}$$

Thus, iterating further on (A.1) and (A.2), we can write  $R_{t,s}b_{t,s} = X'\Omega Y$  and  $R_{t,s} = X'\Omega X$ , where  $X$  collects stacked  $x_{t-1-k}$  and  $Y$  collects stacked  $\pi_{t-k}$  for  $k \in \{0, 1, \dots, t-s\}$ , and  $\Omega$  is diagonal, with diagonal elements

$$\tilde{\omega}_{t,s}(k) = \begin{cases} \gamma_{t,s} & \text{for } k = 0 \\ \gamma_{t-k,s} \prod_{j=0}^{k-1} (1 - \gamma_{t-j,s}) & \text{for } k > 0 \end{cases}. \quad (\text{A.3})$$

Thus,  $b_{t,s} = R_{t,s}^{-1}R_{t,s}b_{t,s} = (X'\Omega X)^{-1}X'\Omega Y$ , i.e., the learning-from-experience scheme is a recursive version of a weighted-least squares estimate with weighting matrix  $\Omega$ .

For comparison, the weighting function in Malmendier and Nagel (2011) assigns observations at time  $t-k$  (with  $k \leq t-s$ ) the weight

$$\omega_{t,s}(k) = \frac{(t-s-k)^\lambda}{\sum_{j=0}^{t-s} (t-s-j)^\lambda}. \quad (\text{A.4})$$

We now show that both weighting schemes are equivalent if the learning-from-experience

gain sequence is chosen to be age-dependent in the following way:

$$\gamma_{t,s} = \frac{(t-s)^\lambda}{\sum_{j=0}^{t-s} (t-s-j)^\lambda}. \quad (\text{A.5})$$

We present a proof by induction. First, the choice of  $\gamma_{t,s}$  in (A.5) implies that  $\tilde{\omega}_{t,s}(0) = \omega_{t,s}(0)$ . It remains to be shown that if  $\tilde{\omega}_{t,s}(k) = \omega_{t,s}(k)$ , then  $\tilde{\omega}_{t,s}(k+1) = \omega_{t,s}(k+1)$  (with  $k+1 \leq t-s$ ). Thus, assume that

$$\tilde{\omega}_{t,s}(k) = \frac{(t-s-k)^\lambda}{\sum_{j=0}^{t-s} (t-s-j)^\lambda}. \quad (\text{A.6})$$

Then, from Eq. (A.3),

$$\begin{aligned} \tilde{\omega}_{t,s}(k+1) &= \gamma_{t-k-1,s} \frac{(1 - \gamma_{t-k,s})}{\gamma_{t-k,s}} \tilde{\omega}_{t,s}(k) \\ &= \frac{(t-k-1-s)^\lambda}{\sum_{j=0}^{t-k-1-s} (t-k-1-s-j)^\lambda} \left( \frac{\sum_{j=0}^{t-k-s} (t-k-s-j)^\lambda}{(t-k-s)^\lambda} - 1 \right) \tilde{\omega}_{t,s} \\ &= \frac{(t-k-1-s)^\lambda}{\sum_{j=0}^{t-k-1-s} (t-k-1-s-j)^\lambda} \left( \frac{\sum_{j=0}^{t-k-1-s} (t-k-1-s-j)^\lambda}{(t-k-s)^\lambda} \right) \tilde{\omega}_{t,s} \\ &= \frac{(t-k-1-s)^\lambda}{\sum_{j=0}^{t-s} (t-s-j)^\lambda} \\ &= \omega_{t,s}(k+1), \end{aligned} \quad (\text{A.7})$$

This concludes the proof.

Finally, we show that the gain sequence (A.5) can be approximated by

$$\gamma_{t,s} \approx \frac{\lambda+1}{t-s}, \quad (\text{A.8})$$

i.e., by the gain specification in (4) with  $\theta = \lambda + 1$ . Focusing on the denominator of (A.5), note that if one were to make the increments of the summation infinitesimally small, the denominator would become  $\int_0^{t-s} x^\lambda dx = \frac{1}{\lambda+1} (t-s)^{\lambda+1}$ . Therefore, in the limiting case of infinitesimal increments, we get

$$\gamma_{t,s} = \frac{\lambda+1}{t-s}. \quad (\text{A.9})$$

In our case with quarterly increments, this approximation in (A.8) is virtually identical with the true gain sequence in (A.5).

## B Michigan Survey data

Before 1960, age was collected as a categorical variable, and so in those years we only have five or nine age groups. From 1960 onwards, the exact birth year was collected as age variable and we have 50 age groups (age 25 to 74).

The one-year inflation expectations data is derived from the responses to two questions. The first is categorical, while the second one elicits a percentage response:

1. “During the next 12 months, do you think that prices in general will go up, or go down, or stay where they are right now?”
2. “By about what percent do you expect prices to go (up/down) on average during the next 12 months?”

We follow Curtin (1996) to adjust the raw data for several known deficiencies, which is also the approach used by the Michigan Survey in constructing its indices from the survey data:

For respondents who provided a categorical response of “up” (“down”), but not a percentage response, we drew a percentage response from the empirical distribution of percentage responses of those who gave the same categorical response of “up” (“down”) in the same survey period. Prior to the February 1980 survey, respondents were not asked about percentage expectations if they responded (in the categorical first part of the question) that they expected prices to decline. We assign a value of -3% to these cases before February 1980. In most survey periods, they account for less than 2% of observations.

Starting in March 1982 the administrators of the Michigan survey implemented additional probing, which revealed that the categorical response that prices will remain the “same” was often misunderstood as meaning that the inflation rate stays the same. We use the adjustment factors developed in Curtin (1996) to adjust a portion of “same” responses prior to March 1982 to “up”, and we assign a percentage response by drawing from the empirical distribution of those observations in the same survey period with a categorical response of “up.”

## C Imputation of percentage expectations from categorical responses

In the early years of the Michigan survey, only categorical responses about prices going “up,” “down,” or staying the “same” were elicited. We attempt to use the information in those surveys by imputing percentage responses from the categorical information. We do so by estimating the relationship between categorical responses, the dispersion of categorical responses, and percentage responses in those periods in which we have both categorical and percentage response data. We conjecture that the average percentage response of individuals in an age group should be positively related to the proportion of “up” responses and negatively to the proportion of “down” responses.

We first calculate the proportion of “up” and “down” responses,  $p_{t,s}^{up}$  and  $p_{t,s}^{down}$ , within each cohort  $s$  at time  $t$  (in this case  $t$  denotes a calendar month). We then run a pooled



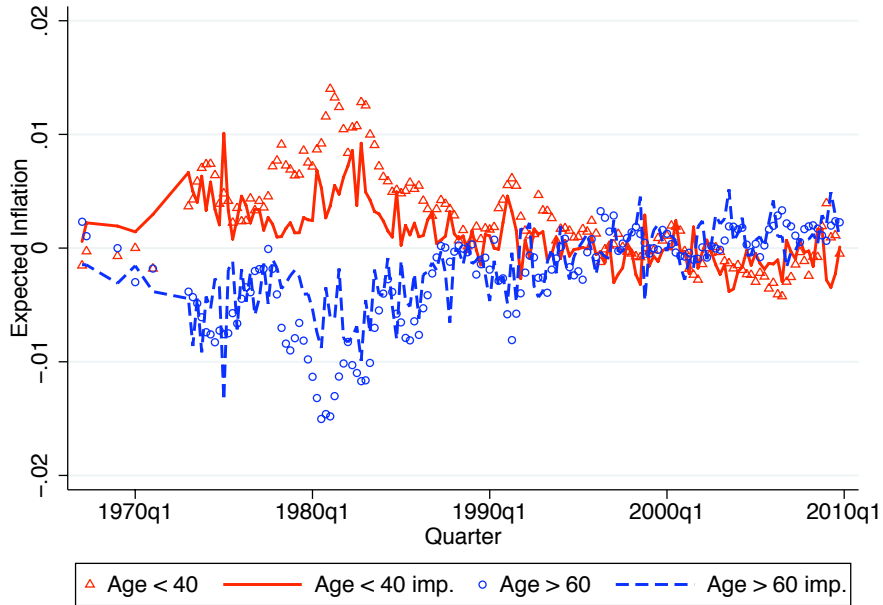


Figure A.1: Actual and imputed one-year inflation expectations in excess of the full-sample cross-sectional mean expectation.

regression of measured percentage inflation expectations,  $\tilde{\pi}_{t+4|t,s}^1$ , on  $p_{t,s}^{up}$  and  $p_{t,s}^{down}$ , including a full set of time dummies, and obtain the fitted values

$$\tilde{\pi}_{t+1|t,s}^1 = \dots \text{time dummies} \dots + 0.056 p_{t,s}^{up} - 0.072 p_{t,s}^{down} \quad (\text{adj. } R^2 = 52.9\%)$$

(0.001)      (0.004)

with standard errors in parentheses that are two-way clustered by quarter and cohort.

Because we employ time dummies in our main analysis, our main concern here is whether the imputed expectations track well cross-sectional differences of expectations across age groups, rather than the overall mean over time, and so we also estimate the relationship between percentage expectations and categorical responses with time dummies included in the regression.

Figure A.1 illustrates how the imputed percentage expectations compare with the actual expectations in the time periods in which we have both categorical and percentage expectations data. To focus on cross-sectional differences between age groups, the figure shows the average fitted and actual values (in terms of four-quarter moving averages) for individuals below 40 and above 60 years of age after subtracting the overall cross-sectional mean expectation in each time period.

Table A.1: Controlling for age-specific inflation rates

The estimation is similar to Table 1, but with interactions of age with the experimental CPI for the elderly in column (ii) and the CPI for gasoline in column (iv) included as control variable. In columns (i) and (ii), the sample runs from 1984 to 2009, the period for which lagged four-quarter inflation rates from the experimental CPI for the elderly are available. In column (iii) the sample extends from 1953 to 2009. Standard errors in parentheses are two-way clustered by time and cohort.

	(i)	(ii)	(iii)
Gain parameter $\theta$	2.561 (0.275)	3.475 (0.591)	3.720 (0.414)
Sensitivity $\beta$	0.408 (0.085)	0.432 (0.092)	0.599 (0.089)
$\frac{\text{Age}}{100}$		-0.004 (0.003)	-0.009 (0.002)
$\frac{\text{Age}}{100} \times (\pi_{t-1}^{4, Elderly} - \pi_{t-1}^4)$		-0.491 (0.938)	
$\frac{\text{Age}}{100} \times (\pi_{t-1}^{4, Gas} - \pi_{t-1}^4)$			-0.011 (0.010)
Time dummies	Yes	Yes	Yes
Adj. $R^2$	0.245	0.246	0.639
#Obs.	5200	5200	8215

## D Controlling for age-specific inflation rates

We re-run the regressions from Table 1 with controls for age-specific inflation-rates. We measure the inflation rates of the elderly from the experimental CPI for the elderly series (CPI-E) provided by the Bureau of Labor Statistics. We calculate annualized quarterly log inflation rates from the CPI-E, similar to our calculation of overall CPI inflation rates. We then include in our regressions the difference between the CPI-E and CPI four-quarter inflation rates,  $\pi_{t-1}^{4, Elderly} - \pi_{t-1}^4$ , interacted with age. (Calculating this difference term with quarterly inflation rates produces similar results.)

Table A.1 presents the results. The inflation series based on the CPI-E is only available from the end of 1983 onwards, and so the sample in columns (i) and (ii) is restricted to 1984Q1 to 2009Q4. As a basis for comparison, we therefore first re-run the regression without the additional age-dependent inflation control on this shorter sample. The results in column (i) show that the estimate of the gain parameter is quite similar to the earlier estimate in Table 1. The sensitivity parameter  $\beta$  is estimated to be lower than before but it remains statistically as well as economically significant. In column (ii) we add the interaction term between age-related inflation differentials and age, as well as age itself. (The  $\pi_{t-1}^{4, Elderly} - \pi_{t-1}^4$

difference term without the interaction is absorbed by the time dummies.) We obtain a small and insignificantly negative coefficient on the interaction term, which is not consistent with the idea that inflation expectations of the elderly are positively related to the inflation rates on the consumption basket of the elderly. Including age and the interaction term does have some effect on the estimates for  $\theta$ . With 3.475, the point estimate is higher than in column (i), though the difference is not significant.

Column (iii) reports similar tests, but with the CPI-E replaced with the gasoline component of the CPI from the Bureau of Labor Statistics. This series is available (with gaps) since 1935. We can use our full sample of survey inflation expectations from 1953 to 2009 in this case, and there is thus no need to rerun the estimation on a shorter sample. The estimates are directly comparable to those in column (i) of Table 1. As column (iii) shows, adding the interaction of  $\pi_{t-1}^{4,Gas} - \pi_{t-1}^4$  with age does not have much effect. The interaction term is insignificantly different from zero,  $\beta$  is largely unaffected, and the estimate of  $\theta$  is only slightly higher than in Table 1.

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