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Abstract

Using the panel component of the Michigan Survey of Consumers, we estimate a learning model of inflation expectations, allowing for heterogeneous use of both private information and lifetime inflation experience. "Life-experience inflation" has a significant impact on individual expectations, but only for one-year-ahead inflation. Public information is substantially more relevant for longer-horizon expectations. Even controlling for life-experience inflation and public information, idiosyncratic information explains a nontrivial proportion of the inflation forecasts of agents. We find that women, ethnic minorities, and less educated agents—groups with perennially high inflation expectations—have a higher degree of heterogeneity in their idiosyncratic information and give less importance to recent movements in inflation. During the 1990s and early 2000s, consumers have believed inflation to be more persistent in the short term. However, quarterly inflation fluctuations have a smaller effect on long-term inflation expectations, especially in recent years, suggesting that agents believe shocks to be temporary.

Key words: inflation expectations, imperfect information, heterogeneous expectations, learning, sticky information

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1 Introduction

Inflation expectations are central to macro-economic models and monetary policy (Sims, 2009), and managing consumers' inflation expectations has become one of the main goals of policy makers (Bernanke, 2004). Indeed, national surveys of public inflation expectations are now conducted in multiple countries.[1] A notable feature of these micro-data is the substantial divergence among individuals' beliefs (Mankiw, Reis, and Wolfers, 2003). Using the Michigan Survey of Consumers' forecasts it is possible to show that, over the last half century, heterogeneity of predictions for future inflation has been one of the main features of agents' beliefs (Fig.1). This dispersion in beliefs (as measured by the interquartile range of expectations) is significant (with a median of about 5 percent) and has persisted over time.

Interpretation of data and policy outcomes is greatly affected by whether models assume rational expectations or some sort of bounded rationality (Lucas, 1972), with disinflationary monetary policy being more costly with irrational agents (Roberts, 1997; Orphanides and Williams, 2003; Adam and Padula, 2011; Eusepi and Del Negro, 2011). Furthermore, heterogeneity in consumers' inflation expectations can generate over-investment in real assets (Sims, 2009), cause financial speculative behavior (Nimark, 2012), and impact the economy's vulnerability to shocks (Badarinza and Buchmann, 2011). Therefore, understanding the determinants of the heterogeneity in inflation expectations is crucial and can also inform modern macroeconomic models.

While previous empirical evidence has shown that individuals are not fully informed about future outcomes, there is little work explaining the heterogeneity of individuals' expectations and how they learn from new information. This paper fills some of this gap. We propose a model where agents provide inflation forecasts based on observable information – such as the previous inflation rates experienced in their lifetime (as in Malmendier and Nagel, 2011, 2013) – and unobservable information, and study how they update their beliefs. Our model improves upon previous work by including idiosyncratic heterogeneity and dynamic updating of each agent's inflation expectations. For this purpose, we use the panel component of the Reuters/University of Michigan Survey of Consumers (1978-2009). Previous studies have focused on the aggregate evolution of beliefs and

[1] These include the Reuters/University of Michigan Survey of Consumers, the Livingston Survey, the Conference Board's Consumer Confidence Survey and the Survey of Professional Forecasters in the US. Other central banks that survey consumers about their inflation expectations include the Bank of England, the European Central Bank, the Bank of Japan, the Reserve Bank of India, and the Sveriges Riksbank.

mostly forgotten about the panel dimension of survey expectations (Keane and Runkle, 1990; Souleles, 2004; and Anderson, 2008, are exceptions). Some studies (Branch, 2004, 2007; Lanne, Luoma and Luoto, 2009) study how different forecasting rules fit the expectations of consumers in the Michigan dataset. However, they study only the heterogeneity of forecasts and do not actually model the updating rule of the same consumers in different periods. Therefore, learning and updating of individuals' beliefs is still largely understudied.[2]

Our model estimates reveal that life experience inflation matters a lot more for near-term forecasts, than for longer-term inflation expectations of agents. Agents attribute a large weight to public information for inflation expectations over the 5-10 year horizon, suggesting that individuals do not believe short-term fluctuations to be persistent over the long term. However, even controlling for demographic information, life experience inflation, and public information, idiosyncratic information explains a non-trivial proportion of the inflation forecasts of agents. Our model finds that the role of life experience inflation is substantially lower than the corresponding estimate of Malmendier and Nagel (2013). This suggests that, accounting for the heterogeneity of idiosyncratic information and persistence over time, life time experiences play a smaller role relative to the mean-cohorts analysis in Malmendier and Nagel.

We find substantial demographic heterogeneity, with individuals differing in how much weight they give to life realizations and how quickly they update their information. In particular, women, ethnic minorities, and less educated agents have larger heterogeneity in beliefs, and are slower to update their expectations, giving a smaller focus to recent inflation events in their life experience. The same demographic groups – women and less educated agents – have been found in the literature to report higher inflation expectations and to be less informed about objective measures of inflation (Bryan and Venkatu, 2001; Bruine de Bruin et al., 2010; Armantier et al., 2012). Since we find that inflation series adjusted for the expenditure patterns of a large range of distinct demographic groups tends to be very similar to overall inflation (McGranahan and Paulson, 2006), the differences in updating and learning that we observe are likely to be driven by different information processing rules and not distinct inflation experiences. We also allow for the coefficients in our model to vary over time in order to control for changes in the macro-environment. Our findings show that, over the years, heterogeneity of expectations for both short-term and long-term inflation has decreased

[2]Note that learning models' estimates from aggregate time series are biased when individuals have different information sets (Keane and Runkle, 1990).

substantially. This is consistent with studies that find inflation was easier to predict in recent times (Stock and Watson, 2007).

The Michigan survey also collects data on subjective income growth rates of respondents. Policy-makers are always concerned about the vicious cycle of inflation expectations feeding into wage demands. We do find that households do incorporate their inflation forecasts in their income growth expectations, but only to a modest degree.

Previous literature on inflation expectations has studied possible explanations for the heterogeneity of agents' beliefs. Souleles (2004) shows that inflation beliefs are systematically heterogeneous and correlated with household expenditures. Also, past studies find that females, racial minorities, and lower income respondents have larger forecast errors than average (Souleles, 2004, Anderson, 2008). Our study uses heterogeneous lifetime experiences of inflation in individuals' updating process, and estimates a structural model of belief-updating, which helps uncover the sources of heterogeneity in consumer inflation expectations. Other studies look at the (cross-sectional) heterogeneity of inflation forecasts and explain it as a result of different lifetime inflation experiences (Malmendier and Nagel, 2013), heterogeneity in both prior information and new signals (Patton and Timmermann, 2010), switching between different prediction rules (Branch, 2004, 2007), or rational inattention (Carroll, 2003; Mankiw, Reis, and Wolfers, 2003). We show our model greatly outperforms these models when trying to explain the heterogeneity in expectations across individuals and over time. Patton and Timmermann (2010), like us, conclude that heterogeneity in observable information signals is not a major factor. However, our model is richer since it measures demographic heterogeneity in expectations and also allows each agent to update public and idiosyncratic information signals differently.[3]

This paper is structured as follows. Section 2 discusses our model of expectations formation and outlines how we deal with both observable information and unobservable idiosyncratic beliefs. Section 3 summarizes the Michigan survey dataset. Section 4 discusses the results of our learning model, analyzing differences across demographic groups and over time. Finally, Section 5 concludes the paper with a summary of our findings.

[3]Note that Patton and Timmermann (2010) identify sources of disagreement in professional forecasters' forecasts of macroeconomic variables, and use the cross-sectional dispersion in forecasts of different time horizons for the same variables for identification. We, on the other hand, exploit the panel nature of the survey to estimate our model of learning.

2 The model of expectation updating

2.1 Basic model

We denote $\pi^{p}_{t',i|t}$ as the prediction for the annualized inflation to be realized in quarter $t' \geq t$ that agent i makes in quarter t. Assume agent i of cohort s learns about future inflation by using an updating parameter for new information θ and vector of previous experiences x_{t-1} lived in his lifetime until the previous period, $\pi^{life}_{t,s}(\theta, x_{t-1})$, plus other public information available to everyone, z_t. Lifetime inflation experience is measured as a prediction based on a weighted average of the previous inflation experiences of the agent, with more recent experiences slowly adding to older ones (as in Malmendier and Nagel, 2013). Public information includes all contemporary information generally known to the public, such as the last reported inflation rate. We assume, for simplicity, a linear updating model for future inflation expectations based on $\pi^{life}_{t,s}(\theta, x_{t-1})$ and z_t:

2.1) $\pi^{p}_{t',i|t} = \beta\pi^{life}_{t,s}(\theta, x_{t-1}) + (1-\beta)z_t + \eta^{p}_{t',i|t}$, with $t' \geq t$,

where β denotes the importance attached to lifetime inflation experiences, and $\eta^{p}_{t',i|t}$ is idiosyncractic information. That is, agents' expectations are assumed to depend on both public and idiosyncratic information. While inflation is an aggregate event, there could be several sources of idiosyncratic information affecting individual agents' predictions. For instance, agents may differ in how frequently they read financial news, if at all, or in the price information observed at their local supermarket. Also, poorer households are more likely to be aware of rent and food price inflation (because of saliency), while richer households should arguably be more aware of prices of durable and luxury goods (see Armantier et al., 2012). Likewise, older households could be more sensitive to health costs. Since the sources of idiosyncratic information differ markedly across households of different background, it is reasonable to assume that $\eta^{p}_{t',i|t}$ is heteroscedastic both across demographic groups and time.

We assume the idiosyncratic information term, $\eta^{p}_{t',i|t}$, follows an AR(1) process:

2.2) $\eta^{p}_{t',i|t} = \lambda\eta^{p}_{t',i|t-1} + u_{t',i|t}$, with $\lambda \leq 1$.

The term λ informs us how slow individuals are to update their idiosyncratic opinions, which can be a mix of both the innovation process in their information sources and of the actual behavioral speed with which the agent updates his predictions. It is assumed $u_{t',i|t}$ is normally distributed ($u_{t',i|t} \sim N(0; \sigma^2_{u_i})$). $\sigma^2_{u_i}$ can be interpreted as a measure of the unexplained heterogeneity or dispersion in agents' beliefs about future inflation. It can also be interpreted as "disagreement" in opinions, as in Mankiw, Reis, and Wolfers (2003) and Rich and Tracy (2006). The Michigan survey data collects information for two time horizons, 1 year and 5-10 years after the forecast. Therefore, our model allows us to learn about the dispersion in expectations at different time horizons.

The variable of lifetime inflation experience, $\pi^{life}_{t,s}(\theta, x_{t-1})$, is given by a simple recursive least squares learning model of the observations in one's lifetime. Suppose individuals are trying to estimate a stochastic process of inflation based on x_t:

2.3.1) $\pi_{t+1} = b'_t x_t + \varepsilon_t.$

This model could imply a simple mean inflation process if, for instance, $x_t = (1)$, or an AR(1) if $x_t = (1, \pi_t)'$. We assume that individuals estimate b_t recursively from past data following

2.3.2) $b_{t,s} = b_{t-1,s} + \dfrac{\theta}{t-s} R^{-1}_{t,s} x_{t-1}(\pi_t - b'_{t-1,s} x_{t-1})$, and
$R_{t,s} = R_{t-1,s} + \dfrac{\theta}{t-s}(x_{t-1}x'_{t-1} - R_{t-1,s}),$

where the recursion starts in period $t = s + 1$, with $b_{s,s} = (0, .., 0)'$ and $R_{s,s} = x_s x'_s$. Also, we define each cohort s as the time quarter in which the agents reaches 13 years of age. These initial conditions assume agents start their life with the naive prior that inflation is 0. We assume agents start their life as forecasters in their teenage years rather than birth, because it is reasonable to think that parents completely decide consumption in early childhood and therefore this period provides little shopping experience to learn about inflation. For $\theta > 1$ past data gets down-weighted relatively fast, therefore our results are not very sensitive towards the initial prior of 0 inflation or the first date of the agents' learning experiences (Malmendier and Nagel, 2013).

The two joint equations in expression 2.3.2) define a recursive least squares algorithm in both the matrix of covariates ($R_{t,s}$) and the vector of coefficients ($b_{t,s}$), in which each time period is assigned a different weight. There could be two reasons why agents use such a recursive learning framework: one, that there are time-varying shocks to the parameters b_t which justify larger weights given to recent periods (Marcet and Sargent, 1989), especially when the observed shock is big (i.e., the forecasting error $\left|\pi_t - b'_{t-1,s}x_{t-1}\right|$ and the change in the covariates matrix $\left|x_{t-1}x'_{t-1} - R_{t-1,s}\right|$ are both large); two, there is some memory loss which justifies under-weighting past data (Malmendier and Nagel, 2013). Marcet and Sargent (1989) show that this learning process is asymptotically consistent under general conditions. The gain parameter θ determines the degree of updating when faced with an inflation surprise, with larger values giving more importance to recent shocks. A positive fixed θ indicates the gain sequence of learning is decreasing in age, since most recent periods get assigned smaller weights. This specification is consistent with empirical evidence showing younger agents to be more overconfident in the reliability of recent information (Barber and Odean, 2001; Vissing-Jorgensen, 2003; Greenwood and Nagel, 2009).

This model of life experience is specified to give a prediction for the next quarterly period, therefore we obtain a forecast $\bar{\tau}_{t+4|t,s}(\theta, x_{t-1})$ for inflation in the next year by iterating the model on the prediction for the previous quarter and then averaging the predictions for the next 4 quarters.[4] Different agents could use different models to measure their lifetime inflation. For instance, some agents could use the past mean inflation observed during their adult life, while other agents use an AR(1) or AR(2) model to get a prediction based on their life experience. However, for simplicity we assume all agents use a Life AR(1) model, $\bar{\tau}_{t+4|t,s}(\theta_1, (1, \pi_{t-1})')$, to predict inflation based on their adult experience[5]:

2.4) $\pi_{t,s}^{life}(\theta, x_{t-1}) = \bar{\tau}_{t+4|t,s}(\theta, (1, \pi_{t-1})').$

This assumption is less restrictive than it seems, since we allow for demographic heterogeneity in the parameter (θ) agents use to update their AR(1) lifetime inflation, and therefore agents do not all use the same lifetime prediction model.

This learning model is therefore summarized in a vector of five parameters: $\varpi \equiv \{z_t, \beta, \theta, \lambda, \sigma_{u_i}^2\}$. θ denotes how rapidly agents include new information in their estimates of lifetime inflation, while β denotes how important lifetime inflation is in agents' expectations.

[4] The exact expression for the average inflation in the next 4 quarters can be obtained by $\bar{\tau}_{t+m|t,s}(\theta, x_{t-1}) = \frac{1}{m}\sum_{h=1}^{m} \tau_{t+h|t,s}$, where each quarterly forecast is obtained by the iteration of $\tau_{t+m|t,s} = b'_{t,s}\tau_{t+h-1|t,s}$ and $\tau_{t|t,s} = x_{t-1}$.

[5] We tested whether agents could use other rules besides a simple AR(1) updating model. For instance, we tested whether agents use a weighted combination of an AR(1) model and a simple mean updating model. However, our results showed that the weight agents put on the simple mean was close to 0, while the weight of the AR(1) updating model was approximately 1.

2.2 Estimation

To study the learning process of inflation expectations we use the panel component of the Michigan Survey of Consumer Expectations. In this survey, respondents give, for two consecutive semesters, their subjective expectations of inflation in the next 12 months and inflation for the next 5-10 years.

The Michigan data allows us to measure observable heterogeneity in expectations updating across different demographic characteristics. Therefore we consider heterogeneity in learning by allowing the empirical model to differ across x_i, i.e.: $\varpi = \varpi(x_i)$, with x_i including income, education, race, and gender. To estimate the model we assume z_t includes all available public information; therefore z_t allows us to measure how much agents approach the ideal rational agent. Since it is difficult to specify all the public information available to agents we consider two different specifications for z_t, as in Malmendier and Nagel (2013): one, z_t includes dummies for each time period (i.e., quarters in our application); two, z_t corresponds to the median prediction for inflation in the next year from the Survey of Professional Forecasters (SPF). Also, we include the interquartile range among the SPF panel in each quarter, i.e., the difference between the 75th and the 25th percentiles of inflation forecasts, as a measure of the heterogeneity of information for each period.

Our panel, however, only includes observations for two periods, which requires specifying a different likelihood for the initial observation. We solve this by specifying the first period error term to be a purely idiosyncratic term $\eta^p_{t',i|t-1} = u^1_{t-1,i}$ and using the AR(1) process, $\eta^p_{t',i|t} = \lambda\eta^p_{t',i|t-1} + u^2_{t,i}$, in the second period. This gives us two variance terms to estimate, $\sigma^2_{u^1_i}$ and $\sigma^2_{u^2_i}$, where the first one is the heterogeneity of expectations in the first interview and the second one represents the innovation in idiosyncratic information after 6 months.[6] Furthermore, we consider parametric forms for $\varpi = \varpi(x_{i,t})$:

3.1) $z_t = \Phi d_t$, where d_t are dummies for each quarter, or $z_t = c_0 + c_1 SPF - Median_t$,

3.2) $\theta = \alpha_\theta x_{i,t}$,

3.3) $\beta = \exp(\alpha_\beta x_{i,t})/(1 + \exp(\alpha_\beta x_{i,t}))$,

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[6]Another option is to impose $\sigma^2_{u^1_i}(t'-t) = \dfrac{\sigma^2_{u^2_i}(t'-t) \times (1-\lambda^{2\times a(i)})}{1-\lambda^2}$, which is the steady-state variance for someone with $a(i)$ quarters of age. Assuming this form has no qualitative differences in our results. We prefer to report the two variance terms for each panel period due to its simplicity.

3.4) $\lambda = 2\dfrac{\exp(\alpha_\lambda x_{i,t})}{1+\exp(\alpha_\lambda x_i)} - 1,$

3.5) $\sigma_{u_i^a} = \exp(\alpha_{u^a} x_{i,t})$ for $a = 1, 2,$

where $x_{i,t} \equiv \{$*Female, Asian, Black, Hispanic, Young, Middle-aged, low-income, middle-income, years of education, half-decade*, π_{t-1}, $|\pi_{t-1} - \pi_{t-2}|$, $SPF - IQR_t\}$. The choice of half-decade dummies (1980-85, and so on) was made as a way to summarize the evolution of the heterogeneity in expectations, without including too many parameters. We also allow $\sigma^2_{u_i}$ to depend on the inflation change observed in the previous period, since previous studies find that individuals are more uncertain in periods of high and volatile inflation rates (Rich and Tracy, 2006). Note that β is standardized as a logit ratio between 0 and 1, implying that the weights given to public information and life experience sum to one for each agent.

This empirical model is estimated by Maximum Likelihood.[7] Our likelihood function must account for two aspects: one, the selection probability that the respondent i was selected to be a part of the Michigan Survey; two, the inflation predictions of the same agent i in the first interview at time t and the second interview 6 months later are correlated. The first component takes into account that the Michigan Survey selects respondents of different demographic backgrounds. This component is typically summarized by survey statisticians as the expansion factor or population weight of each observation. In our case this population weight is the inverse of the selection probability that a respondent i with characteristics X_i was selected for a first interview, $S_{i,1} = 1$, times the probability of being interviewed a second time $S_{i,2} = 1$:

4.1) $f_i = \dfrac{1}{\Pr(S_{i,1} = 1 \mid X_i)\Pr(S_{i,2} = 1 \mid X_i, S_{i,1} = 1)},$

where $\Pr(S_{i,1} = 1 \mid X_i)$ is given in the Michigan Survey and $\Pr(S_{i,2} = 1 \mid X_i, S_{i,1} = 1)$ is a logit function of the follow-up interview based on gender, age, marital status, household size, income, census region, and education. The second term accounts for the possibility that attrition in the panel follow-up is non-random (as shown to be the case by Anderson, 2008). In applied terms, some analysts interpret the population weight as the number of households represented by each observation in the sample, since it takes into account that the sample is a subset of the population and the sample representation of each demographic group is different.

[7] It is also possible to estimate our model by using just the conditional moments of the mean, variance, and auto-correlation of the expectations. These GMM estimates do not require the normality assumption.

Now our likelihood must also take into account that the inflation predictions of the same agent i are correlated in both interviews. Let $\phi(\pi^p_{t+4,i|t}, \pi^p_{t+6,i|t+2})$ represent the joint probability of individual i reporting an inflation prediction $\pi^p_{t+4,i|t}$ at time t and reporting a prediction $\pi^p_{t+6,i|t+2}$ at time $t+2$. By Bayes rule, we can simplify this probability as a multiple of the probability of the inflation prediction in the first period, $\phi(\pi^p_{t+4,i|t})$, times the probability of the inflation prediction of the 2nd period $\phi(\pi^p_{t+6,i|t+2} \mid \pi^p_{t+4,i|t})$ conditional on the first period prediction. Since the unobservable idiosyncratic terms are assumed to be bivariate normal distributed, then their probability density functions can be summarized as:

4.2) $\phi(\pi^p_{t+4,i|t}) = \dfrac{1}{\sqrt{2\pi}\sigma_{u_i^1}} \exp(-\dfrac{(\pi^p_{t+4,i|t} - (\beta\pi^{life}_{t,s}(\theta, x_{t-1}) + (1-\beta)z_t))^2}{2\sigma^2_{u_i^1}})$, and

$$4.3)\ \phi(\pi^p_{t+6,i|t+2} \mid \pi^p_{t+4,i|t}) = \frac{1}{\sqrt{2\pi}\sqrt{\sigma^2_{u_i^2} + \lambda^2\sigma^2_{u_i^1}}\sqrt{1 - (\lambda\frac{\sigma_{u_i^1}}{\sqrt{\sigma^2_{u_i^2} + \lambda^2\sigma^2_{u_i^1}}})^2}} \times$$

$$\times \exp(-\frac{(\pi^p_{t+6,i|t+2} - (\beta\pi^{life}_{t+2,s}(\theta, x_{t+1}) + (1-\beta)z_{t+1}) - \lambda(\pi^p_{t+4,i|t} - (\beta\pi^{life}_{t,s}(\theta, x_{t-1}) + (1-\beta)z_t))^2}{2(1 - (\lambda\frac{\sigma_{u_i^1}}{\sqrt{\sigma^2_{u_i^2} + \lambda^2\sigma^2_{u_i^1}}})^2)(\sigma^2_{u_i^2} + \lambda^2\sigma^2_{u_i^1})}).$$

Finally, the population Likelihood function for all agents $i = 1, ..., N_t$ interviewed at all periods t is given by

5) $L = \sum_{t=1}^{T}\sum_{i=1}^{N_t} f_i \ln(\phi(\pi^p_{t+4,i|t})\phi(\pi^p_{t+6,i|t+2} \mid \pi^p_{t+4,i|t}))$,

subject to expressions 2.3.1)-2.4) and 3.1)-3.5). Asymptotically consistent standard-errors and confidence intervals can be obtained with 100 bootstrap replicas (Rao and Wu, 1988).[8] Also, to avoid giving more weight to quarters where the population is highest, we standardize the sum of the weights in each quarter to be the same, i.e., $\sum_{i=1}^{N_t} f_i = P$, for any t.[9]

[8] Another method for computing asymptotically valid standard-errors is to compute the Robust Huber-White variance matrix by applying the weights $\frac{f_i}{\sum_{i=1}^{N_t} f_i}$ to each observation i. One advantage of bootstrap standard-errors is that each sample replica incorporates uncertainty about the true panel attrition process and the value of the population weights f_i, while the Robust Variance Matrix assumes that the true panel attrition process is known with certainty. The robust standard-errors are available from the authors upon request.

[9] This essentially prevents recent periods (when the American population is largest) from having a larger importance relative to past periods. Without loss of generality we normalize P to be 300 million individuals.

The updating rule for $\pi_{t,s}^{life}(\theta, x_{t-1})$ expressed in 2.3.1) to 2.4) is highly non-linear in the inflation rates of previous periods and the age of the respondents, requiring the algorithm to go over all the lifetime inflation rates of each cohort and compute a different weight for each period. To reduce the computation burden of this exercise we computed the life inflation series of each cohort $\bar{\tau}_{t+4|t,s}(\theta, (1, \pi_{t-1})')$ at 244 different values of θ and then used a linear interpolation rule to compute the life inflation at intermediate values.[10] Note that this approximation does not mean that the likelihood function is maximized in two steps. We maximize the likelihood function of 5) in a single step for all parameters. However, since the values of $\bar{\tau}_{t+4|t,s}(\theta, (1, \pi_{t-1})')$ are approximated with some error, then there is an additional precision error in our estimation. According to Judd (1998), approximating a function through linear interpolation between points gives consistent and shape-preserving estimates of the true function as the number of evaluation points increases to infinity. Since we use 244 points to approximate a function of one unknown parameter, it is reasonable to expect that the approximation error is small. There is a correlation above 99.9% between adjacent series of θ around 2 and 4.5, which represent the most likely values for the parameters. The correlation between life inflation at adjacent points is high, therefore there is little measurement error involved in this approximation.

3 Data

The Michigan Survey of Consumer Expectations has been conducted monthly by the University of Michigan between 1978 to the present day, based on telephone interviews of a sample of approximately 500 respondents representative of the US population. The survey incorporates a rotating sample design, where 40% of the monthly sample are re-contacts from six-months before, and the remaining 60% are new respondents. Although this survey has been implemented since 1953, the panel data are only available after 1978. Rather surprisingly, few studies have exploited this feature of the Survey of Consumer Expectations; exceptions include Souleles (2004) and Anderson (2008).

In this survey, respondents provide their subjective expectations of inflation in the next 12 months and inflation for the next 5-10 years by answering the following questions:

[10] We chose {0, 0.5, 1, 1.25, 1.5, 1.6, (1.75: 0.05: 2.00), (2.025: 0.025: 2.25), (2.26: 0.01: 4.25), (4.275: 0.025: 4.5), (4.55: 0.05: 4.75), (4.80: 0.10: 5.00), (5.25: 0.25: 6.25)}, as the exact values of θ, where : a : denotes an arithmetic progression in steps of a. The life inflation model was computed for all cohorts and time periods at these 244 values of θ. However, intermediate values of θ within this range were approximated by a linear interpolation.

During the next 12 months, do you think that prices in general will go up, or go down, or stay where they are now?

By about what percent do you expect prices to go (up/down) on the average, during the next 12 months?

In addition, households are asked to forecast their personal income growth over the next year:

During the next 12 months, do you expect your income to be higher or lower than during the past year?

By about what percent do you expect your income to (increase/decrease) during the next 12 months?[11]

Therefore the Michigan survey measures the expectations of more than 85,000 individuals at two different points in time in the period 1978 to 2009.

We also use long-term historical data on the Consumer Price Index (CPI) collected by Robert Shiller to calculate the US quarterly inflation rates and the life experience inflation rates for each cohort. In addition, we use data on the year-head inflation forecasts of respondents in The Survey of Professional Forecasters (SPF). The SPF currently conducted by the Federal Reserve Bank of Philadelphia, has been conducting quarterly surveys of economists and professionals since 1968. It collects data on point forecasts and density forecasts of several macro variables over a range of forecast horizons.

3.1 Descriptive analysis

Before estimation of the updating model described in Section 2, we show some descriptive patterns in the data. We retain the full sample for this purpose and do not restrict to the respondents who are re-surveyed. Figure 1 shows the median one-year ahead inflation expectations in the Michigan survey. Compared to realized one-year ahead inflation the median underestimates the realized inflation up to the early 1990s. After that, the median expectation slightly overestimates the realized inflation. The visual depiction of the two series suggests that inflation expectations lag behind realized inflation, i.e., they seem to be anchored to realized inflation in the survey

[11] Our analysis assumes that this question elicits the percent change in income in nominal terms.

year. The figure also reports the 25th and 75th percentiles of the expectations distributions. The interquartile range – a measure of respondents' disagreement – is quite large. Though the range is larger in periods of high inflation, the interquartile range is about 5% even in periods of low inflation. This indicates substantial heterogeneity in point forecasts of survey respondents.

To shed light on differences in expectations, we regress the respondents' point forecast of one-year ahead inflation onto a set of demographic variables plus the annual rate of inflation prevalent at the time of the survey as well as the actual realized one-year ahead inflation. The first two columns of Table 1 show that female, Black, Hispanic, young, the less wealthy, and less educated respondents report higher expectations, similar to results found in previous studies (Bryan and Venkatu, 2001, Bruine de Bruin et al., 2010). Also, the coefficient on current inflation is about 0.4, while the magnitude of the coefficient on one-year ahead inflation is close to 0. This suggests that respondents are closer to adaptive expectations than to rational expectations.

Column (3) of Table 1 shows the heterogeneity in revisions of one-year ahead inflation expectations by regressing the absolute change in point forecasts between the two surveys onto a set of demographic variables plus the absolute error in the respondent's forecast in the first survey (defined as the absolute gap between the respondent's point forecast of one-year ahead inflation and actual realized one-year ahead inflation) and the realized change in inflation between the two surveys. We see that females, minorities, young, lower-income, and less-educated agents make larger absolute revisions. These are the same demographic groups that report larger inflation forecasts (the first two columns of the table), and therefore have more to learn in order to approach less biased expectations. Furthermore, the absolute error in the respondent's forecast and the realized change in inflation between the two surveys have positive and statistically significant coefficients. Therefore respondents with worse forecasts in the first survey tend to make larger revisions, and respondents revise their beliefs more during periods of more variable inflation.

The last two columns of Table 1 report the OLS estimates of a regression of the absolute error in the respondent's point forecast for one-year ahead inflation in each of the two surveys that respondents answer. We conclude that demographic groups who report larger point forecasts and revise more between the two surveys - females, minorities, young, the less wealthy and the less educated – also make larger forecast errors. Also, even when interviewed the second time, error patterns by demographics look similar. These results are consistent with Souleles (2004) and

Anderson (2008) who also find that females, racial minorities, and low income respondents make larger forecast errors than average. We also find a positive relationship between the absolute error in the first survey and the error in the second survey, i.e., there is persistence in forecast errors of respondents.

Why do certain demographic groups report larger point forecasts, make larger forecast errors, and revise more? It could be that females, lower-income individuals, less educated, young, and minorities have different actual inflation experiences and hence report larger point forecasts. Also, groups facing more volatile inflation rates could show less persistence in their inflation expectations. However, we find that this explanation is unlikely and should play a minor role. The Chicago Fed IBEX 12 month inflation series (1983-2005) takes the different inflation experiences of various socioeconomic and demographic groups into account.[12] The series uses Consumer Expenditure Survey (CEX) data and price data produced by the Bureau of Labor Statistics to construct a group-specific inflation rate, and includes the inflation rates for 42 distinct demographic groups with a monthly frequency between January of 1983 and December of 2005, which corresponds to a time series of 324 observations for each group. McGranahan and Paulson (2006) find that lower income and lower education groups have somewhat more variable inflation than higher income and higher education groups. We estimate the correlation of the inflation rates of each one of these demographic groups with the aggregate monthly inflation series of the Bureau of Labor Statistics (BLS). We find that the correlation of each demographic group's inflation rate with the BLS inflation is above 90% during the period 1983 to 2005.[13] Therefore it is unlikely that the small differences in the inflation rate experienced by each group can explain the large heterogeneity of inflation expectations observed in the data, which is consistent with evidence in previous empirical studies (McGranahan and Paulson, 2006; Hobijn et al., 2009). Malmendier and Nagel (2013) also show that group-specific inflation rates have little significance in explaining cohort inflation expectations, once the lifetime weighted average inflation experience of the cohorts is accounted for.

Other possible explanations for demographic differences in inflation expectations include different expectations formation and information-processing rules. More specifically, there could be either demographic differences in heterogeneity of idiosyncratic information, or the speed at which different

[12] Description of the series is available at http://www.chicagofed.org/webpages/research/data/ibex/ibex_inflation.cfm.

[13] In fact the correlation of each demographic group's specific inflation rate with the BLS inflation is above 95% for 41 (out of the 42) demographic groups. The single exception is the group defined as "Food-stamp recipients"; their specific inflation rate has a correlation of 92% in relation to the BLS aggregate inflation.

groups update their inflation expectations. Heterogenous updating of expectations has implications for steady-state inflation, fiscal deficits, and asset savings, and understanding the underlying channels is important for effective monetary policy. We next explore sources of demographic differences in updating in our model.

4 Interpreting the heterogeneity of prediction rules

4.1 Heterogeneity of information use across the population

We start by reporting a few summary values of how heterogeneous the expectations process is across the population of respondents. Instead of focusing on each single demographic group ($x_{i,t}$) and time period (t), we look instead at the broad heterogeneity of forecasting model parameters of different percentiles of the population, in particular the 10, 25, 50, 75 and 90 percentiles. In Table 2, we report the estimated population means for the overall mean inflation forecasts in the first and second interviews ($E\left[\pi^p_{t+4,i|t}\right]$, $E\left[\pi^p_{t+6,i|t+2}\right]$), the weights given to the AR(1) life experience inflation (β), and the public information set ($1-\beta$), the updating speed of the life experience (θ), and the heterogeneity of idiosyncratic information ($\sigma_{u_i^1}, \sigma_{u_i^2}$) as well as its persistence (λ). In this table we only consider the summary results of the expectations model with the SPF forecasts as public information, although the results are similar with the quarterly dummies. The first two rows show how the mean expectations of agents, $E\left[\pi^p_{t+4,i|t} \mid x_{i,t}, z_t\right]$, conditional on their information set, z_t, and socioeconomic characteristics, $x_{i,t}$, differ. It shows that the mean agent in each socioeconomic group would have an inflation forecast between 2.8% and 4.6%.

How much of the inflation forecasts can be attributed to different sources of information? Table 2 reports that the life experience AR(1) of each respondent has a significant impact on individual expectations of one year ahead inflation. The median respondent gives a weight of 29% to their life experience AR(1) when forming one year ahead expectations. However, respondents' weight for their life experience AR(1) can vary from as low as 5% (the bottom 10th percentile in the population) to as high as 80% (the highest 90th percentile in the population). Most Michigan respondents also attribute a large weight to public information (the $(1-\beta)$ term), with its importance changing from as low as 20% to as high as 95%.

Interestingly, the 5-10 year expectations of the agents have little relation to the life experience of the agents, with the highest 90th percentile giving a weight of only 40.1% for the AR(1) life model and the median weight being 9.6%. Instead, in the case of inflation expectations at the 5-10 year horizon, almost all the agents attribute a large weight to public information, with the importance of public information ranging from 59.9% (10th percentile) to as high as 99.9% (the 90th percentile). This is interesting, because it shows people do not believe short-term fluctuations to be persistent over the long term. This is a strong sign that consumers during the recent crisis trust the ability of the Federal Reserve to revert short-term inflation fluctuations over the long term.

The median agent's updating speed of life experience in the AR(1) component is 3.98 for the one-year ahead inflation rate and 4.19 for 5-10 year inflation. Our estimates reveal little heterogeneity for the updating speed of 5-10 year life inflation experience. However, the updating factor of the life AR(1) model for one year ahead inflation varies from a low of 3.43 (the 10th percentile) to 4.53 (the 90th percentile).

The results estimated for θ are similar to the ones reported by Malmendier and Nagel (2013) using means of cohorts as observations instead of individual agents. However, the estimates for β differ substantially. Malmendier and Nagel (2013) report θ for one year-ahead expectations to be 3.04 (with time dummies) and 3.98 (with SPF forecasts) for the life AR(1) model. The estimate of β in Malmendier and Nagel (2013) is around 0.67 for both the model with time dummies and SPF forecasts, which is substantially higher than the β of 0.29 we find for the median agent. Therefore our model, accounting for the heterogeneity of idiosyncratic information and its persistence over time, shows that the role of life experience is substantially lower relative to the mean-cohorts case of Malmendier and Nagel.

Finally, our estimates show that the role of idiosyncratic information is significant across all the socioeconomic groups. The standard-error of the idiosyncratic information component, $\sigma_{u_i^1}$, for the one year-ahead expectations varies from a low of 2.79 (the 10th percentile) to a median of 3.78, with values as high as 5.25 (at the 90th percentile). Therefore, even after conditioning on the information of the demographic group ($x_{i,t}$), the life experience ($\pi_{t,s}^{life}(\theta, x_{t-1})$), and the public information (z_t), most agents differ from the mean inflation forecast by several percentage points. Also, this idiosyncratic information is not purely the result of a fixed type of bias in forecasts, from say agents that always report high inflation or low inflation. The persistence of the idiosyncratic information component, λ, of the one-year ahead expectations varies from as low as 0.26 (the 10th percentile) to as high as 0.35 (at the 90th percentile). While this shows substantial persistence in the AR(1) process of idiosyncratic information of the agents, the parameter is clearly far below 1; this, therefore, indicates that there is substantial revision of the expectations after 6 months. The parameter $\sigma_{u_i^2}$ denotes the standard-error of the innovation in the idiosyncratic information of the agent after 6 months, which ranges from a low of 2.62 (at the 10th percentile) to a median of 3.52, with values as high as 4.77. It is relevant to note that the standard-error of idiosyncratic information for the 5-10 year inflation forecasts is significantly smaller than for the one-year horizon. This result makes sense, since long-term inflation faces smaller shocks than the inflation rate of a single year.

4.2 Differences across demographic groups and over time

We next report all the coefficient estimates of our inflation expectations learning model in Tables 3, 4 and 5 and its variation across different demographic groups. Table 3 shows the coefficients for the mean expectations process and its weighting between public information versus life experience (z_t and β). Table 4 reports the coefficients for the life experience learning (θ). Finally, Table 5 shows the parameters of the dispersion and persistence in idiosyncratic information ($\sigma_{u_i^1}, \sigma_{u_i^2}, \lambda$).

There are 4 distinct regressions in Tables 3, 4, and 5. The first two regressions in each table show the fit for the Michigan respondents' expectations of one year ahead inflation. These regressions include two alternative measures of the public information vector, z_t. The first alternative uses dummies for all the quarterly periods (except the first quarter) in the 1978-2009 Michigan sample as a measure of public information. The second alternative instead uses only a constant and the quarterly median expectation of one-year ahead inflation from the Survey of Professional Forecasters (SPF), which as a well-informed group represents a plausible way to summarize the public information available. Since the SPF panel only elicits inflation forecasts after 1981, this second regression applies only to the 1981-2009 Michigan sample period. Furthermore, this second alternative regression includes the interquartile range as a measure of the heterogeneity about inflation perceptions. In the same way, we report two alternative regressions explaining the 5-10 year inflation expectations of the Michigan sample. The first alternative considers again quarterly dummies as a measure of public information, while the second alternative uses the SPF median forecast for the mean inflation rate in the next 10 years. As in the case for the near-term horizon, we take into account the interquartile range of the 10-year inflation rate among the SPF sample as a proxy for heterogeneity of information. An important aspect is that the SPF survey only elicits forecasts of inflation at a 10-year horizon since 1991, although it elicits information of inflation in the next 12 months since 1981. For this reason we include both the SPF median forecast at a 10-year horizon for the period after 1991, and the one-year ahead SPF forecast for the period before 1991. Both coefficients are reported in the tables 3, 4 and 5.

Table 3 shows the estimated coefficients and standard errors for the mean expectations process, z_t, β, and θ. The coefficients for z_t show that agents give little value to the information in SPF inflation forecasts at the one-year horizon. In fact, the content of the Michigan agents' public information is well approximated by a constant and changes very little with predictable moves in inflation such as the ones expected by the median SPF forecaster. This indicates that most Michigan agents are not forward-looking rational agents, incorporating every new piece of information. Instead, the Michigan consumers simply look at their recent life experience or personal information sources to revise their near-term inflation expectations. However, the Michigan sample agents' expectations are highly correlated with the SPF forecasts at the 5-10 year horizon. This suggests that, over the longer-horizon, individuals tend to rely on professional forecasters' predictions. In a regime with well-anchored and stable long-term inflation expectations, this makes sense. Our estimates for α_β show that women, blacks, Hispanics, lower income and less educated agents put a lower weight in their life AR(1) experience. This happens both at the one-year and 5-10 year horizons. Since the regression of one year ahead inflation expectations with the SPF forecasts shows that the public information component is close to being a constant over time, these socioeconomic groups that put less weight on their life AR(1) inflation experience are slower to respond to recent movements in inflation. On the contrary, Asians and younger agents put more weight on their life AR(1) experience at the one-year horizon, but give less importance to life experience at the 5-10 year horizon.

The persistence of inflation shocks in macro models may depend on how much expectations incorporate changes in the previous inflation rates (Orphanides and Williams, 2003). If we look at the dummies for each half-decade for α_β, it is clear that agents gave more importance to their AR(1) inflation experience during the period 1991-2005. This result is consistent with the findings of Stock and Watson (2007), who show that the statistical power of the last observed inflation for the next-year inflation forecasts increased substantially in the 1990s. This increased reliance on the previous inflation experience was reversed after 2006, perhaps as the result of greater uncertainty due to the Great Recession. The coefficient for the half-decade of 1981-85 for 5-10 year expectations is close to 0 and not statistically significant. This is interesting, because it suggests that people in the early 1980s were slow to react to the credibility of the new regime imposed by Volcker.

Our estimation of the life experience AR(1) model (θ) is similar across demographic groups and also over different time periods (Table 4). This is interesting because it shows that agents show a constant learning gain over the last 30 years, and that there were no periods of faster convergence towards a different AR(1) process.

Table 5 shows that women, ethnic minorities, the young, lower income, and less educated agents have a higher degree of heterogeneity in their expectations (i.e., larger estimates of $\sigma^2_{u_i}$). Also, there is a higher dispersion (or disagreement) in the inflation predictions of households in periods of higher inflation and more volatile inflation (as measured by the absolute change of inflation in the previous two quarters). This is true for the heterogeneity of expectations both at the one-year and 5-10 year horizons. Estimates of λ show that there is little (economic or statistically) significant difference over the persistence in the use of idiosyncratic information across different demographic groups or time periods. We also show how the heterogeneity of opinions, $\sigma^2_{u_i}$, has evolved over the years through the dummies for each half-decade. Again, it is clear that the heterogeneity of inflation forecasts decreased significantly during the Great Moderation period of 1991-2005. This result is consistent with the evidence shown by Stock and Watson (2007), who find that inflation has been easier to forecast in the last two decades. However, the heterogeneity of inflation expectations has increased (in relative terms) since 2006, perhaps as a consequence of the greater uncertainty due to the economic crisis.

Lower-income agents have a higher heterogeneity of expectations both at short-term and long-term horizons. A potential explanation could be that lower income households consume different consumption baskets and may have a higher consumption share in items, such as food, that have more volatile prices at both the local level and at different time periods (Mankiw, Reis, and Wolfers, 2003). However, using the quarterly average of the Chicago Fed IBEX inflation rate as a regressor instead of the CPI does not change the results significantly, suggesting that different inflation volatility across demographic segments does not play a significant role (results not reported here; available from the authors upon request).

4.3 Personal income growth forecasts

Economists are often worried that inflation expectations could affect wage demands. We explore this issue by studying how the households' personal income growth forecasts in the next year relate to their inflation expectations. The first two columns of Table 6 regress the subjective income growth expectation reported in the first and second surveys on various demographic variables and controls, respectively. Male, young and middle-age respondents report economically and statistically significant higher income growth expectations, which is consistent with actual life-cycle patterns (Attanasio, Banks, Meghir, and Weber, 1999).

The elasticity of income growth expectations with respect to inflation expectations is 0.030, suggesting that respondents perceive a positive but weak link between wage fluctuations and inflation. The last column reports the coefficient estimates of regressing the absolute change in income expectations on the various covariates. Low income and young respondents revise their income expectations more, which could be the result of their labor market experiences being more volatile. Absolute revisions in income expectations are positively correlated with absolute revisions of inflation expectations, but not with realized changes in inflation. This makes a strong case for central banks to contain inflation expectations, since the estimates imply that rises in inflation expectations are tied to an expected increase in wages.

4.4 Model Fit

As we discussed before, several explanations and models have been offered to explain the evolution of inflation expectations and its heterogeneity, including, for instance, sticky expectations (Mankiw, Reis and Wolfers, 2003) and different life experiences (Malmendier and Nagel, 2013). In relation to the previous alternatives in the literature, our model includes heterogeneity in the use of information both in terms of observable information (demographic groups attach different importance to their lifetime experiences) and unobservable idiosyncratic information. In this section we compare the fit of our model, which we label as Heterogeneous Idiosyncratic Updating (HIU) model, with three other alternatives: i) the Malmendier-Nagel model of public information and life AR(1) experience

(MN-AR(1)), ii) the Malmendier-Nagel model of public information and life mean experience (MN-Mean), and iii) the Heterogeneous Sticky Expectations (HSE) model (Mankiw, Reis and Wolfers, 2003, Branch, 2007).

To make the models easier to compare, we specify that all the public information in the HIU model and its three alternatives is summarized by the SPF median forecasts. The Malmendier and Nagel models are nested by our HIU model specified in section 2, except that the vector of parameters $\varpi \equiv \{\beta, \theta, \lambda, \sigma^2_{u_i}\}$ is estimated without heterogeneity. The Heterogeneous Sticky Expectations model considers that agents make use of available public information, but update their forecasts at infrequent periods. Obviously, we do not observe when was the last quarter in which each agent i may have updated his prediction. Therefore we calculate a set of linear forecasts based on the information of the 8 previous quarters and then select the prediction closest to agent i's forecast: $\pi^{HSE}_{i,t+4} = \arg\min_{h\in\{1,\ldots,8\}} \left|\pi^p_{t+4,i|t} - \pi^{LP}_{t-h+4}\right|$. The prediction is obtained by doing a linear regression in each period t of $E\left[\pi_{t-1} \mid t, SPF_{t-1}, \pi_{t-2}\right] = \alpha_t(1, SPF_{t-1}, \pi_{t-2})'$, based on all the information observed until t. This set of regressions gives a linear prediction (LP) of future inflation in the next quarter $t+1$ of $\pi^{LP}_{t+1} = \alpha_t(1, SPF_t, \pi_{t-1})'$, which can be iterated to obtain a prediction for mean inflation in the next 12 months $\tilde{\pi}^{LP}_{t+4} = \frac{1}{4}\sum_{h=1}^{4} \pi^{LP}_{t+h}$. We similarly obtain a sticky expectations prediction for the next 5-10 years, using the SPF median forecasts for the mean inflation in the next 10 years and 1 year horizons.

After producing the predictions from these distinct models, we compare the probability density distribution of their forecasts with the distribution of the individual agents' production, $\eta^p_{t',i|t}$, in the real data. The probability density functions for the forecasts of each model m are estimated non-parametrically for each quarter using a kernel estimator, $\hat{p}_{m,t}(x) = \frac{1}{h\sum_{i=1}^{N_t} f_i}\sum_{i=1}^{N_t} f_i K(\dfrac{x_{m,i} - x}{h})$, where we choose $K()$ to be the Epanechnikov function and the bandwidth $h = \frac{0.9IQR(x_{m,i})}{N_t^{0.2}}$, which is a choice that is asymptotically consistent and minimizes the sample mean square error (Pagan and Ullah, 1999). Also, for each quarter we compute the Kullback-Leibner distance measure between each model m and the distribution of the data, $KB_{m,t} = \int_x \hat{p}_{Data,t}(x)\ln(\frac{\hat{p}_{Data,t}(x)}{\hat{p}_{m,t}(x)})\partial x$. The Kullback-Leibner is a measure of the expected log-distance between two different density functions, therefore the bigger it is the worse is the fit between the model and the data.

Figure 2.1 plots the estimated density functions for the one-year ahead inflation forecasts in the data, our model (HIU) and the three alternative models. Since it is inconvenient to show the density distributions for each quarter we concentrated on two periods: i) the average across all quarters, ii) the year before the last financial crisis, i.e., between the 2nd quarter of 2005 and the 1st quarter of 2006. Also, we differentiate between the density functions for the first interview of the respondents and their re-interview six months later. It is clear that our HIU model is much closer to the actual distribution of the data than the alternatives. The data shows that inflation forecasts are spread between 0% and 10%, a feature which our HIU model replicates well. However, the alternative models show that predictions should be heavily concentrated between 2% and 4%. The results are very similar whether we look at the first or the second interviews. Figure 2.2 plots the estimated density functions for the 5-10 year inflation expectations for the same periods. Again, the data shows there are forecasts all over the interval of 0 to 10%, which is a characteristic that only our model replicates, while the alternatives are highly concentrated around a narrow interval of 2% to 3%.

Now we look at the plot of the Kullback-Leibner distance of each model for every quarter in the last 3 decades. Figure 3.1 plots the Kullback-Leibner distance of the 4 alternative models for the one-year ahead inflation expectations in the first interview, while Figure 3.2 plots the distance for the second interview. It is clear the HIU model outperforms its alternatives, since the highest Kullback-Leibner distance of our model is 0.5, while the lowest value for the other alternative models is 2. The same is true for the 5-10 year inflation expectations plotted for the first (Fig. 3.3) and second (Fig. 3.4) interviews, with again the highest distance presented for the HIU model being 0.5. Our model does less well (but still outperforms the other models) in explaining the one-year ahead inflation expectations during the 2000s, especially between 2005 and 2008 (Fig. 3.1 and 3.2). This effect is perhaps due to the uncertainty caused by the sudden change in Fed policy, with the federal funds rate target increasing very abruptly in 2004, followed by a sudden decrease in interest rates in 2007.

5 Conclusion

Differences in inflation expectations across agents are large and persistent over time (Figure 1).This paper proposes a model where agents provide inflation forecasts based on observable information - such as the previous inflation rates - and unobservable information. In our model, upon receipt of new information, agents may update both the public information as well as their idiosyncratic information. We use the panel data of the Michigan Survey of Consumers to estimate the model, and show that individuals are highly heterogeneous in their updating of inflation expectations. Our model vastly outperforms other models in explaining the heteroscedasticity of agents' expectations, confirming that differences in the dynamic updating of information is an important feature in inflation expectations data.

Our model estimates reveal that life experience inflation has a significant impact on near-term inflation expectations of individuals. However, despite controlling for demographics, life experience inflation, and public information, we find that idiosyncratic information matters in the inflation forecasts of agents. Notably we find a smaller role of life experience inflation than Malmendier and Nagel (2013). Our model differs from them in that it accounts for the heterogeneity of idiosyncratic information and persistence over time.

We also find that, over the years, heterogeneity of expectations for both short-term and long-term inflation has decreased substantially. Also, in the recent decades, agents rely more on previous observed inflation to forecast future inflation rates. This result is consistent with studies that find inflation and earnings have become easier to predict in more recent years (Stock and Watson, 2007). During the 2000's the previous period inflation rate matters more for the one-year horizon inflation forecast than for long-term inflation expectations, showing contemporary consumers expect inflation shocks will revert over the long term.

One notable finding is that individuals differ in how much weight they give to their observable life experience in how shocks feed into future inflation (though there is little variation across individuals in the gain parameter for life experience inflation). In particular, women, Blacks, Hispanics, lower income and less educated agents are slower to update their expectations. This slowness in the updating of new information could explain why these groups systematically report inaccurate expectations. In addition, we find that the same subgroups have greater heterogeneity in their beliefs, which cannot be explained by their different experiences. Overall, these results suggest that there is room for information interventions, and have normative implications for central bank communication. Our findings suggest that a multi-pronged approach targeting different sub-populations should be more effective in reducing the disagreement in agents' expectations.

This conclusion is relevant for improvements in future macro modeling of agents' reactions, since it shows heterogeneity is a much more essential feature of the data than the dichotomy between rational expectations versus backward looking expectations or adaptive updating. Several structural macro models do not have a stable equilibrium when there is heterogeneity of inflation expectations and updating (Giannitsarou, 2003), implying that standard monetary policy is unable to make inflation converge to the best possible outcome. Also, heterogeneous learning dynamics imply that monetary and fiscal policy has different effects on agents' savings (agents that believe in higher future inflation will save and invest less), as well as on the steady-state rate of government deficits (Evans, Honkapohja and Marimon, 2001). Therefore, our finding that agents' learning about inflation is highly heterogeneous should have important implications for the simulation of realistic macro models and policy-making.

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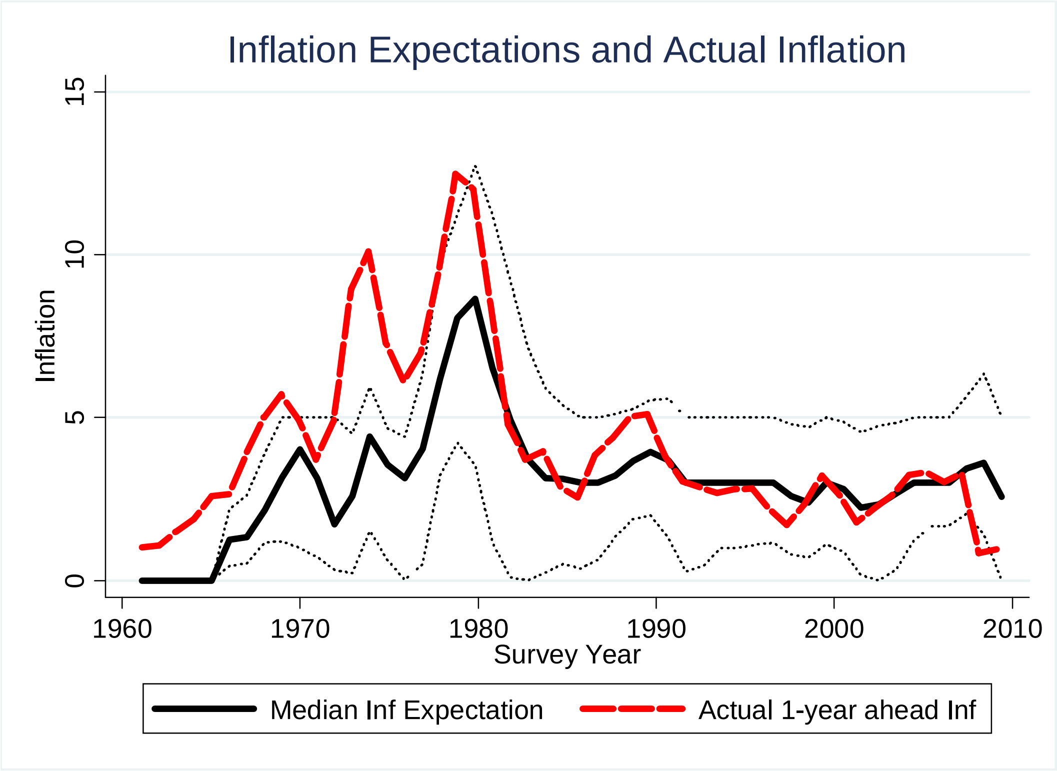

Figure 1: The figure shows the median inflation expectations as well as the 25th and 75th percentiles of the cross-sectional data (source: Michigan Survey of Consumers). Realized one-year ahead inflation also reported.

Figure 2.1: Pdf of one year-ahead Inflation expectations for selected models

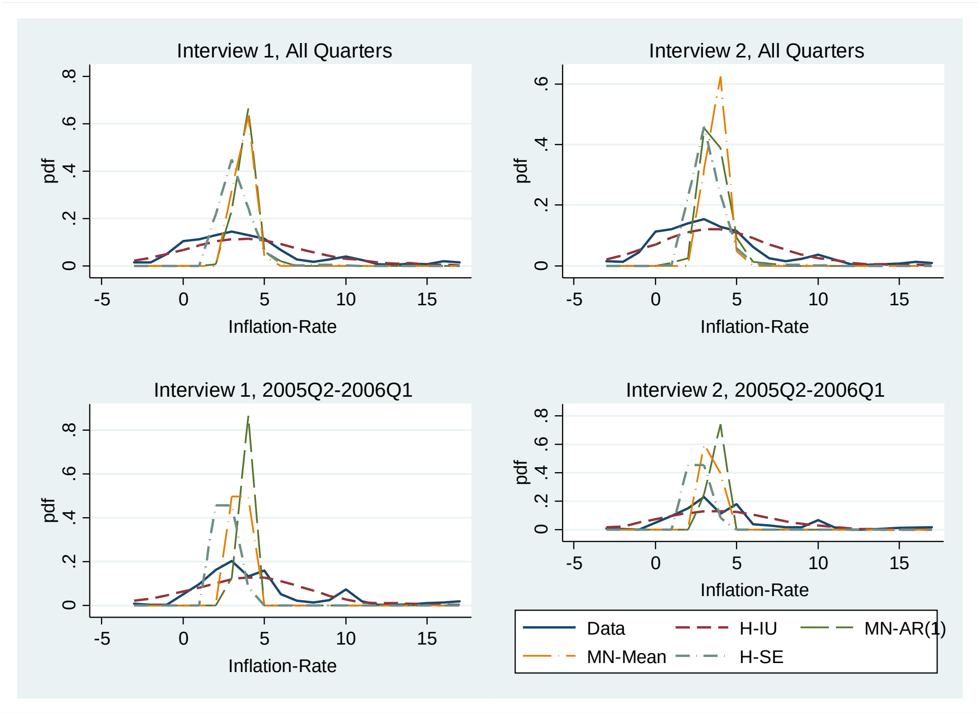

Figure 2.2: Pdf of 5-10 year ahead Inflation expectations for selected models

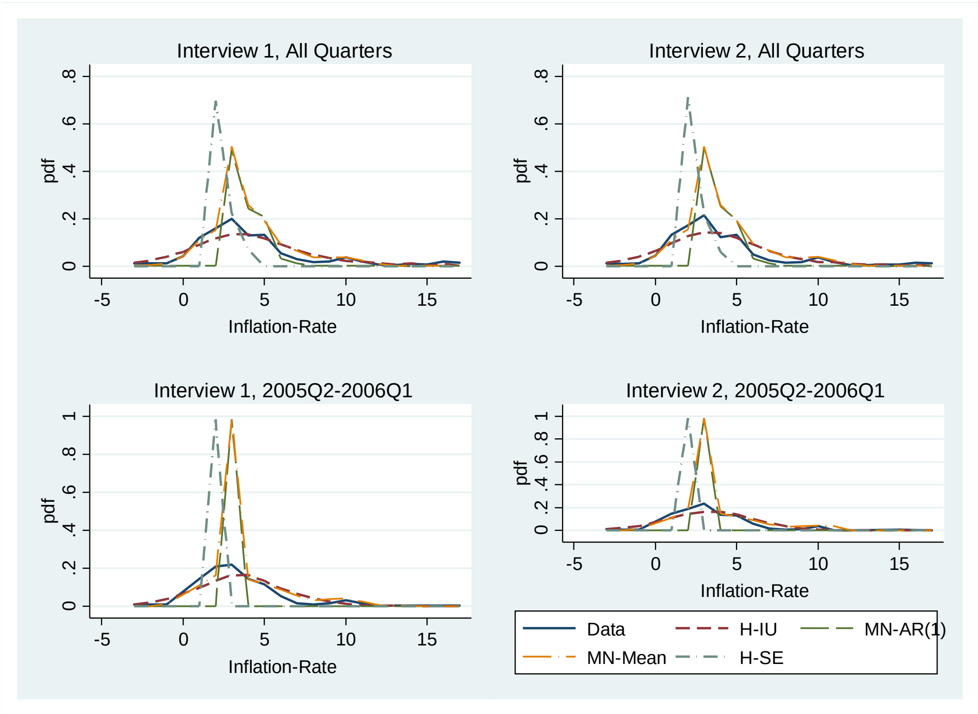

Figure 3.1: Kullback-Leibner distance measure for selected models

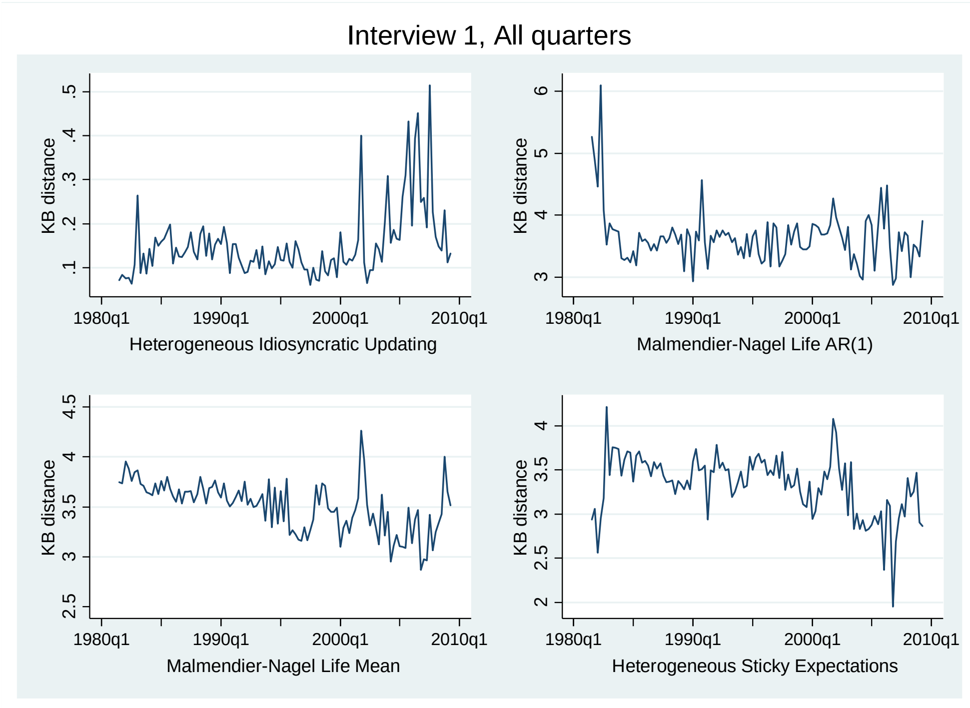

Figure 3.2: Kullback-Leibner distance measure for selected models

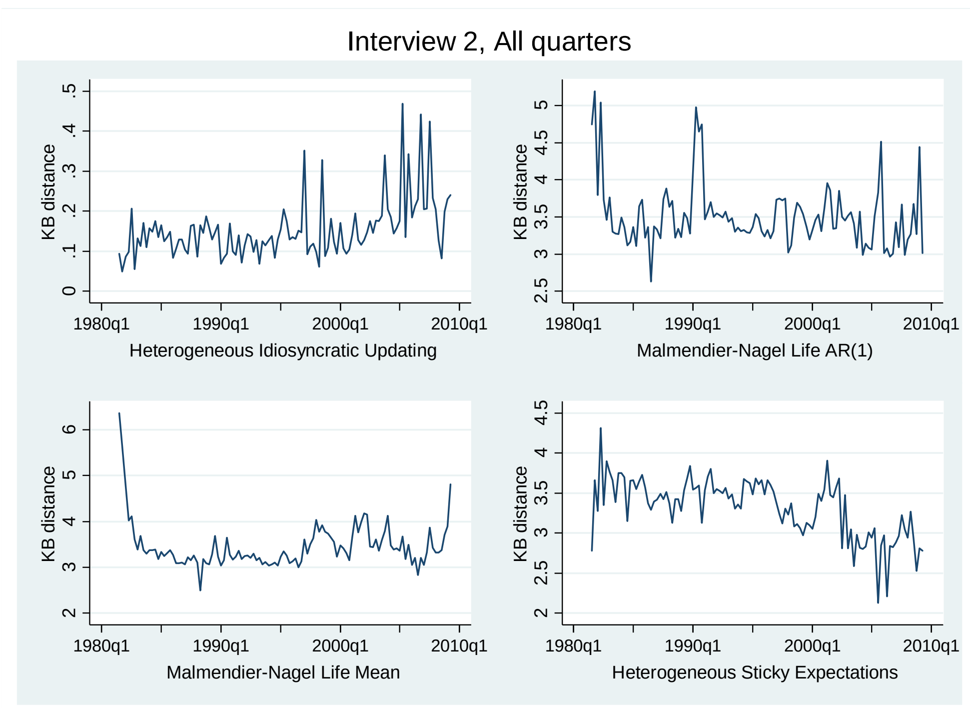

Figure 3.3: Kullback-Leibner distance for 5-10 year ahead Inflation expectations

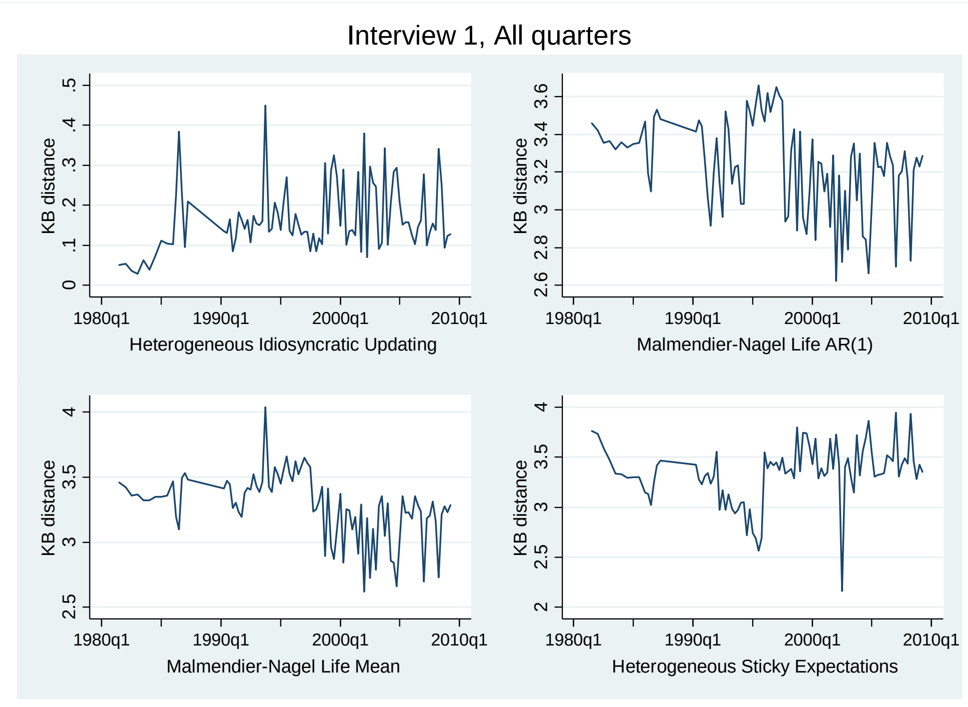

Figure 3.4: Kullback-Leibner distance for 5-10 year Inflation expectations

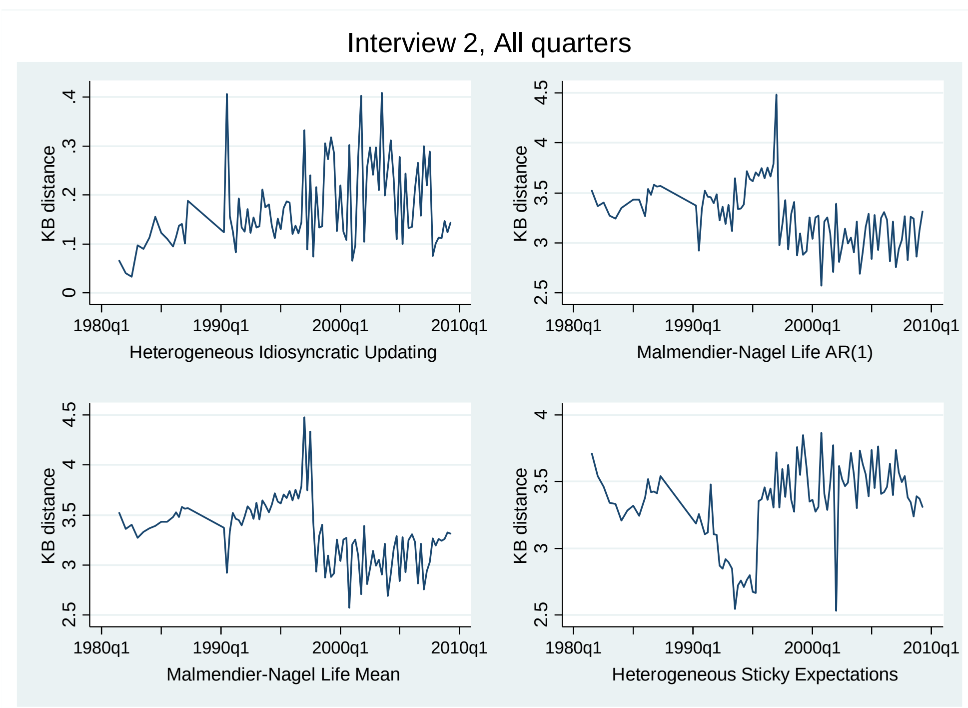

Table 1: Heterogeneity in 1-year Inflation Expectations by Various Demographics

	1-yr inflation forecast		Abs Revision of	Absolute Error[b]	
	1st Survey	2nd Survey	Point Forecasts[a]	1st Survey	2nd Survey
	(1)	(2)	(3)	(4)	(5)
Female	0.963***	1.074***	0.487***	1.007***	0.591***
	(0.0456)	(0.0462)	(0.0374)	(0.0369)	(0.0322)
Asian	0.105	0.744***	0.553***	0.594***	0.602***
	(0.188)	(0.191)	(0.153)	(0.1530)	(0.1320)
Black	1.184***	0.944***	0.600***	1.734***	0.767***
	(0.0852)	(0.0868)	(0.0707)	(0.0688)	(0.0606)
Hispanic	1.117***	1.057***	0.306***	1.387***	0.648***
	(0.121)	(0.123)	(0.101)	(0.0989)	(0.0871)
Young[c]	1.067***	0.453***	-0.0262	0.183***	-0.0215
	(0.0716)	(0.0732)	(0.0595)	(0.0578)	(0.0506)
Mid-age	0.790***	0.424***	-0.156***	-0.0614	-0.0454
	(0.0606)	(0.0624)	(0.0509)	(0.0492)	(0.0436)
Lowest Income tercile	0.922***	0.724***	0.267***	0.399***	0.263***
	(0.0761)	(0.0773)	(0.0624)	(0.0618)	(0.0547)
Middle Income tercile	0.386***	0.152**	-0.00255	0.0737	0.0478
	(0.0647)	(0.0658)	(0.0524)	(0.0526)	(0.0460)
Education	-0.118***	-0.150***	-0.117***	-0.218***	-0.134***
	(0.00976)	(0.00990)	(0.00815)	(0.00789)	(0.00696)
Inflation in Survey Month	0.401***	0.437***	-	-	-
	(0.0334)	(0.0280)			
Realized 1-yr ahead Inflation	-0.0970***	0.0698***	-	-	-
	(0.0328)	(0.0260)			
Absolute Error in First Survey	-	-	0.648***	-	0.245***
			(0.00369)		(0.00317)
Actual $\triangle$Inflation between Surveys	-	-	0.0512**	-	-
			(0.0212)		
Constant	3.492***	3.948***	2.738***	6.200***	4.020***
	(0.273)	(0.230)	(0.123)	(0.116)	(0.104)
Observations	78756	65957	61837	76861	71248
R-squared	0.113	0.139	0.387	0.116	0.18

[a] Defined as |1-yr ahead inflation point forecast reported in Second Survey - 1-yr ahead inflation point forecast reported in First Survey |.

[b] Defined as | Actual realized 1-yr ahead inflation - Respondent's Expectation of 1-yr ahead inflation |

[c] Young is defined as age < 31; Mid-age is defined as age > 30 & age < 61.

OLS estimates reported of a regression onto various demographics.

Standard Deviations in Parentheses. ***, **, * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 2: Population percentiles of the Inflation learning model (w/ SPF forecasts)

		1 year inflation					5-10 year inflation				
		p10	p25	p50	p75	p90	p10	p25	p50	p75	p90
$E\left[\pi^{p}_{t+4,i\|t} \mid x_{i,t}, z_t\right]$	12-month inflation forecast, 1st survey	3.006	3.524	4.167	4.457	4.623	3.209	3.427	3.525	4.324	5.070
$E\left[\pi^{p}_{t+6,i\|t+2} \mid x_{i,t+2}, z_{t+2}\right]$	12-month inflation forecast, 2nd survey	2.850	3.305	3.772	4.093	4.266	3.120	3.313	3.403	4.016	4.730
β	weight for lifetime inflation	0.050	0.112	0.290	0.594	0.800	0.001	0.004	0.096	0.251	0.401
$(1-\beta)$	weight for public information	0.200	0.406	0.710	0.888	0.950	0.599	0.749	0.904	0.996	0.999
θ	updating speed for life AR(1) inflation	3.430	3.829	3.984	4.096	4.533	4.134	4.161	4.190	4.219	4.249
$\sigma_{u_i^1}$	heterogeneity of idiosyncratic info, 1st survey	2.790	3.206	3.786	4.510	5.248	2.039	2.429	3.051	3.962	5.044
$\sigma_{u_i^2}$	heterogeneity of idiosyncratic info, 2nd survey	2.628	3.014	3.526	4.152	4.769	1.985	2.335	2.908	3.697	4.629
λ	persistence of idiosyncratic information	0.264	0.284	0.308	0.330	0.350	0.268	0.292	0.321	0.354	0.393

Table 3: Mean process of the inflation expectations learning model (with attrition weights)

	1 year ahead inflation expectations				5-10 year ahead inflation expectations			
	w/ time dummies		w/ SPF forecasts		w/ time dummies		w/ SPF (1 yr / 10 yr)	
Variables	Coef	Std-error	Coef	Std-error	Coef	Std-error	Coef	Std-error
		z_t					z_t	
time dum.	yes		no		yes		no	
SPF-median			0.031	0.019*			0.833 / 0.877	0.030 / 0.051***
constant	6.522	0.269***	4.379	0.097***	8.726	0.107***	1.322	0.136***
		z_{t+2}					z_{t+1}	
time dum.	yes		no		yes		no	
SPF-median			0.081	0.018***			0.670 / 0.672	0.026 / 0.045***
constant	6.396	0.253***	3.792	0.076***	7.425	0.112***	1.705	0.119***
		α_β					α_β	
Female	-0.756	0.088***	-1.307	0.096***	-0.657	0.051***	-1.278	0.145***
Asian	0.370	0.246	0.156	0.275	-0.208	0.136	-0.853	0.501*
Black	-0.550	0.132***	-0.689	0.169***	-0.382	0.076***	-0.727	0.315**
Hispanic	-0.587	0.166***	-0.833	0.233***	-0.655	0.090***	-1.155	0.527**
Young	0.523	0.097***	0.292	0.148**	-0.614	0.103***	-0.644	0.200***
Mid-aged	0.181	0.083**	-0.101	0.119	-0.586	0.071***	-0.876	0.145***
low-income	-0.904	0.103***	-1.373	0.128***	-0.469	0.057***	-1.259	0.275***
mid-income	-0.365	0.078***	-0.536	0.093***	-0.144	0.047***	-0.266	0.121**
education	0.205	0.019***	0.204	0.020***	0.098	0.010***	0.130	0.028***
1981-85	-1.211	0.246***			1.471	0.594**		
1986-90	-1.404	0.449***	0.838	0.197***	1.300	0.725*	14.383	2.653***
1991-95	2.473	0.208***	2.812	0.200***	5.546	0.395***	17.886	0.492***
1996-00	2.082	0.203***	2.750	0.194***	3.513	0.460***	17.892	0.513***
2001-05	1.414	0.215***	2.162	0.197***	2.306	0.464***	17.528	0.500***
2006-09	-0.259	0.212	-0.723	0.265***	-15.844	2.089***	-5.001	2.037**
constant	-3.483	0.327***	-3.839	0.366***	-3.429	0.416***	-19.268	0.674***
N	71,266		61,325		47,106		45,780	

***, **, * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 4: Updating of Inflation Life Experience (with attrition weights)

	1 year ahead inflation expectations				5-10 year inflation expectations			
	w/ time dummies		w/ SPF forecasts		w/ time dummies		w/ SPF (1 yr / 10 yr)	
Variables	Coef	Std-error	Coef	Std-error	Coef	Std-error	Coef	Std-error
		θ					θ	
SPF-IQR			0.001	0.093			-0.034 / 0.033	0.044 / 0.080
Female	0.074	0.338	0.119	0.280	0.330	0.754	0.031	0.271
Asian	0.025	0.369	0.059	0.386	-0.117	0.404	0.007	0.041
Black	-0.180	0.285	0.074	0.193	-0.298	0.779	0.012	0.109
Hispanic	0.050	0.167	0.104	0.214	-0.223	0.449	0.002	0.036
education	-0.035	0.342	0.006	0.383	-0.024	0.496	-0.006	0.173
1981-85	-0.170	0.446			-0.827	0.968		
1986-90	0.029	0.288	0.059	0.409	-0.104	0.330	-0.012	0.033
1991-95	0.515	0.366	-0.182	0.335	0.497	0.630	-0.012	0.138
1996-00	0.126	0.400	0.574	0.286**	0.701	0.534	-0.022	0.081
2001-05	-0.274	0.240	-0.624	0.269**	-0.162	0.568	0.056	0.156
2006-09	-0.212	0.383	0.018	0.150	0.000	0.164	0.000	0.000
constant	2.836	0.388***	3.009	0.717***	1.702	0.576***	4.254	0.165***

***, **, * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 5: Unobserved Heterogeneity of inflation expectations (with attrition weights)

	1 year ahead inflation expectations				5-10 year inflation expectations			
	w/ time dummies		w/ SPF forecasts		w/ time dummies		w/ SPF (1 yr / 10 yr)	
Variables	Coef	Std-error	Coef	Std-error	Coef	Std-error	Coef	Std-error
		α_{u^1}					α_{u^1}	
Female	0.191	0.008***	0.200	0.009***	0.242	0.011***	0.251	0.011***
Asian	0.092	0.028***	0.096	0.033***	0.127	0.041***	0.126	0.038***
Black	0.217	0.012***	0.217	0.014***	0.263	0.015***	0.267	0.019***
Hispanic	0.191	0.020***	0.189	0.018***	0.199	0.024***	0.219	0.024***
Young	0.045	0.011***	0.056	0.011***	0.115	0.015***	0.128	0.016***
Mid-aged	-0.001	0.011	0.005	0.010	0.037	0.013***	0.045	0.014***
Low-income	0.141	0.013***	0.144	0.012***	0.194	0.015***	0.197	0.016***
Mid-income	0.055	0.012***	0.058	0.012***	0.082	0.015***	0.082	0.014***
education	-0.038	0.001***	-0.039	0.002***	-0.051	0.002***	-0.052	0.002***
1981-85	0.104	0.013***			0.066	0.033**		
1986-90	-0.095	0.018***	-0.153	0.017***	-0.160	0.039***	-0.167	0.026***
1991-95	-0.079	0.020***	-0.117	0.020***	-0.259	0.039***	-0.277	0.043***
1996-00	-0.253	0.024***	-0.285	0.020***	-0.515	0.040***	-0.491	0.044***
2001-05	-0.193	0.023***	-0.212	0.024***	-0.541	0.041***	-0.492	0.044***
2006-09	-0.069	0.024***	-0.101	0.020***	-0.473	0.042***	-0.442	0.046***
π_{t-1}	0.026	0.002***	0.022	0.003***	0.019	0.003***	0.023	0.004***
$\|\pi_{t-1} - \pi_{t-2}\|$	0.060	0.008***	0.076	0.007***	0.035	0.011***	0.028	0.011***
SPF-IQR			0.103	0.020***			0.135 / 0.210	0.027 / 0.036***
constant	1.631	0.026***	1.612	0.037***	1.851	0.055***	1.715	0.058***
		α_{u^2}					α_{u^2}	
Female	0.194	0.008***	0.203	0.009***	0.237	0.010***	0.241	0.012***
Asian	0.169	0.035***	0.173	0.039***	0.106	0.035***	0.101	0.040**
Black	0.171	0.013***	0.175	0.017***	0.250	0.018***	0.253	0.020***
Hispanic	0.138	0.021***	0.133	0.019***	0.160	0.029***	0.168	0.026***
Young	0.042	0.012***	0.042	0.013***	0.084	0.017***	0.089	0.018***
Mid-aged	0.011	0.010	0.008	0.010	0.006	0.015	0.007	0.016
Low-income	0.144	0.014***	0.140	0.014***	0.206	0.019***	0.205	0.018***
Mid-income	0.051	0.012***	0.050	0.015***	0.095	0.016***	0.095	0.016***
education	-0.036	0.002***	-0.038	0.002***	-0.057	0.002***	-0.058	0.003***
1981-85	0.051	0.018***			-0.066	0.036*		
1986-90	-0.110	0.021***	-0.117	0.017***	-0.280	0.044***	-0.190	0.029***
1991-95	-0.142	0.026***	-0.126	0.019***	-0.351	0.047***	-0.281	0.047***
1996-00	-0.244	0.024***	-0.233	0.021***	-0.555	0.047***	-0.465	0.048***
2001-05	-0.173	0.026***	-0.168	0.022***	-0.584	0.047***	-0.476	0.047***
2006-09	-0.028	0.028	-0.064	0.018***	-0.474	0.049***	-0.374	0.049***
π_{t-1}	0.029	0.002***	0.014	0.004***	0.020	0.004***	0.022	0.005***
$\|\pi_{t-1} - \pi_{t-2}\|$	0.064	0.007***	0.061	0.009***	0.029	0.012**	0.026	0.012**
SPF-IQR			0.164	0.023***			0.056 / 0.110	0.031* / 0.042***
constant	1.491	0.034***	1.452	0.040***	1.906	0.060***	1.769	0.064***
		α_{λ}					α_{λ}	
Female	0.006	0.020	0.006	0.021	-0.072	0.024***	-0.062	0.027**
Asian	0.007	0.098	-0.018	0.104	-0.178	0.076**	-0.181	0.081**
Black	0.003	0.033	0.017	0.035	-0.003	0.042	0.013	0.046
Hispanic	0.062	0.056	0.077	0.060	0.005	0.062	0.062	0.059
Young	-0.042	0.032	-0.067	0.032**	0.052	0.040	0.070	0.042*
Mid-aged	0.019	0.027	0.002	0.030	0.074	0.033**	0.078	0.035*
Low-income	-0.019	0.034	-0.022	0.034	-0.065	0.039*	-0.063	0.040
Mid-income	0.017	0.027	0.002	0.031	-0.076	0.033**	-0.081	0.035**
education	-0.003	0.004	-0.005	0.005	-0.002	0.006	-0.005	0.006
1981-85	0.051	0.057			-0.028	0.121		
1986-90	0.018	0.058	-0.020	0.038	0.006	0.143	0.036	0.074
1991-95	0.009	0.072	0.018	0.048	-0.213	0.135	-0.071	0.119
1996-00	-0.043	0.078	-0.026	0.052	-0.191	0.137	-0.090	0.120
2001-05	-0.067	0.077	-0.050	0.051	-0.192	0.135	-0.112	0.120
2006-09	-0.007	0.079	0.010	0.052	-0.095	0.144	-0.015	0.124
π_{t-1}	0.017	0.006***	0.036	0.010***	0.015	0.010	0.003	0.013
$\|\pi_{t-1} - \pi_{t-2}\|$	-0.040	0.021*	-0.044	0.021**	-0.069	0.026***	-0.063	0.027**
SPF-IQR			0.083	0.055			0.023 / -0.098	0.074 / 0.090
constant	0.633	0.104***	0.570	0.096***	0.853	0.153***	0.865	0.155***

***, **, * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 6: Correlates of Income Growth Expectations, and Changes in Income Expectations

	Income Expectations		Absolute change in income expectations
	1st Survey	2nd Survey	
	(1)	(2)	(3)
Female	-1.51***	-1.62***	-0.44***
	(0.12)	(0.13)	(0.14)
Asian	0.71	0.17	-0.56
	(0.50)	(0.53)	(0.54)
Black	0.51**	0.65***	0.011
	(0.23)	(0.25)	(0.26)
Hispanic	0.33	0.94***	-0.14
	(0.33)	(0.35)	(0.37)
Young[a]	8.62***	9.06***	7.67***
	(0.19)	(0.21)	(0.223)
Mid-age	4.44***	4.64***	4.40***
	(0.16)	(0.18)	(0.19)
Lowest Income tercile	3.25***	3.13***	2.19***
	(0.20)	(0.22)	(0.23)
Middle Income tercile	0.76***	0.65***	0.023
	(0.17)	(0.182)	(0.19)
Education	0.65***	0.63***	0.35***
	(0.027)	(0.029)	(0.031)
Inflation exp in 1st survey	0.030***	-	-
	(0.010)		
Inflation exp in 2nd survey	-	0.036***	-
		(0.012)	
Actual change in income between surveys (in 000s)	-	-	-0.010***
			(0.0022)
Abs Change in inflation exp between surveys	-	-	0.19***
			(0.013)
Realized change in inflation between surveys	-	-	-0.12
			(0.074)
Constant	-7.91***	-8.02***	-1.79***
	(0.40)	(0.43)	(0.47)
Observations	71194	65510	55277
R-squared	0.051	0.054	0.033

OLS estimates of income growth expectations reported of a regression onto various demographics.
Standard Deviations in Parentheses. ***, **, * denote significance at the 1, 5, and 10 percent levels, respectively.