Inflation Experience and Expected Inflation Bias*

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Preliminary. Do not circulate.

Abstract

We empirically quantify to what extent individuals' experienced inflation affect their inflation expectations based on the Michigan Survey of Consumers. To summarize individuals' life-time inflation experience, we build frequency distributions consist of individuals' experienced inflation and estimate a functional regression model that connects inflation expectation of respondents to the distributions reflecting their inflation experiences. We find that individuals expect higher inflation when they have faced higher actual inflation more often during their life-time. This remains intact even if we control the average life-time experienced inflation and heterogeneity in demographic characteristics such as income, education level and gender of respondents. A counterfactual analysis shows that realized inflation that exceeds 2% since March 2021 has considerably increased inflation expectations and that the contribution of realized high inflation to one-year ahead inflation expectations in July 2022 is about 0.6 to 0.7%p.

Keywords: Inflation Expectations, Expectation Formation, Functional Regression
JEL Classification: C21, E31, E71

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1 Introduction

"An entire generation of young adults has grown up since the mid-1960's knowing only inflation, indeed an inflation that has seemed to accelerate inexorably. In the circumstances, it is hardly surprising that many citizens have begun to wonder whether it is realistic to anticipate a return to general price stability, and have begun to change their behavior accordingly. - Volcker (1979)"

Recently, the US economy has witnessed unusually inflation surge which was last seen about more than forty years ago. At the same time, expected inflation is also rising and remains at higher levels especially inflation expectations surveyed general public. This situation raises important questions related to the future developments of expected and realized inflation, the cost of disinflation, and the ways that central banks should take to tame inflation and to re-gain credibility on their commitment on price stability. Among these utmost important questions, this research investigates long-term influences of high inflation experience on future inflation by analyzing the impacts of individuals' inflation experience on their expected inflation.

We focus on the roles of experienced inflation and expected inflation in shaping inflation dynamics for following reasons. First, the growing literature on inflation expectations suggests that full information rational expectations (FIRE, hereafter) which are widely assumed in a standard macroeconomic analysis are not supported by empirical evidence (Coibion and Gorodnichenko, 2015a) and that individual inflation experience affects not only on perception of current inflation, but also in inflation expectations formation.[1] If economic agents have full information and unlimited information processing capacity, as are assumed under FIRE, individual inflation experience will not affect its future expected inflation because what matters for expectation formation is future developments of the state of the economy, not past inflation experienced. That is, even if two households have undergone different past inflation, they should predict the same inflation in the future as long as FIRE is satisfied. However, any deviation from FIRE leaves experienced inflation a room for manipulating inflation expectations. When information is not complete, individuals' experienced inflation can serve as a noisy signal of aggregate inflation and can feed into formation of future inflation expectations. Similarly, inattention and cognitive constraints would make it difficult for the general public to form accurate expected inflation. For these reasons, the idea that individuals' personal inflation experiences play an important role in shaping inflation expectations is widely accepted not only in academic research, but also in policy discussions

[1] See Coibion et al. (2018) and Binder and Kamdar (2022) for the recent survey related to this matter.

nowadays (Schnabel, 2022; Malmendier and Nagel, 2016).

Second, accounting for inflation expectations is crucial in analyzing inflation dynamics as inflation expectations are an important driver in inflation (Powell, 2019).[2] If inflation expectations of private agents, such as households and firms increase, the possibility of persistently higher inflation will rise (Binder and Kamdar, 2022). In an empirical study, it is also found that shocks to inflation expectations, especially long-term expectations, persistently affect actual inflation (Clark and Davig, 2008). In the historical perspective, it is well known that the high inflation period of the 1970s and the following disinflation emphasized the importance of anchoring expected inflation to maintain stable inflation. More recently, Coibion and Gorodnichenko (2015b) provide an explanation regarding 'missing disinflation' during the Great Recession based on the rise in public inflation expectations between 2009 and 2011. Hence, we find it worthwhile to examine how inflation experience shapes inflation expectations.

In this research, we quantify to what extent individuals' experienced inflation affect their inflation expectations to investigate long-term influences of individuals' inflation experience on future inflation using 535 waves of monthly survey with more than 250,000 respondents from the Michigan Survey of Consumers (MSC). To summarize and to incorporate individuals' life-time inflation experience in a tractable way, we build frequency distributions consist of individuals' monthly experienced inflation from the age of 15 to the date of survey conducted. Then, we estimate a functional regression model that connects inflation expectation of respondents to the distributions reflecting their inflation experiences. In this paper, we do not attempt to model how individuals form their inflation expectations. Rather, we empirically test the relevance of experienced inflation in forming inflation expectation.

First, we find that individuals' inflation experiences affect their inflation expectations. In particular, the estimated coefficient function implies that individuals expect higher (lower) inflation in general in a year ahead when they face actual inflation approximately 2% (yoy) or more (less). This influence remains intact even if we control the average life-time experienced inflation of individual and heterogeneity in demographic characteristics such as income, education level and gender of respondents. Therefore, individuals inflation experience create upward or downward pressure, depending on their life-time experience, that is not explained by macroeconomic developments or other cross-sectional heterogeneity. We label this part of individual inflation expectations as expected inflation bias. Second, a counterfactual analysis which is devised to display the economic significance of the role of experienced inflation shows that realized inflation that exceeds the 2% inflation target of

[2] In the closely related literature, Binder and Kamdar (2022) and Ang et al. (2007) show that using inflation expectations is one of the best to predict actual inflation.

the Federal Reserve since March 2021 has increased inflation expectations considerably and the size of impact also shows a rising trend. For instance, the contribution of realized high inflation since March 2021 to one-year ahead inflation expectations in July 2022 is about 0.6 to 0.7%p. Given that the median expected inflation from 2010 to 2020 is around 2.89% and that the influence of experience survives throughout individual life-time, this impact can be considered economically significant. Lastly, we find a weak support for the finding in Malmendier and Nagel (2016) that individuals lose their distant memory implied by their learning from experience model. In particular, even when we randomly drop individuals' inflation experience with higher dropping probability for more distant experienced inflation, the explanatory power of the model does not deteriorate. That is, omitting distant memory does not affect the impact of inflation experience as a whole on inflation expectations.

This article primarily contributes to the discussion on the impact of heterogeneous attributes of individuals, including experienced inflation, on expected inflation. Perhaps the most closely related previous study is Malmendier and Nagel (2016) which finds that individuals put a higher weight on realizations of inflation experienced during their life-times compared with other available historic data when forming inflation expectations based on MSC.[3] Similarly, Cavallo et al. (2017) also document that consumers rely heavily on their experienced price changes when forming their inflation expectations based on the survey experiment.[4] While these studies investigate the influence of experienced inflation on inflation expectations through the lens of a specific learning rule, we directly analyze the impact of experience as a whole on expectations.

Bryan and Venkatu (2001) report that women tend to have higher inflation expectations even after controlling for individual heterogeneity, such as race, education, marital status, income and age and Bruine de Bruin et al. (2010) similarly document that higher inflation expectations have been reported by individuals who are female, poorer, single and less educated. In this paper, we also find supporting evidence on these findings even if we control experienced inflation either.

In this paper, we provide a novel application of the technique of functional data analysis (FDA) to the problem of individuals' inflation expectations formation. FDA is adequate to the analysis of big data such as the sets of distributions which are infinite dimensional objects (Tsay, 2016). There have been some previous studies that apply FDA in macroeconomic analyses related to inflation. For instance, Meeks and Monti (2019) estimate a New Keyne-

[3] In a related context, Malmendier et al. (2021) find that the FOMC members with higher inflation experiences are significantly more likely to forecast higher inflation and to cast a hawkish dissent. This finding indicates strong and long-lasting effects of personal inflation experiences even among experts.

[4] In a related study, Georganas et al. (2014) find that consumers' perceptions of aggregate inflation are systematically biased toward the perceived inflation rates of the frequently purchased items.

sian Phillips curve while exploiting the heterogeneity in inflation expectations. Chaudhuri et al. (2016) develop a functional autoregressive model to the density forecasting analysis of national inflation rates using sectoral inflation rates in the UK. Chang et al. (2022) examine how macroeconomic shocks affect the household inflation expectations distribution. To the best of our knowledge, this is the first attempt to analyze the role of life-time experienced inflation on inflation expectations formation based on FDA.[5]

This paper is organized as follows. Section 2 introduces the empirical framework and data used in the analysis. Section 3 provides the main findings of this research. Finally, Section 4 concludes.

2 Empirical Framework

2.1 Data

The primary data set we employ in this research is the Michigan Survey of Consumers (MSC) which is the most widely used survey for general public that contains inflation expectations for a long horizon. In particular, we use the monthly report which is available since January 1978. The availability of older vintage data is quite appealing in this study as this provides more heterogeneity in individuals' inflation experience. For instance, some respondents had experienced deflation during the Great Depression periods while some other respondents only had lived high inflation periods in 70s among the survey respondents in 1978. The survey asks questions about 'prices in general' without specifying a particular inflation measure. In particular, it asks respondents to report their point forecast for prices changes over the following year.[6]

One caveat applies, however. While MSC provides rich cross-section data available for a long periods, this is repeated cross-sectional data, not panel data as the respondents rotate and this makes it impossible to track the responses of identical individual. Hence, this feature limits the econometric methodology to a pooled regression, rather than a panel regression.

Given the data, the next step required is to transform individuals' histories of experienced inflation which are observed discretely into continuous frequency distribution functions as dealing with functions is a good way to overcome the problem of dimensionality while preserving rich information (Meeks and Monti, 2019). To do so, we collect the time series of

[5]There are also previous studies that apply FDA to macroeconomic analyses. Among others, Chang et al. (2021a) develops and applies an econometric tool that provides evidence about the interaction of distributional and aggregate dynamics.

[6]The survey also asks to report expected inflation for next five years. However, we do not use five-year ahead inflation expectations in this research as this data has become available since 1990 in monthly frequency.

changes in consumer price index for the last 12 months ranging from the month that the respondent became 15-year old to the month of the survey conducted for each respondent in each month. Then we obtain the frequency distribution for each respondent-month pair by applying Kernel density estimation to the histogram of the collected monthly year-over-year CPI inflation. Therefore, the distributions derived above contain information about individuals' life-time inflation experience reported over about 45 years.[7] Finally, we obtain centered distributions by subtracting the median distribution which is derived by taking the point-wise median among all distributions as similar in Meeks and Monti (2019).

2.2 Model

To investigate to what extent individuals' inflation experiences affect their expected inflation, we implement the functional regression model given by

$$\pi^e_{it} = d_t + \int_a^b \beta(r) x_{it}(r) dr + z_{it} + e_{it} \tag{1}$$

where i and t represent the index for survey respondents and the date that the survey is reported. π^e_{it} is the expected price changed for the next 12 months reported by a respondent i at time t. d_t is the time dummy that captures macroeconomic developments which are common for all respondents at time t. x_{it} is a functional regressor with functional regression coefficient β. In this research, x_{it} is a frequency distribution of experienced monthly inflation of a respondent i constructed at time t.[8] To be specific, the frequency distribution presents frequency of the monthly consumer price index changes over a year experienced by individual i. Each individual's frequency distribution contains monthly CPI inflation time series which starts at the time that individual becomes age 15 through time t. The argument r signifies the level of inflation and a and b are lower and upper bounds of experienced inflation. z_{it} is the vector of additional control variables and e_{it} is the regression error. Finally, β is the regression coefficient function. For the subsequent analysis, we assume that β and x_{it} are all square integrable and are elements in a Hilbert space $\mathbb{H}$.

The connection between a scalar variable (individual's expected inflation) and a functional variable (frequency distribution of individual's experienced inflation) makes Equation 1 an example of a functional linear model (Ramsay and Silverman, 2005).

In this functional regression, the effect of more inflation experienced around r% on ex-

[7]The vintage of actual inflation contained in the data goes back to even early 20th century.

[8]As discussed above, the distributions are centered around the median frequency distribution.

pected inflation can be approximated by

$$\int_{r-\delta}^{r+\delta} \beta(s)ds \tag{2}$$

for small $\delta > 0$ and the coefficient function $\beta(r)$ can be interpreted as the instantaneous effect of experienced inflation on inflation expectations.

The use of the entire set of micro data is important for our empirical strategy. To be precise, we exploit cross-sectional differences of experienced inflation among survey respondents and relates them to the cross-sectional differences of expected inflation. As the method relies on cross-sectional heterogeneity, we are able to include time dummies to control any other time-specific determinants such as macroeconomic conditions of the economy and news regarding the future developments of the economy announced by professional forecasters.

2.3 Estimation

The above equation is not directly estimable as a functional variable is infinite-dimensional object. Hence, it is necessary to summarize the functional variations based their finite-dimensional approximations.

For instance, let (v_i) be an orthonormal basis of a Hilbert space $\mathbb{H}$. Then any $\omega \in \mathbb{H}$ can be represented as

$$\omega = \sum_{i=1}^{\infty} < v_i, \omega > v_i$$

ω can be approximated as

$$\omega \approx \sum_{i=1}^{m} < v_i, \omega > v_i$$

for an appropriately chosen m. We rely on the framework and the theory developed by Chang et al. (2021b) to select an appropriate orthonormal basis and truncation m and to estimate the functional regression model.

Consider a mapping π on $\mathbb{H}$ defined as

$$\pi : \omega \rightarrow \begin{pmatrix} < v_1, \omega > \\ \vdots \\ < v_m, \omega > \end{pmatrix} \tag{3}$$

for any $\omega \in \mathbb{H}$. If $\mathbb{H}_m$ is the subspace of $\mathbb{H}$ spanned by the sub-basis $(v_i)_{i=1}^m$, the mapping π defines an isometry between $\mathbb{H}_m$ and $\mathbb{R}^m$. That is, for any $\omega = \sum_{i=1}^m c_i v_i \in \mathbb{H}_m$, there exists one and only one m-dimensional vector $\pi(\omega) = (c_1, \cdots, c_m)'$ such that

$$||\omega||^2 = ||\pi(\omega)||^2$$

where the norm notations denote the Hilbert space norm in $\mathbb{H}$ for ω, $< \cdot, \cdot >$, on the left-hand side and the usual Eucleadian norm in $\mathbb{R}^m$ for $\pi(\omega)$ on the right-hand side.

Any $\omega \in \mathbb{H}$ can be decomposed into two parts as $\omega = \Pi_m \omega + (1 - \Pi_m)\omega$ where Π_m and $1 - \Pi_m$ are the projection on $\mathbb{H}_m$ and on the orthogonal complement of $\mathbb{H}_m$. In this paper, we approximate a function ω by $\Pi_m \omega$ and then convert it to an m-dimensional vector using the isometry π.

Then, using the notation introduced above, we may rewrite Equation 1 as

$$\pi_{it}^e = d_t + < \beta, x_{it} > + z_{it} + e_{it} = d_t + < \beta, \Pi_m x_{it} > + < \beta, (1 - \Pi_m) x_{it} > + z_{it} + e_{it} \tag{4}$$

where

$$< \beta, x_{it} > = \int_a^b \beta(r) x_{it}(r) dr \tag{5}$$

is a usual inner product defined in $\mathbb{H}$. The approximation error $< \beta, (1 - \Pi_m) x_{it} >$ disappears in the limit as $m \to \infty$. We estimate β by approximating it onto an appropriate subspace spanned by basis $(v_i)_{i=1}^m$ and then applying the mapping $\pi(\cdot)$ defined above to convert functional coefficient and explanatory variable to vectors on the usual Euclidean space $\mathbb{R}^m$. Then, we can estimate the resulting equation by the usual least squares method. Therefore, we can easily estimate Equation 1 once an orthonrmal basis $(v_i)_{i=1}^m$ is fixed.

In this research, we rely on functional principal component analysis (FPCA) for dimension reduction and use the functional principal components as the basis functions as in Lee (2022), Chang et al. (2021b), Meeks and Monti (2019), and Park and Qian (2012). Eventually, we are going to estimate the following pooled regression model:

$$\pi_{it}^e = d_t + \sum_{k=1}^{K} \beta_k s_{kit} + z_{it} + e_{it} \tag{6}$$

where s_{kit} are the principal component scores that can be derived by $s_{kit} = < x_{it}, \mathbf{e}_k >$ for all k, i, and t, and β_k for all k are coefficient to estimate. In the subsequent, we explain how to derive Equation 6.

Let

$$Q = \sum_{i,t} (x_{it} \otimes x_{it}) \tag{7}$$

where $\otimes$ is the tensor product defined in $\mathbb{H}$ which reduces to the outer product when $\mathbb{H}$

is finite-dimensional. In particular, if we denote two functions f and h as long vectors consisting of their values in the ordinate that corresponds to a fine grid in the abscissa, say $\tilde{f}$ and $\tilde{h}$, the tensor product $f \otimes h$ can be interpreted as an outer product $\tilde{f}\tilde{h}'$. The functional principal component analysis is generalized from the ordinary principal component analysis. That is, the functional principal components, $\mathbf{e}_i(\cdot)$, are defined as the eigenfunctions of Q in Equation 7 associated with its largest eigenvalues.

One particularly important advantage of using FPCA is that the principal component functions form the optimal basis in a sense that their linear combination minimizes the integrated square error criterion given below (Meeks and Monti, 2019; Chang et al., 2021b).

$$\sum_{i,t} ISE_{it}^{(K)} = \sum_{i,t} \int \{\hat{x}_{it}^{(K)}(r) - x_{it}(r)\}^2 dr \tag{8}$$

where

$$\hat{x}_{it}^{(K)}(r) = \sum_{k=1}^{K} s_{kit}\mathbf{e}_k(r) \tag{9}$$

subject to the constraint that the principal component functions $\mathbf{e}_i(\cdot)$ satisfy $<\mathbf{e}_i, \mathbf{e}_i>= 1$, for all i and $<\mathbf{e}_i, \mathbf{e}_j>= 0$, for any $i \neq j$.

In addition, using the principal components, which are orthonormal, as the basis functions prevents the omitted variable bias even if we omit $<\beta, (1 - \Pi_m)x_{it}>$ term in Equation 4 which is reproduced below for convenience.

$$\pi_{it}^{e} = d_t + <\beta, \Pi_K x_{it}> + <\beta, (1 - \Pi_K)x_{it}> + z_{it} + e_{it} \tag{10}$$

The frequency distributions, x_{it}, and the coefficient function β can be approximated in terms of linear combinations of eigenfunctions, $\mathbf{e}_i(\cdot)$, truncated at K as below:

$$x_{it}(r) \approx \sum_{k=1}^{K} s_{kit}\mathbf{e}_k(r), \quad \beta(r) \approx \sum_{k=1}^{K} \beta_k \mathbf{e}_k(r)$$

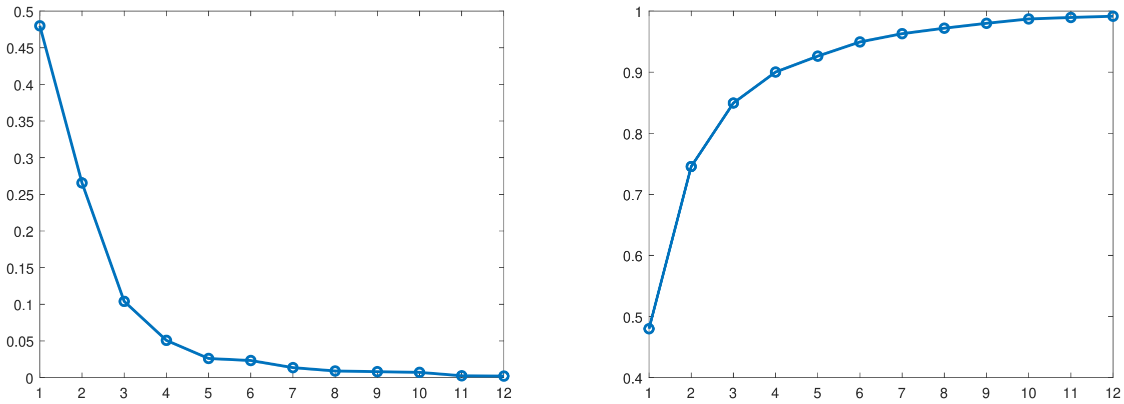
Therefore, the integral term in Equation 1 can be expressed as

$$\int \left(\sum_{k=1}^{K} \beta_k \mathbf{e}_k(r)\right)\left(\sum_{k=1}^{K} s_{kit}\mathbf{e}_k(r)\right) dr = \sum_{k=1}^{K} \beta_k s_{kit} \int \mathbf{e}_k(r)^2 dr = \sum_{k=1}^{K} \beta_k s_{kit}$$

where the second equality comes from the characteristics of orthonormal basis. Then we arrive at Equation 6.

Adding more principal components, increasing K, leads to lower approximation errors.

Based on the scree plot that displays a number of largest normalized eigenvalues associated with each principal component function, we choose $K = 12$ so that the selected eigenfunctions explain more than 99% of of variation in frequency distributions as shown in Figure 1.



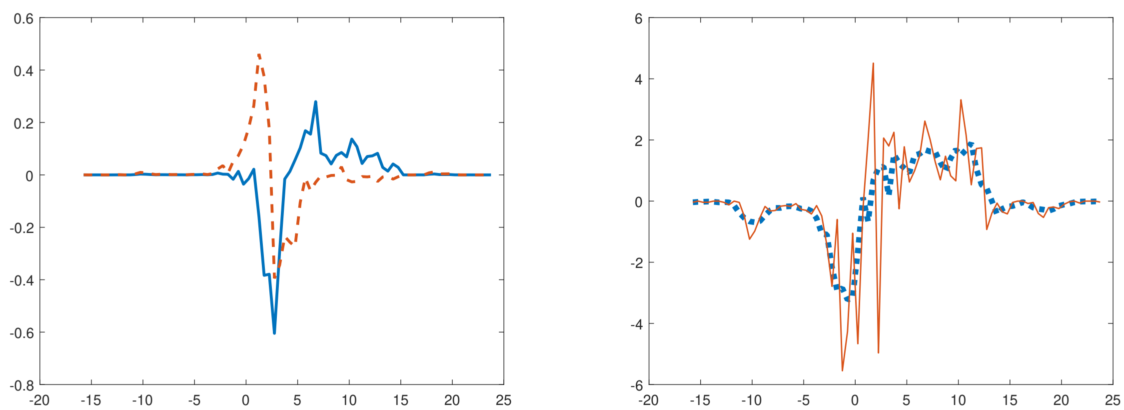
(a) Share of variances

(b) Cumulative share of variances

Figure 1: Shares and cumulative shares of variations in frequency distributions explained by the leading principal component functions

3 Results

3.1 Basis and Estimated Coefficient Functions

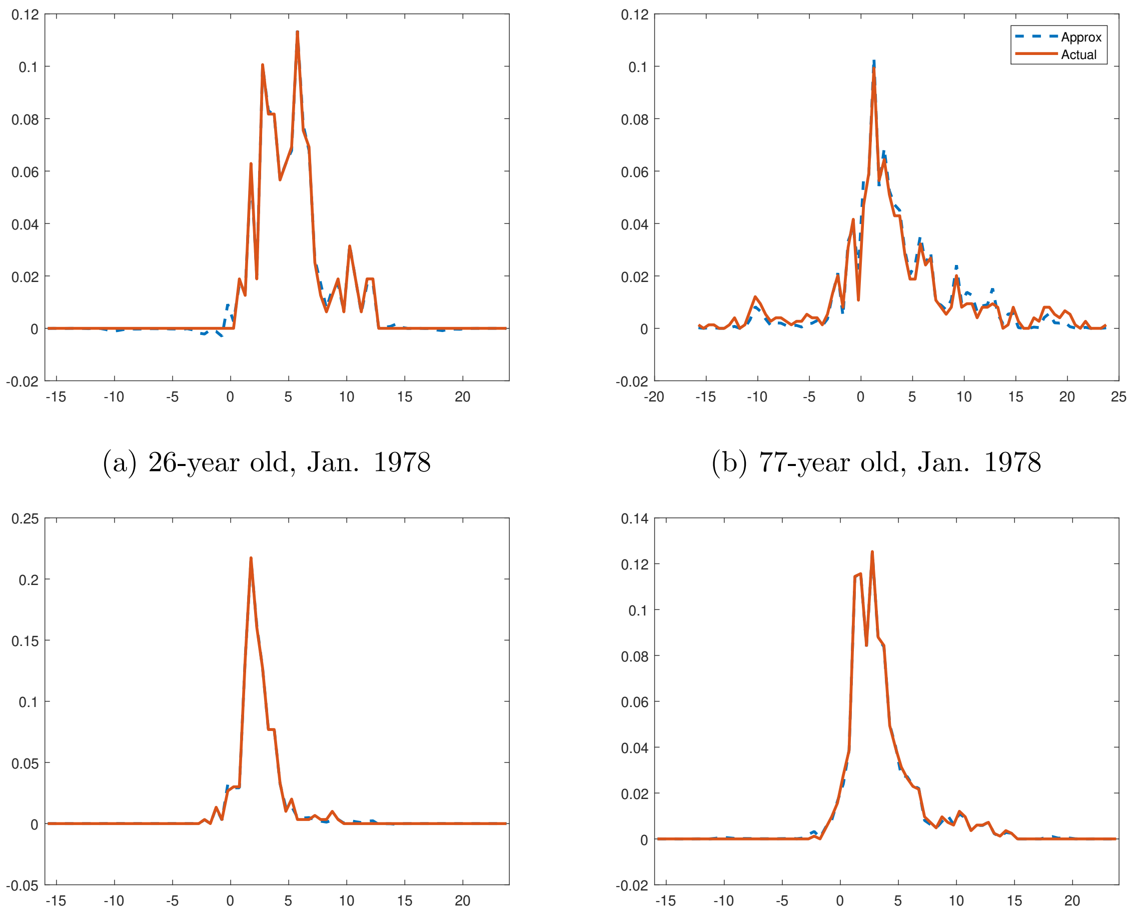


(a) First Two Basis Functions

(b) Estimated Coefficient Function

Figure 2: Basis Functions and Estimated Coefficient Function in the Baseline Specification

Firstly, we report the shapes of the basis functions and the estimated coefficient function (obtained from specification (1) explained below) in Figure 2.[9] The left panel shows the selected eigenfunctions associated with the two largest eigenvalues. The blue solid line and the red dashed line represents the eigenfunction associated with the largest and the second largest eigenvalue, respectively. The right panel presents the estimated coefficient function $\hat{\beta}(r)$ (red solid line). The blue dotted line is the smoothed function of $\hat{\beta}(r)$ that allows a better interpretation. It clearly shows that the coefficient function tends to be positive when inflation is greater than about 2% while it becomes negative otherwise. This can be interpreted that individuals who had experienced higher inflation, say exceeds 2% over the year, more often, they expect higher inflation over the next year given that the coefficient function is indeed statistically significant.



(a) 26-year old, Jan. 1978 (b) 77-year old, Jan. 1978

(c) 39-year old, Jul. 2022 (d) 84-year old, Jul. 2022

Figure 3: Approximations of Frequency Distributions for Selected Respondents

Next, we present the examples of the frequency distributions used in the estimation in

[9]The estimated coefficient functions are qualitatively similar across the regression model specifications. See Figure 5.

Figure 3. To highlight the heterogeneity of inflation experience among the survey respondents, we choose an old and a young respondents from the two different survey waves. In particular, we select January 1978 and July 2022 waves which are the first and the last survey waves used on the estimation. The red solid lines are the actual distributions and the blue dashed lines are the approximated distributions based on the K principal components. Overall, Figure 3 shows that the approximation is quite accurate even for the complex distributions observed in 1978.

Panel (a) shows the frequency distribution of a 26-year old respondent surveyed in Jan. 1978. As the respondent had lived through high inflation period of 70s since age of 15, the distribution is positive in only positive region and has a thick right-tail. On the other hand, an old respondent had very different distribution compared to the young respondent's one as shown in Panel (b). As the respondent had experiences of long deflation periods along with great inflation during the Great Depression, the distribution seems more balanced between positive and negative inflation.

Compared to the respondents surveyed in 1978, the respondents' inflation experience have become more homogeneous as is evident in Panel (c) and (d) due to extended periods with stable low inflation since the Great Moderation. However, the difference is still observed between young and old generations. The respondent reported in Panel (d) experienced the Great Inflation period during 70s and early 80s. Hence, this distribution has a long and thick right-tail which is not clearly shown in the young respondent's one shown in Panel (c).

3.2 Regression Results

	(1)	(2)	(3)	(4)
Dependent variable	year-ahead expected inflation			
Distribution	sig. [0.00]	sig. [0.00]	sig. [0.00]	sig. [0.00]
Average inflation	-	-	-	0.43 (0.00)
Income	-	-	-0.45 (0.00)	-
Female	-	-	0.84 (0.00)	-
College	-	-	-0.47 (0.00)	-
Sample period	Jan. 1978 - Jul. 2022			
Time dummy	Yes	Yes	Yes	Yes
Number of basis	12	12	12	12
R^2	0.42	0.42	0.43	0.42
Number of Obs.	253,846	253,846	253,846	253,846

Table 1: Estimation results

Note: Model (1) represents the baseline specification with only frequency distribution and time dummies. Model (2) is the model with memory loss consideration. Model (3) and (4) show specifications with additional features: individual heterogeneity (income, gender and education) and the average experienced inflation. Parentheses represent p-values for scalar explanatory variables. p-values for F test for the functional explanatory variable appear in brackets.

The primary regression outputs are reported in Table 1. In this analysis, we consider four regression specifications. The first specification in column (1) represents the baseline specification with only frequency distribution and time dummies. The second one in column (2) is the model with memory loss consideration that will be explained in the subsequently. Specifications in column (3) and (4) show the regression with additional features such as individual heterogeneity (income, gender and education) and the average experienced inflation.

The first row denoted as 'Distribution' shows to what extent frequency distributions explain individuals' expected inflation. To establish whether a relationship exists between individuals' inflation expectations and the frequency distributions of individuals' experienced inflation, we test the null hypothesis that $\beta(r) = 0$ for all inflation level r which is equivalent to:

$$H_0 : \beta_1 = \beta_2 = \cdots = \beta_K = 0, \quad H_a : \beta_i \neq 0 \text{ for at least one } i, 1 \leq i \leq K \tag{11}$$

Then, the null hypothesis can be tested using the F-statistic given below (Meeks and Monti, 2019):

$$F = \frac{\mathbf{y}'(\mathbf{P}_X - \mathbf{P}_Z)\mathbf{y}/K}{\mathbf{y}'(\mathbf{I} - \mathbf{P}_X)\mathbf{y}/(N-K-L)} \sim F_{K,N-K-L} \tag{12}$$

where $\mathbf{y}$ is a $(N \times 1)$ column vector that stacks the dependent variable of the regression (individuals' expected inflation). Denoting $\mathbf{M}$ and $\mathbf{Z}$ the $(N \times K)$ matrix of orthogonal principal component scores s_{kit} and the $(N \times L)$ matrix of additional scalar regressors such as time dummies, average experienced inflation, income, gender and education, $\mathbf{P}_X$ and $\mathbf{P}_Z$ are projection matrices defined as

$$\mathbf{P}_X = \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}', \quad \mathbf{P}_Z = \mathbf{Z}(\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{Z}' \tag{13}$$

where $\mathbf{X} = [\mathbf{M} \;\; \mathbf{Z}]$. The p-values for the F-test appear in brackets.

The rows denoted as 'Average inflation', 'Income', 'Female', and 'college' contain estimated parameters for those variables when they are included in the regression. Parentheses represent p-values for those scalar explanatory variables. In the all specifications, the monthly time dummies are included to control the influences from macroeconomic developments or news that can commonly affect all survey respondents as in Malmendier and Nagel (2016).

Overall, it turns out that individuals' inflation experience have a statistically significant impact on their inflation expectations regardless of the specification. For all specifications, the null hypothesis of zero coefficient function can be easily rejected based on the F-test even under 99% confidence level. Given the shape of the estimated coefficient function shown in the right panel of Figure 2, we can conclude that the more high inflation experienced, the higher expected inflation is. That is, individuals' high inflation experiences create a upward pressure on their expected future inflation that we call 'expected inflation bias'. This result is in line with the previous literature such as Malmendier and Nagel (2016) and Cavallo et al. (2017). However, ours differs from those studies as we directly analyze the influence of individual's inflation experience as a whole on inflation expectations formation using a novel empirical framework.

This expected inflation bias survives even when we include additional control variables. First, individuals' average experienced inflation is included in Specification (4). This variable can be considered as the first moment of the functional explanatory variable. The result shows that the average is statistically significant. In particular, if a respondent's average experienced inflation increases by 1%, his inflation expectations for the next year gets 0.43% higher. At the same time, the frequency distribution is still highly significant. This indicates that the distribution as a whole contains a lot larger information than the first moment that is helpful to predict individuals' inflation expectations. This result is similar to that in Meeks and Monti (2019) in which they find that the cross-sectional distribution of subjective inflation expectations gathered from the MSC helps to describe the inflation dynamics using a New Keynesian Phillips curve even if the mean subjective inflation expectations presents in the model.

Second, additional variables that describe respondents' demographic heterogeneity are considered in Specification (3). On the one hand, the result shows that the distribution variable is still significant even after we control various demographic variables. This provides additional evidence on the robustness of our main result. On the other hand, the result indicates that the additional demographic variables are also statistically significant, providing a support to the previous literature that demographics affect inflation expectations formation. In particular, the respondent who earns more income, is a male, and finished college education tends to expect lower inflation. When an individual's income is larger than 100% of the average income, his expected inflation is lower than 0.45% compared to those who earn the average income. In addition, a female respondent tends to report a higher inflation expectations as high as 0.84% on average. Finally, a college graduate expects 0.47% lower inflation on average compared to those who did not finish their college education. These results are in line with those reported in Bryan and Venkatu (2001) and Bruine de Bruin et al. (2010).

3.3 Quantitative Implication: An example of Inflation Surge 2021-22

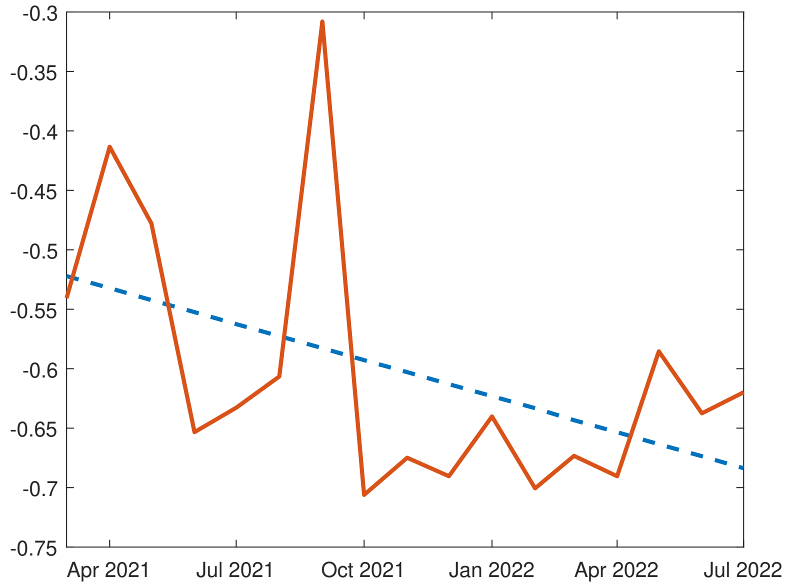


Figure 4: Impact of Inflation Surge 2021-22
Note: The red solid line shows the amount of the median inflation expectations decreases in the counterfactual scenario. The blue dashed line presents the linear trend of the red line.

While it is straightforward to interpret the result qualitatively, using functional coefficient and explanatory variable makes it difficult to measure the quantitative influence of experienced inflation on expected inflation. To overcome this problem and to provide a policy implication, we conduct a counterfactual analysis based on the recent inflation surge episode in 2021-22. To be specific, we compute the counterfactual individuals' expected inflation under the counterfactual scenario that realized inflation has been 2% during Mar. 2021 - Jul. 2022 period. We choose this particular period as this period has revived inflation fear that has been absent for more than several decades since the end of the Great Inflation in early 80s. The specific months are chosen as CPI inflation over a year was higher than 2% during that period.

Figure 4 presents the changes in the median expected inflation under the counterfactual inflation path. It shows a decreasing trend over the period. That is, high inflation experienced during this period has increased inflation expectations considerably and the size of impact magnifies. This result reflects the qualitative result obtained above either. As the period of high inflation gets longer, individuals' experienced inflation now contain more high inflation episodes. Hence, given the positive contribution of the estimated coefficient function in high inflation region, individuals' inflation expectations should have risen. In particular, the contribution of realized high inflation since March 2021 to one-year ahead inflation expectations in July 2022 is about 0.6 to 0.7%p. Given that the median expected inflation from 2010 to 2020 was around 2.89% and that the influence of experience survives throughout individual life-time, this impact can be considered economically significant.

3.4 Additional Discussion on Memory Loss

In Specification (2) in Table 1, we test whether individuals lose their distant memory implied by their learning from experience model as reported in Malmendier and Nagel (2016). This analysis is important not only in theoretical perspective related to learning behavior, but also in policy perspective as the existence of memory loss weakens expected inflation bias. To do so, we randomly drop individuals' inflation experience with higher dropping probability for more distant experienced inflation. In particular, based on the observation in Malmendier and Nagel (2016), it is assumed that the dropping probability decreases by 1/600 per month. Hence, the respondents lose their memories regarding past inflation perfectly in 50 years.[10]

The result seems to weakly support the memory loss found in Malmendier and Nagel (2016). In particular, even when we remove some inflation experiences from the memory, the explanatory power of the model does not deteriorate. That is, omitting distant memory does not affect the impact of inflation experience as a whole on inflation expectations.

4 Conclusion

In this paper, we empirically quantify to what extent individuals' experienced inflation affect their inflation expectations based on a functional regression model that connects inflation expectation of respondents to the distributions reflecting their inflation experiences. We find that individuals expect higher inflation when they have undergone high inflation periods more often during their life-time. This result remains intact even if we control the average life-time experienced inflation and heterogeneity in demographic characteristics such as income, education level and gender of respondents. In a counterfactual analysis that is devised to gauge the quantitative implication of the estimated result, it is shown that realized inflation that exceeds 2% since March 2021 has increased inflation expectations and that the contribution of realized high inflation to one-year ahead inflation expectations in July 2022 is about 0.6 to 0.7%p.

[10]Therefore, memory of experienced inflation at age 15 starts to be removed perfectly when the respondent becomes age 65 as the CPI memory recording begins at age 15.

Our results carry salient policy implications. First, stabilizing expected inflation and inflation becomes difficult when actual inflation deviates away from the target for an extended period as that experience generates expected inflation bias as described above. cohorts that have lived through high inflation periods have higher expected inflation than those who have experienced stable low inflation. This implies that monetary policymakers must consider the risk of inflation expectations becoming unanchored and of inflation remaining elevated for an extended period given the recent increases in expectations and realized inflation. Second, central banks should focus more on the headline inflation. Individuals inflation perception is more closely related to headline inflation measures such as changes in consumer price index, rather than core inflation measures that exclude energy and food price changes which are more relevant for inflation perception of general public (Coibion and Gorodnichenko, 2015b). The result derived in this paper implies that expected inflation may become unanchored even if core inflation remains stable as long as prices of non-core items diverge away from the target and become unstable. Finally, policy analyses based on FIRE models should be interpreted cautiously. Policy institutions around the world including central banks and international organizations, implement policy evaluations based on the large dynamic stochastic general equilibrium models that generally assume full information rational expectations.[11] Because expected inflation depends on past realized inflation for a long period, policy evaluations based on FIRE assumption may overestimate effectiveness of monetary policy. Related to the dispute regarding the cost of disinflation, the outcome derived in this paper suggests that the cost of disinflation may be much higher than previously calculated using the models with FIRE assumption.[12]

[11] There are exceptions. For instance, FRB/US model allows switching to non-rational expectations that compute expectations based on a VAR model other than rational (model-consistent) one.

[12] Similarly, Park (forthcoming) also document that policy evaluations based on FIRE assumption may overestimate the effectiveness of monetary policy as they do not take evolving central bank credibility into account.

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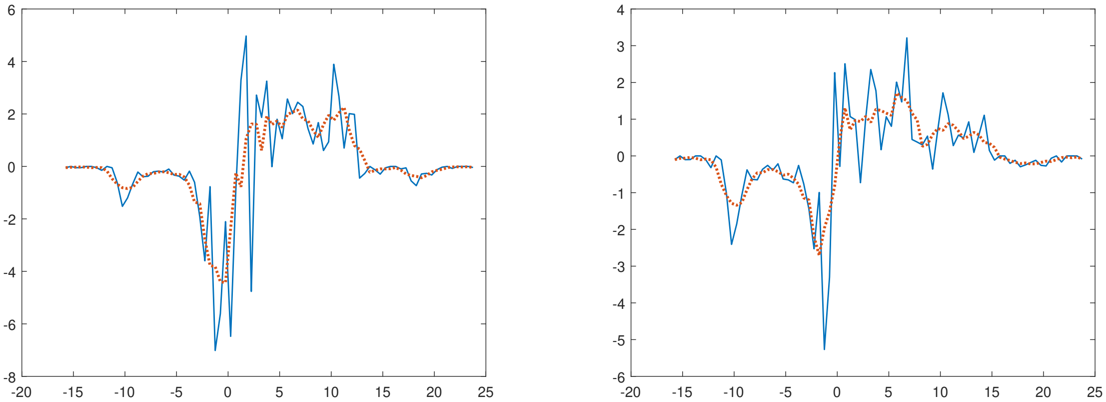
Appendices

A Additional Figures



(a) Estimated Coefficient Function: Additional Heterogeneity

(b) Estimated Coefficient Function: Memory Loss Case

Figure 5: Additional Estimated Coefficient Functions