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The Role of Individual Experience

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Abstract

We explore the implications of heterogeneous, history-dependent inflation expectations in a general equilibrium setting. We propose an experience-based expectations-augmented Kalman filter to represent consumers' heterogeneous inflation expectations, where heterogeneity arises from an anchoring-to-the-past mechanism. Using survey data, we show that the model replicates US consumers' inflation expectations and their heterogeneity across cohorts. We introduce this mechanism into a New Keynesian model and find that heterogeneous expectations anchor aggregate responses to the agents' inflation history, producing sluggish expectations dynamics. Central banks should be active to prevent inflationary episodes that agents will remember far into the future.

JEL classifications: D84, E31, E58, E71
Keywords: Belief formation, Heterogeneous expectations, Survey data, Over-extrapolation

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1 Introduction

Inflation expectations matter for decisions at both the firm and the household levels (Coibion et al., 2023, 2020; Hajdini et al., 2022b). Given their importance, there is a growing interest in measuring them and exploring what determines their formation process. The recent literature shows that individuals form inflation expectations, for instance, based on their recent buying experience (D'Acunto et al., 2021) as well as historical experiences regarding aggregate inflation (Malmendier & Nagel, 2016). While most studies on this topic provide empirical evidence regarding how differences in inflation expectations arise at the individual level and their effects on different micro-level decisions, there is less understanding of the aggregate implications associated with the inflation expectations heterogeneity observed in the data. There is a noticeable gap in the literature between these empirical micro-level findings and macroeconomic models.

This paper aims to fill this gap. First, using new US and international evidence, we show that individuals' inflation expectations depend on their personal history of inflation, confirming the findings that show how inflation history affects inflation expectations (Malmendier & Nagel, 2016; Braggion et al., 2024; Salle et al., 2024).[1] Using detailed micro-level data, we document several key findings: i) inflation expectations are heterogeneous across cohorts, ii) inflation experiences are clustered by age, iii) individual inflation history is positively correlated with inflation expectations, and iv) there are no significant differences between cohorts in updating to current information, once controlling for their own inflation history.

These facts suggest that consumers use their history of inflation to form expectations by positively weighing their past inflationary experiences.[2] To capture this behavior, we propose a model of inflation expectation formation where consumers weigh past experiences. We depart from the full information rational expectations model by presenting a framework where individuals use their past inflation histories and compare them to current information rationally gathered from signals.

[1]While Malmendier & Nagel (2016) rely on data from the University of Michigan's Survey of Consumers (MSC), Sections 3 and 4 of this paper provide external validity to their results by using a different dataset with panel characteristics: the Survey of Consumer Expectations (SCE) from the Federal Reserve Bank of New York. In addition, in Appendix H, we demonstrate that these findings hold at the international level, even after controlling for common cohort characteristics.

[2]This behavior can be interpreted through the lens of the availability bias (Tversky & Kahneman, 1973), where consumers use the available information, in this case, their own experience, to form expectations, potentially overweighing their history instead of using more complex models necessary to form expectations about future economic variables.

Under the proposed framework, inflation expectations have two components: a common forecast made with current, shared information across agents, and an idiosyncratic referential term that depends on individuals' past experiences. We structurally estimate the key parameter governing this expectations-formation process, simulating the history of forecasts consumers would make in the model according to signals associated with their shopping experiences. As all respondents access the same current information, we control for the common forecast component using time-fixed effects. The resulting estimation for the coefficient is negative, implying that consumers positively weigh their inflation history to the detriment of current unexpected news.[3]

We model the shared component following a standard signal-extraction procedure. Based on works exploring reference prices through consumers' shopping experiences (D'Acunto et al., 2021) and recent evidence showing that consumers use certain food prices when forming inflation expectations (D'Acunto & Weber, 2022), we use the lagged inflation rate of the food component of the CPI as a signal of the non-observed aggregate inflation variable.[4] Then, we construct a cohort-specific inflation expectations measure using i) the already computed shared component, ii) an idiosyncratic element related to the inflation history of the cohort, and iii) the coefficient value estimated in the empirical section of the paper.

With our cohort-specific inflation expectations measure, we obtain model-based forecasts that closely match the inflation expectations observed in the data across cohorts and time. Regressing our model-based cohort-specific expectations on the individual expectations observed in survey data delivers a statistically significant coefficient of 1.069. Although the model-based inflation forecasts do not use micro-level information on inflation expectations, they predict consumers' survey data remarkably well. By using these two simple consumer references– shopping experience and history of inflation—we can effectively model survey households' expectations. This paper shows that consumer expectations surveys contain relevant and meaningful information that can be modeled.

As in Bianchi et al. (2021) and L'Huillier et al. (2021), we incorporate our proposed expectation

[3]Notice that this result does not imply that agents cannot overreact to current news. Our empirical exercise demonstrates that the proposed expectation modeling framework explains the heterogeneity observed across cohorts. However, the presence of a common component in the modeling still allows for a common overreaction to some current news.

[4]Our results are robust to using more specific signals, including more narrowly defined components such as CPI's food at home or dairy categories that, according to D'Acunto & Weber (2022), are the prices that US consumers primarily consider when forming inflation expectations.

formation process into a New Keynesian model.[5] Our framework both complements and departs from these prior works. Bianchi et al. (2021) and L'Huillier et al. (2021) rely on a rational expectations operator, such that agents overreact to news in a representativeness heuristic way (Kahneman & Tversky, 1972) and where full information characterizes the most likely scenario.[6] We instead model an experience-based heuristic. We explicitly incorporate agents' history into the model and use it as their referential information in forming expectations. This approach allows us to exploit cohort-specific, time-evolving history and show that consumers use this availability heuristic in their expectation formation process. Hence, agents' inflation experiences are over-sampled (Bordalo et al., 2023) as the past is over-extrapolated (Angeletos et al., 2021).

We then explore the macro implications of this micro-level heterogeneity in expectations, where we allow households to form expectations according to the proposed framework. In our model, while old generations have their expectations shaped mainly by their past, new generations are highly influenced by recent developments. We find that heterogeneous expectations anchor the aggregate inflation and output gap response to agents' history. At the same time, they also increase the duration of the effects of the shocks.[7] After an inflationary shock, the model produces hump-shaped expectations. This reaction is consistent with over-extrapolation, as in Angeletos et al. (2021). Consumers react slowly to the inflationary shock in the first few periods, as they are tied to their reference from the steady state. This first reaction is consistent with randomized controlled trial evidence showing that consumers weigh their priors and do not react one-to-one to current or future inflation news (Weber et al., 2023). After witnessing higher inflation (and new cohorts entering the economy in a high-inflation environment), consumers get tied to this new inflationary reference and over-extrapolate the shock, overreacting in their forecast. From the aggregate results, we infer individual heterogeneous consumption and labor reactions.

We perform an optimal Taylor rule exercise where the central bank seeks to minimize the ex-

[5]Both papers include the diagnostic expectation model proposed by Bordalo et al. (2020) into a Dynamic Stochastic General Equilibrium (DSGE) model. While Bordalo et al. (2020)'s model is an overreaction model, we use and extend their framework to allow for a negative distortion parameter corresponding to the diagnosticity parameter in their case. In the following sections, we detail the microfoundations of our approach. Notice that Bianchi et al. (2021) and L'Huillier et al. (2021) solution methods also apply to our type of model.

[6]See Benjamin (2019) for a discussion on the implications of the assumptions of the diagnostic expectations model.

[7]While we could incorporate other forms of heterogeneity and biases related to experience-based mechanisms on the firm or the government side of the economy, in this paper, we introduce non-rational heterogeneous expectations only at the household level. We opt for this option mainly because of data availability motives.

pected volatility of the economy by optimally selecting the parameters of a standard Taylor rule. When we allow for heterogeneous expectations in the model, agents exhibit long memories and remember current shocks far into the future. This persistence influences the optimal monetary policy response. After a negative supply shock or a positive demand shock, the optimal response of the central bank is to be more active compared to the benchmark of full information rational expectations. With a more aggressive response, the monetary authority prevents inflation from rising and prevents agents from incorporating a high inflation episode into their memories.

This paper has important implications for explaining past inflation dynamics and learning about the future consequences of recent economic developments. Since 2021, a new cohort of consumers worldwide has been experiencing relatively high inflation for the first time. According to our findings, this high-inflation episode could have consequences in the medium run since consumers incorporate this episode into their history of inflation, adjusting future expectations.[8] Our framework shows that accommodating high inflation produces higher and more persistent inflation expectations, which in turn generate a higher and more persistent inflation rate in the future. Our findings help us understand why inflation has persisted in the past, why consumers' inflation expectations are persistent today, what to expect from episodes of unusually high inflation, and how central banks should react to such episodes.

The rest of the paper is organized as follows. Section 2 discusses recent works on the topic. Section 3 provides empirical results regarding consumers' heterogeneity in inflation expectations. We empirically model inflation expectations depending on the history of inflation experienced by cohorts in Section 4. Section 5 discusses the aggregate implications arising from heterogeneous inflation expectations. Section 6 shows results obtained for an optimal Taylor rule exercise. We analyze the high-inflation episode of 2021 through the lens of our theoretical model in Section 7. Finally, Section 8 concludes.

[8] In recent work, Salle et al. (2024) finds that people use their lifetime inflation experiences to form expectations. These implications can also have long-run effects, as high inflation expectations can affect future generations as well, as shown in Braggion et al. (2024).

2 Literature Review

Although a large body of literature documents significant heterogeneity in inflation expectations across firms (Coibion et al., 2018) and households (Hajdini et al., 2022c), fewer works incorporate these findings into macroeconomic models to explore their aggregate implications. Afrouzi (2020) shows that heterogeneity in firm-level inflation expectations amplifies monetary non-neutrality. Our paper focuses on the heterogeneity of expectations from the household side and explores their aggregate implications.

Malmendier & Nagel (2016) document that households present learning from past inflation mechanisms when forming inflation expectations. They use adaptive learning to approximate cohorts' heterogeneous inflation expectations. Instead, we opt for a constant forecasting revision Kalman filter model, as our empirical evidence suggests. While we also rely on constant gain, the selection of parameters in our framework is primarily data-driven. Our approach allows us to incorporate a current shared forecast component using a standard Kalman filter and a structure incorporating past inflation experiences. In Appendix I, we show that our model successfully predicts individual inflation expectations, even after controlling for the individual inflation expectations implied by Malmendier & Nagel (2016). Salle et al. (2024) also finds that people use their lifetime inflation experiences to form expectations.

Our modeling follows Malmendier & Nagel (2016) by incorporating a method consistent with the availability heuristic by using past experiences and allowing agents to use the new information to form expectations. Kuchler & Zafar (2019) show that consumers use their personal experience to form expectations. Following recent evidence showing that agents form expectations based on their shopping experiences (D'Acunto et al., 2021; D'Acunto & Weber, 2022), we use a Kalman filter approach where agents get signals from current food prices to model the expectation formation process. In addition, our approach is flexible enough to be incorporated into a general equilibrium framework like some other recent studies (Bianchi et al., 2021; L'Huillier et al., 2021).

In this paper, we focus on how a single generation is affected by past inflation. Our findings emphasize medium-run consequences and the implications for monetary policy responses, given these intertemporal costs. However, recent evidence suggests that the influence of inflationary experiences can extend beyond the directly affected generation. More precisely, Braggion et al. (2024)

shows that the experience of hyperinflation in Germany during the 1920s had lasting effects on the inflation expectations of subsequent generations. While our model does not explicitly account for the intergenerational transmission of beliefs, the findings from Braggion et al. (2024) highlight the need for monetary authorities to be even more aware of how high inflation can shape expectations in present and future cohorts.

Households' inflation expectations depend on more than just past experiences. Empirical evidence shows that they also respond to other variables, including professional forecasts (Carroll, 2003), price exposure (D'Acunto et al., 2021), socioeconomic characteristics (D'Acunto et al., 2022b), and local environment (D'Acunto & Weber, 2022), among others.[9] This deviation from full information rational expectations and the presence of heterogeneity are particularly relevant, as inflation expectations influence a wide range of households' decisions (Roth & Wohlfart, 2020; Hajdini et al., 2022b). For instance, Malmendier & Nagel (2016) show that inflation expectations influence individuals' financial decisions, while Coibion et al. (2023) confirm that inflation expectations play a significant role in shaping households' spending decisions, particularly on durable goods. Additionally, Coibion et al. (2022) also find that changes in inflation expectations lead to corresponding variations in consumer spending. Similarly, D'Acunto et al. (2022a) show that higher inflation expectations induced by unconventional fiscal policy can significantly influence consumer spending behavior. While our paper focuses on one source of heterogeneity to explore its macroeconomic implications, it is important to recognize that other forms of heterogeneity may have different implications for the broader economy.

Our model closely follows the literature enclosing behavioral New Keynesian models such as those proposed by Branch & McGough (2010), Gabaix (2020), Gáti (2020), and Pfäuti & Seyrich (2023), as well as behavioral overlapping generations models as in Adam (2003). By considering overlapping generations in a New Keynesian context, we relate to Gali (2021). Bardóczy & Velásquez-Giraldo (2024) studies the aggregate and distributional consequences of cohort heterogeneity, focusing on their life-cycle decisions in a heterogeneous agents model. Our model also uses a setting similar to that in L'Huillier et al. (2021) and Bianchi et al. (2021) to incorporate a

[9] Although our focus is on the household side of the economy, research has shown that professional forecasters also depart from rational expectations (Coibion & Gorodnichenko, 2015; Bordalo et al., 2020; Gáti, 2020). On the other hand, due to limited data availability, evidence on firms' expectations remains notably scarce (Candia et al., 2022b).

behavioral bias into a general equilibrium model, which in their case is diagnostic expectations (Bordalo et al., 2020).

3 Empirical Facts

This section reviews some empirical facts related to heterogeneous inflation expectations at the household level. We show how these expectations are correlated with past experiences regarding the aggregate inflation variable. These empirical facts motivate and guide the theoretical model of the paper.

Malmendier (2021) and D'Acunto et al. (2022b) document that consumers' experiences influence their inflation expectations. Thus, individual experiences are a source of expectation heterogeneity. This paper focuses on how aggregate inflation experiences influence idiosyncratic inflation expectations, as in Malmendier & Nagel (2016). In the US economy, this heterogeneity in inflation expectations became more evident after the high-inflation episode of 2021, when inflation surged after 30 years of low and stable rates.

For this section, we use data from the Survey of Consumer Expectations (SCE) of the Federal Reserve Bank of New York. This dataset is a US-wide rotating panel with information between March 2013 and December 2021, where each respondent is surveyed for a maximum of 12 contiguous months. This dataset is handy for our purposes because it provides high-frequency data on American households' inflation expectations in two different periods of the US economy: one with low inflation and one with high inflation. In particular, we focus our analysis on respondents' 12-months-ahead point forecast. The 12-months-ahead inflation rate is computed as the inflation rate existing between the current month and 12 months after the current month.[10]

Fact 1: Inflation expectations are heterogeneous across cohorts.

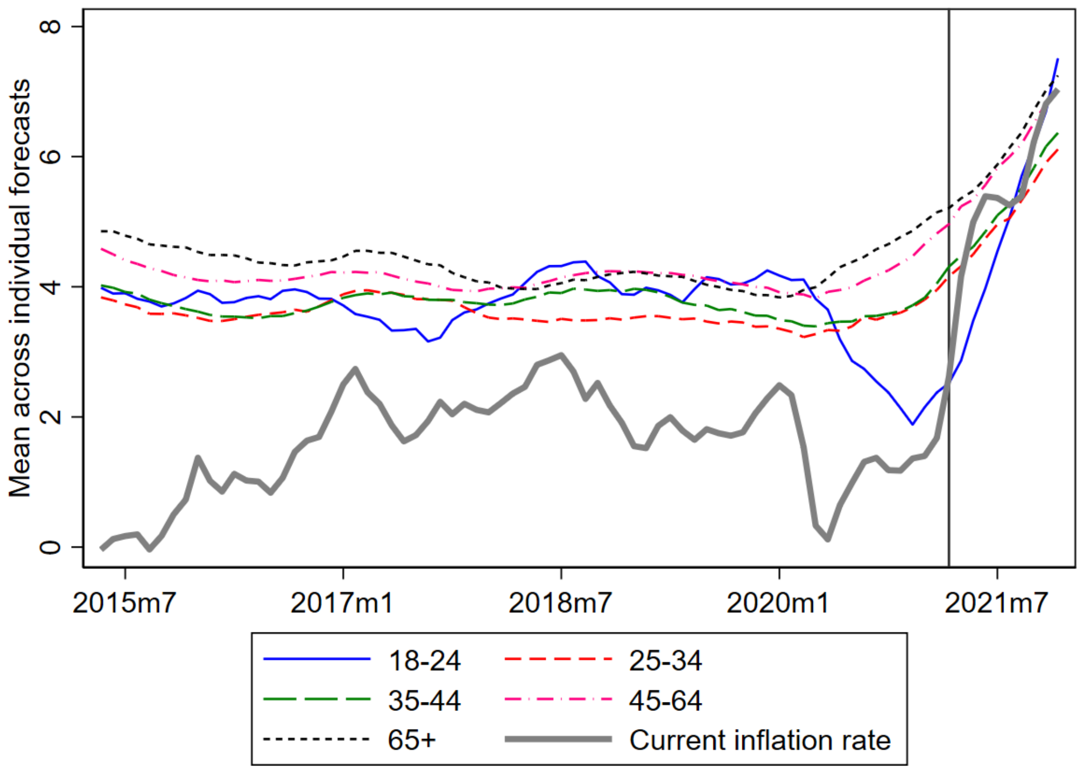
Figure 1 shows the mean 12-months-ahead inflation forecast by cohort. The heterogeneity across cohorts is evident.[11] The oldest (65+) and the second oldest cohort (45-64) have higher mean in-

[10]Specifically, consumers are asked to answer first the following question: "The next few questions are about inflation. Over the next 12 months, do you think that there will be inflation or deflation?" After indicating if they forecast inflation or deflation, they are asked to give a numerical answer to the following question:"What do you expect the rate of inflation/deflation to be over the next 12 months? Please give your best guess. "

[11]The figure also reveals an upward bias in inflation expectations for most cohorts and time periods. This pattern

flation expectations throughout most of the sample. Those cohorts experienced a period of high inflation in the 60s, 70s, and early 80s. Regarding inflation forecast value, these cohorts are followed by intermediate cohorts (25-34 and 35-44), who experienced the stable and low inflation rates of the 90s, 00s, and 10s. Finally, the youngest cohort (18-24) shows the most volatile mean, following the current inflation rate most of the time. The mean value of this cohort notably increased after the high-inflation episode of 2021, surpassing older cohorts' expectations.

Figure 1: Average 12-months-ahead Inflation Expectations



Note: The figure shows the 12-month moving average for the 10 percent and 90 percent trimmed mean for each cohort using the point forecast. We use population weights. Data goes from June 2013 to December 2021. Ages correspond to the interviewee's age at the time of the survey. The vertical line denotes March 2021. The current inflation rate measure is based on the monthly YoY percentage variation of the CPI.
Source: Survey of Consumer Expectations, Federal Reserve Bank of New York.

is consistent with previous findings (D'Acunto et al., 2022b) and may be explained by biases related to cognitive abilities (D'Acunto et al., 2023), financial constraints (Ehrmann et al., 2018), pessimism (Kamdar & Ray, 2024), and purchasing behavior (D'Acunto & Weber, 2022), among others. In this paper, we focus on how individuals' inflation histories influence the level but also changes in expectations. This distinction is important, as prior work has shown that changes in expectations, conditional on a given level, can significantly influence consumers' behavior (Candia et al., 2022a; Coibion et al., 2023).

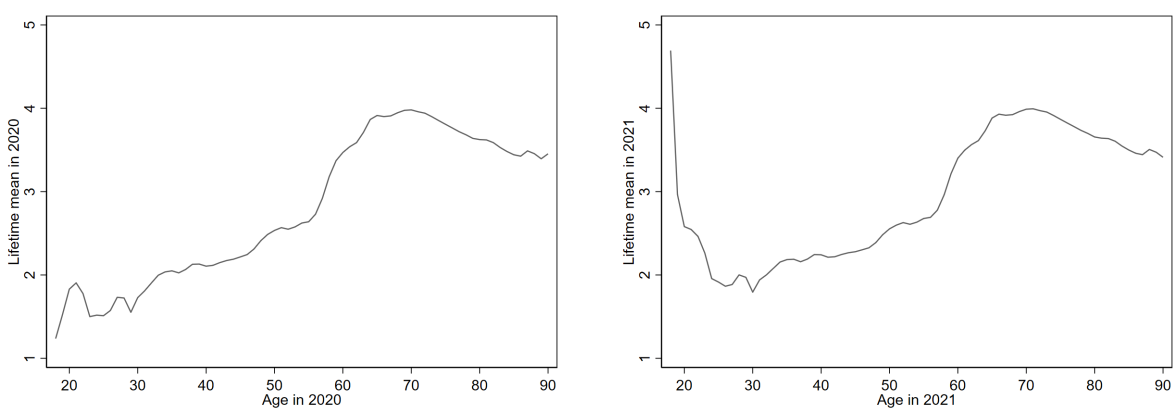
Fact 2: Inflation experiences are clustered by age.

Figure 2 plots the average lifetime inflation rate people have experienced according to their age in the years 2020 and 2021. In the United States, average lifetime inflation rates are clustered by age.

The heterogeneity of average experienced inflation rates across cohorts results from the different inflation-related events Americans have gone through. Older cohorts have experienced events such as the Great Inflation period (1965-1982), characterized by high and persistent inflation. Thus, these cohorts have a higher lifetime average inflation rate, regardless of the year we calculate. Meanwhile, intermediate cohorts have experienced low and stable inflation rates throughout the 80s, 90s, 00s, and 10s. Therefore, they present lower values on the lifetime average inflation rate. For older and intermediate cohorts, experiencing the high-inflation episode of 2021 did not significantly affect their lifetime average inflation rate.

In contrast, the youngest cohorts show a significant change between 2020 and 2021. Until 2020, the youngest cohorts had not experienced high inflation, showing low lifetime average inflation rates. However, after being exposed to the high-inflation episode of 2021, their lifetime average inflation rate dramatically increased.

Figure 2: Lifetime Average Inflation Rate among Respondents



(a) 2020 (b) 2021

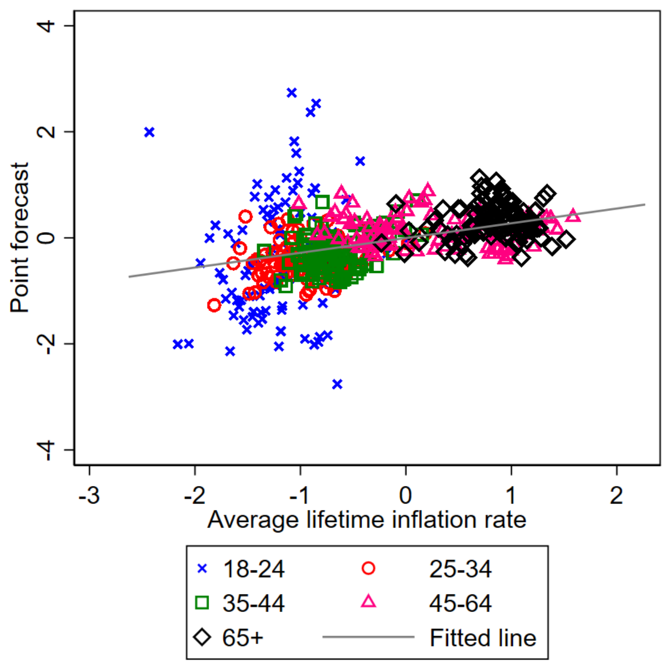
Note: The figure shows the mean of the monthly YoY CPI-based inflation rate that people of the age indicated in the years 2020 and 2021 have experienced in their lifetimes, starting when they were age 18.
Source: Bureau of Labor Statistics.

Fact 3: A higher average lifetime inflation rate is correlated with a higher point forecast.

Tying together both previous empirical facts, Figure 3 shows that people who have experienced higher average inflation rates during their lifetimes, when surveyed, tend to give a higher inflation point forecast.[12] We formally test this result in Table 1. Columns 3 and 4 of this table conclude that the inflation experienced significantly affects individuals' inflation expectations, even after controlling for the current environment and individual characteristics.

This fact provides empirical support for the literature on learning from past experiences (Malmendier & Nagel, 2016; Malmendier, 2021; Malmendier et al., 2021; Malmendier & Wachter, 2022), pointing to a possible source of heterogeneity in inflation expectations: past experiences with the aggregate inflation variable.

Figure 3: Inflation Point Forecast and Average Lifetime Inflation



Note: The figure shows a binned scatterplot across lifetime average inflation bins. We residualized the variables by respondent gender and commuting zone. The data goes from June 2013 to December 2021. Ages correspond to the interviewee's age at the time of the survey. The average lifetime inflation rate measure is based on the monthly YoY percentage variation of the CPI.
Source: Survey of Consumer Expectations, Federal Reserve Bank of New York and Bureau of Labor Statistics.

While the evidence we provide here is for the US economy, in Appendix H, we find similar evidence for a panel of European countries. With this European dataset, we show that the pattern i) is present beyond the United States, and ii) does not arise from cohorts' systematic characteristics

[12] We control for observable characteristics of the respondent except for the age and period variables.

but rather from cross-country heterogeneous inflation experiences. In the panel of countries we use, we observe different inflation histories across countries that are not necessarily similar to the US experience. Again, we find that average inflation experience positively relates to individual inflation expectations, even after including country-time fixed effects and, more importantly, cohort fixed effects. This last set of fixed effects controls for the fact that cohorts can have biases because of motives related to their age. In this sense, Hajdini et al. (2022a) finds similar evidence using a survey for a panel of countries.

Table 1: Effects of Current and Experienced Inflation Rates on Inflation Expectations

Dep. var.: Inflation expectations	(1)	(2)	(3)	(4)
Average lifetime inflation	0.332***	0.269***	0.299***	0.250***
	(0.029)	(0.080)	(0.027)	(0.024)
Current inflation	0.524***	0.632***		
	(0.056)	(0.121)		
Cohort 25-34		-0.080		
		(0.318)		
Cohort 35-44		-0.131		
		(0.308)		
Cohort 45-64		-0.010		
		(0.360)		
Cohort 65+		0.062		
		(0.379)		
Current inflation $\times$ 25-34		-0.163		
		(0.127)		
Current inflation $\times$ 35-44		-0.099		
		(0.125)		
Current inflation $\times$ 45-64		-0.080		
		(0.127)		
Current inflation $\times$ 65+		-0.141		
		(0.127)		
Time FE	No	No	Yes	Yes
Controls	No	No	No	Yes
Observations	105,415	105,415	105,415	105,402
R-squared	0.057	0.058	0.091	0.198

Note: Table shows regressions where the dependent variable is inflation expectations according to the Survey of Consumer Expectations (SCE) of the Federal Reserve Bank of New York. Column 1 shows controls by the average lifetime inflation of respondents of a given age at each period of time and the last inflation measure. Column 2 follows (1) but adds cohort fixed effects and the interaction of those cohort fixed effects with current inflation. Column 3 follows Column 1 but adds time fixed effects and, hence, omits the current inflation variable. Column 4 follows Column 1 but adds time fixed effects and demographic controls. The demographic controls are income, gender, Hispanic origin, race, educational level, numerical proficiency, and commuting zone. The current inflation rate measure is based on the monthly YoY percentage variation of the CPI. Standard errors clustered by age and period. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is trimmed, dropping the lower and upper 10 percent of answers in each period.

Fact 4: After controlling for the average lifetime inflation rate, younger cohorts do not react more strongly to inflation news than older cohorts.

We test whether younger generations react more strongly to the current economic environment after controlling for their average lifetime inflation. This exercise aims to inform the modeling approach we will take. The marginal contribution of new information for younger cohorts is higher, as they have a shorter history. Assuming constant weights implies that new information will matter more, especially in the context of persistent inflation. From a modeling perspective, we want to know whether cohorts react differently to news, conditional on their cohort-dependent marginal contribution of new information. These findings help us to discriminate between models.

We test this hypothesis through individual-level regressions presented in Table 1. Similar to the results of other papers using information treatment (Hajdini et al., 2022b), Column 1 of this table shows that, on average, individuals react to current inflation events. These results also confirm the existence of a positive relationship between the inflation forecasts and average lifetime inflation rates, as we saw previously in Figure 3, even after considering current inflation.

To study whether there are different reactions across cohorts, we run regressions that consider interactions of current inflation with a cohort indicator variable. Column 2 of Table 1 shows the corresponding results. After controlling for average lifetime inflation, the interaction term has no statistically significant effect. There are no different reactions to current inflation news across cohorts. We confirm the finding by performing an F-test where the null hypothesis is that all interactions are jointly equal to zero. The test gives a p-value of 0.39, so we cannot reject the null hypothesis. In addition, this conclusion holds in a sample of European countries, as we show in Table A7 of Appendix H. Together, these results suggest that the main source of heterogeneity across cohorts comes from different past experiences regarding inflation.[13]

4 A Simple Model with Heterogeneous Expectations

In this section, we propose an experience-based expectations-augmented Kalman filter as the process by which agents form their inflation expectations. In Appendix B, we begin with a simple

[13]Furthermore, in Appendix E we assume the structure of a standard Kalman filter and provide empirical evidence that provides support for the hypothesis of different cohorts not reacting differently to inflation signals.

model that provides a good starting point where differences in agents' personal experiences do not imply heterogeneity in expectations. Given the absence of private information, we show that the observed heterogeneity cannot arise from a standard Kalman filter. In this section, we introduce an experience-based expectations-augmented Kalman filter, we explain how the private inflation history distorts the expectations, producing inflation forecast heterogeneity. Moreover, we estimate the corresponding distortion parameter and close the section by comparing the heterogeneous rates of inflation expectations generated by our proposed framework and those observed in the data and presented in Figure 1.

4.1 Experience-based Kalman Filter

4.1.1 Setup

In this section, we depart from the standard Kalman filter framework outlined in Appendix B and introduce a model of non-Bayesian beliefs where consumers revise their forecast using a reference based on their experienced inflation history.[14] Within this framework, consumers receive signals about inflation and compare them to their history of forecasts for the next period. By comparing both elements when forecasting, consumers may rely more heavily on the new information they receive or on their past history-specific information. Our analysis allows for both scenarios.

When consumers place greater weight on new information when forming expectations, our setting aligns with Bordalo et al. (2019) and relates to the concept of representativeness heuristic. In contrast, when consumers rely more heavily on their past history-specific information, their behavior can be associated with the availability heuristic (Tversky & Kahneman, 1973). In this case, when forming expectations, consumers use their available information related to their past experiences instead of sampling the complex, current information required to forecast the future. This version of the model also connects with the concept of conservatism bias (Edwards, 1968), as consumers underweight new signals when forming their beliefs.

This setting aims to model a specific source of heterogeneity in inflation expectations rather than

[14]Our framework can be viewed as an extension of the diagnostic expectations framework. Unlike the original formulation, we do not restrict the parameter θ to be strictly positive. Thus, using the terminology of the diagnostic expectations, the model accommodates overreaction (θ>0), underreaction (θ<0), or unbiased updating (θ=0). A similar extension of the diagnostic expectations theory is discussed in Liao (2023).

to provide a general statement about expectation formation processes. This source of heterogeneity is relevant, consistently observed across different expectation surveys, and complements other findings on inflation expectation formation. The flexibility of this framework allows us to align the model closely with our empirical setting and to learn about how individuals incorporate their history of inflation when forming expectations.

We denote the true conditional distribution of the unknown inflation variable in a given period t as $f(\pi_{t+1} \mid \mathscr{I}_t)$, where the term $\mathscr{I}_t$ denotes the common set of information available at that period. Given this definition, we assume that the inflation belief distribution for agent i is given by

$$f_{i,t}^{\theta}(\pi_{t+1}) = f(\pi_{t+1} \mid \mathscr{I}_t) D_{i,t}^{\theta}(\pi_{t+1}) Z_{i,t}, \tag{1}$$

where

$$D_{i,t}^{\theta}(\pi_{t+1}) = \left[\frac{f(\pi_{t+1} \mid \mathscr{I}_t)}{f\left(\pi_{t+1} \mid \mathscr{I}_{i,t}^{ref}\right)^{\frac{1}{(t-k_i)}}} \right]^{\theta}.$$

In this setup, the parameter $\theta \in \mathbb{R}$ governs the level of distortion that the likelihood ratio $\left[D_{i,t}^{\theta}(\pi_{t+1})\right]^{\frac{1}{\theta}}$ introduces into agents' beliefs. The normalizing parameter $Z_{i,t}^{-1} = \int f_{i,t}^{\theta}(\pi_{t+1})\, d\pi_{t+1}$ ensures that the distribution $f_{i,t}^{\theta}(\pi_{t+1})$ integrates to one in each period t for every agent i. Each agent compares the current common information set $\mathscr{I}_t$ against her referential information set $\mathscr{I}_{i,t}^{ref}$. Later, we assume that this idiosyncratic referential information set relates to each agent's past inflation experiences. As previously mentioned, the parameter θ captures the extent of distortion existing in the model. In the standard Kalman filter framework, we have $\theta = 0$, which implies $D_{i,t}^{\theta}(\pi_{t+1}) = 1$. In this case, agents' beliefs are undistorted and coincide with the true conditional distribution, i.e. $f_{i,t}^{\theta}(\pi_{t+1}) = f(\pi_{t+1} \mid \mathscr{I}_t)$. Beliefs are systematically distorted when $\theta \neq 0$, as we discuss below.

Notice that the no private information assumption implies that the information associated with the true conditional distribution is common to all agents. Therefore, under the proposed signal extraction framework, in any period t, the expected value associated with the true conditional distribution of the unknown inflation variable is identical to every agent and corresponds to $\mathbb{E}_t^{KF}[\pi_{t+1}]$. Given the normality assumption on the error term of the inflation process, the true conditional distribution satisfies $f(\pi_{t+1} \mid \mathscr{I}_t) \sim \mathscr{N}\left(\mathbb{E}_t^{KF}[\pi_{t+1}], \sigma_\pi^2\right)$. As we detail below, this normality result implies that the distribution associated with the referential information set $\mathscr{I}_{i,t}^{ref}$ is also normal. Based on these results, we can show that agent i's belief distribution satisfies $f_{i,t}^{\theta}(\pi_{t+1}) \dot{\sim} \mathscr{N}\left(\mathbb{E}_{i,t}^{\theta}[\pi_{t+1}], \sigma_\pi^2\right)$, where the mean value has the following linear structure

$$\mathbb{E}_{i,t}^{\theta}[\pi_{t+1}] = \mathbb{E}_t^{KF}[\pi_{t+1}] + \theta\left(\mathbb{E}_t^{KF}[\pi_{t+1}] - \mathbb{E}_{i,t}^{ref}[\pi_{t+1}]\right), \tag{2}$$

where $\mathbb{E}_{i,t}^{\theta}[\pi_{t+1}]$ is the distorted forecast associated with the belief distribution $f_{i,t}^{\theta}(\pi_{t+1})$, and $\mathbb{E}_{i,t}^{ref}[\pi_{t+1}]$ is the expected value obtained according to the distribution associated with the referential information set $\mathscr{I}_{i,t}^{ref}$.[15] We refer to this linear composition of the standard Kalman filter as our experience-based-augmented Kalman filter.

Up to this point, the variables in our framework are history-independent. Recall that the standard Kalman filter is Markovian since it only requires the previous period's beliefs for updating. However, this simple filter does not reproduce the set of empirical facts we aim to capture. To address this, we now introduce a role for past experiences through the reference term $\mathbb{E}_{i,t}^{ref}[\pi_{t+1}]$. For the representative agent of cohort i', we define the reference term as

$$\mathbb{E}_{i,t}^{ref}[\pi_{t+1}] = \frac{\sum_{j=1}^{t-k_i} \mathbb{E}_{i,t-j}^{KF}[\pi_{t+1}]}{(t-k_i)}, \tag{3}$$

where k_i denotes the period in which cohort i begins forecasting. Notice that the reference term contains all past expectations of this cohort-specific agent about future inflation. Since it uses food prices as a signal, the reference contains the history of how consumers of a given cohort used the food prices to which they were exposed to forecast aggregate inflation. Panel (b) of Figure A10 illustrates how the reference inflation rate, defined according to equation 3, evolves over time for some selected cohorts. Older cohorts, which have gone through episodes of higher inflation during their lifetimes, exhibit higher reference points compared to younger cohorts, who have not experienced relevant inflationary episodes.

We now turn to the interpretation of the parameter θ. When $\theta > 0$, agents "overreact" to the current information they receive relative to their prior beliefs. For instance, if agents receive news about inflation being different from what they expected, they will overreact by assigning a greater

[15] See Appendix C for a more detailed derivation.

weight to current information, under-weighting their inflation history. In contrast, if $\theta < 0$, agents "underreact" to the incoming information, placing more weight on their references relative to current information. In this case, if agents observe inflation values different than their priors, they will tend to anchor their current expectations to their past beliefs. As discussed in Section 3, recent economic developments show that older consumers had higher inflation expectations when aggregate inflation was low, such as during the period between 2010 and 2020. Meanwhile, when inflation was high in 2021, consumers reacted moderately, not increasing their expectations significantly. This idea goes in line with agents anchoring their expectations to their experience or, in our framework, with a parameter satisfying $\theta < 0$. Lastly, when $\theta = 0$, there are no distortions in beliefs and $\mathbb{E}^{\theta}_{i,t}[\pi_{t+1}] = \mathbb{E}^{KF}_{t}[\pi_{t+1}]$ for every cohort i.

Given the random walk structure assumed for the inflation variable, and for any forecast horizon $h \geq 1$, we conclude $\mathbb{E}^{KF}_{t}[\pi_{t+h}] = \mathbb{E}^{KF}_{t}[\pi_{t+1}]$. Since the reference term is a linear composition of expected values associated with the true conditional distribution, we must have $\mathbb{E}^{ref}_{i,t}[\pi_{t+h}] = \mathbb{E}^{ref}_{i,t}[\pi_{t+1}]$. Therefore, when $h \geq 1$, we observe $\mathbb{E}^{\theta}_{i,t}[\pi_{t+h}] = \mathbb{E}^{\theta}_{i,t}[\pi_{t+1}]$.

4.1.2 Estimation and Forecasting Exercise

In this section, we estimate the parameter θ directly from the data. Under our current assumptions, from equation 2 we know that cohort i's forecast for period $t+12$ corresponds to

$$\mathbb{E}^{\theta}_{i,t}[\pi_{t+12}] = (1+\theta)\,\mathbb{E}^{KF}_{t}[\pi_{t+12}] - \theta\mathbb{E}^{ref}_{i,t}[\pi_{t+12}]. \tag{4}$$

Since the first term is common across all cohorts, it can be captured by a time-fixed effect γ_t. Regarding the distorted expectation, we use data on the 12-month-ahead forecast of each agent m from cohort i presented in the SCE survey. We denote this variable as $\mathbb{E}^{SCE}_{m,i,t}[\pi_{t+12}]$. Finally, to compute $\mathbb{E}^{ref}_{i,t}[\pi_{t+12}] = (t-k_i)^{-1}\sum_{j=1}^{k_i}\mathbb{E}^{KF}_{i,t-j}[\pi_{t+12}]$ we return to the standard Kalman filter from Section B and recover the different terms $\mathbb{E}^{KF}_{i,t-j}[\pi_{t+12}]$, which are optimal forecasts under the given setup.[16] Given this setting, we run the following regression

$$\mathbb{E}^{SCE}_{m,i,t}[\pi_{t+12}] = \gamma_t + \varphi\mathbb{E}^{ref}_{i,t}[\pi_{t+12}] + \varepsilon_{m,i,t}. \tag{5}$$

[16]This result relies on the assumption that the inflation rate is a random walk (see Appendix B), so that we can obtain $\mathbb{E}^{KF}_{i,t}[\pi_{t+12}] = \mathbb{E}^{KF}_{i,t}[\pi_{t+1}]$ from the standard Kalman filter.

We present the results in Table 2. Column 1 shows our main specification, from which we obtain $\widehat{\theta} = -\widehat{\varphi} = -0.374$. Because the estimated parameter satisfies $\widehat{\theta} < 0$, we conclude that when agents forecast, they positively weigh their reference sets (i.e., their past inflation history, their priors coming from their experiences with food prices). In the remaining columns of Table 2, we show that the negative coefficient is robust to the inclusion of control variables.[17]

This result contrasts with the diagnostic expectations literature (for instance, Bordalo et al. 2020), where a positive θ is the usual result using a similar empirical structure. However, this positive θ result is based on an experience-based expectations formation process with a different reference point. Instead of using agents' past inflation history, the diagnostic expectations literature usually uses the one-period lagged information set as their reference point. Moreover, their finding is also conceptually different from ours, as most of the previous empirical literature on diagnostic expectations relies on surveys of professional forecasters, who are better informed about the economy than the households surveyed in the SCE.[18]

Table 2: Parameter Estimation

	(1)	(2)	(3)	(4)
$\mathbb{E}_{i,t}^{ref}\left[\pi_{t+12}\right]$	0.374*** (0.045)	0.384*** (0.037)	0.268*** (0.038)	0.210*** (0.034)
Time FE	Yes	Yes	Yes	Yes
Controls	No	Gender, commuting zone	Gender, commuting zone, HH income	Gender, commuting zone, HH income, educational degree
Observations	83,991	83,969	83,969	83,969
R-squared	0.100	0.168	0.194	0.211

Note: Table shows results of estimating equation 5. $\mathbb{E}_{i,t}^{ref}\left[\pi_{t+12}\right]$ is the reference constructed for a respondent of age i as explained in the main text. We use population weights. Column 1 has only a time fixed effect as an additional control. Columns (2), (3) and (4) add different levels of controls. Robust standard errors in parentheses. Standard errors clustered by age and period. Dependent variable trimmed at 10 percent and 90 percent in each period. *** p<0.01, ** p<0.05, * p<0.1.

[17] In Figure A2 of Appendix A we show the results of estimating equation 5 but leaving one cohort out of the sample in successive regressions. We find that the coefficient of interest remains stable throughout the successive estimations and, thus, does not depend on the inclusion or exclusion of any particular cohort in the sample.

[18] While it has not been central to the previous discussion in the broader diagnostic expectations literature, the result of $\theta < 0$ is not necessarily a rare sight. For instance, Bordalo et al. (2020) find $\theta < 0$ for the forecasts of a subset of variables in the Survey of Professional Forecasters. For a further discussion see Liao (2023).

The value of the parameter θ is also conditional on the expectation formation process. In Bordalo et al. (2019, 2020), current news is processed with a Kalman filter, so, in a sense, current forecasts are partly processed with past information. With that modeling approach, surprises with respect to a reference based on the previous period also come from a reference based on the available individual experience, as suggested by Tversky & Kahneman (1973).

However, this result changes when we consider other forms for current expectations instead of a Kalman filter, such as rational expectations (for instance, Bianchi et al. 2021 and L'Huillier et al. 2021). In that case, agents know the model's features, so their reference is based on everything contained within the model, which is considered more likely (as in Kahneman & Tversky 1972). Given the assumption of full information, agents will overreact to any shock that was not expected in the previous period; as agents understand the shock and its effects as soon as they see it, it is immediately more likely.[19]

We take a different approach, as we explicitly model the reference of the agents given their cohort. Agents also optimally generate a forecast with a Kalman filter and a signal we provide. Then, they combine this optimal forecast with their past experience to produce their final forecasts. Our framework allows for a common component that might come from the news (Carroll, 2003), common price experiences (D'Acunto et al., 2021), among other reasons. While the time fixed effect would capture any of those factors, we model it with a common adjustment to their price experience. Then, we explicitly model the reference, given their history. Our findings are consistent with consumers using an availability heuristic to form expectations. In this case, people use their history of forecasts to positively weigh them given current developments in prices. When events deviate from what an agent has experienced, they tend to revise their expectation toward their historical forecasts. Our empirical results strongly point in that direction. This finding is consistent with consumers' survey-based evidence that shows that consumers, after receiving news about the economy, do not overweigh that news, keeping a positive weight on their prior or reference, as shown, for example, in Weber et al. (2023).

Using our estimate for the parameter, we perform a forecasting exercise using the Kalman filter. Panel (c) of Figure A10 shows the 12-months-ahead inflation forecasts for different cohorts. We can see that the experience-based Kalman filter can generate a heterogeneous pattern across co-

[19]See Benjamin (2019) for a discussion of these assumptions

horts, similar to the one we saw in the data in Figure 1.[20] First, older cohorts show higher inflation expectations than the rest of the cohorts throughout most of the sample, based on their experiences of high inflation in the 60s, 70s, and early 80s. Second, the intermediate cohorts show lower inflation expectations than the other cohorts because they went through the stable and low inflation rates of the 90s, 00s, and 10s. The youngest cohort shows the highest inflation expectations after being exposed to the high inflation rates of 2021.

To study the external validity of our results, in Appendix H, we repeat the exercises but using data from the Consumer Expectations Survey of the European Central Bank, which contains observations for six countries: Belgium, France, Germany, Italy, the Netherlands, and Spain. We find evidence that corroborates our main findings. Inflation expectations are also heterogeneous in Europe and partially explained by the history of consumers' inflation experiences. We find support for the use of an experience-based Kalman filter as a way of modeling heterogeneous inflation expectations.

Moreover, given the cross-country panel structure, we control for a common cohort fixed effect in this exercise, as in Hajdini et al. (2022a). This is a highly relevant step since common cohort characteristics (i.e., different patterns of inflation exposure over the life cycle) could affect our results. By controlling for cohort fixed effects, we rule out those common cohort characteristics and cleanly exploit differences in the inflation experienced by the different cohorts across different countries. We find similar results after adding our set of controls, implying that the heterogeneity does not stem from common cohort characteristics but from different inflation experiences in different countries. Thus, we have that our findings are also valid for Europe.

4.1.3 Goodness of Fit

This subsection studies how the time and individual variation of our experience-based Kalman filter expectations compare to the data. We run a regression where the dependent variable is the survey individual inflation expectation, while the right-hand side variable is our experience-based Kalman filter expectation. Our formulation has two components: one comes from the standard Kalman filter that uses common food inflation data as a signal, and the second arises from cohorts references and a parameter θ estimated using survey data. As we use a time fixed effect

[20] We show the forecasts for the full sample in Figure A1 in Appendix A.

for the parameter estimation, individual survey data do not provide the time variation observed in our inflation expectations measure. Column 1 of Table 3 shows that the slope between the survey forecast and the forecast produced by our experience-based Kalman filter is 1.069. This result confirms that our inflation expectations formulation effectively reproduces consumers' expectations. After considering the time and cross-section variation, our estimates provide a good prediction of heterogeneous inflation expectations.

Table 3: Goodness of Fit

	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}_{i,t}^{\theta}[\pi_{t+12}]$	1.069***			1.068***	0.931***	0.871***
	(0.164)			(0.195)	(0.072)	(0.081)
$\overline{\pi_{i,t}}$		0.310***		0.003		0.109**
		(0.040)		(0.074)		(0.044)
π_{t-1}			0.535***		0.470***	0.479***
			(0.074)		(0.041)	(0.042)
Observations	83,991	83,991	83,991	83,991	83,991	83,991
R-squared	0.041	0.006	0.043	0.041	0.074	0.075

Note: Table shows results of a regression where the dependent variable is consumers' inflation expectations according to the Survey of Consumer Expectations (SCE) of the Federal Reserve Bank of New York. We use population weights. $\mathbb{E}_{i,t}^{\theta}[\pi_{t+12}]$ is our estimated measure of inflation expectations. $\overline{\pi_{i,t}}$ is average inflation expectations. π_{t-1} is the lagged inflation rate. Standard errors clustered at the date-of-birth and period level in parentheses. Dependent variable trimmed at 10 percent and 90 percent in each period. *** p<0.01, ** p<0.05, * p<0.1.

An alternative measure to explain the heterogeneity in survey data inflation expectations is the cohort i's lifetime average inflation rate $\overline{\pi_{i,t}} = (t - k_i + 1)^{-1} \sum_{j=0}^{k_i} \pi_{t-j}$. Column 2 of Table 3 shows that the history of inflation by cohort can also predict part of the variation in the data. Also, we can consider the lagged inflation rate π_{t-1} as a predictor of inflation expectations, akin to following an adaptive expectations process. Column 3 of Table 3 presents that the lagged inflation also has predictive power when it comes to inflation expectations.

Furthermore, we can we can make the experience-based Kalman filter compete with the other two measures and see which one better predicts the forecasts observed in the data. Column 4 of Table 3 shows that in a horserace with the lifetime average inflation rate, our model forecast is superior for explaining the observed heterogeneity. The coefficient for our measure is close to one and statistically significant. In contrast, the coefficient for the history of inflation by cohort approaches zero in magnitude and becomes statistically insignificant.

Column 5 of Table 3 performs a similar exercise against the lagged inflation rate. While both measures are statistically significant, the experience-based Kalman filter has a larger coefficient. Given that both variables have the same scale, we find that the experience-based Kalman filter adds more information relative to the lag when it comes to predicting observed inflation expectations.

Finally, Column 6 of Table 3 shows the comparison between the three measures. The experience-based Kalman filter has a larger coefficient in comparison to the other measures, which confirms the previous two results. While the main coefficient is close to one and statistically significant, the R-squared remains relatively small. This is a common feature across the literature attempting to understand how consumers form expectations, largely due to the substantial dispersion in consumers' expectations. Our findings emphasize that personal inflation history is a relevant factor in explaining inflation expectations, accounting for a comparable share of variation relative to other papers that focus on alternative drivers of consumers' expectation formation process (Hajdini et al., 2022c; D'Acunto et al., 2023).

Figure A3 of Appendix A visually presents the results of Column 1 in Table 3. The slope associated with the regression and a 45-degree line are very close. Our measure effectively models the time and cross-sectional variation of consumers' inflation expectations.

Overall, our measure exhibits a very good fit with the data. We can replicate heterogeneous inflation expectations at the individual level using a relatively simple expectations model. By relying on current inflation and heterogeneous personal inflation histories, our framework effectively replicates both the time-series and cross-sectional variation observed in individual-level survey data on inflation expectations. Additionally, in Appendix I, we demonstrate that, within our dataset and period of analysis, our proposed experience-based measure provides a better fit than alternative specifications based on the modeling approach of Malmendier & Nagel (2016).

5 Aggregate Implications of Heterogeneous Expectations

In the previous sections, we demonstrated that an experience-based Kalman filter effectively captures the empirical patterns in consumers' inflation expectations. We now turn to examining the aggregate implications of this expectation formation process. Specifically, we explore how consumers behave under this framework and how their expectations interact with the broader economy, depending on the nature of the shocks and the policy responses. To do so, we require a model that is sufficiently rich to capture these macroeconomic interactions while also allowing for heterogeneity in inflation experiences. This heterogeneity is crucial as it generates a realistic inflation history that shapes expectations differently across cohorts.

This section introduces an overlapping generations model that incorporates an expectation formation process designed to replicate the heterogeneity observed in inflation expectations data (i.e., Figure 1). Agents in the model follow the experience-based Kalman filter and the assumptions outlined in Section 4.1. The long history of references inherent to this approach enables past inflation experiences to shape current inflation expectations differently across cohorts.

5.1 Households

On the demand side, we assume that an infinite number of cohorts populates the economy. Each cohort comprises a continuum of households whose situation is summarized by a single cohort-specific representative agent. These cohorts are heterogeneous in their date of birth and past inflation experiences. We follow the perpetual youth approach presented in Blanchard (1985) and Yaari (1965) to model the different cohorts. This approach considers that households have uncertainty regarding the date on which they will die. Each household faces a constant probability $\lambda \in (0,1)$ of dying every period. At the same time, a new cohort of size λ is born each period. As a result, in any period t, the size of a cohort born in period $k \leq t$ corresponds to $\lambda\,(1-\lambda)^{t-k}$.

We assume that households form expectations using the experience-based Kalman filter presented in Equation 2 and that the assumptions outlined in Section 4.1 hold.[21] Agents assume that the output gap and the inflation variable follow random walk processes. As in Gutiérrez-Daza (2022), agents cannot directly observe these variables; instead, they receive signals on each of them.[22] Given these assumptions, the representative household of cohort i solves

[21] Our evidence focuses on inflation, as evidence on output gap expectations is significantly less available. Our assumption is supported by suggestive evidence related to unemployment expectations. Assuming that consumers form expectations using the experience-based Kalman filter only for inflation, the results would be somewhat milder. However, the general conclusions would not be significantly affected. The assumptions we bring from Section 4.1 are that i) the belief distribution for an agent about future values of the variable of interest features a diagnostic distortion (equation 1), ii) the reference term of this belief distribution contains information from all past expectations about future realizations of the variable in question (equation 3), and iii) the standard Kalman filter forecast assumes the variable follows a random walk process.

[22] For simplicity, we assume that these signals correspond to the lagged value of the forecasted variables.

$$\max_{\left\{C_{i,j},L_{i,j},B_{i,j+1}\right\}_{j\geq t}} \left(\frac{C_{i,t}^{1-\sigma}}{1-\sigma}-\frac{L_{i,t}^{1+\eta}}{1+\eta}\right)+\mathbb{E}_{i,t}^{\theta}\left[\sum_{j>t}\left[\beta\left(1-\lambda\right)\right]^{j-t}\left(\frac{C_{i,j}^{1-\sigma}}{1-\sigma}-\frac{L_{i,j}^{1+\eta}}{1+\eta}\right)\right],$$

subject to

$$P_tC_{i,t}+\left(1-\lambda\right)\frac{B_{i,t+1}}{\left(1+i_t\right)}=W_tL_{i,t}+B_{i,t}+T_{i,t},$$

where $C_{i,t}$ is consumption, $L_{i,t}$ is the labor supply, $B_{i,t}$ are nominal savings in a risk-less bond, P_t is the aggregate price level, W_t are nominal wages, $T_{i,t}$ are transfers received by the household, and i_t is the nominal interest rate associated with this economy's bond. Also, β is the subjective discount factor, σ is the inverse of the intertemporal elasticity of substitution, and η is the inverse of the Frisch elasticity.

Transfers $T_{i,t}$ are crucial in our model as they incorporate two essential mechanisms. First, as in Blanchard (1985) and Yaari (1965), we assume that households insure themselves to receive a flow of income every period they are alive. The insurance company confiscates any residual wealth upon death, thereby eliminating accidental bequests. Second, as in Mankiw & Reis (2006), we assume that the payouts households receive from the insurance company are structured such that households start each period with the same wealth and that the nominal savings market clears. Therefore, we abstract from complexities related to wealth distribution. Lastly, and as a way of closing the model, transfers also incorporate the benefits of firms producing in the intermediate goods sector.

The transversality condition of the problem corresponds to

$$\lim_{T\to\infty}\mathbb{E}_{i,t}^{\theta}\left[\frac{\left(1-\lambda\right)^T}{\Pi_{h=0}^{T-1}\left(1+i_{t+h}\right)}B_{i,t+T}\right]=0.$$

We introduce expectations in a general equilibrium setting as in Bianchi et al. (2021) and L'Huillier et al. (2021). The expectations operator used by households is $\mathbb{E}_{i,t}^{\theta}\left[.\right]$, which works under the assumptions made in Section 4.1. Therefore, the first-order conditions characterizing the household's optimization problem are

$$\left(P_tC_{i,t}^{\sigma}\right)^{-1}=\beta\left(1+i_t\right)\mathbb{E}_{i,t}^{\theta}\left[\left(P_{t+1}C_{i,t+1}^{\sigma}\right)^{-1}\right], \tag{6}$$

$$C_{i,t}^{\sigma} L_{i,t}^{\eta} = \frac{W_t}{P_t}, \tag{7}$$

where the first equation corresponds to our Euler equation, capturing optimal consumption-savings behavior under distorted expectations. The second condition denotes a standard labor supply condition, equating the marginal rate of substitution between consumption and leisure to the real wage.

To simplify the analysis, we further assume that agents have full information regarding the current state of the economy. Accordingly, for any log-linearized variable x_t, we impose $\mathbb{E}_{i,t}^{\theta}[x_{t-h}] = x_{t-h}$ when $h \geq 0$. Otherwise, as L'Huillier et al. (2021) explains, agents will over or underreact when predicting this variable's present or past values. Under this assumption, and using the experience-based Kalman filter described in equation 2, the log-linearization of equation 6 yields

$$c_{i,t} = \begin{array}{c} (1+\theta)\,\mathbb{E}_t^{KF}[c_{i,t+1}] - \frac{1}{\sigma}\left(i_t - (1+\theta)\,\mathbb{E}_t^{KF}[\pi_{t+1}]\right) \\ -\theta\left(\mathbb{E}_{i,t}^{ref}[c_{i,t+1}] + \dfrac{1}{\sigma}\mathbb{E}_{i,t}^{ref}[\pi_{t+1}]\right), \end{array} \tag{8}$$

where lower-case variables denote log-deviations from their steady state values.[23] This expression represents the Euler equation for cohort i.

5.1.1 Aggregation

Since the steady-state value is identical across the different cohorts, the aggregate consumption gap c_t corresponds to the weighted sum of all the different cohort-specific consumption gaps. Therefore, we establish

$$c_t = \lambda \sum_{k \geq 0} (1-\lambda)^k c_{k,t}. \tag{9}$$

We further assume that household k, when forecasting its future individual consumption gap,

[23] An intermediate step in the log-linearization of equation 6 results in $c_{i,t} = \mathbb{E}_{i,t}^{\theta}[c_{i,t+1}] - \dfrac{1}{\sigma}\left(i_t - \mathbb{E}_{i,t}^{\theta}[\pi_{t+1}]\right) + \dfrac{1}{\sigma}\sum_{j=0}^{k_i+1}\left(\mathbb{E}_{i,t}^{\theta}[\pi_{t-j}] - \pi_{t-j}\right)$, where the last term arises from the fact that $\mathbb{E}_{i,t}^{\theta}[X_{t+1}Z_t] \neq \mathbb{E}_{i,t}^{\theta}[X_{t+1}]\,Z_t$ (L'Huillier et al., 2021). The term $\mathbb{E}_{i,t}^{\theta}[\pi_{t-j}]$ could imply that agents have distorted beliefs about the past. Since we assume $\mathbb{E}_{i,t}^{\theta}[\pi_{t-j}] = \pi_{t-j}$ for $j \geq 0$, beliefs about the past align with observed realizations. This assumption allows us to focus on how the reference distortions affect beliefs about the future, which is the main focus of our analysis. It also simplifies the computational burden of solving the model, as we no longer need to keep track of the belief history of each cohort.

believes that all other households will behave similarly, such that $\mathbb{E}_{k,t}^{ref}\left[c_{k,t+1}\right]=\mathbb{E}_{k,t}^{ref}\left[c_{t+1}\right]$. Incorporating the cohort-specific equation 8 into the aggregate consumption gap expression in equation 9 and using the market clearing condition in the goods market, we derive the aggregate IS curve of our model

$$y_t = \begin{array}{l} (1+\theta)\mathbb{E}_t^{KF}\left[y_{t+1}\right]-\frac{1}{\sigma}\left(i_t-(1+\theta)\mathbb{E}_t^{KF}\left[\pi_{t+1}\right]\right) \\ -\theta\lambda\sum\limits_{k\geq 0}(1-\lambda)^k\left(\mathbb{E}_{k,t}^{ref}\left[y_{t+1}\right]+\dfrac{1}{\sigma}\mathbb{E}_{k,t}^{ref}\left[\pi_{t+1}\right]\right). \end{array} \tag{10}$$

Equation 10 is the IS curve implied by our model. It resembles the standard IS curve but features two different distortions associated with parameter θ. In this version of the IS curve, the past matters in the sense that current realizations are affected by the history experienced by cohorts.[24]

We identify two distinct effects shaping aggregate demand from equation (10). On one side, the ex-ante real interest rate depends not only on the regular Kalman filter $((1+\theta)\mathbb{E}_t^{KF}\left[\pi_{t+1}\right])$, but also on the reference point weighted by the cohort shares $(\theta\lambda\sum\limits_{k\geq 0}(1-\lambda)^k\left(\mathbb{E}_{k,t}^{ref}\left[\pi_{t+1}\right]\right))$. Then, if the history of inflation is lower than the current shock, the effective ex-ante real interest rate becomes higher, thereby exerting a contractionary effect on economic activity. On the other side, the expected output also exhibits a history-dependent component. Suppose the reference of the cohorts is associated with the steady state. In that case, the current output gap may be lower in response to, for example, an expansionary inflationary shock, such as in the case of a demand shock, or it may be higher if the inflationary shock decreases output. Then, depending on the reaction of firms and monetary authority, the actual inflation will depend on how important those demand considerations are and how much they influence prices.

5.2 Firms

On the supply side, we assume that a final good producer operates in a perfectly competitive market, and this firm produces using a continuum of intermediate goods as inputs. Each intermediate good is produced by a separate firm operating under monopolistic competition. These intermediate goods producers are subject to Calvo pricing frictions, implying that only a fraction of firms can adjust prices in any given period. We assume these firms follow rational expectations

[24]Notice that if agents do not over or underreact when forming expectations, i.e., $\theta=0$, the IS curve reduces to a conventional structure $y_t=\mathbb{E}_t^{KF}\left[y_{t+1}\right]-\frac{1}{\sigma}\left(i_t-\mathbb{E}_t^{KF}\left[\pi_{t+1}\right]\right)$.

when setting their prices, as their behavior is model-consistent. Accordingly, we adopt the standard firms framework associated with the New Keynesian setting to derive the standard New Keynesian Phillips curve.[25]

5.3 Monetary Policy

The central bank sets the interest rate following a standard Taylor rule. Then, we have

$$\frac{(1+i_t)}{(1+\bar{i})} = \left[\frac{(1+\pi_t)}{(1+\overline{\pi})}\right]^{\chi_\pi} \left[\frac{Y_t}{\overline{Y}}\right]^{\chi_y}, \tag{11}$$

where the bars denote steady state values and χ_π and χ_y represent the central bank's reaction to deviations from the steady state of the inflation rate and output, respectively.

After log-linearizing, the model is summarized by

$$y_t = \begin{array}{c} (1+\theta)\,\mathbb{E}_t^{KF}[y_{t+1}] - \frac{1}{\sigma}\left(i_t - (1+\theta)\,\mathbb{E}_t^{KF}[\pi_{t+1}]\right) \\ -\theta\lambda \sum\limits_{k\geq 0} (1-\lambda)^k \left(\mathbb{E}_{k,t}^{ref}[y_{t+1}] + \dfrac{1}{\sigma}\mathbb{E}_{k,t}^{ref}[\pi_{t+1}]\right) + u_t^{taste}, \end{array} \tag{12}$$

$$\pi_t = \frac{(1-\phi)(1-\phi\beta)}{\phi}(\sigma+\eta)\left(y_t + u_t^{cost}\right) + \beta\mathbb{E}_t[\pi_{t+1}], \tag{13}$$

$$i_t = \chi_\pi \pi_t + \chi_y y_t, \tag{14}$$

where equation 12 is the dynamic IS curve augmented with a taste shock, equation 13 is the Phillips curve, and equation 14 is the Taylor rule. Notice that the Phillips curve follows the rational expectations operator $E_t[.]$, while the IS curve results from following the experience-based Kalman filter operator $E_t^{\theta}[.]$.

We consider a cost shock u_t^{cost} and a taste shock u_t^{taste} that behave as an AR(1) process, such that

$$u_t^{cost} = \rho_{cost} u_{t-1}^{cost} + \varepsilon_t^{cost}, \tag{15}$$

$$u_t^{taste} = \rho_{taste} u_{t-1}^{taste} + \varepsilon_t^{taste}, \tag{16}$$

[25]We present the details associated with the supply side of the economy in Appendix J.

where ρ_{cost} and ρ_{taste} are the persistence parameter and ε_t^{cost} and ε_t^{taste} are the unexpected innovations.

5.4 Calibration

The model is calibrated to a monthly frequency. The parameters from Table A1 in Appendix A show a fairly standard calibration. We calibrate the price stickiness parameter ϕ so that the expected duration of a given price quote is 12 months. We also calibrate the mortality rate λ so that the expected life span is 80 years.[26]

Regarding the experience-based Kalman filter, we need to calibrate the Kalman gain K and the parameter θ. We calibrate both according to the results from Sections B and 4.1. We must make an additional assumption around these two parameters. While we only used inflation rate data in the previous sections, we assume these parameters also hold for the output gap.

5.5 Simulations

In this section we compare three different cases: i) households form their expectations according to full information rational expectations (FIRE), ii) households form their expectations according to a standard diagnostic expectations operator with overreaction,[27] and iii) households form their expectations according to the experience-based Kalman filter from equation 2.[28]

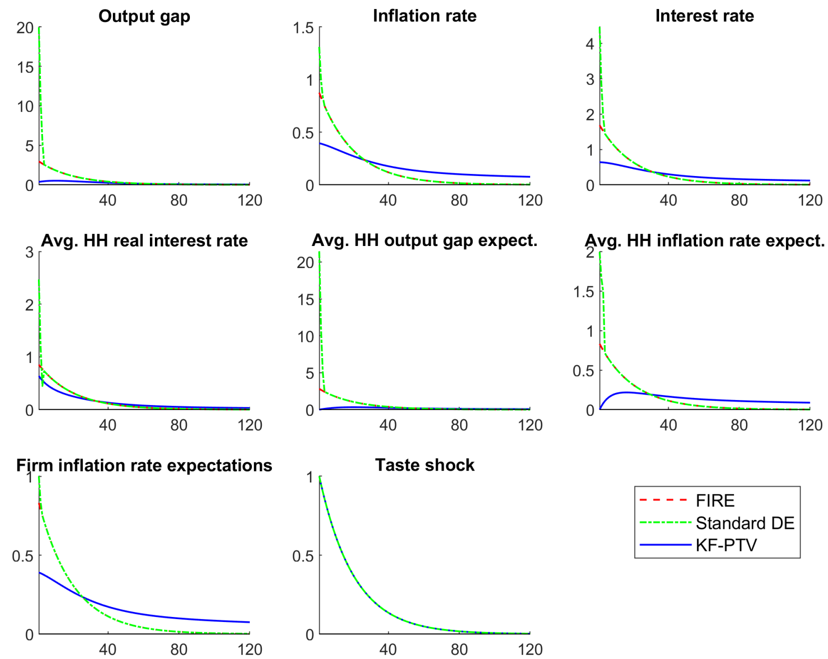
Figure 4 presents the impulse response functions to a taste shock and a cost shock. In Panel (a), we see that inflation and the output gap increase after a taste shock. The FIRE case shows the usual reaction, and the standard diagnostic expectations model presents an overreaction that lasts three periods, consistent with the reference used. In the case of the experience-based Kalman filter model, we first see a milder reaction in terms of inflation and output gap. Agents remember the past (in this case, the steady state), so their expectations tend to stay closer to such value. This allows the

[26]Because we assume that agents become economically active and relevant at age 18, this means agents expect to consume and work for 62 years

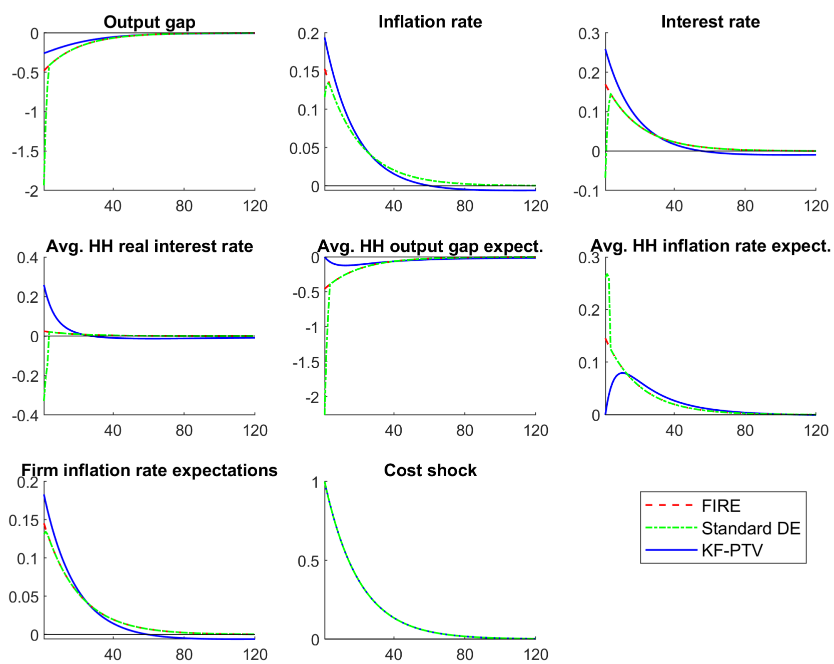
[27]We include the standard diagnostic expectations model because it serves as an useful benchmark that features overreaction. Because our model is a generalization of the diagnostic expectations model, following L'Huillier et al. (2021), we set the parameter $\theta = 0.992$ to obtain the desired overreaction result.

[28]For our Kalman filter operator we assume each cohort differs in its beliefs. In Appendix K we analyze the consequences of dropping this assumption and having all cohorts follow the same beliefs while keeping the Kalman filter structure.

Figure 4: Impulse Response Functions



(a) Taste shock



(b) Cost shock

Note: Figure shows impulse response functions for a selected group of variables after the mentioned shocks. The red dashed line shows the results for the case of the full information rational expectations model (FIRE), the green dotted line shows the results of a standard diagnostic expectations operator and the solid blue line shows the experience-based Kalman filter model. For the standard diagnostic expectations case we assume that agents use the expectations operator $\mathbb{E}_t^{\theta,s}[X_{t+h}] = \mathbb{E}_t[X_{t+h}] + \varpi(\mathbb{E}_t[X_{t+h}] - \mathbb{E}_{t-3}[X_{t+h}])$ with $\varpi > 0$. Horizontal axis denotes months after the shock.

central bank to reduce the size of its hike in the interest rate, resulting in a slightly lower real interest rate. In addition, firms reduce the size of their price increase. Overall, under the experience-based Kalman filter, agents anchor their expectations to the past, reducing the magnitude of the responses on impact.

While inflation is lower on impact with the experience-based Kalman filter, it takes longer to return to its steady state values when compared to the other cases (the FIRE and standard diagnostic expectations cases have inflation going back to a steady state at the same pace of the persistence of the shock). This is because, with the experience-based Kalman filter, agents remember the high inflation period. This effect is exacerbated by new cohorts that have only experienced inflation above the steady state.

Panel (b) of Figure 4 shows the responses for a cost shock. In the experience-based Kalman filter case, there are two forces going in opposite directions. There is a high persistence in inflation, but we also have consumers who remember the zero output gap of the steady state, which reduces the pressure on prices. Thus, the IS curve becomes more inelastic to the shock with the experience-based Kalman filter. Then, in this economy, rational firms can raise prices by more than they would under FIRE. This is followed by a central bank that must raise the interest rate more strongly than in the rational economy.

We have that for our experience-based Kalman filter case, the household expectation IRFs show two important characteristics: i) they do not jump on impact, and ii) they display a hump-shape. Both characteristics fall in line with what has been shown previously in the literature (for instance, see Angeletos et al. 2021 for the case of professional forecasters and Pfajfar & Roberts 2018 for the case of household survey expectations). Consumers underreact to the inflationary shock in our setting initially, as their memories are tied to the steady state. After the inflationary shock, they incorporate the inflationary episode into their memories, over-extrapolating it, as in Afrouzi et al. (2023).

Furthermore, another feature to notice in the experience-based Kalman filter case is that, while the household inflation rate expectations have a hump shape, actual inflation does not. This is because firms are always rational. Thus, firm expectations follow the shock very closely (no hump shape because of the AR(1) nature of the shock), and they set prices accordingly.

5.6 Implied Heterogeneous Responses

After obtaining the aggregate responses to the shocks, we now check the responses at the cohort-specific level implied by the aggregate variable paths of the previous section. Thus, we use the individual-level equations to see how the informational frictions of the model generate heterogeneous consumption and labor patterns depending on cohorts' past experiences. We must stress that this result just shows a reaction starting akin to a partial equilibrium exercise taking the aggregate variable paths as given and is not the result of a full heterogeneous agents model.

First, we calculate the within-model response of the output gap and inflation rate expectations for each cohort according to the framework of Section 4.1 and the aggregate variable paths following the shocks studied in the previous section. Figures A4 and A5 of Appendix A present the heterogeneity in expectations across cohorts under the experience-based Kalman filter. We see that, after both shocks, the expectations of the older cohorts remain anchored to the steady state, whereas the young react more strongly.

Then, we obtain a cohort-specific consumption gap according to equation 8, which contains common and heterogeneous components across cohorts. Similarly, we obtain the cohort-specific paths of labor supply gap from the individual labor supply problem. Figure A6 in Appendix A shows the consumption and labor supply gap responses of the different cohorts after a taste shock. We see that older cohorts consume less and work more, relative to the younger ones. For this result, there are two forces working simultaneously. In the first place, output gap expectations are lower for older cohorts, which brings their consumption down. Second, inflation rate expectations are lower for older cohorts, which relates to a higher real interest rate and reinforces lower consumption. Because the older cohorts believe the future aggregate output gap will be lower and perceive a higher real interest rate, they end up supplying more labor relative to the young.

Figure A7 of Appendix A shows the responses of the consumption and labor supply gap across cohorts after a cost shock. Older cohorts consume more and supply less labor than the young. Contrary to the previous exercise, in this case, this outcome is explained by two channels going in opposite directions. First, older cohorts have higher output gap expectations than younger ones, which drives their consumption upwards. Second, older cohorts have lower inflation rate expectations that translate into higher real interest rates, such that their consumption goes down. In the end, we see that the first channel dominates over the second. That is, even though older cohorts perceive a higher real interest rate, their more optimistic beliefs over the future output gap drive their consumption upwards relative to the young cohorts.

We highlight that these results are specific to this exercise, where the economy starts in the steady state. The heterogeneous responses are determined by the heterogeneous experiences of households, which, given the experience-based biases when forming expectations, create heterogeneous ex-ante real interest rates. In Section 7, we explore a data-based inflation scenario that will result in different ex-ante real interest rates across cohorts.

6 Optimal Taylor Rules

Now we analyze the use of an optimal Taylor rule in each of the different cases from the previous section. The Taylor rule we use in this section is

$$i_t = \chi_\pi^* \pi_t + \chi_y^* y_t. \tag{17}$$

We assume that the central bank chooses the time-invariant parameters χ_π^* and χ_y^* such that it solves the problem

$$\min \mathbb{E}_t \left[\pi_t^2 + \vartheta y_t^2 \right],$$

subject to the equations of the model in Section 5 and ϑ is the weight of the output gap in the objective function.[29] That is, the central bank, given the model setup, seeks to minimize the volatility of both the inflation rate and the output gap. Notice that we assume that the central bank has rational expectations.

The optimal parameters are dependent on which shocks exist in the model (cost or taste). Therefore, we will have two sets of parameters, one for each shock.[30]

We start by analyzing the response to a cost shock under the optimal Taylor rule. Panel (b) of Figure 5 shows that, when responding to this shock, the central bank faces the usual trade-off

[29]Following Gali (2015) we define $\vartheta = \frac{(1-\phi)(1-\phi\beta)(\sigma+\eta)}{\phi\varepsilon} = 0.0017$.

[30]Tables A2 and A3 in Appendix A show the optimal parameters.

between the output gap and the inflation rate. After the cost shock, the inflation rate goes up, and the output gap goes down after the interest rate hikes. In this particular exercise, we will have that, given the relative importance of the output gap in the objective function, the central bank will favor reducing the volatility of the inflation rate.

After the shock hits, the central bank becomes more active in the experience-based Kalman filter than in the FIRE case. This behavior takes place because inflation history plays a role when there are experience-based expectations. The central bank knows that people will remember the current shock far into the future, affecting future inflation expectations. By being more active under the experience-based Kalman filter case, the central bank can quickly lower inflation expectations. While in the baseline results from Figure 4 the inflation expectations remained high for a long period, the optimal Taylor rule brings them down. In fact, it even generates deflation expectations that later spill over to the observed inflation rate.

Panel (a) of Figure 5 shows the impulse response functions to a taste shock and an optimal response from the central bank. As is well known in the literature, upon a taste shock, the optimal response of the central bank is to raise the interest rate strongly. What follows is that the central bank manages to bring down both the output gap and the inflation rate to their steady state values.

We find no significant difference in the central bank's response between the FIRE and experience-based cases. The optimal Taylor rule case says that the central bank should always be active when facing a taste shock, no matter the type of expectations agents have. In this manner, the central bank can close the output gap and lower the inflation rate faster than the baseline results. Moreover, with the active stance recommended by the optimal Taylor rule, the output gap and inflation expectations are positive but very close to zero in all cases.

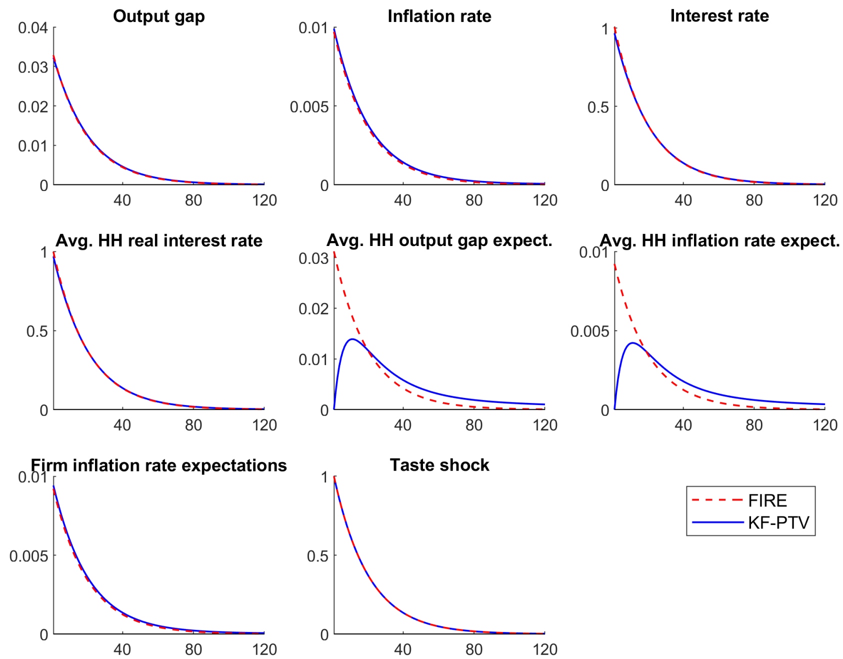
7 Analyzing an Episode of High Inflation

This section analyzes the model's behavior after the high-inflation episode of 2021.[31] To do so, we feed the model from Section 5 with actual monthly data on the output gap, inflation rates, and interest rates up to December 2021.[32] Afterward, we produce forecasts using the different versions

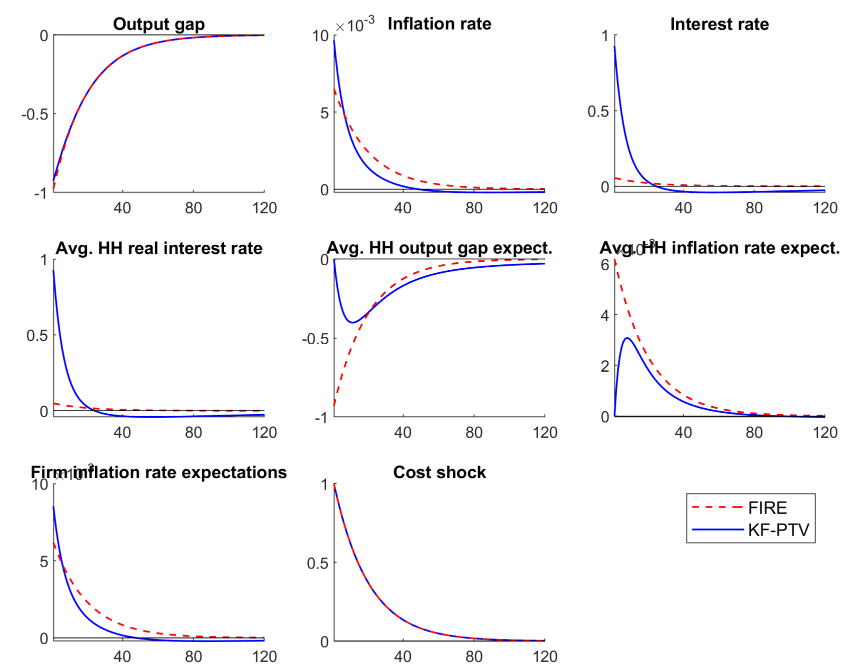
[31] In this part, we go back to the basic calibration of Table A1.

[32] We use monthly series from March 1967 to December 2021. We go as far as the data allow us to build the agents' references. We use the National Activity Index (CFNAI) from the Federal Reserve Bank of Chicago for the output

Figure 5: Impulse Response Functions, Optimal Taylor Rule



(a) Taste shock



(b) Cost shock

Note: Figure shows impulse response functions for a selected group of variables after the mentioned shocks under an optimal Taylor rule. The red dashed line shows the results for the case of the full information rational expectations model (FIRE), and the solid blue line shows the experience-based Kalman filter model. Horizontal axis denotes months after the shock.

of the model.[33]

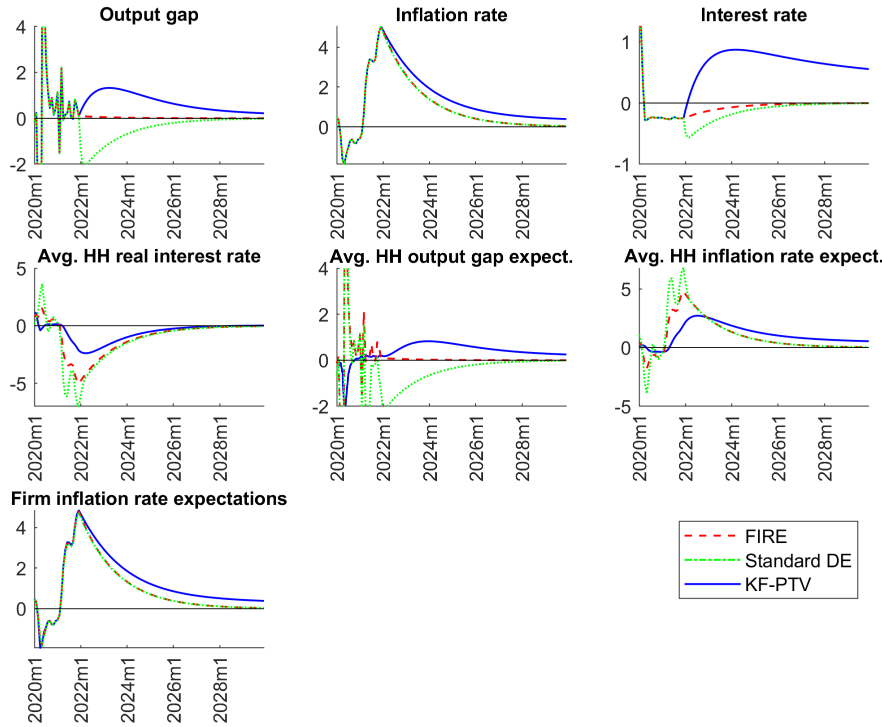
We first analyze the experience-based Kalman filter case. Figure A8 of Appendix A shows the inflation rate expectations by cohort according to our model and the data. Before 2021, older cohorts had the highest inflation expectations. This result occurs because older cohorts experienced the high-inflation episodes of the 60s, 70s, and early 80s. They are followed by the intermediate cohorts and finally by the youngest cohorts, who experienced low and stable inflation rates from the 90s to the 10s. With the inflationary shock, those expectations changed as newer cohorts experienced a significant part of their lives in a high-inflation environment.

Figure 6 presents how variables evolve based on our model and the data. After 2021, when we allow for an experience-based Kalman filter, average inflation expectations are higher and more persistent with respect to other cases. This result is because agents remember and anchor their expectations to what they experienced in the past. Hence, the central bank must react more strongly.

gap. For the interest rate, we use the effective federal funds rate. For the inflation rate, we use the CPI 12-month percentage change.

[33]We present the shocks that, according to our model, explain the observed data in Figure A9 in Appendix A.

Figure 6: Impulse Response Functions, Forecast



Note: Figure shows impulse response functions for a selected group of variables according to the model and the data (up to December 2021). The red dashed line shows the results for the case of the full information rational expectations model (FIRE), the green dotted line shows the results of a standard diagnostic expectations operator, and the solid blue line shows the experience-based Kalman filter model. For the standard diagnostic expectations case we assume that agents use the expectations operator $\mathbb{E}_t^{\theta,s}[X_{t+h}] = \mathbb{E}_t[X_{t+h}] + \varpi(\mathbb{E}_t[X_{t+h}] - \mathbb{E}_{t-3}[X_{t+h}])$ with $\varpi > 0$. Horizontal axis denotes months.

Because of their historical reference, agents who follow an experience-based Kalman filter remember the high inflation episode far into the future when compared to the other cases case. As a consequence, the observed inflation rate and the interest rate also remain higher for longer.

8 Conclusions

This paper studies the macroeconomic consequences of heterogeneous inflation expectations. First, we show that inflation expectations are heterogeneous across cohorts. Then, we introduce a Kalman filter augmented with experience-based expectations to model the inflation forecast formation process. We structurally estimate the relevant parameter, concluding that individuals effectively consider their past inflation histories when forecasting.

Our expectation formation process includes two known and relevant aspects of consumers' expectations processes. On one side, we consider the history of inflation each cohort has experienced. On the other side, we consider the current inflation experience, particularly with salient prices such as grocery prices. Our proposed framework can predict the heterogeneity prevalent in consumers' inflation expectations across cohorts remarkably well, even though we only feed our model with monthly CPI inflation data and an estimated parameter. We show that consumer inflation expectations data can be modeled and predicted and contain meaningful information.

Our modeling approach also has the advantage of being flexible, such that we can incorporate it into a general equilibrium model. This heterogeneous expectation process has relevant aggregate implications. Heterogeneous expectations anchor aggregate response to agents' history of inflation while increasing the persistence of the effect of the shocks.

This result has implications for monetary policy: when inflation starts rising, the optimal response of monetary authorities is to take an active stance, as agents have a long history and remember current shocks far into the future. An energetic response of the central bank under inflationary pressures prevents current inflation from rising and, more importantly, prevents agents from incorporating high-inflation episodes into their memories, thus preventing higher future inflation expectations.

Our results also have relevant implications for the current macroeconomic environment. The model suggests that the 2021 high-inflation episode, even though it may be transitory, could have long-lasting effects: new cohorts incorporate the high-inflation episode into their memories of inflation, adjusting future inflation expectations upwards.

While in this work we focus on the aggregate implications of this firm of heterogeneous expectations, future research can focus on the distributional consequences. For instance, the focus could be on i) how experience-based inflation expectations interact with financial constraints and labor market decisions at different stages of the life cycle, ii) the implications of those interactions for the effectiveness of monetary policy, and iii) how monetary and fiscal policy can deal with the distributional consequences of such interactions.

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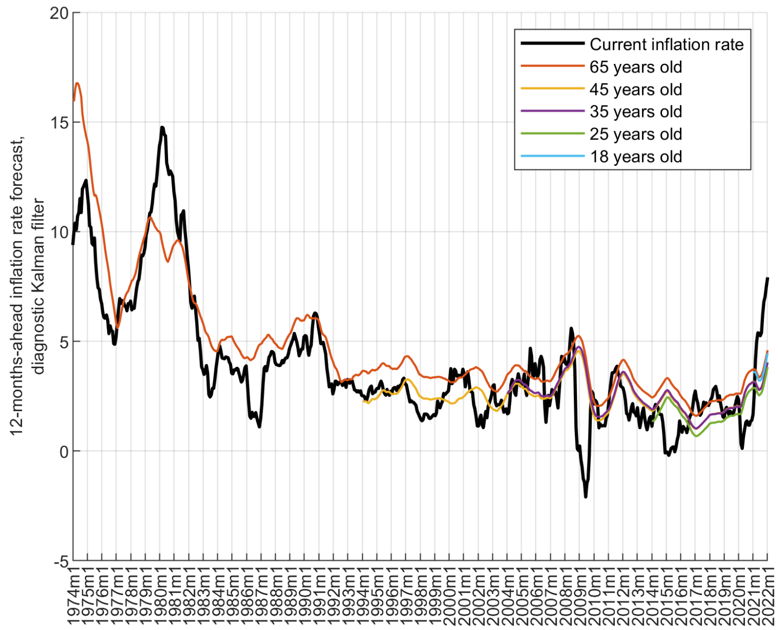
Online Appendix (Not for publication)

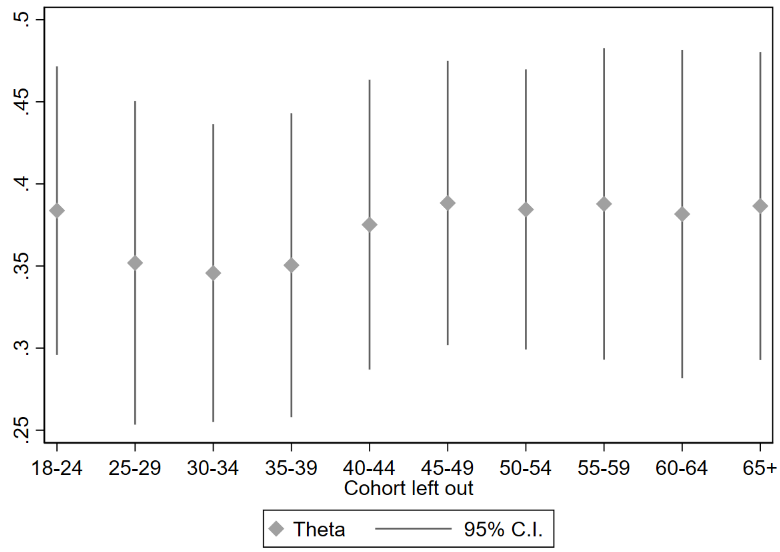
A Additional figures and tables

Figure A1: Experience-based Kalman-filter-based Inflation Forecasts by Cohort, Full Sample



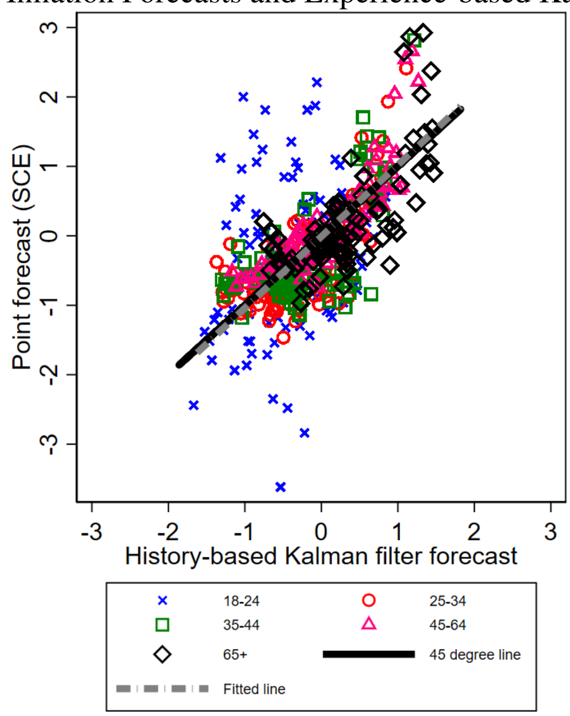
Note: Figure shows forecasts for selected cohorts according to the Kalman-filter-augmented expectations and considering the estimate for θ from Column 1 of Table 2. Selected cohorts differentiated by their age in 2021. We further assume that each cohort starts forecasting when they become 18 years old. The current inflation rate measure is based on the monthly YoY percentage variation of the CPI.

Figure A2: Parameter Estimation, Stability by Cohorts



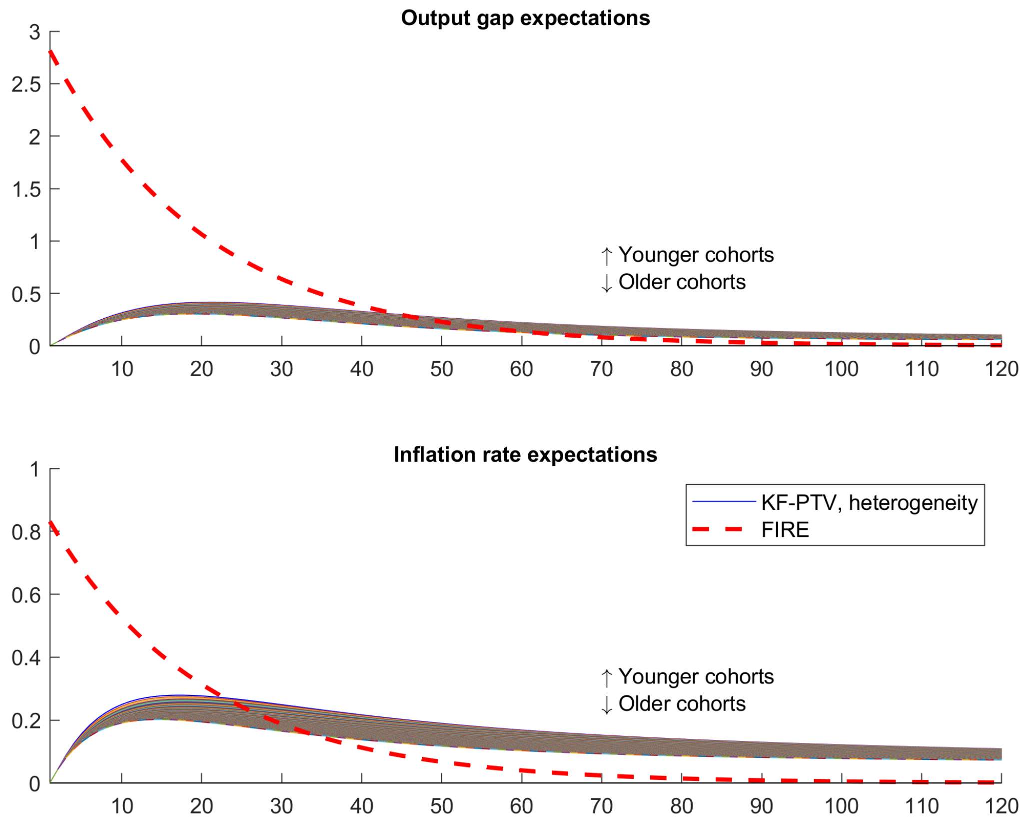
Note: Figure shows the coefficient resulting from estimating equation 5, but leaving one cohort out of the sample. The cohort left out of the estimation changes across the horizontal axis.

Figure A3: Observed Inflation Forecasts and Experience-based Kalman Filter Forecasts



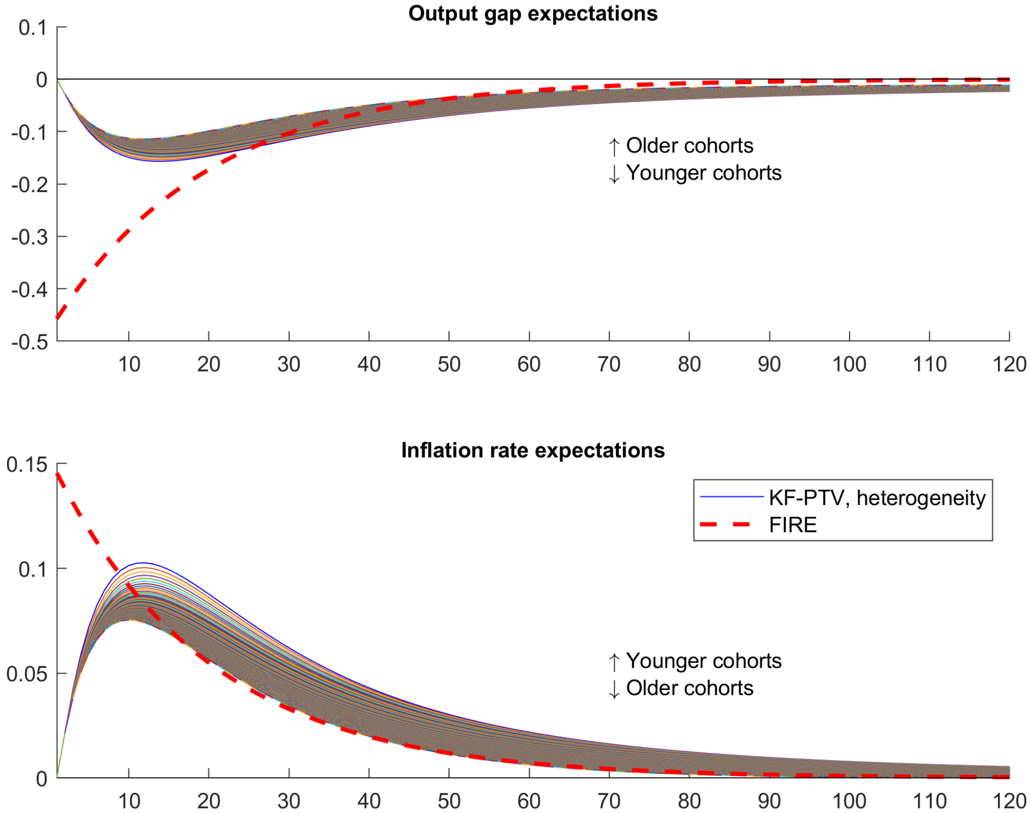
Note: Figure shows binned scatterplot across experience-based Kalman filter forecasts (x-axis) and point forecast inflation expectations according to the Survey of Consumer Expectations (SCE) of the Federal Reserve Bank of New York (y-axis). Variables demeaned by the intercept. Data go from June 2013 to December 2021. SCE variable trimmed at 10 percent and 90 percent in each period.

Figure A4: Impulse Response Functions, Experience-based Expectations by cohort, Taste Shock



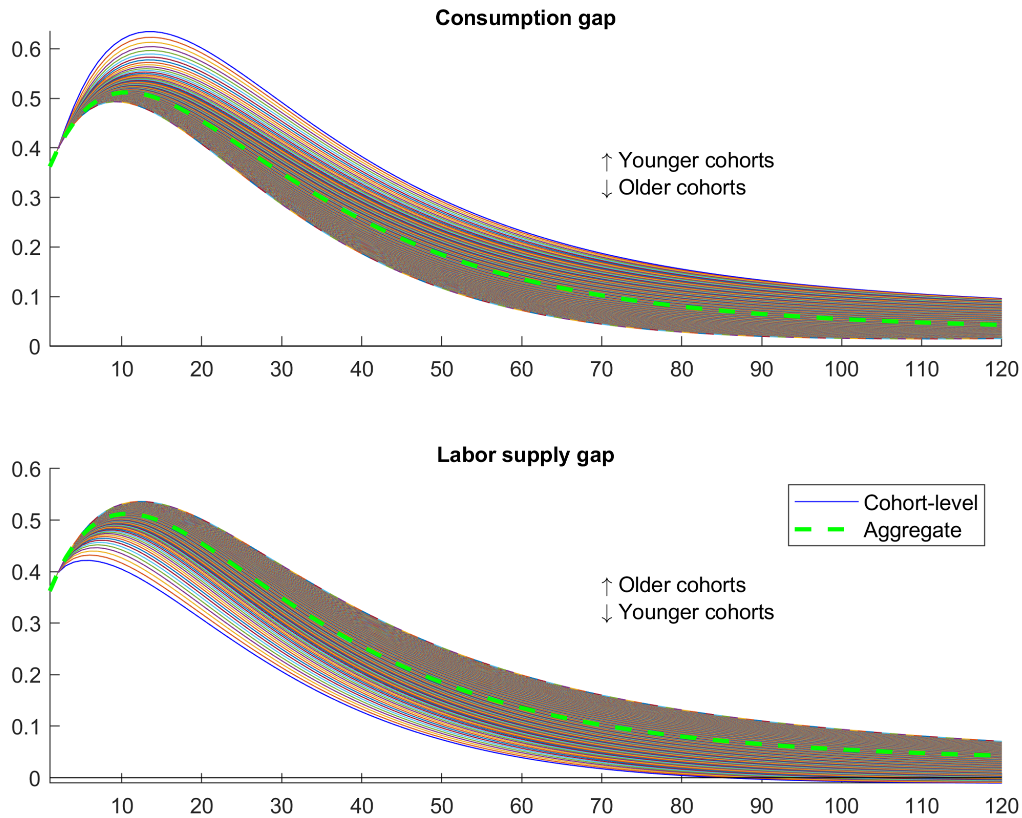
Note: Figure shows the heterogeneous expectations generated by the experience-based Kalman filter. Cohorts denote age at the time of the shock. The solid lines represent different cohorts in the experience-based Kalman filter model. The dashed red line is the full information rational expectations model. Horizontal axis denotes months after the shock.

Figure A5: Impulse Response Functions, Experience-based Expectations by Cohort, Cost Shock



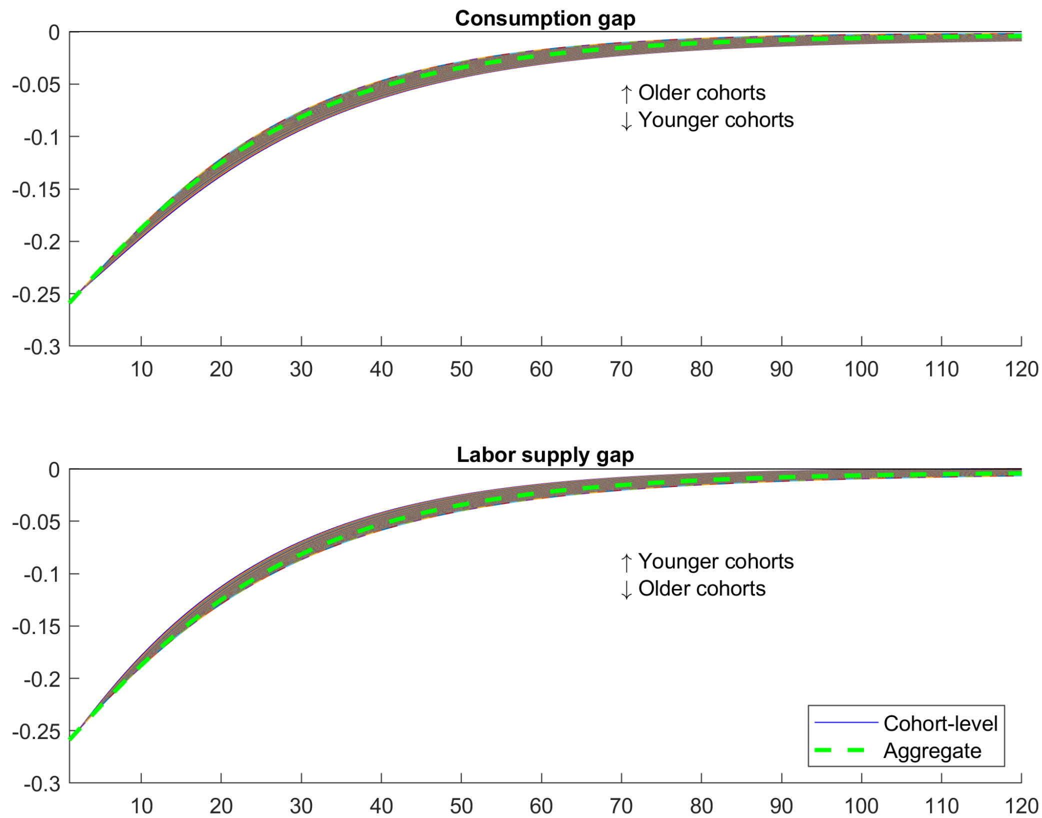
Note: Figure shows the heterogeneous expectations generated by the experience-based Kalman filter. Cohorts denote age at the time of the shock. The solid lines represent different cohorts in the experience-based Kalman filter model. The dashed red line is the full information rational expectations model. Horizontal axis denotes months after the shock.

Figure A6: Impulse Response Functions, Consumption and Labor Supply by Cohort, Experience-based KF with Heterogeneity, Taste Shock



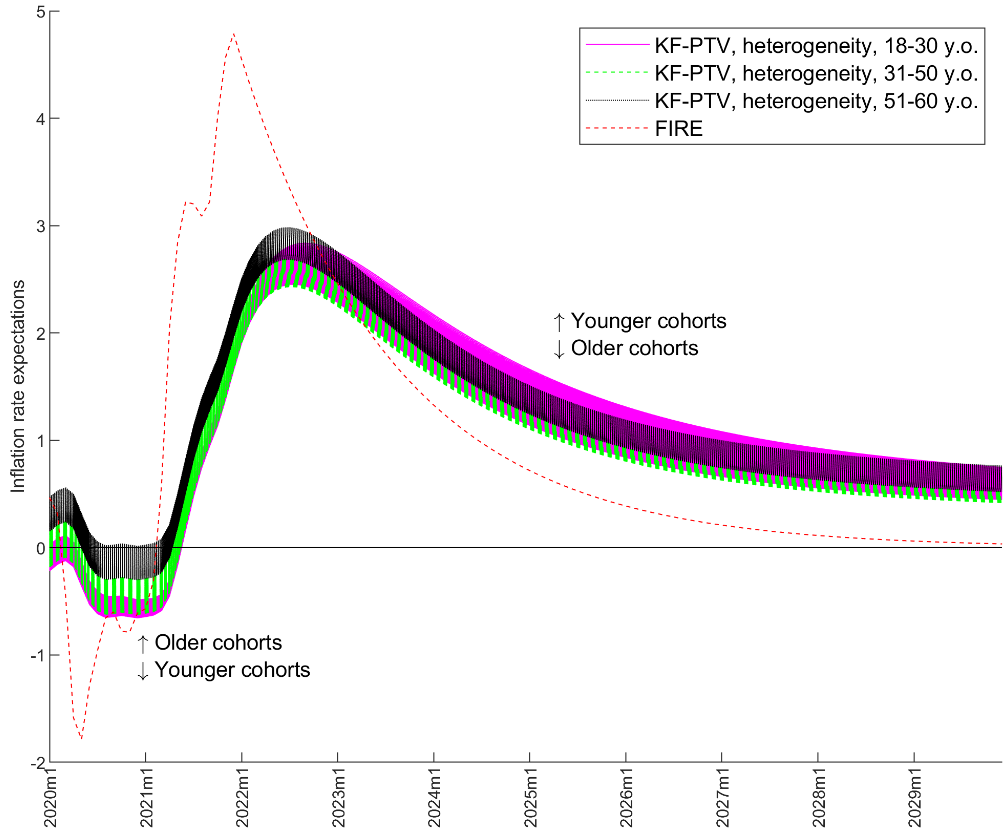
Note: Figure shows the heterogeneous consumption and labor supply gaps generated in the case where expectations follow the experience-based Kalman filter. Cohorts denote age at the time of the shock. The solid lines represent different cohorts in the experience-based Kalman filter model. The dashed red line is the aggregate. Horizontal axis denotes months after the shock.

Figure A7: Impulse Response Functions, Consumption and Labor Supply by Cohort, Experience-based KF with Heterogeneity, Cost Shock



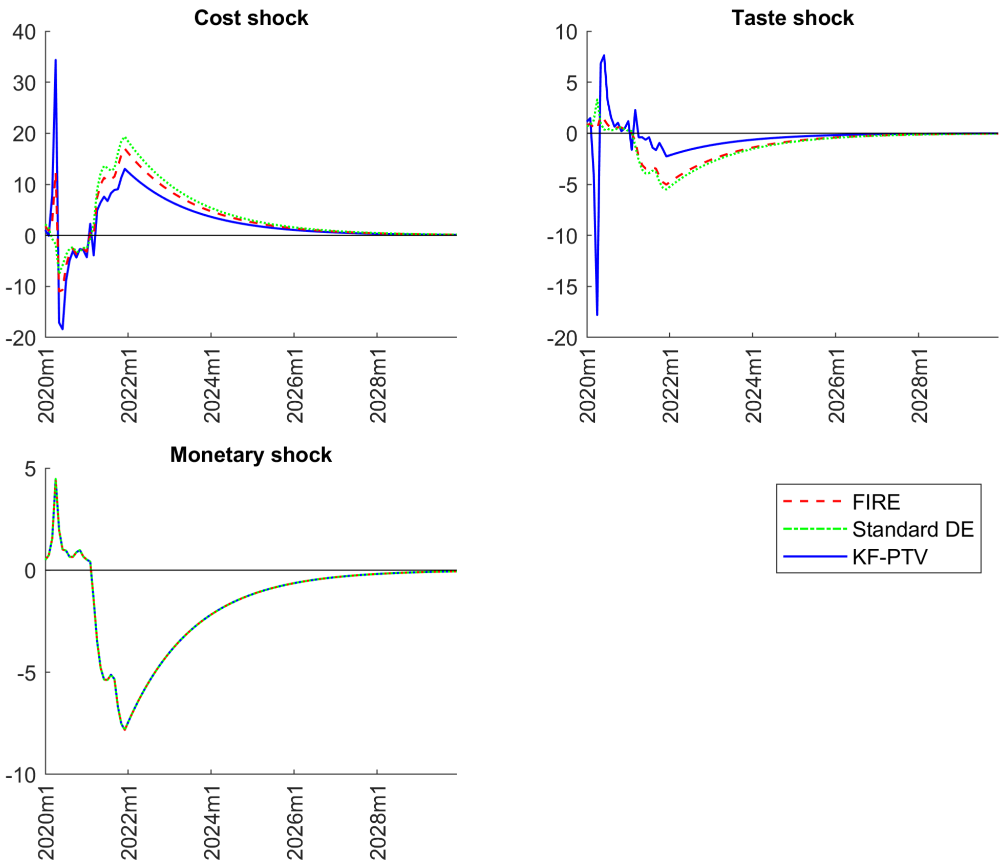
Note: Figure shows the heterogeneous consumption and labor supply gaps generated in the case where expectations follow the experience-based Kalman filter. Cohorts denote age at the time of the shock. The solid lines represent different cohorts in the experience-based Kalman filter model. The dashed red line is the aggregate. Horizontal axis denotes months after the shock.

Figure A8: Impulse Response Functions, Inflation Rate Experience-based Expectations by Cohort, Forecast



Note: Figure shows the heterogeneous expectations generated by the experience-based Kalman filter and the data (up to December 2021). Cohorts denote age in 2021. Horizontal axis denotes months.

Figure A9: Impulse Response Functions, Shocks, Forecast



Note: Figure shows the paths shocks follow according to the model and the data (up to December 2021). The red dashed line shows the results for the case of the full information rational expectations model (FIRE), the green dotted line shows the results of the standard diagnostic expectations operator, and the solid blue line shows the experience-based Kalman filter model. For the standard diagnostic expectations case, we assume that agents use the expectations operator $\mathbb{E}_t^{\theta,s}[X_{t+h}] = \mathbb{E}_t[X_{t+h}] + \zeta(\mathbb{E}_t[X_{t+h}] - \mathbb{E}_{t-3}[X_{t+h}])$ with $\zeta > 0$. Horizontal axis denotes months.

Table A1: Model Calibration

Parameter	Value	Parameter	Value
β	0.9967	χ_y	0.125
η	1	ρ^{cost}	0.9
ϕ	0.9167	ρ^{taste}	0.9
σ	1	λ	0.001
ε	9	K	0.1751
χ_π	1.5	θ	-0.374

Note: Table shows the parameters used for the model. We follow a standard monthly calibration.

Table A2: Optimal Taylor Rule Parameters, Cost Shock

	χ_π^*	χ_y^*
FIRE	119.20	0.74
Experience-based KF-PTV	140.79	0.47

Note: Table shows the Taylor rule parameters that minimize objective function $\mathbb{E}_t\left[\pi_t^2 + \vartheta y_t^2\right]$ when an unexpected cost shock hits the economy.

Table A3: Optimal Taylor Rule Parameters, Taste Shock

	χ_π^*	χ_y^*
FIRE	8.73	28.10
Experience-based KF-PTV	9.18	27.19

Note: Table shows the Taylor rule parameters that minimize objective function $\mathbb{E}_t\left[\pi_t^2 + \vartheta y_t^2\right]$ when an unexpected taste shock hits the economy.

B Standard Kalman Filter

B.1 Setup

The economy is populated by different cohorts indexed by i. These cohorts are heterogeneous in their dates of birth and the inflation history they have experienced. Since there is no heterogeneity within cohorts, a single representative agent summarizes the situation of each one of these groups. In a given period $t+1$, the level of inflation π_{t+1} is defined according to the following random walk process[34]

$$\pi_{t+1} = \pi_t + \varepsilon_t,$$

where ε_t is a normally independent and identically distributed inflation shock. We assume that, in a given period t, agents wish to forecast the future inflation rate π_{t+1}, but they only observe a noisy signal of this variable. In other words, the agents face a standard signal extraction problem. To simplify the analysis, in a given period t, we assume that the signal s_t is defined as

$$s_t = \zeta \pi_{t+1} + \upsilon_t,$$

where the coefficient $\zeta \geq 0$ denotes the pass-through existing between the unobserved variable π_{t+1} and its corresponding signal s_t, and υ_t is a signal noise. We assume that this noise is a normally independent and identically distributed variable. Moreover, we allow for a non-zero covariance between both shocks to consider the existence of some elements causing correlated movements in both the observed signal and the unobserved variable. Therefore, we have

$$\begin{pmatrix} \varepsilon_t \\ \upsilon_t \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\varepsilon^2 & \sigma_{\varepsilon\upsilon} \\ \sigma_{\varepsilon\upsilon} & \sigma_\upsilon^2 \end{pmatrix} \right).$$

As a further simplification, we assume the model has no private information. In other words, all of the agents receive precisely the same signal. Since the agents face a standard signal extraction

[34] We opt for a random walk process instead of a first-order auto-regressive (AR(1)) specification because the data cannot reject the hypothesis that the monthly inflation rate has a unit root. We provide a more thorough discussion in Appendix D. Also, see Pivetta & Reis (2007) for a discussion on the very high persistence of the (quarterly) inflation rate in the United States. To complete our analysis, in Appendix F, we show the model's results when the inflation series follows an AR(1) process. These results are very similar to those found under the random walk assumption.

problem, we assume they generate inflation forecasts using this variable's conditional expected value. More precisely, given their information set in period t, the agents apply a linear Kalman filter to forecast inflation in period $t+1$. Therefore, the inflation's predicted value is given by

$$\mathbb{E}_{i,t}^{KF}\left[\pi_{t+1}\right] = (1-\zeta K)\,\mathbb{E}_{i,t-1}^{KF}\left[\pi_{t+1}\right] + K s_t, \tag{18}$$

where K denotes a standard Kalman gain.[35] Conditional on agents' past and current signals, the Kalman filter approach allows us to characterize the forecasted distribution of the unobserved variable π_{t+1} in any period t. When the signal is perfectly revealing the true state of the variable, we observe $\zeta = 1$, $\upsilon_t = 0$, and $\sigma_{\varepsilon\upsilon} = 0$. Therefore, we conclude $K = \zeta K = 1$ and $\mathbb{E}_{i,t}^{KF}\left[\pi_{t+1}\right] = s_t = \pi_{t+1}$. The presence of a signal noise induces $K \in [0,1)$ even without a correlation between both error terms.

Regarding long-run values of inflation expectations, from the Kalman-based forecast equation and using the random walk structure associated with the inflation variable, we conclude that given $h \geq 1$, we must have

$$\mathbb{E}_{i,t}^{KF}\left[\pi_{t+h}\right] = \mathbb{E}_{i,t}^{KF}\left[\pi_{t+1}\right].$$

Finally, and considering the parameter $\gamma = (1-\zeta K) \in [0,1]$, the Kalman filter prediction can be written recursively as

$$\mathbb{E}_{i,t}^{KF}\left[\pi_{t+1}\right] = \gamma^{t+1}\mathbb{E}_{i,-1}^{KF}\left[\pi_0\right] + K\sum_{j=0}^{t}\gamma^{t-j}\left(\zeta\pi_{j+1} + \upsilon_j\right)$$

Therefore, using this simple version of the model, we conclude that higher values of past inflation imply a higher forecasting value of this same variable. However, agents' personal experiences are not associated with heterogeneity in expectations. According to this model, agents who lived

[35] As usual in the literature, this signal-to-noise ratio is defined such that it minimizes the variance of the prediction error associated with the unobserved variable, i.e., $\pi_{t+1} - \mathbb{E}_{i,t}^{KF}\left[\pi_{t+1}\right]$. The Kalman gain that solves this optimization problem depends on the covariance existing between the error associated with the observed signal and the unobserved variable and the constant $\Sigma_{t+1|t-1} = \mathbb{V}\mathrm{ar}\left[\pi_{t+1} - \mathbb{E}_{i,t-1}^{KF}\left[\pi_{t+1}\right]\right]$. See Cheung (1993) for an example of a Kalman gain that considers these terms. Regarding the constant $\Sigma_{t+1|t-1}$, it can be shown that it must satisfy $\left(\Sigma_{t+1|t-1} - \sigma_\varepsilon^2\right)\left(\zeta^2\Sigma_{t+1|t-1} + \sigma_\upsilon^2 + 2\zeta\sigma_{\varepsilon\upsilon}\right) - \left(\sigma_\upsilon^2\Sigma_{t+1|t-1} - \sigma_{\varepsilon\upsilon}^2\right) = 0$. We opt for a constant Kalman gain as it is a convenient assumption for the dynamic model explored in the following sections. However, we find similar results when we use time-varying gains.

through episodes of high inflation forecast an inflation value identical to those who lived through episodes of low inflation. Given a starting point assumption where every agent observes the initial level of inflation, i.e., $\mathbb{E}^{KF}_{i,-1}[\pi_0] = \pi_0$ for every agent i, we conclude that $\mathbb{E}^{KF}_{i,t}[\pi_{t+1}] = \mathbb{E}^{KF}_{t}[\pi_{t+1}]$ must hold for every agent. In what follows, to simplify the analysis, we assume $\zeta = 1$.

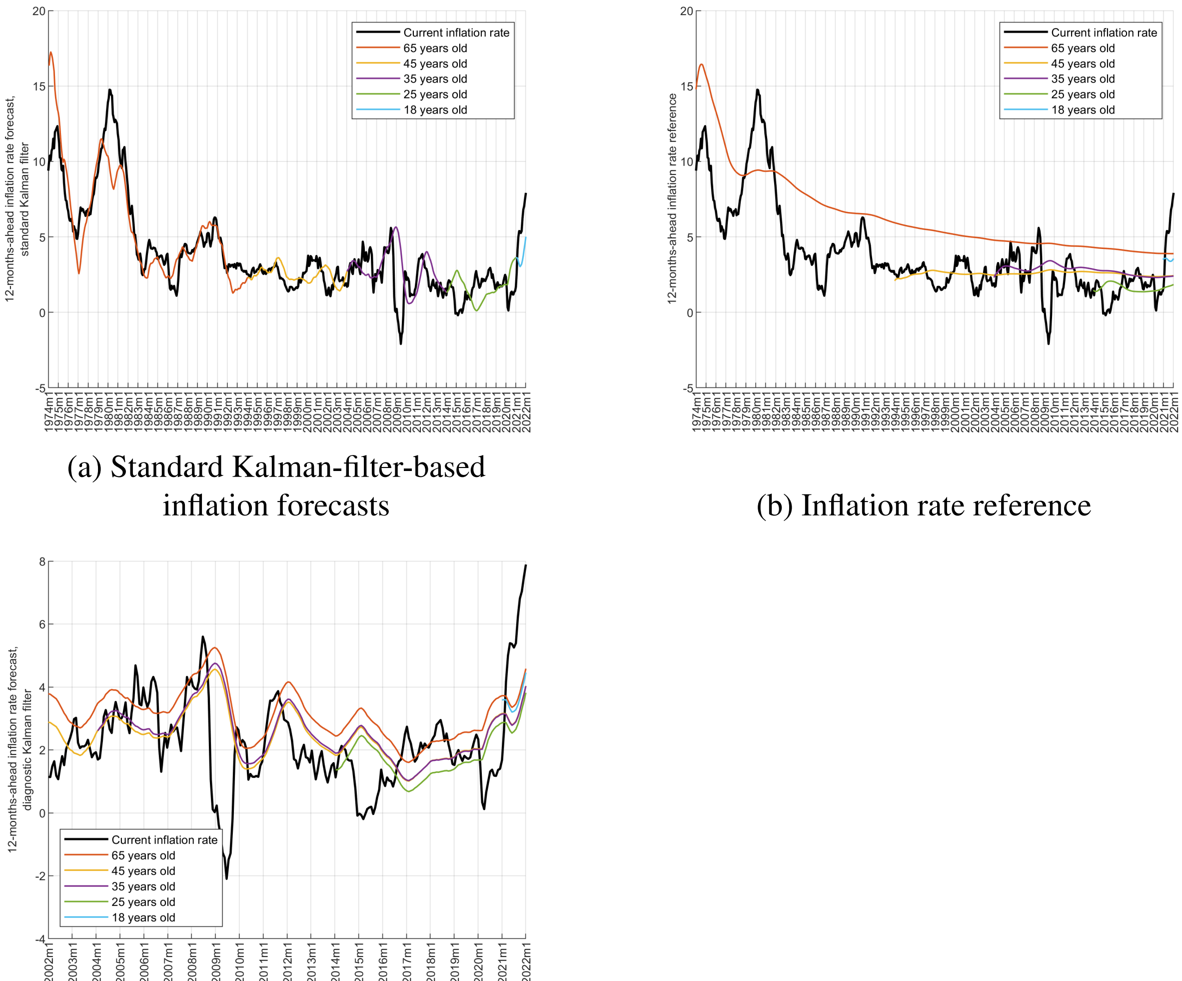
To identify an appropriate signal for the empirical counterpart of the expectations formation model, we follow the evidence presented in D'Acunto et al. (2021), which shows that agents use their consumption experience to form expectations. More specifically, Campos et al. (2022), using the University of Michigan's Survey of Consumers, concludes that consumers highly weigh CPI's food components when forming inflation expectations. Dietrich (2022) finds similar evidence using different data sources. Although differences in the composition of individual expenditures could lead to differences in perceived inflation (D'Acunto et al., 2021), according to data from the US Bureau of Labor Statistics, the share of food expenditure has no relevant variation across US cohorts. This fact supports our assumption of a common signal on the underlying aggregate inflation represented by the food component of the CPI. Finally, D'Acunto & Weber (2022) shows that consumers use food prices as a reference to form inflation expectations. Therefore, we use the food component of the CPI as a common inflation signal for all consumers.[36]

Because of timing issues, we use the lagged year-over-year percentage variation of the CPI's food component. Consumers use past changes in food prices as a signal to forecast future aggregate inflation. For example, suppose that in December, an agent forecasts aggregate inflation for the next 12 months, and we presume that consumers make this prediction at the beginning of the month. In that case, we assume this agent considers November's food inflation to forecast. Therefore, for the empirical counterpart of the expectations formation model, we assume $s_t = \pi^{food}_{t-1}$ where π^{food}_{t-1} denotes food inflation in period $t-1$. D'Acunto & Weber (2022) show that this behavior is consistent with consumers' use of food prices to form expectations, as they show that consumers weigh changes of observed reference food prices, in their case milk, to form inflation expectations. Hence, we use annual changes in the CPI's food component for the baseline specification primarily because of data availability motives and consistency with recent evidence. In Appendix G, we show

[36] Food prices can still be a source of heterogeneity if consumers have different consumption baskets. D'Acunto et al. (2021) shows that exposure to certain prices explains heterogeneity in inflation expectations. While those works show some interesting patterns, the common component here focuses on the fact that many of those goods are consumed by many consumers, and as they are tradable goods, price shocks can affect all consumers simultaneously.

that our results are robust to alternative signals also consistent with the recent empirical evidence on reference prices.

Figure A10: Experience-based Kalman-filter-based Inflation Forecasts by Cohort



(a) Standard Kalman-filter-based inflation forecasts

(b) Inflation rate reference

(c) Experience-based Kalman-filter-based inflation forecasts

Note: Panel (a) shows the Kalman filter forecast for the common component for selected cohorts, differentiated by their age in 2021. Panel (b) shows the references for selected cohorts obtained according to the Kalman filter and given the history of inflation experienced by the corresponding age group. Panel (c) shows forecasts for selected cohorts according to the Kalman-filter-augmented expectations and considering the estimate for θ from Column 1 of Table 2. Selected cohorts are differentiated by their age in 2021. We further assume that each cohort starts forecasting when they become 18 years old. The current inflation rate measure is based on the monthly YoY percentage variation of the CPI.

Using monthly data on aggregate and food inflation, we obtain $\sigma_\varepsilon^2 = 0.15$, $\sigma_\upsilon^2 = 4.09$ and $\sigma_{\varepsilon\upsilon} = -0.03$, concluding $K = 0.1751$.[37]

We now perform a forecasting exercise using monthly inflation data and distinguishing agents

[37]We detail how we obtain this calibration in Appendix D, while Appendix E provides empirical support for the Kalman gain being constant across cohorts.

by cohorts. Given the recursive structure of the Kalman filter and to initialize the cohort-specific forecasting process, we assume that in the period in which the cohort representative agent reaches adulthood and begins forecasting, she uses the previous period's Kalman filter expected value as a starting point. We denote the period when agent i starts forecasting as period k_i. Given the starting point assumption where the initial level of inflation is common knowledge, we have $\mathbb{E}^{KF}_{i,k_i-1}[\pi_{k_i}] = \mathbb{E}^{KF}_{k_i-1}[\pi_{k_i}]$ for every agent i. Panel (a) of Figure A10 presents the 12-month-ahead inflation forecasts of different cohorts produced according to the standard Kalman filter. This figure plots the actual inflation rate and the forecast made by some selected cohorts. The standard Kalman filter cannot generate the heterogeneous pattern in expectations observed in the data (i.e., Figure 1). Under this framework, inflation expectations evolve following an identical process across cohorts. Therefore, we need to move to a more sophisticated framework to replicate the facts observed in the data.

C Normality of Experience-based Expectations

Let $f\left(\pi_{t+1}|\mathscr{I}_t\right)$ be the true distribution of future inflation conditional on the currently available information set $\mathscr{I}_t$. We assume this behaves as

$$f\left(\pi_{t+1}|\mathscr{I}_t\right) \sim N\left(\mathbb{E}_t^{KF}\left[\pi_{t+1}\right], \sigma_\pi^2\right),$$

where $\mathbb{E}_t^{KF}\left[\pi_{t+1}\right]$ is the expectation computed according to the standard Kalman filter. On the other hand, let $f\left(\pi_{t+1}|\mathscr{I}_{i,t}^{ref}\right)$ be the distribution of the inflation rate conditional on the referential information set associated with cohort i. Under our current assumptions, this distribution behaves as

$$f\left(\pi_{t+1}|\mathscr{I}_{i,t}^{ref}\right) \sim N\left(\mathbb{E}_{i,t}^{ref}\left[\pi_{t+1}\right], \left(t-k_i\right)^{-1}\sigma_\pi^2\right),$$

where

$$\mathbb{E}_{i,t}^{ref}\left[\pi_{t+1}\right] = \frac{\sum_{j=1}^{t-k_i}\mathbb{E}_{i,t-j}^{KF}\left[\pi_{t+1}\right]}{\left(t-k_i\right)}.$$

Given these two elements, we define the distribution as

$$f_{i,t}^{\theta}\left(\pi_{t+1}\right) = f\left(\pi_{t+1}|\mathscr{I}_t\right) D_{i,t}^{\theta}\left(\pi_{t+1}\right),$$

where

$$D_{i,t}^{\theta}\left(\pi_{t+1}\right) = \left[\frac{f\left(\pi_{t+1}|\mathscr{I}_t\right)}{f\left(\pi_{t+1}|\mathscr{I}_{i,t}^{ref}\right)^{\frac{1}{t-k_i}}}\right]^{\theta} Z_{i,t},$$

where $Z_{i,t}^{-1} = \int f_{i,t}^{\theta}\left(\pi_{t+1}\right) d\pi_{t+1}$ is a term that ensures that $f_{i,t}^{\theta}\left(\pi_{t+1}\right)$ integrates to one. Therefore, under some algebraic procedure, the probability density function of the distribution can be written as

$$f_{i,t}^{\theta}\left(\pi_{t+1}\right)=\frac{\left[\frac{1}{\sigma_{\pi}\sqrt{2\pi}}\exp\left\{-\frac{\left(\pi_{t+1}-\mathbb{E}_{i,t}^{KF}\left[\pi_{t+1}\right]\right)^{2}}{2\sigma_{\pi}^{2}}\right\}\right]^{(1+\theta)}Z_{i,t}}{\left[\frac{1}{\sigma_{\pi}\sqrt{2\pi}}\exp\left\{-\frac{\left(\pi_{t+1}-\mathbb{E}_{i,t}^{ref}\left[\pi_{t+1}\right]\right)^{2}}{2\sigma_{\pi}^{2}}\right\}\right]^{\theta}},$$

and we can make the following approximation

$$f_{i,t}^{\theta}\left(\pi_{t+1}\right)\approx\frac{1}{\sigma_{\pi}\sqrt{2\pi}}\exp\left\{-\frac{\left(\pi_{t+1}-\mathbb{E}_{i,t}^{\theta}\left[\pi_{t+1}\right]\right)^{2}}{2\sigma_{\pi}^{2}}\right\}Z_{i,t},$$

where

$$\mathbb{E}_{i,t}^{\theta}\left[\pi_{t+1}\right]=\mathbb{E}_{t}^{KF}\left[\pi_{t+1}\right]+\theta\left(\mathbb{E}_{t}^{KF}\left[\pi_{t+1}\right]-\mathbb{E}_{i,t}^{ref}\left[\pi_{t+1}\right]\right).$$

Thus, we conclude that

$$f_{i,t}^{\theta}\left(\pi_{t+1}\right)\sim N\left(\mathbb{E}_{i,t}^{\theta}\left[\pi_{t+1}\right],\sigma_{\pi}^{2}\right).$$

D Monthly Inflation as a Random Walk

Throughout the paper, we consider the monthly inflation to be a random walk process. The reason behind this is that, with monthly inflation data, we cannot reject the hypothesis of unit root. To further expand on this, in Table A4 we present the results of AR(1) regressions on the monthly US inflation rate from January 1960 to March 2022. Column 1 does not consider a constant, while Column 2 does.

Table A4: AR(1) Regression for Monthly Inflation

	(1)	(2)
π_{t-1}	0.999*** (0.993 - 1.005)	0.992*** (0.982 - 1.002)
Observations	747	747
R-squared	0.993	0.981

Note: Table shows the results of AR(1) regressions with the monthly inflation rate in the United States from January 1960 to March 2022. Column 1 does not consider a constant while Column 2 does. The current inflation rate measure is based on the monthly YoY percentage variation of the CPI. 95 percent confidence intervals in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

We see that in both specifications, the autoregressive coefficient is very close to 1. Furthermore, the value of 1 falls within the 95 percent confidence intervals. Also, the F-test in which the null hypothesis is that the autoregressive coefficient is equal to 1 gives a p-value of 0.66 when we do not consider a constant and a p-value of 0.12 when we consider a constant, such that we cannot reject the null hypothesis in any of the two cases. Lastly, an augmented Dickey-Fuller test on the monthly inflation gives a p-value of 0.52, so we cannot reject the null hypothesis of a unit root. These findings are in line with those of Pivetta & Reis (2007), who find that there is a very high persistence in the quarterly inflation rate in the United States.

Given that we take the inflation rate to be a random walk process, we now turn to the calibration of the Kalman filter of Section B. There, we defined the agents assume that inflation behaves as

$$\pi_{t+1} = \pi_t + \varepsilon_t,$$

where ε_t is a normally independent and identically distributed inflation shock.

Agents also receive a signal s_t given by

$$s_t = \pi_{t+1} + \upsilon_t,$$

where υ_t is a normally independent and identically distributed signal noise.

Furthermore, we assume that the signal is $s_t = \pi_{t-1}^{food}$ where π_{t-1}^{food} denotes the inflation in period $t-1$ of the food component of the CPI. By manipulating the equations, we get

$$\varepsilon_t = \pi_t - \pi_{t+1},$$

$$\upsilon_t = s_t - \pi_{t+1} = \pi_{t-1}^{food} - \pi_{t+1}.$$

Then, armed with the US monthly inflation and food inflation series from January 1960 to March 2022 we calculate the variances σ_ε^2, σ_υ^2 and the covariance $\sigma_{\varepsilon\upsilon}$.

E Constant Kalman Gain across Cohorts

In Section 3, we argued that cohorts do not react differently to inflation news. Here, we provide further empirical evidence that supports this fact in a structurally-based fashion. We start from the standard Kalman filter specification to obtain

$$\mathbb{E}_{i,t}\left[\pi_{t+1}\right] = \mathbb{E}_{i,t-1}\left[\pi_{t+1}\right] + \kappa\left(s_t - \mathbb{E}_{i,t-1}\left[\pi_{t+1}\right]\right),$$

where $\mathbb{E}_{i,t}\left[\pi_{t+1}\right]$ is the inflation expectation of cohort i, s_t is the signal and κ is the Kalman gain.

In order to uncover whether cohorts react differently to the signal they are receiving, we estimate κ by cohorts as

$$\mathbb{E}^{SCE}_{m,i,t}\left[\pi_{t+1}\right] = \mathbb{E}^{SCE}_{m,i,t-1}\left[\pi_{t+1}\right] + \sum_{i \neq 1941}^{2002} \kappa_i \left(s_t - \mathbb{E}^{SCE}_{m,i,t-1}\left[\pi_{t+1}\right]\right) \times \mathbb{I}_i, \tag{19}$$

where we use the inflation expectations coming from agent m of cohort i in period t from the Survey of Consumer Expectations as the empirical counterpart for the theoretical inflation expectations[38]. $\mathbb{I}_i$ serves as an indicator variable for each cohort, which is defined by the date of birth. If different cohorts react differently to the signal they are receiving, then we should obtain different coefficients across cohorts.

Panel (a) of Figure A11 shows the results. We find that there are no systematically significant differences across cohorts when it comes to the Kalman gain. We interpret this as evidence that supports our fact of cohorts not reacting differently to the inflation signals they receive.

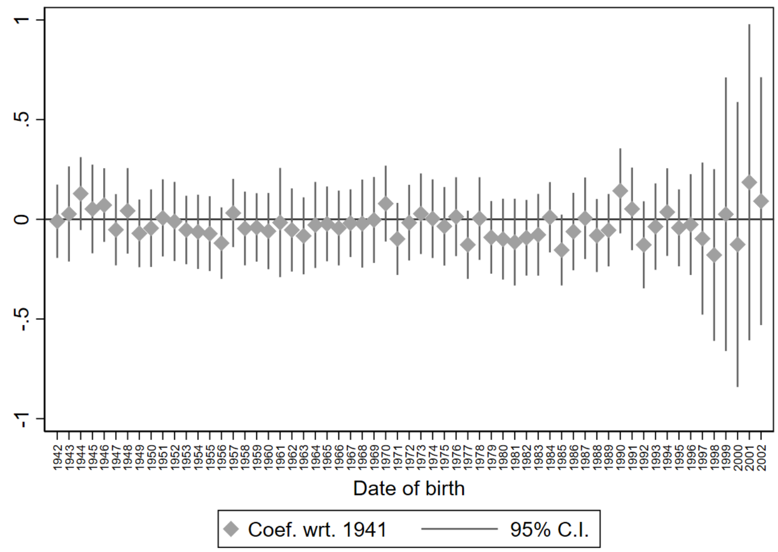
An alternative way of defining cohorts is by the age of the agents at the moment of the survey. Under this definition, we estimate

$$\mathbb{E}^{SCE}_{m,i,t}\left[\pi_{t+1}\right] = \mathbb{E}^{SCE}_{m,i,t-1}\left[\pi_{t+1}\right] + \sum_{i \neq 18}^{80} \kappa_i \left(s_t - \mathbb{E}^{SCE}_{m,i,t-1}\left[\pi_{t+1}\right]\right) \times \mathbb{I}_i, \tag{20}$$

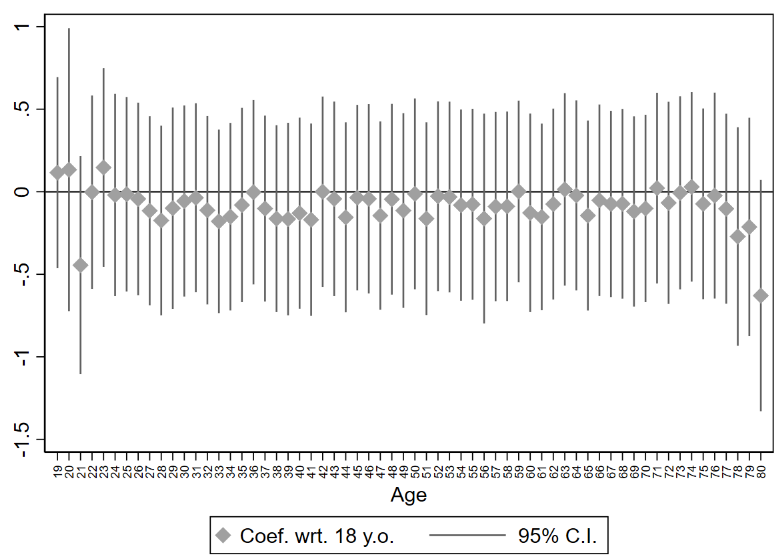
Panel (b) of Figure A11 presents the results. As before, we find there are no systematic differences in the Kalman gain across cohorts when defined by current age.

[38] In order to obtain $\mathbb{E}^{SCE}_{m,i,t-1}\left[\pi_{t+1}\right]$ we assume agents believe inflation behaves as a random walk.

Figure A11: Constant Kalman Gain across Cohorts



(a) Cohorts by date of birth



(b) Cohorts by age

Note: Figure shows the coefficient resulting from estimating Equations 19 and 20. The base cohort in Panel (a) is those born in 1941. The base cohort in Panel (b) is those who were 18 years old at the moment of the survey. We control for period and individual fixed effects.

F Experience-based Kalman Filter with AR(1) Assumption

In this section, we repeat the forecasting exercise from Section 4 but replacing the random walk assumption with an AR(1) specification. Therefore, agents assume that inflation behaves as

$$\pi_{t+1} = \rho_\pi \pi_t + \varepsilon_t,$$

where the coefficient $\rho_\pi \in [0,1]$ captures the mean-reversion of the inflation variable. Here, we assume the inflation rate has been properly demeaned.

As before, we assume that the signal is given by

$$s_t = \zeta \pi_{t+1} + \upsilon_t.$$

The forecasted value of the inflation variable is

$$\mathbb{E}_{i,t}^{KF}[\pi_{t+1}] = (1-\zeta K)\mathbb{E}_{i,t-1}^{KF}[\pi_{t+1}] + K s_t,$$

where the difference now lies in the fact that agents use the AR(1) assumption to forecast the inflation rate such that

$$\mathbb{E}_{i,t}^{KF}[\pi_{t+h}] = \rho_\pi^{h-1}\mathbb{E}_{i,t}^{KF}[\pi_{t+1}].$$

In this section we assume $\zeta = 1$, $\rho = 0.99$, $\sigma_\varepsilon = 0.15$, $\sigma_\nu = 4.09$ and $\sigma_{\varepsilon\nu} = -0.06$.[39] This gives $K = 0.175$.

Table A5 presents the result of the parameter estimation. In this case, $\theta = -0.612$. Finally, Figure A12 presents the comparison of the forecasts with the AR(1) assumption and the observed forecasts in the data. We find that, as with the random walk process, this version of the forecast based on an AR(1) assumption provides a good fit to the data.

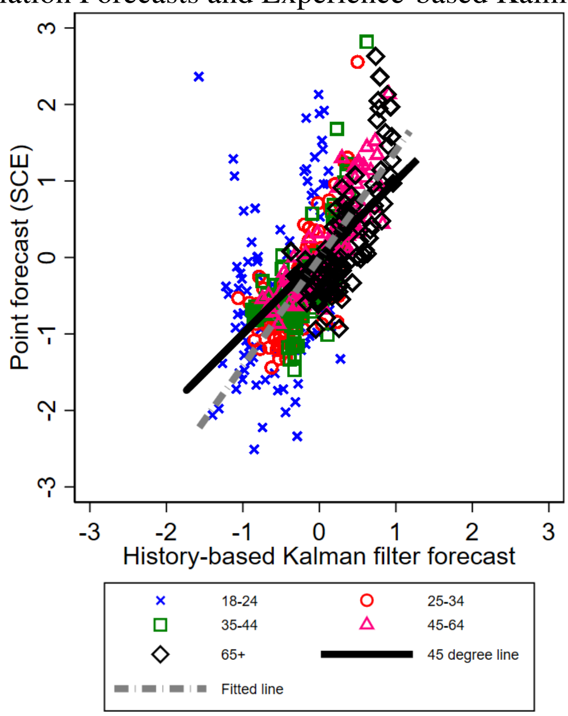
[39] We calibrate the variances and covariance according to Appendix D.

Table A5: Parameter Estimation, AR(1)

	(1)
$\mathbb{E}_{i,t}^{ref}\left[\pi_{t+12}\right]$	0.612***
	(0.075)
Time FE	Yes
Observations	83,991
R-squared	0.100

Note: Table shows results of estimating Equation 5 under an AR(1) assumption. $\mathbb{E}_{i,t}^{ref}\left[\pi_{t+12}\right]$ is the reference constructed for a respondent of age i as explained in the main text. We use population weights. Column 1 has only a time fixed effect as an additional control. Robust standard errors in parentheses. Standard errors clustered by age and period. Dependent variable trimmed at 10 percent and 90 percent in each period. *** p<0.01, ** p<0.05, * p<0.1.

Figure A12: Observed Inflation Forecasts and Experience-based Kalman Filter Forecasts, AR(1)



Note: Figure shows binned scatterplot across experience-based Kalman filter forecasts (x-axis) and point forecast inflation expectations according to the Survey of Consumer Expectations (SCE) of the Federal Reserve Bank of New York (y-axis). Variables demeaned by the intercept. Data go from June 2013 to December 2021. SCE variable trimmed at 10 percent and 90 percent in each period.

G Experience-based Kalman Filter with Alternative Signals

Throughout the paper, we use the lagged inflation rate of the food component of the CPI as a signal of the non-observed aggregate inflation variable. This is based on previous papers that study how consumers form their inflation expectations based on shopping experiences and food prices (D'Acunto et al., 2021; D'Acunto & Weber, 2022). In this section, we consider two alternative components of the CPI as the signals consumers use: food at home and dairy.

Table A6 presents the estimation of the parameter according to each signal. In all cases, we find a positive weight on the reference. Moreover, the parameter is close to the baseline from Table 2.

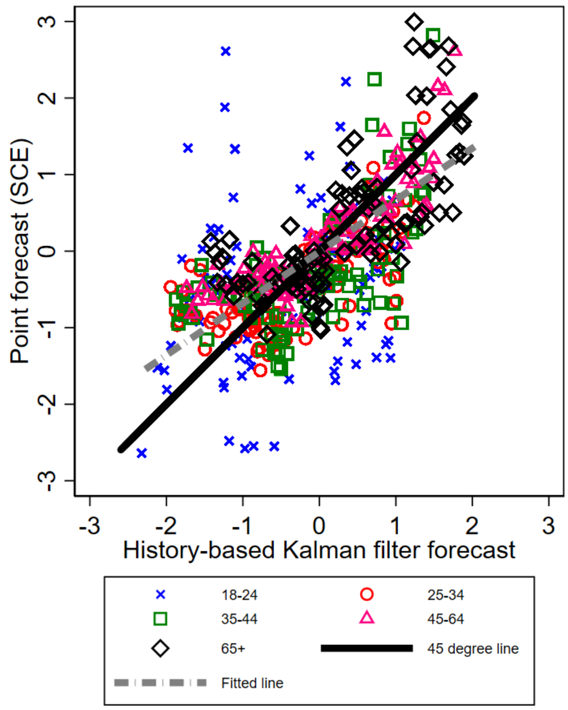
Figure A13 shows how the experience-based Kalman filter forecasts with alternative signals fare against the observed inflation forecasts. Using the food at home and dairy CPI components as a signal provides a decent fit to the observed data.

Table A6: Main Parameter Estimation, Alternative Signals

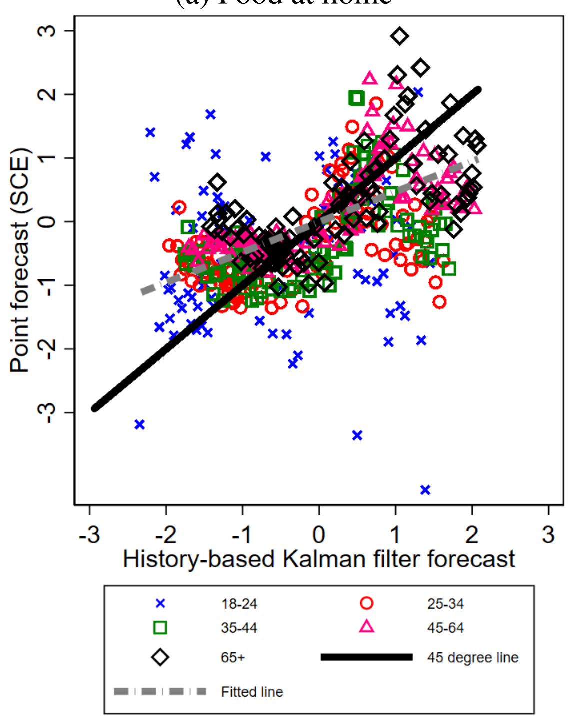
	Food at home	Dairy
$\mathbb{E}_{i,t}^{ref}[\pi_{t+12}]$	0.359***	0.380***
	(0.043)	(0.048)
Observations	83,991	83,991
R-squared	0.101	0.100

Note: Table shows results of estimating equation 5 using alternative CPI components as the signal. $\mathbb{E}_{i,t}^{ref}[\pi_{t+12}]$ is the reference constructed for a respondent of age i as explained in the main text. We use population weights. Columns have only a time fixed effect as an additional control. Robust standard errors in parentheses. Standard errors clustered by age and period. Dependent variable trimmed at 10 percent and 90 percent in each period. *** p<0.01, ** p<0.05, * p<0.1.

Figure A13: Observed Inflation Forecasts and Experience-based Kalman Filter Forecasts, Alternative Signals



(a) Food at home



(b) Dairy

Note: Figure shows binned scatterplot across experience-based Kalman filter forecasts (x-axis) and point forecast inflation expectations according to the Survey of Consumer Expectations (SCE) of the Federal Reserve Bank of New York (y-axis) using alternative CPI components as the signal. Variables demeaned by the intercept. Data go from June 2013 to December 2021. SCE variable trimmed at 10 percent and 90 percent in each period.

H External Validity: European Data

We check the external validity of our results using data from the Consumer Expectations Survey (CES) of the European Central Bank. It contains monthly data between April 2020 and September 2022 for six countries: Belgium, France, Germany, Italy, the Netherlands, and Spain.[40]

We see that in Europe, lifetime experiences with the inflation rate are also heterogeneous across cohorts, as we show in Figure A15. Moreover, we see that by 2020 the youngest cohorts had not been exposed to high inflation rates, but this changes after the high inflation rate episode of 2021 and 2022. After this, the youngest cohorts are the ones that show the highest lifetime average for the inflation rate, even larger than that of the people who experienced the high inflation rates of the 80s.

In Figure A16 we relate the two previous facts and find that in Europe, similarly to the United States, the larger the inflation rate individuals have experienced in their lifetimes, the higher their inflation expectations.

Table A7 shows that in Europe, as happened in the United States, after controlling for the average lifetime inflation rate, younger generations do not react more strongly to inflation news than older cohorts.[41]

We now turn to the experience-based Kalman filter of Section B. Table A8 shows the parameters that go into the Kalman filter calibration after using the European inflation rate and the food inflation rate. Then, we estimate the parameter according to Equation 5.[42] In Table A9 in our baseline specification of Column 1 we find $\theta^{eur} = -0.156$. With this parameter, in Figure A17 we plot inflation expectations according to our experience-based Kalman filter, across cohorts and in each of the six countries in our sample. We find that the oldest cohorts have the highest inflation

[40]There is a relevant difference between the datasets of United States and Europe. In the former, we have the exact age of the respondents. In the latter, we do not have detailed information on the age of the respondents, as they are classified in 4 age groups: 18-34, 35-49, 50-70 and 71+.

[41]We confirm the finding with an F-test where the null hypothesis is that all of the interactions are jointly equal to zero. The test gives a p-value of 0.35, so we cannot reject the null hypothesis.

[42]Because we do not know the exact age of the respondents, we do not know which are the exact lifetime average inflation rates they have experienced. Therefore, for this estimation, we assume that every agent in cohort 18-34 has the lifetime average inflation rate of a 25-year-old, every agent in cohort 35-49 has the lifetime average inflation rate of a 35-year-old, every agent in cohort 50-70 has the lifetime average inflation rate of a 50-year-old and every agent in cohort 71+ has the lifetime average inflation rate of a 71-year-old. On the signals used, because the series on the inflation rate of the food component of the CPI have varying starting dates in the different countries, we replace the missing values with the observed inflation rate in order to make the starting dates of all countries uniform.

expectations before 2021. Then, after 2021 the youngest cohorts start catching up with the oldest ones and even surpass them in some countries.

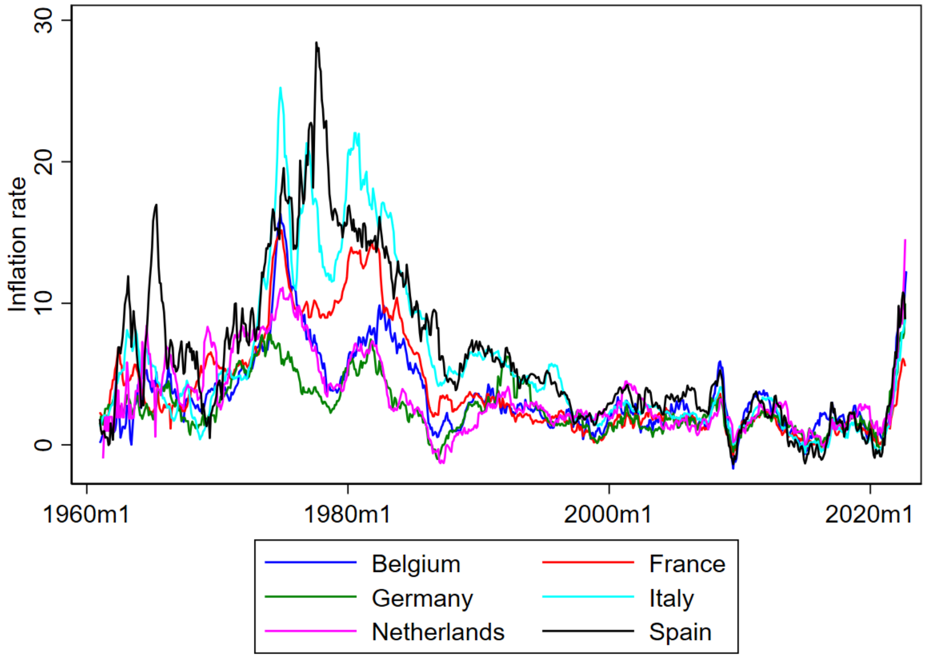
Table A9 also shows additional specifications of the estimation of equation 5. We find that after controlling for cohort and country fixed effects, we still find that agents positively weight their references when forming their expectations. These additional specifications also tell us that the heterogeneity in expectations across cohorts is not due to people of different ages or from different countries facing different consumption bundles or having different preferences, but to the proposed anchoring-to-the-past mechanism. Thus, it is past experiences that define expectations, not age or the geographic location per se.[43]

Lastly, in Figure A18, we compare the inflation expectations generated by our experience-based Kalman filter to the survey data. We see that we have a decent fit to the data.

We conclude that our findings from the main text are also valid for Europe. We find evidence that supports the claim that i) inflation expectations are also heterogeneous in Europe and ii) they can also be modeled by an experience-based Kalman filter with positive weight on their historical reference.

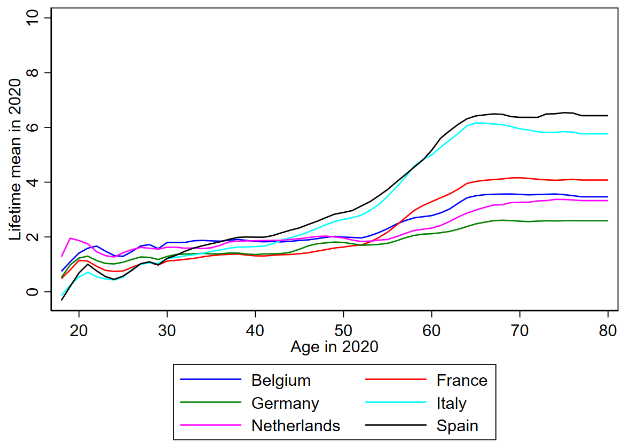
[43] See Hajdini et al. (2022a) for a further discussion on this.

Figure A14: Inflation Rate, Europe

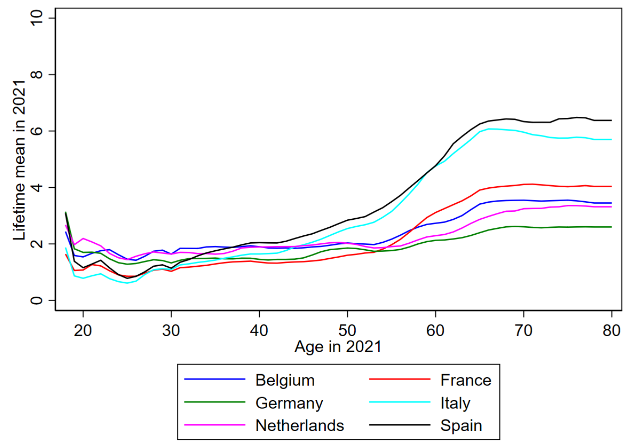


Note: The current inflation rate measure is based on the monthly YoY percentage variation of the CPI.
Source: FRED.

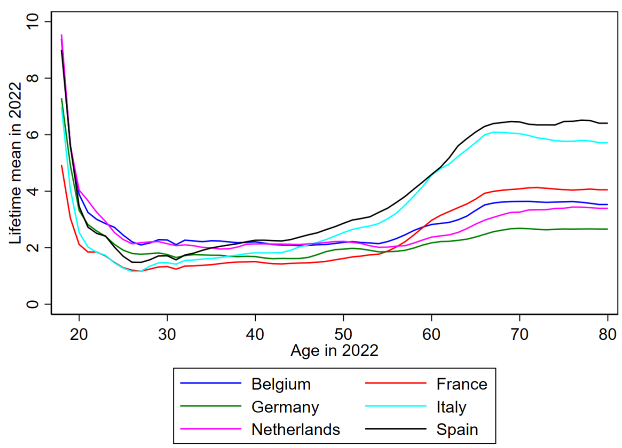
Figure A15: Lifetime Average Inflation Rate among Respondents, Europe



(a) 2020



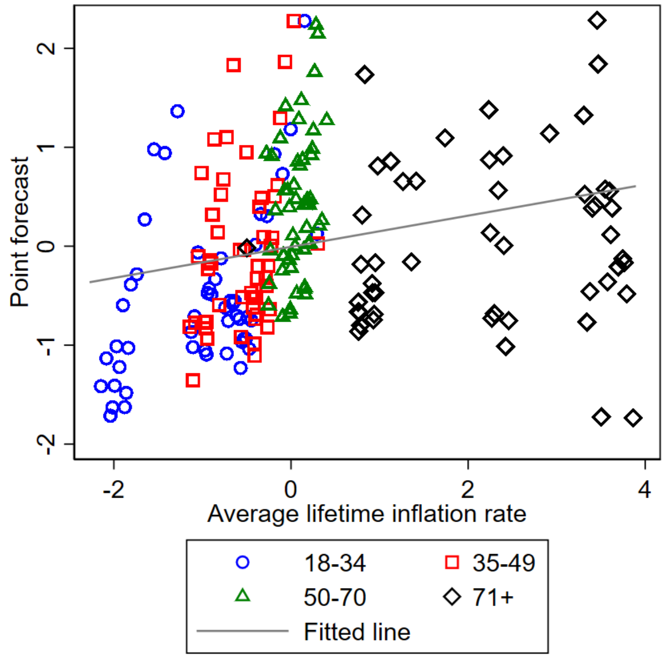
(b) 2021



(c) 2022

Note: Figure shows the mean of the monthly YoY inflation rate that people of the age shown in 2020, 2021, and 2022 have experienced in their lifetimes, starting when they were age 18. The current inflation rate measure is based on the monthly YoY percentage variation of the CPI.
Source: FRED.

Figure A16: Inflation Point Forecast and Average Lifetime Inflation Rate, Europe



Note: Figure shows a binned scatterplot across lifetime average inflation rate bins. Variables were residualized by respondent gender and commuting zone. The data range from April 2020 to September 2022. Ages correspond to the interviewee's age at the time of the survey. The average lifetime inflation rate measure is based on the monthly YoY percentage variation of the CPI.
Source: Consumer Expectations Survey.

Table A7: Effects of Current and Experienced Inflation Rates on Inflation Expectations, Europe

Dep. var.: Inflation expectations	(1)	(2)	(3)	(4)
Average lifetime inflation rate	0.276*	0.244**	0.301*	0.252*
	(0.132)	(0.100)	(0.149)	(0.129)
Current inflation	0.351***	0.275***		
	(0.033)	(0.057)		
Cohort 35-49		0.155		
		(0.090)		
Cohort 50-70		0.203*		
		(0.112)		
Cohort 71+		-0.401		
		(0.348)		
Current inflation × 35-49		0.074		
		(0.074)		
Current inflation × 50-70		0.122		
		(0.069)		
Current inflation × 71+		0.124		
		(0.083)		
Time FE	No	No	Yes	Yes
Controls	No	No	No	Yes
Observations	294,232	294,232	294,232	294,232
R-squared	0.128	0.135	0.152	0.164

Note: Table shows regressions where the dependent variable is inflation expectations according to the Consumer Expectations Survey (CES) of the European Central Bank. Column 1 shows controls for the average lifetime inflation of respondents of a given age at each period in time and the last inflation measure. Column 2 follows Column 1 but adds cohort fixed effects and the interaction of those cohort fixed effects with the current inflation. Column 3 follows Column 1 but adds time fixed effects and, hence, omits the current inflation variable. Column 4 follows Column 1 but adds time fixed effects and demographic controls. The demographic controls are income, gender, educational level, and country. The current inflation rate measure is based on the monthly YoY percentage variation of the CPI. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by age. The dependent variable is trimmed, dropping the lower and upper 10 percent of answers in each period.

Table A8: Experience-based Kalman Filter Parameters, Europe

	σ_ε^2	σ_υ^2	$\sigma_{\varepsilon\upsilon}$	K
Belgium	0.16	2.51	-0.28	0.24
France	0.09	2.63	-0.14	0.17
Germany	0.12	3.13	-0.15	0.18
Italy	0.23	3.38	-0.38	0.24
Netherlands	0.13	3.54	-0.18	0.18
Spain	0.45	5.83	-0.65	0.26

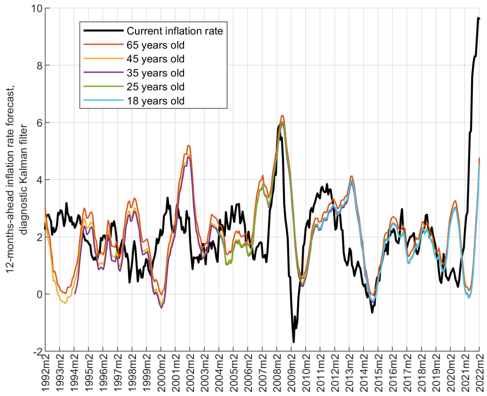
Note: We obtain this calibration for each country following the steps outlined in Appendix D. The data for these calculations goes from January 1971 to October 2022.

Table A9: Parameter Estimation, Europe

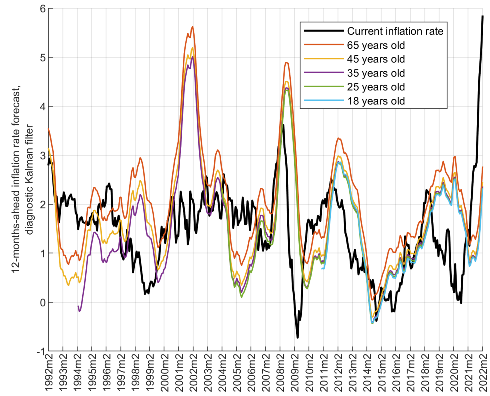
	(1)	(2)	(3)	(4)
$\mathbb{E}_{i,t}^{ref}\left[\pi_{t+12}\right]$	0.156***	0.208***	0.094***	0.060***
	(0.011)	(0.016)	(0.011)	(0.018)
Time FE	Yes	Yes	Yes	Yes
Controls	No	Cohort	Country	Cohort, country
Observations	271,311	271,311	271,311	271,311
R-squared	0.122	0.130	0.132	0.140

Note: Table shows results of estimating equation 5, but changing the dependent variable for inflation expectations according to the Consumer Expectations Survey (CES) of the European Central Bank. We use population weights. The independent variable $\mathbb{E}_{i,t}^{ref}\left[\pi_{t+12}\right]$ is the reference constructed for a respondent of age i as explained in the main text. Column 1 considers a time fixed effect as a control. Column 2 has time and cohort fixed effects. Column 3 has time and country fixed effects. Column 4 has time, cohort, and country fixed effects. Robust standard errors in parentheses. Dependent variable trimmed at 10 percent and 90 percent in each period. *** p<0.01, ** p<0.05, * p<0.1.

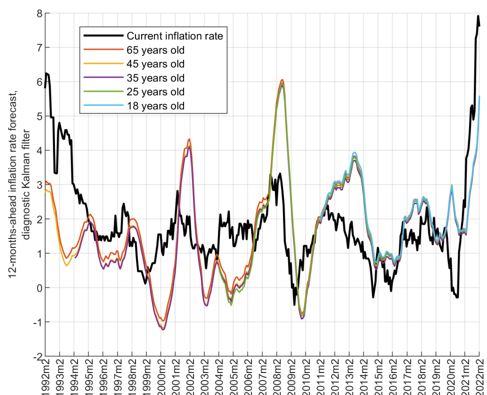
Figure A17: Experience-based Kalman-filter-based Inflation Forecasts by Cohort, Europe



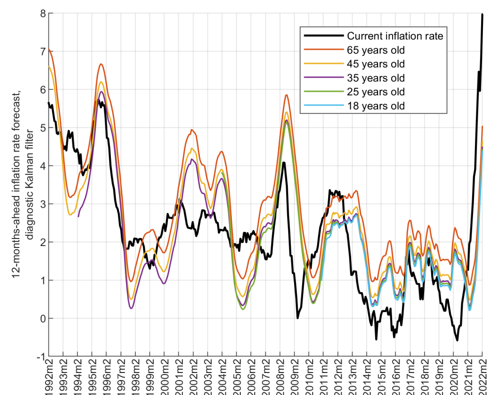
(a) Belgium



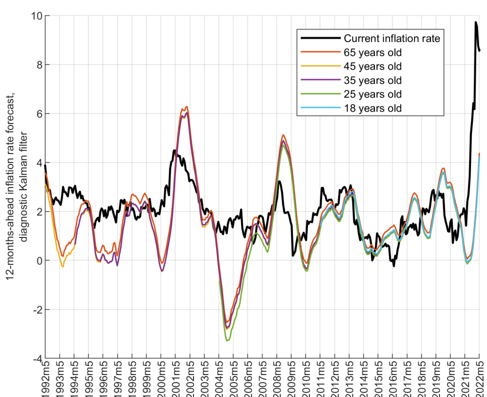
(b) France



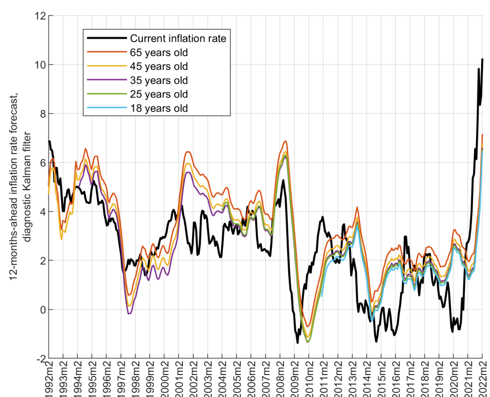
(c) Germany



(d) Italy



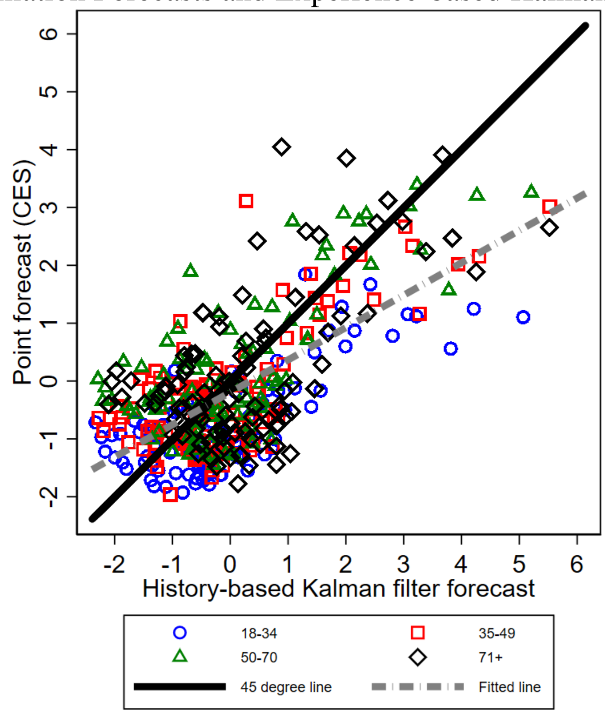
(e) Netherlands



(f) Spain

Note: Figure shows forecasts for selected cohorts according to the Kalman-filter-augmented expectations and considering the estimate for θ from Column 1 of Table A9. Selected cohorts differentiated by their age in 2021. We further assume that each cohort starts forecasting when they become 18 years old. The current inflation rate measure is based on the monthly YoY percentage variation of the CPI.

Figure A18: Observed Inflation Forecasts and Experience-based Kalman Filter Forecasts, Europe



Note: Figure shows binned scatterplot across experience-based Kalman filter forecasts (x-axis) and point forecasts of inflation expectations according to the Consumer Expectations Survey (CES) of the European Central Bank (y-axis). Variables demeaned by the intercept. The data range from April 2020 to September 2022. SCE variable trimmed at 10 percent and 90 percent in each period.

I Comparison with Malmendier & Nagel (2016)

In this section, we run a horse race between our measure and the measure of Malmendier & Nagel (2016). To do this comparison, we use our data, i.e., the SCE, but we consider different version mof their model to account for those changes. Using the information from their paper, and build their measure of inflation for the sample we use. In particular, we use:

$$\pi^{MN}_{t+12|t,s} = \beta \tau_{t+12|t,s} + (1-\beta) f_t$$

where $\pi^{MN}_{t+1|t,s}$ is the predicted inflation expectation for an individual of cohort s in time t. $\tau_{t+1|t,s}$ is the cross-sectional component that varies at each period of time t for a given cohort s. As explained in Malmendier & Nagel (2016), this component depends on a gain parameter θ. We start by using the estimate from their paper to then estimate one that is closely related to the data and period we are using in this paper. θ depend on the common variable f_t use, in their case, the lagged Survey of Professional Forecasters prediction for the period (SPF_{t-1}) or the average $\tau_{t+1|t,s}$ for all cohorts at a given period of time $\bar{\tau}_{t+1|t}$. In the case of their paper $\theta = 3.044$ when $f_t = \bar{\tau}_{t+1|t}$ and $\theta = 3.976$ when $f_t = SPF_{t-1}$.

We then run a regression where we replicate Table 3 for the draft, but including the Malmendier & Nagel (2016) measures. We start with the version with $\theta = 3.976$ and $f_t = SPF_{t-1}$, in that case, we also have $\beta = 0.664$. Table A10 shows the results.

Table A10: Horserace with Malmendier & Nagel (2016), Using Their Estimate and SPF

	(1)	(2)	(3)	(4)	(5)	(6)
$E^{\theta}_{i,t}\left[\pi_{t+12}\right]$	1.069***		0.932***	0.931***	0.873***	0.872***
	(0.163)		(0.072)	(0.072)	(0.082)	(0.081)
$\pi^{MN}_{t+12\|t,s}$		0.890***	0.782***	0.514	0.797***	0.483
		(0.118)	(0.073)	(0.535)	(0.073)	(0.496)
$\bar{\pi}_{i,t}$					0.106**	0.108**
					(0.045)	(0.045)
π_{t-1}				0.162		0.190
				(0.319)		(0.298)
Constant	2.033***	2.715***	0.791***	1.027*	0.578**	0.852*
	(0.325)	(0.230)	(0.241)	(0.526)	(0.237)	(0.486)
Observations	83,991	83,991	83,991	83,991	83,991	83,991
R-squared	0.041	0.043	0.074	0.074	0.075	0.075

We can see that in terms of predictive power, both our and the Malmendier & Nagel (2016) version have a similar power and coefficient. In terms of R-squared, it is almost the same. In terms of coefficient, ours is slightly larger when we see results in Column 3, but when we normalize them by the variation of each variable and the dependent variable, the coefficients are even closer (0.187 vs 0.194) and not statistically different (p value of 0.74). One striking difference comes up when we add the other controls, such as the average experienced inflation and the lag inflation. In that case the coefficient of Malmendier & Nagel (2016) is not statistically significant anymore. This results could be explained by the fact that we are using the version of their estimate with SPF, and that can explain most of their coefficient predicting power. Instead of that version, we move to Column 6 of Table I in Malmendier & Nagel (2016), where they use the $f_t = \bar{\tau}_{t+1|t}$. In that case they use $\theta = 3.044$ and $f_t = \bar{\tau}_{t+1|t}$. Additionally, they find $\beta = 0.672$. Table A11 shows the results

Table A11: Horserace with Malmendier & Nagel (2016), Using their Estimate and Average History

	(1)	(2)	(3)	(4)	(5)	(6)
$E_{i,t}^{\theta}\left[\pi_{t+12}\right]$	1.069***		0.917***	0.904***	0.855***	0.838***
	(0.163)		(0.072)	(0.072)	(0.082)	(0.085)
$\pi_{t+12\|t,s}^{MN}$		0.626***	0.545***	1.093*	0.556***	1.167*
		(0.082)	(0.049)	(0.633)	(0.050)	(0.619)
$\bar{\pi}_{i,t}$					0.113**	0.116**
					(0.045)	(0.047)
π_{t-1}				-0.477		-0.531
				(0.543)		(0.533)
Constant	2.033***	3.276***	1.327***	1.175***	1.111***	0.936***
	(0.325)	(0.162)	(0.205)	(0.289)	(0.201)	(0.279)
Observations	83,991	83,991	83,991	83,991	83,991	83,991
R-squared	0.041	0.045	0.074	0.074	0.075	0.075

We find similar results. The predictive power is similar, and the normalized coefficient is not statistically different from each other (0.184 vs 0.195, p-value of 0.74). After the controls, the coefficient of $\pi_{t+12|t,s}^{MN}$ is statistically significant, but only at 10 percent, while the statistical significance of our coefficient remains unchanged, as the standard error only increases slightly with these controls.

We can go a step further and use the Malmendier & Nagel (2016) variables. These coefficients are estimated using quarterly data and their history of data. A different approach would be to estimate, using their method and data, the θ and β, but using monthly data. The disadvantage of using monthly data is that we only have data for the CPI inflation since 1917. They use data from Shiller (2005) that go back to 1872 at a quarterly frequency. But, as our data start in 2011, it is not a problem for the cohorts we have. We calibrate their model with their data a history of monthly inflation and obtain a new set of parameters with both methods. In this case, we get a $\theta = 2.500$ and a $\beta = 0.078$ for the SPF estimation and a $\theta = 3.057$ and a $\beta = 0.966$ for the estimation with the average history. These results show that the estimation is now not very stable, where the weight on the common variable changes significantly between one method and the other. We still use these estimates and run the *horserace* between our method, the Malmendier & Nagel (2016) method, the average history of an individual and the lagged inflation. Table A12 shows the results for the estimations using SPF.

Table A12: Horserace with Malmendier & Nagel (2016), Using Monthly Data and SPF

	(1)	(2)	(3)	(4)	(5)	(6)
$E_{i,t}^{\theta}[\pi_{t+12}]$	1.069***		1.181***	0.872***	1.170***	0.782***
	(0.163)		(0.095)	(0.089)	(0.108)	(0.106)
$\pi_{t+12\mid t,s}^{MN}$		1.861***	2.353***	-0.663	2.355***	-0.857
		(0.694)	(0.364)	(0.533)	(0.365)	(0.533)
$\bar{\pi}_{i,t}$					0.021	0.130***
					(0.049)	(0.047)
π_{t-1}				0.566***		0.605***
				(0.080)		(0.084)
Constant	2.033***	0.592	-3.150***	2.832**	-3.193***	2.979***
	(0.325)	(1.402)	(0.903)	(1.132)	(0.879)	(1.117)
Observations	83,991	83,991	83,991	83,991	83,991	83,991
R-squared	0.041	0.014	0.063	0.074	0.064	0.075

Again we find similar conclusions compared to the previous results. Then, in Table A13, we run the same exercise, but using $f_t = \bar{\tau}_{t+1|t}$.

Table A13: Horserace with Malmendier & Nagel (2016), Using Monthly Data and Average History

	(1)	(2)	(3)	(4)	(5)	(6)
$E_{i,t}^{\theta}[\pi_{t+12}]$	1.069***		0.918***	0.916***	0.855***	0.852***
	(0.163)		(0.072)	(0.071)	(0.082)	(0.083)
$\pi_{t+12\mid t,s}^{MN}$		0.627***	0.546***	0.613	0.558***	0.666*
		(0.083)	(0.050)	(0.410)	(0.051)	(0.395)
$\bar{\pi}_{i,t}$					0.113**	0.114**
					(0.046)	(0.047)
π_{t-1}				-0.057		-0.094
				(0.349)		(0.338)
Constant	2.033***	3.274***	1.324***	1.305***	1.107***	1.075***
	(0.325)	(0.165)	(0.205)	(0.244)	(0.201)	(0.236)
Observations	83,991	83,991	83,991	83,991	83,991	83,991
R-squared	0.041	0.045	0.074	0.074	0.075	0.075

We find similar results as before. The estimate of Malmendier & Nagel (2016) has predicting value by itself, but this predicting value tends to be noisier after controlling for the lagged inflation. Also, these controls do not significantly change the predicting power of our estimate. There seems to be a difference between which common factor we consider for the Malmendier & Nagel (2016) expectation, but in general, it seems that a big part of its predictive power is similar to what lagged inflation would add.

We can go a step further by using their method using the NY Fed SCE data. This would fit their data better to the data we are trying to predict, but it has the disadvantage that it has a lower history of inflation, which can be more relevant for their method. We again estimate the parameters β and θ using the NY Fed data from 2011 to 2022, as in our paper. We obtain $\beta = 0.169$ and $\theta = 0.333$ using the SPF as a common factor; for the average as a common factor, we obtain $\beta = 3.752$ and $\theta = 4.269$. As seen in both cases, there are values that are at odds with the main findings of Malmendier & Nagel (2016). On one side, $\theta = 0.333 < 1$, meaning that observations early in live weight more compared to later in live as with their main parametrization. On the other side, when we use the average, β is not between zero and one, producing negative weight to the common factor variable. Table A14 shows the results for the SPF and Table A15 for the average.

Table A14: Horserace with Malmendier & Nagel (2016), Using NY Fed Data and SPF

	(1)	(2)	(3)	(4)	(5)	(6)
$E^{\theta}_{i,t}[\pi_{t+12}]$	1.069***		1.112***	0.900***	1.078***	0.829***
	(0.081)	(0.085)	(0.090)	(0.098)		
$\pi^{MN}_{t+12\|t,s}$		1.705***	1.820***	-0.350	1.835***	-0.440
		(0.443)	(0.216)	(0.453)	(0.218)	(0.454)
$\bar{\pi}_{i,t}$					0.066	0.116**
					(0.046)	(0.046)
π_{t-1}				0.547***		0.576***
				(0.098)		(0.101)
Constant	2.033***	0.919	-1.874***	2.144**	-2.025***	2.097**
	(0.325)	(0.888)	(0.566)	(0.920)	(0.559)	(0.904)
Observations	83,991	83,991	83,991	83,991	83,991	83,991
R-squared	0.041	0.024	0.068	0.074	0.069	0.075

Table A15: Horserace with Malmendier & Nagel (2016), Using NY Fed Data and Average

	(1)	(2)	(3)	(4)	(5)	(6)
$E^{\theta}_{i,t}[\pi_{t+12}]$	1.069***		0.909***	0.929***	0.852***	0.868***
	(0.078)	(0.073)	(0.091)	(0.083)		
$\pi^{MN}_{t+12\|t,s}$		0.634***	0.540***	0.035	0.550***	0.038
		(0.081)	(0.064)	(0.094)	(0.063)	(0.087)
$\bar{\pi}_{i,t}$					0.101**	0.109**
					(0.050)	(0.045)
π_{t-1}				0.443***		0.449***
				(0.088)		(0.084)
Constant	2.033***	3.265***	1.359***	1.472***	1.165***	1.264***
	(0.325)	(0.159)	(0.222)	(0.192)	(0.214)	(0.190)
Observations	83,991	83,991	83,991	83,991	83,991	83,991
R-squared	0.041	0.042	0.071	0.074	0.071	0.075

The main patterns of the previous findings are confirmed. We can see that, in general, the Malmendier & Nagel (2016) has predictive power, but it does not decrease the predictive power of our estimate. Additionally, simple controls like past inflation reduce the significance of their estimate while leaving our estimate similar. We conclude that our estimate is still relevant after controlling for theirs and that our estimate is effective after considering time and cross-sectional variation on inflation.

J Derivations for Firm Block

J.1 Final Good Producer

The final good producer operates in a perfectly competitive market. It produces the final good Y_t using a CES basket composed of a continuum of intermediate goods $Y_t(j)$ with $j \in [0,1]$. Therefore, the optimization problem of the firm is

$$\max_{\{Y_t(j)\}_{j\in[0,1]}} P_t Y_t - \int_{j\in[0,1]} P_t(j)\, Y_t(j)\, dj,$$

subject to

$$Y_t = \left[\int_{j\in[0,1]} Y_t(j)^{\frac{\varepsilon-1}{\varepsilon}}\, dj \right]^{\frac{\varepsilon}{\varepsilon-1}},$$

where $P_t(j)$ is the price of intermediate good j, and $\varepsilon > 1$ is the elasticity of substitution in the CES basket. As a solution, we obtain the corresponding downward-sloping demand curve $\forall$ $j \in [0,1]$

$$Y_t(j) = \left(\frac{P_t(j)}{P_t} \right)^{-\varepsilon} Y_t,$$

where the price of this production basket is given by

$$P_t = \left[\int_{j\in[0,1]} P_t(j)^{1-\varepsilon}\, dj \right]^{\frac{1}{1-\varepsilon}},$$

J.2 Intermediate Good Producers

There is a continuum of monopolistically competitive firms indexed by $j \in [0,1]$. Each firm $j \in [0,1]$ produces the intermediate good $Y_t(j)$ with a production function given by

$$Y_t(j) = A_t L_t(j),$$

where A_t is a process that represents technology, and $L_t(j)$ is the labor employed by firm j. The intermediate good producer will pay a nominal wage w_t to workers.

We assume that intermediate good producers face price rigidities Ã la Calvo, where the probability of price change corresponds to $(1-\phi) \in (0,1)$. Therefore, a reoptimizing intermediate good producer $j \in [0,1]$ solves

$$\max_{\{P_t(j)\}} \mathbb{E}_t \left[\sum_{k \geq t} \phi^{k-t} Q_{t,k} \left(P_t(j) Y_{k|t}(j) - \Psi_k \left(Y_{k|t}(j) \right) \right) \right],$$

where $\Psi_t(.)$ is a well-defined cost function. Here, $Q_{t,k} = \beta^{k-t} (C_k/C_t)^{-\sigma} (P_t/P_k)$ with $k \geq t$ is the household's stochastic discount factor used by firms. We assume that intermediate goods producers use the stochastic discount factor associated with the aggregate consumption level. This optimization is subject to the following sequence of demand for $k \geq t$:

$$Y_{k|t}(j) = \left(\frac{P_t(j)}{P_k} \right)^{-\varepsilon} Y_k.$$

The first-order condition of this problem leads to

$$Y_{t|t}(j) \left[1 - \mu MC_{t|t}(j) \left(\frac{P_t}{P_t(j)} \right) \right] + \mathbb{E}_t \left[\sum_{k>t} \phi^{k-t} Q_{t,k} Y_{k|t}(j) \left[1 - \mu MC_{k|t}(j) \left(\frac{P_k}{P_k(j)} \right) \right] \right] = 0,$$

where $MC_{k|t}(j) = \Psi_k' \left(Y_{k|t}(j) \right) / P_k$ denotes real marginal costs for $k \geq t$, and $\mu = \varepsilon/(\varepsilon - 1) > 1$ is the desired frictionless mark-up. Under the assumption of symmetry across all firms, the solution implies $P_t(j) = P_t \ \forall \ j \in [0,1]$. Therefore, the previous first-order condition reduces to

$$Y_{t|t}(j) \left(1 - \mu MC_{t|t}(j) \right) + \mathbb{E}_t \left[\sum_{k>t} \phi^{k-t} Q_{t,k} Y_{k|t}(j) \left(1 - \mu MC_{k|t}(j) \right) \right] = 0.$$

Regarding the cost structure of this model, i.e., the $\Psi_t(.)$ function, we assume that the only cost of firms is labor costs

$$\Psi_k \left(Y_{k|t}(j) \right) = \frac{W_k Y_{k|t}(j)}{A_k},$$

which implies $MC_{k|t}(j) = W_k / (A_k P_k) = MC_k \ \forall \ j \in [0,1]$ and

$$\mathscr{M}_t = P_t MC_t \quad = \quad \frac{W_t}{A_t}.$$

Using the aggregate market clearing condition in the market of goods, i.e.,$Y_t = C_t \; \forall t$, the optimal price P_t^* must satisfy:

$$P_t^* = \mu \frac{\mathbb{E}_t \left[\sum_{k \geq t} \phi^{k-t} Q_{t,k} Y_{k|t}(j) \mathscr{M}_k \right]}{\mathbb{E}_t \left[\sum_{k \geq t} \phi^{k-t} Q_{t,k} Y_{k|t}(j) \right]} \quad = \quad \mu \frac{\mathbb{E}_t \left[\sum_{k \geq t} (\phi\beta)^{k-t} P_k^{\varepsilon} C_k^{1-\sigma} MC_k \right]}{\mathbb{E}_t \left[\sum_{k \geq t} (\phi\beta)^{k-t} P_k^{\varepsilon-1} C_k^{1-\sigma} \right]}.$$

A log-linearization of the previous equation leads to the following condition for the optimal price

$$p_t^* = \mu + (1 - \phi\beta) \mathbb{E}_t \left[\sum_{k \geq t} (\phi\beta)^{k-t} (p_k + mc_k) \right].$$

Finally, and following the standard procedure in the literature, we can derive the New Keynesian Phillips curve. Under our framework, this equation corresponds to

$$\pi_t = \beta \mathbb{E}_t [\pi_{t+1}] + \frac{(1-\phi)(1-\phi\beta)}{\phi} (\sigma + \eta) y_t.$$

K Heterogeneous Cohorts

In the baseline exercises, we assumed an experience-based Kalman filter operator where history varies by cohort, as in equation 2. In this section, we analyze a variation of such operator, where we assume that history is fixed across all cohorts. We define this alternative experience-based Kalman filter operator as

$$E_t^{\theta,alt}\left[X_{t+h}\right] = E_t^{KF}\left[X_{t+h}\right] + \theta\left(E_t^{KF}\left[X_{t+h}\right] - \sum_{j=1}^{J}\frac{E_{t-j}^{KF}\left[X_{t+h}\right]}{J}\right),$$

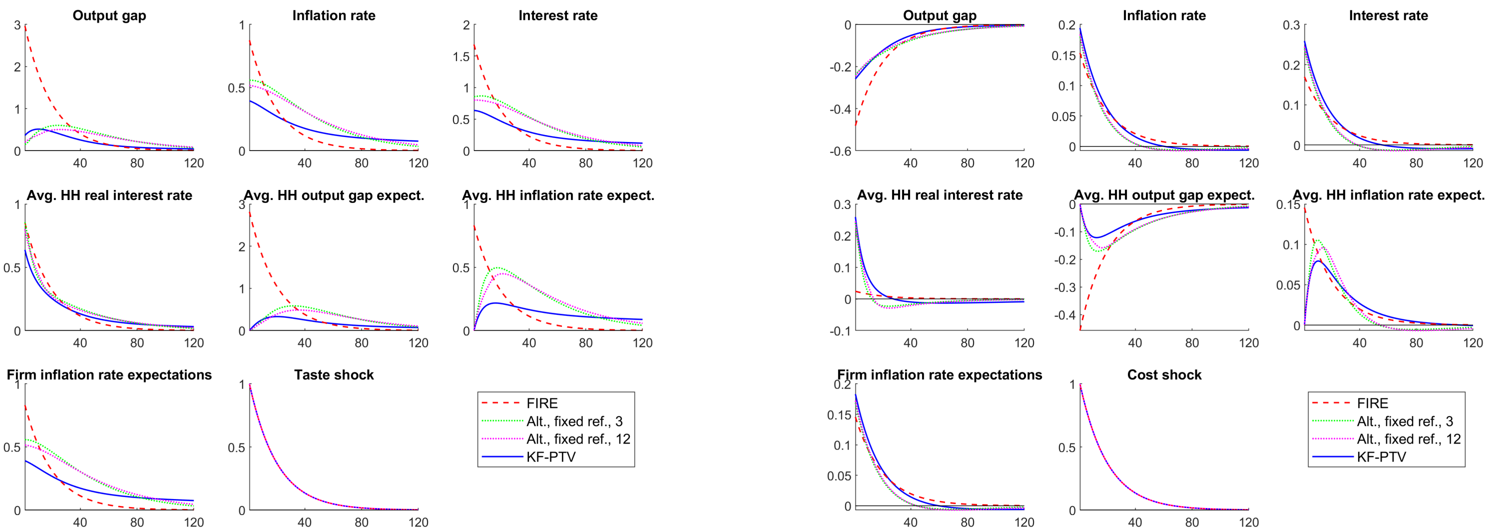
where agents remember what occurred in the last J periods. As in the baseline case, we set $\theta = -0.374$.

Figure A19 shows the impulse response functions to a cost shock and a taste shock according to our model of Section 5. Besides the responses coming from the FIRE and experience-based Kalman filter cases with varying history across cohorts, we also consider the two cases for the alternative experience-based Kalman filter operator: fixing the history of all cohorts to the last 3 periods and fixing the reference of all cohorts to the last 12 periods.

We see that the three cases follow the same pattern when compared to the FIRE case. However, the expectations under the fixed reference cases show a stronger reaction to the shocks. This is because the history span in these two alternative fixed reference cases is shorter than in the full-fledged experience-based case. While the latter remembers and is pegged to the steady state for longer, the former cases do not.

It could be argued that if we choose a sufficiently long history with the alternative fixed-reference Kalman filter operator, then we could closely replicate the results coming from the full-fledged experience-based case with different cohorts. However, we prefer the full-fledged experience-based case with different cohorts as it picks up the richness of the data and introduces it in the model: there are different cohorts living at the same time, each has had different life experiences, and each has different beliefs.

Figure A19: Impulse Response Functions, Comparison with Alternative Experience-based Kalman Filter Operator



(a) Taste shock

(b) Cost shock

Note: Figure shows impulse response functions for a selected group of variables after the mentioned shocks. The red dashed line shows the results for the case of the full information rational expectations model (FIRE), the green and magenta dotted lines show the results of experience-based Kalman filter model with fixed reference, and the solid blue line shows the experience-based Kalman filter model where the reference varies by cohort. Horizontal axis denotes months after the shock.