Beliefs About the Economy are Excessively Sensitive to Household-Level Shocks: Evidence from Linked Survey and Administrative Data*

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Abstract

We study how people's beliefs about the economy covary with household-level events, utilizing a unique link between Danish administrative data and a large-scale survey of consumer expectations. We find that compared to actual inflation, people's inflation forecasts covary much more strongly (and negatively) with both recently realized household income changes and measures of expected future household income changes. We formally establish that these findings are stark deviations from the Bayesian rational expectations benchmark. Similar results hold for perceptions of past inflation ("backcasts"), suggesting that imperfect recall is a key mechanism for biased forecasts. Building on this, a series of additional tests, some of which utilize data on adverse health events, suggests that the forecast biases are at least partly due to affect-cued recall. That is, negative (positive) household-level events cue negative (positive) recollections, which lead to pessimistic (optimistic) forecasts.

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People's forecasts of the economy are a key ingredient for determining forward-looking economic behaviors such as consumption, saving, and labor force participation. How do people use their information to make such forecasts? Recent work suggests that people do not utilize all freely available information (e.g., Coibion and Gorodnichenko, 2012, 2015), consistent with early work on information dispersion in Lucas (1972) or more recent theories of rational inattention (e.g., Mankiw and Reis, 2002; Sims, 2003; Mackowiak and Wiederholt, 2009). This raises the question of what information people do use to form economic forecasts and whether they use it correctly, in line with theories of rational expectations.

In this paper, we leverage a novel link between survey and administrative data in Denmark to study how *household-level* events—specifically, recently realized and expected future income changes—shape beliefs about the economy. These household-level events are largely idiosyncratic and thus have very weak associations with actual inflation. And yet, we find that people's inflation *forecasts* are strongly and negatively related to their income changes. We formally show that this is inconsistent with rational expectations, and provide suggestive evidence that biases in forecasts are due, at least in part, to selective recall, as suggested by theories such as those of Mullainathan (2002), Bordalo et al. (2018), and Bordalo et al. (2024).

Our analysis is enabled by establishing a previously unexploited link between the Danish Consumer Expectations Survey, a large survey administered each month by Statistics Denmark, and the Danish registry. The survey provides data on people's quantitative forecasts of inflation, as well as people's qualitative forecasts of how they expect household-level variables to change. The survey also provides data on people's "backcasts" (i.e., beliefs about what has happened in the recent past) of inflation, which we use to explore mechanisms related to memory. The link to the Danish administrative registry data provides detailed data on households' income and assets, adverse health events, and a rich set of demographics. The linkage between the consumer expectations survey and the rich administrative registry data makes Denmark an ideal laboratory.[1]

To organize the interpretation of our empirical findings, we formalize a series of empirical tests to differentiate between rational expectations and its possible violations. The null hypothesis of rational expectations encompasses a broad class of models in which people form Bayesian forecasts using both full and potentially limited information, including rational inattention or memory constraints (e.g., Azeredo da Silveira et al., 2024). The tests involve regressing both actual and forecasted inflation on a household-level variable and comparing the coefficients on the household-level variable from the two regressions. The first test applies when the household-level variable is plausibly in the respondent's information set or, more generally, when it does not carry additional information about inflation beyond what is in a respondent's information set. This condition

[1]To our knowledge, such linkages are not yet feasible, for example, with commonly used US surveys, such as the University of Michigan Survey of Consumers, the NY Fed Survey of Consumer Expectations, the Survey of Professional Forecasters, and the Blue Chip Survey.

applies to concurrently-elicited survey responses, recent and salient household health events, and perhaps recent changes in household income. Rational expectations imply that the coefficients on the household-level variable should be identical in the two regressions. Intuitively, this test leverages the implication that, with rational expectations, the inflation forecast error (actual inflation minus forecasted inflation) cannot be predicted by anything within the information set.

The second test generalizes the first to household-level variables that are not fully in respondents' information sets, such as future changes in household income. Rational expectations no longer imply that the coefficients of actual inflation and the inflation forecast on the household-level variable should be equal. Nevertheless, we show that, under a set of natural assumptions, the null of rational expectations requires the difference between these coefficients to be bounded by a small number, as most household-level income changes in our data are idiosyncratic.

We start by investigating how actual and forecasted inflation covary with recent changes in household income. The data are stark: the coefficient on recent income changes in the actual inflation regression is a tightly estimated near-zero, while the coefficient on recent income changes in the inflation forecast regression is large in magnitude, significantly different from zero, and negative. This result immediately rejects rational expectations under the assumptions of our first test. It also rejects rational expectations via our second test: the difference in coefficients is an order of magnitude larger than the bound from the test.

The results are robust to varying sets of controls, alternative measures of income changes, and several different subsamples: high- versus low-income respondents, respondents who do not experience unemployment, marriage, or retirement transitions, respondents with income changes bounded to be relatively small in magnitude, and respondents who are public employees. The result weakens only in the subsample of college-educated respondents. Finally, we conduct a placebo test where instead of recent income changes we use income changes that occurred significantly further in the past. We find that there is no meaningful relationship between inflation forecasts and this income change variable. This helps us rule out that our results are driven by persistent, person-level differences in optimism/pessimism about inflation that are correlated with income growth trajectories. Instead, people's inflation forecasts appear to be excessively sensitive to recent changes in their income.

A natural next question is whether inflation forecasts covary with *expected* future income changes, similar to recent income changes. We thus examine how inflation forecasts covary with proxies of people's expected future household income changes. First, we utilize respondents' forecasts of how they expect their household financial situation to change over the next 12 months, which we show contain significant information about future income changes. Analogous to our first result, we find that these forecasts do not covary with realized inflation, but covary strongly and negatively with forecasted inflation. This violates our first test of rational expectations, which is applicable here because survey responses cannot contain information outside a respondent's information set.

Our second approach to studying how inflation forecasts relate to expected future income changes is to directly regress actual and forecasted inflation on realized household future income changes. Analogous to the results about recent income changes, the difference in the coefficients on future income changes in the two regressions is an order of magnitude larger than the bound implied by the second test of rational expectations. Together, our results provide strong evidence that people's inflation forecasts also appear to co-move excessively negatively with news about their future income changes.

In the second part of the paper, we investigate the mechanisms of the excess sensitivity of inflation forecasts to household income changes, focusing on the role of imperfect recall and affect. The analysis of imperfect recall is facilitated by a key and rare feature of our survey data, which is the elicitation of inflation *backcasts*—i.e., people's perceptions of how much prices have changed over the last twelve months. We first show that inflation backcasts predict inflation forecast errors, and conversely that inflation forecasts predict inflation backcast errors. This shows that memory is imperfect, and that errors in forecasts are linked to imperfect recall.

We then estimate regressions analogous to those described above for forecasted inflation, except that we consider realized inflation from the past twelve months and respondents' backcasts of it. We find analogous results: although regressions of actual inflation on recent household income changes and measures of expected future household income changes generate tightly estimated near-zero coefficients, inflation backcasts are significantly negatively associated with household income change measures. In fact, we find that inflation backcasts are more strongly associated with household income changes than forecasts are—not just for recent income changes, but also for measures of expected future income changes. This is consistent with the hypothesis that the relationship between household income changes and inflation forecasts is mediated by memory. That is, household income changes influence what people recall, which in turn influences what people forecast. Consistent with this, we also find that the coefficients on the income change measures are significantly smaller in the regressions that include backcasts as a covariate than in regressions that don't include backcasts.

We then provide evidence that household-level events influence backcasts and forecasts through *affective association*: negative (positive) household-level events generate negative (positive) affect, which, in turn, leads to higher (lower) inflation backcasts and forecasts. Under this hypothesis, other household-level events that influence people's affect but are unrelated to the economy should also influence inflation backcasts and forecasts. We test this prediction with data on emergency room (ER) visits by the respondent or the respondent's immediate family members, which are proxies for negative events in the health domain. We find that controlling for overall household propensity to visit the ER, respondents who are randomly asked to take the survey in the month of a family ER visit have higher inflation backcasts and forecasts. Moreover, family ER visits have significantly larger effects on backcasts than on forecasts, consistent with the hypothesis that memory plays a mediating role in respondents' forecasts.

Motivated by the evidence of imperfect recall and affect, we introduce a memory-based model of belief formation that provides a unified explanation of all empirical facts. In the model, households' inflation forecasts are influenced by affect-cued recall. Specifically, the probability of recalling a past inflation experience increases with the similarity between the experience's affective valence and the affective valence of household-level events serving as the cue. For example, since large price increases carry negative affect for most people, another negative experience, such as a decrease in income or an adverse health event, increases the likelihood that people recall those large price increases when asked about inflation. The recalled inflation experience is then used to form inflation backcasts and forecasts.

We provide additional survey evidence, from participants both in the United States and Denmark, supporting the model's assumptions and predictions. The first finding is that recalled personal experiences with price changes shape inflation expectations as much as macroeconomic factors. Second, positive (negative) cues are more likely to trigger recall of positive (negative) events. Third, a key manifestation of the second finding is that positive (negative) cues are more likely to trigger the recall of low (high) inflation.

Our paper contributes to the literature on how economic forecasts deviate from rational expectations, and is the first, to our knowledge, to document the important role of affect-cued recall.[2] Bordalo et al. (2020) show that, at the individual forecaster level, revisions in forecasts about macroeconomic variables can predict forecast errors of these variables. This finding rules out rational expectations but leaves open the question of whether household-level or macroeconomic shocks generate such empirical results. Angeletos et al. (2021) and Broer and Kohlhas (2024) show that forecasts initially underreact and then overreact to macroeconomic shocks but do not pinpoint the psychological foundations. Andrade et al. (2022) document that French manufacturing firms' macroeconomic forecasts respond persistently to industry-level shocks that have no aggregate effects, but show that (limited information) rational expectations are consistent with their findings.

Our paper also complements studies of how personal experiences affect macroeconomic expectations and economic decisions (e.g., Malmendier and Nagel, 2011, 2016; Cavallo et al., 2017; Kuchler and Zafar, 2019; D'Acunto et al., 2021b; Cenzon, 2025). The scope of our paper is broader because we also study the impact of news about household-level events, and because we provide evidence of imperfect recall and affective association as a mechanism. Additionally, we expand this literature by (i) developing and implementing formal tests of rational expectations, (ii) focusing on different, but universally experienced household-level events (household income changes and health shocks),

[2] There is a large literature rejecting full-information rational-expectations (FIRE); see, e.g., Coibion and Gorodnichenko (2012), Coibion and Gorodnichenko (2015) and the overviews in Weber et al. (2022) and D'Acunto et al. (2023b). Violations of FIRE can be due to limited information or systematic deviations from Bayesian updating.

(iii) leveraging a link to detailed and rich administrative panel data on household experiences rather than relying on less-detailed survey-reported experiences or macroeconomic trends, and (iv) studying how experiences in one domain affect economic expectations in a different domain.[3]

Methodologically, our paper contributes to a recent set of papers that exploit links between consumer expectations surveys and the administrative data. Caplin et al. (2023) and Lee and Sæverud (2024) study subjective earnings expectations and compare them with actual realizations. Vellekoop and Wiederholt (2021) and Coibion et al. (2022) link inflation forecasts with data on actual household spending and saving and study their relation.[4] Coibion et al. (2020) use randomized information treatment to study how inflation forecasts impact firms' decisions. Briggs et al. (2024) and Caplin et al. (2024) develop novel methodology for combining survey and administrative data. To our knowledge, our paper is the first to utilize such linkages to test and articulate concrete deviations from Bayesian updating.

Our paper also contributes to theories of belief formation and overreaction; see Barberis (2018) and Benjamin (2019) for further reviews. In particular, we contribute to work linking forecasting biases to imperfect memory (e.g., Bénabou and Tirole, 2002, 2004; Mullainathan, 2002; Zimmermann, 2020; Gagnon-Bartsch et al., 2023; Huffman et al., 2022; Afrouzi et al., 2023; Sial et al., 2023; Azeredo da Silveira et al., 2024), and especially on the role of associative memory (Bordalo et al., 2018, 2020, 2023, 2024; Enke et al., 2024). D'Acunto and Weber (2024), Gennaioli et al. (2024), Salle et al. (2024), and Link et al. (2025) demonstrate the role of associative memory in shaping inflation forecasts, but they emphasize cues other than income changes and mechanisms distinct from affective association. In financial markets, Jiang et al. (2025) document that a rising market prompts investors to recall past experiences more positively, leading to more optimistic expectations of future stock returns. Together with Bodoh-Creed (2020), our paper is among the first to propose and empirically validate that associativity through affect is an important source of selective recall.

The rest of the paper is organized as follows. Section 1 describes the data. Section 2 sets up a template for analysis. Section 3 contains our main tests about how recent and expected future income changes relate to inflation forecasts. Section 4 provides additional evidence on the role of selective recall and affect in explaining forecast biases. Section 5 provides a unified explanation of empirical results and additional supporting survey evidence. Section 6 concludes.

[3]In recent work on cross-domain extrapolation, Binder and Makridis (2022), Xiao and Yan (2023), and Cenzon (2025) find that rising gas prices, information about COVID cases among social contacts, and personal credit rejections, respectively, lead to pessimism about the macroeconomy. Also, Tsiaplias (2021) finds that inflation forecasts are negatively related to self-reported household income changes over the past twelve months. This analysis is limited to relying on self-reported changes in household finances and does not involve inflation backcasts, measures of expected future income changes, or tests of the affective association hypothesis.

[4]A growing body of recent evidence documents a causal effect of inflation forecasts on household behavior (Coibion et al., 2023; Candia et al., 2024; Georgarakos et al., 2024) and shows that inflation forecasts predict behavior (Vellekoop and Wiederholt, 2021; Bachmann et al., 2015; Burke and Ozdagli, 2023).

1 Data, Sample Selection, and Variable Construction

1.1 The Danish Consumer Expectations Survey

The Danish Consumer Expectations Survey is available in its current high-quality format starting from 2008. The current survey follows a repeated cross-section design with a target population encompassing all individuals residing in Denmark between the ages of 16 and 74. Each month, Statistics Denmark contacts a new wave of 1500 individuals selected through simple random sampling from the registry of the Danish Civil Registration System (CPR Registret).[5] Sampled individuals receive a link to participate in the online survey through the Danish Digital Post system. Each Danish resident receives a unique account to the Digital Post system at the age of 15 and can use it as a secure way to communicate with all public authorities. Individuals who cannot receive digital mail are contacted through physical letters. Non-respondents first receive reminders and, if there is no follow-up, Statistics Denmark attempts a final contact through telephone interviews. Individuals are classified as non-respondents whenever they do not reply by the closing date of the survey wave—two days before the publication of the Statistical Newsletter. Overall, the official, government-branded means of contact and persistent follow-ups lead to high response rates. The average monthly response rate is 64%.

In its current iteration, the Consumer Expectations Survey is administered as the first module in Statistics Denmark's Omnibus Survey. The Consumer Expectations module includes several key questions that focus on participants' expectations and experiences related to inflation, household economic situation, general economic situation, and unemployment. The questions in the Danish Consumer Expectations Survey are harmonized with those in the European Commission's Consumer Confidence Survey. The rest of the omnibus survey includes rotating questions on topics such as housing market expectations or the public perception of taxation.

Appendix A.3 contains the questions asked in the survey. Here we summarize the questions we use in our study. The elicitation of forecasts of future inflation and perceptions of past inflation always begins with a qualitative Likert question. The elicitation of inflation forecasts begins by asking *"By comparison with the past 12 months, how do you expect that consumer prices will develop in the next 12 months?"* Respondents choose between *1-Prices will rise faster than today*, *2-Prices will rise at the same pace*, *3-Prices will rise slower than today, 4-Prices will stay the same,* and *5-Prices will drop a bit.* This qualitative question is also followed by a quantitative elicitation in percentage points if the Likert response implies a price change. For example, if a respondent indicates that prices will increase, they are then asked to quantify it in percentage points in a number box: *"By what percentage do you think prices will go up in the next 12 months?"* A respondent who states that prices will stay the same is attributed a forecast of 0. Perceptions of

[5]The data collection takes place within the first two weeks of the month. Individuals are also contacted a few days before the first day of the reference month to improve monthly response rates.

past inflation over the last 12 months (backcasts) are elicited analogously (Appendix A.3).

The survey also includes a question about forecasted changes in household financial situation, which we use in some of our analysis: "*How do you expect the financial position of your household to change over the next 12 months?*" The possible responses lie in a 5-point Likert scale ranging from *1-Much Worse* to *5-Much Better.*

1.2 Administrative Registry Data

We obtain yearly data on income and other financial variables from the registries maintained by the Danish Tax and Customs Authority (SKAT). The data are considered to be of very high quality because wage income and household-level balance sheet data are subject to third-party reporting, and tax evasion is minimal in Denmark (Kleven et al., 2011). We construct yearly measures of household total income, labor income, liquid assets, and net wealth. Total income is measured before taxes and labor market contributions, and includes labor income, public sector transfers, property income, and most other non-classifiable income sources that are taxable and can be attributed to the individual.[6] Labor income encompasses total taxable wage income, benefits, bonuses, severance pay, and the value of stock options. We follow Andersen et al. (2020) for the construction of the liquid assets variable by including the total value of bank deposits, stocks, and bonds as reported by Danish financial institutions to SKAT. Total net wealth captures the net value of total household assets, excluding non-deposited cash and foreign assets.[7] In some of our robustness analyses, we also use measures of income net of taxes. In these cases, we subtract the full amount of taxes paid from gross income, using the total tax liability reported in the annual tax records by SKAT at the end of each fiscal year.[8] All economic quantities are reported at the individual level using unique anonymized CPR codes (i.e., a unique individual identification number akin to the U.S. Social Security Number). To aggregate the economic variables at the household level, we look for the presence of a spouse in the Danish Civil Registration System (CPR Registret). If a spouse is present, we consider the average value of the two spouses. If no spouse is present, we simply keep the value as is.[9]

[6]Total income does not include the following: imputed rental value of own house, employers' and employees' contributions to employer-administered pension schemes, and lottery winnings.

[7]To measure total net wealth we use a measure developed for tax purposes by SKAT. This measure does not consider large durable assets such as cars and yachts. Relatedly, real estate wealth is accounted for at its tax-assessed values, which might not fully reflect market value.

[8]Our tax bill variable includes a comprehensive set of taxes levied at different levels of government and on all taxable income sources. It incorporates state and municipal taxes, which represent direct income taxation at the national and local levels. We also account for the health contribution tax, introduced in 2007 to fund healthcare expenditures. Additionally, we include property value tax and taxes on dividends and capital gains, ensuring consistency with our income measure, which includes the corresponding income sources.

[9]Since we take averages between spouses when aggregating household income, marriages and divorces might create substantial income changes to our sample if the household income is disproportionally attributable to one member of the couple. This is unlikely to be a concern in our setting for two reasons. First, only 17% of respondents experience marriage transitions in years around survey response. Second, we show robustness of all our main results by excluding all respondents who experienced marriage transitions in the years around survey response (See Column 4 of Table 2

We obtain additional demographic information (age, gender, and number of children) from the Danish Civil Registration System. Finally, we obtain the level of education from the Danish Ministry of Education (Undervisningsministeriet). This register identifies the highest level of education and the resulting professional qualifications. On this basis, we calculate the education level of survey respondents using single digit ISCED codes from the 2011 revision.

We use data on emergency room visits from the Danish National Patient Registry (NPR). The NPR contains information about all hospital patients at Danish hospitals, both public and private. We use the second, updated version of the NPR, which includes information about emergency room visits for the years 1994-2018.

1.3 Sample Construction

Our main analysis uses monthly survey data from the years 2012 to 2019, avoiding the years of the Great Recession and the Covid-19 pandemic.[10] In each table, we demonstrate that our main results still hold starting from 2008, the year that the Danish Consumer Expectations Survey became available in its current high-quality format.

Our primary sample consists of survey respondents between the ages of 25 and 60 at the time of the survey response. This minimizes drastic income changes driven by entry into or exit from the labor force. We also exclude survey respondents if (i) they have non-trivial self-employment income, as this can lead to unreliable income measurements;[11] (ii) if they declined to answer any of the key survey forecast or backcast questions mentioned above;[12] (iii) if there is missing income or demographic information. Overall, we have 55171 survey respondents who satisfy our age restrictions between 2012 and 2019. After imposing the additional restrictions and trimming income changes (described below), we are left with 35050 usable responses (see Table A1 for a breakdown of how each restriction impacts sample size).

For a household interviewed in the Danish Consumer Expectations Survey in any month of year t, changes in households' log nominal income are constructed as the log nominal income of year $t-1$ minus that of year $t-2$. This measure captures the recent changes in households' log nominal income that occurred before the interview.[13] Similarly, we measure future log nominal

and Column 4 in all tables in Appendix B.4.2).

[10] To avoid including years affected by the Great Recession, whenever inflation backcasts are used as the main dependent variable, we also omit the year 2012 and limit ourselves to 2013-2019.

[11] Specifically, we classify an observation as problematic due to self-employment if more than one fourth of household income comes from self-employment in any of the years from the four years preceding the interview to the year after the interview. We exclude income from self employment because it is not subject to third-party reporting and thus more prone to misreporting in our tax data (Kleven et al., 2011).

[12] We omit all respondents who selected *Do not know* for any of the following Likert questions: (i) past and future of inflation, (ii) past and future sentiment about the general Danish economic situation, (iii) backcasts and forecasts of the family financial situation, and (iv) forecasts of the general unemployment situation. We also drop respondents who refused to fill in the number boxes in the quantitative inflation elicitations and those who filled in the number box with implausibly large numbers (forecasted inflation greater than 100 percentage points over 12 months).

[13] Because income at time t is measured at the end of the year, we opt to compare income at years $t-1$ and $t-2$

income changes by comparing log nominal incomes in years $t+1$ versus $t-1$.[14] We construct similar measures of income changes using only labor income. Finally, we trim all income changes at the 2.5 and 97.5 percentiles.[15]

In some of our analyses, we refer to the Population sample. In this case, we use observations for all Danish residents that we observe in the register starting from 1991. We impose the same age restrictions as we do for our main sample. Further, we drop all individuals who have non-trivial self-employment income or whose demographic information is missing, according to the same criteria that we apply to our survey sample.

In Appendix B.1, Table B.1 summarizes the characteristics of our survey-respondent sample and compares them to contacted individuals and to the whole Danish population. Table B.2 provides summary statistics of our survey responses.

2 Template for Analysis

To guide our empirical analysis of how household-level events relate to beliefs about the economy, this section presents the notation used throughout the paper, defines the rational expectations benchmark, and introduces our tests of rational expectations.

In our empirical analysis, the key dependent variables are realized and forecasted inflation in the 12 months that follow person i's survey response in calendar month τ. We denote these by Y_τ and $\mathbb{F}_{i,\tau}[Y_\tau|I_{i,\tau}]$, respectively, where $I_{i,\tau}$ is respondent i's information set in month τ. We use the operator $\mathbb{F}$ rather than $\mathbb{E}$ to denote forecasts because we allow deviations from the Bayesian benchmark. We also consider inflation over the past 12 months, and respondent i's perception (backcast) of it: $Y_{\tau-12}$ and $\mathbb{F}_{i,\tau}[Y_{\tau-12}|I_{i,\tau}]$, respectively. The main "right-hand-side" variables $X_{i,\tau}$ that we will consider are recent household income changes, future household income changes, and household health events. For example, as discussed in the previous section, recent household income changes are constructed as the log nominal income of year $t(\tau)-1$ minus that of year $t(\tau)-2$, where $t(\tau)$ is the year that includes the survey response month τ (recall that our primary measures of household income are at the yearly level). The time subscripts help make it clear that the "Y variables" and the "X variables" can be related to each other through time-varying macroeconomic shocks. But to economize on notation and simplify exposition of our tests of rational expectations,

to make sure that recent income changes are fully realized before the survey response. This makes the assumptions of Test 1 more plausible.

[14] For our future income changes, we opt to compare income at years $t+1$ and $t-1$. We do so to guarantee that, for all households, past income is already fully realized before the survey response, while future income lies fully in the future.

[15] To maintain a consistent sample in all analyses, we continue trimming in this way even in analyses that don't involve income changes. For supplementary analyses involving labor income shocks, we adopt a similar trimming scheme, where we exclude labor income changes below the 2.5th percentile or above the 97.5th percentile (relative to the full sample before trimming the income changes). For analyses studying wealth changes, we trim the changes analogously. We trim both to increase precision and because we have less confidence in the sources of large income changes, which may result from unusual events such as voluntary leaves.

we will typically drop the time subscripts and simply write Y, $\mathbb{F}_i[Y|I_i]$, and X_i. Unless otherwise stated, our formal tests apply irrespective of whether Y and X_i denote recent or future outcomes, irrespective of whether $\mathbb{F}_i[Y|I_i]$ denotes forecast or backcast, and to any macroeconomic variable Y and household-level variable X_i.

We first define the null hypothesis that the forecast (backcast) $\mathbb{F}_i[Y|I_i]$ is given by rational expectations:

Definition 1. Under rational expectations, the survey forecast (backcast) of Y is given by

$$\mathbb{F}_i[Y|I_i] = \mathbb{E}[Y|I_i] + \eta_i \quad \text{where} \quad \eta_i \perp I_i, X_i, Y, \tag{1}$$

where $\mathbb{E}[Y|I_i]$ denotes the Bayesian forecast, given information set I_i and a prior belief about (Y, I_i) that corresponds to the objective statistical one.

Under rational expectations, the Bayesian forecast $\mathbb{E}[Y|I_i]$ requires that people update their beliefs in a Bayesian fashion based on the information in I_i, and start with a correct prior. Deviations from rational expectations can arise from incorrectly reacting to information I_i. They can also arise from *prior bias*, where people are persistently over- or under-pessimistic for all I_i (Patton and Timmermann, 2010; Das et al., 2020; Farmer et al., 2024). The definition in (1) allows the possibility that the survey elicitation of the inflation forecast (backcast) is contaminated by idiosyncratic noise or measurement error, η_i (Gillen et al., 2019; Kučinskas and Peters, 2024; Juodis and Kučinskas, 2023).

Full-information rational-expectations (FIRE) is nested as the special case in which I_i incorporates all available information in the economy. But more generally, I_i may not include all available information because of limited availability of information (e.g., Lucas, 1972), rational inattention (e.g., Mankiw and Reis, 2002; Sims, 2003; Mackowiak and Wiederholt, 2009), or memory constraints (e.g., Azeredo da Silveira et al., 2024). Consequently, our definition of rational expectations includes Bayesian learning, as long as there is no prior bias.[16]

We provide two formal tests of rational expectations. In both tests, we examine linear regressions of actual inflation Y and the inflation forecast (backcast) $\mathbb{F}_i[Y|I_i]$ on household-level variable X_i,

$$Y = \beta_0^X + \beta_1^X X_i + \epsilon_i^X \ \text{ v.s. } \ \mathbb{F}_i[Y|I_i] = \tilde{\beta}_0^X + \tilde{\beta}_1^X X_i + \tilde{\epsilon}_i^X, \ \text{ where } Cov\left(\epsilon_i^X, X_i\right) = Cov\left(\tilde{\epsilon}_i^X, X_i\right) = 0, \tag{2}$$

and compare the regression coefficients β_1^X and $\tilde{\beta}_1^X$.

Test 1. *Assume that the household-level variable X_i is in person i's information set I_i ($\mathbb{E}[X_i|I_i] = X_i$ for all i) or, more generally, X_i contains no information about Y beyond the information set ($X_i \perp Y|I_i$). Rational expectations imply that the two regression coefficients in* (2) *are equal, $\beta_1^X = \tilde{\beta}_1^X$.*

[16] Farmer et al. (2024) includes both prior bias and Bayesian learning, and thus does not fit our definition of rational expectations.

This test applies to any survey response, such as household forecasts about their financial situation changes. Any survey response is a function of the household information set I_i plus idiosyncratic survey response noise, so it satisfies the assumption that $X_i \perp Y|I_i$. Arguably, this test also applies to salient household-level variables plausibly in the person's information set, such as recent changes in household income, although we also allow for the possibility that recent income changes are not fully observed in the second test we introduce below.

Intuitively, Test 1 leverages the implication that, with rational expectations, information is used efficiently and thus the forecast error $Y - \mathbb{F}_i[Y|I_i]$ cannot be predicted by anything within the information set. As a result, in a regression of the forecast error $Y - \mathbb{F}_i[Y|I_i]$ on X_i, rational expectations imply that the coefficient on X_i, $\beta_1^X - \tilde{\beta}_1^X$, is zero—or, equivalently, that the two regression coefficients in (2) are equal, $\beta_1^X = \tilde{\beta}_1^X$. Idiosyncratic survey response noise η_i does not alter this prediction, and neither does pooling across people with different information sets. The test also does not require any functional form assumptions, such as $\mathbb{E}[Y|X_i]$ being linear in X_i.

This test is in the spirit of work that examines whether individual-level forecast errors are predictable by individual-level forecast revisions (e.g., Bordalo et al., 2020), which builds on earlier tests of full-information rational expectations (FIRE) (e.g., Coibion and Gorodnichenko, 2015). Unlike this prior work, however, our tests require only a repeated cross-section of survey responses, rather than a panel, because our right-hand-side variables X_i do not involve revisions to survey responses. Instead, we leverage the panel structure of the administrative registry data to generate right-hand-side variables X_i.

The second test focuses on the case where the household-level variable X_i is not in person i's information set I_i, and their information is summarized by the signal s_i. This test is useful when X_i represents realized future changes in household income not plausibly fully contained in the person's current information set, or when X_i represents imperfectly observed recent changes in household income.

In this case, the two regression coefficients in (2) need not be equal. To illustrate, consider the case that the signal s_i is a noisy signal about household income changes, i.e., $s_i = X_i + \delta_i$, where $\delta_i \perp X_i, Y$. Set $X = \int X_i di$ to be the aggregate component of X_i. When $\mathbb{E}\left[Y|s_i\right]$ is linear in the signal s_i (which holds if Y and s_i are jointly normal), it can be shown that the two regression coefficients in (2) are given by

$$\tilde{\beta}_1^X = \frac{Cov\left(X,Y\right)}{Var\left(X_i\right) + Var\left(\delta_i\right)} \neq \frac{Cov\left(X,Y\right)}{Var\left(X_i\right)} = \beta_1^X.$$

The coefficients are not equal to each other, but the difference between them can be bounded by

$$\left|\tilde{\beta}_1^X - \beta_1^X\right| = \left|\frac{Cov\left(X,Y\right)Var\left(\delta_i\right)}{Var\left(X_i\right)\left(Var\left(X_i\right) + Var\left(\delta_i\right)\right)}\right| \leq \frac{\sqrt{Var\left(X\right)Var\left(Y\right)}}{Var\left(X_i\right)},$$

which is small when most of the variation in X_i is idiosyncratic—i.e., when $Var\left(X\right)$ is small relative to $Var\left(X_i\right)$. Below, we provide a result that generalizes this and other plausible cases that involve partial information about X_i.

Assumption 1. *Person i's information is given by* $I_i = \{s_i\}$, *where* $\mathbb{E}[Y|s_i]$ *is linear in the signal* s_i. *Furthermore, the household-level variable* X_i *and the signal* s_i *are given by:* $X_i = Z_i + \gamma Y + \nu_i$, $s_i = Z_i + \delta_i$ *and* $Z_i = Z + \omega_i$, *where* $\nu_i, \delta_i, \omega_i$ *are mean-zero, mutually independent, and independent of both* Y *and* Z.[17]

In words, Z_i is the (partially) observable component of the household-level variable about which the person receives a signal s_i. The partially observable component is the sum of an aggregate component Z and an idiosyncratic component ω_i. We assume that the noise δ_i in the signal is idiosyncratic, but in Appendix C.2.1 we extend the test to the case in which the noise can also depend on aggregates. The household-level variable may also contain an unobservable component $\gamma Y + \nu_i$, which can depend on the aggregate Y and include an idiosyncratic component ν_i. While we restrict to single-dimensional signals in the body of the paper to improve exposition, in Appendix C.2.5 we generalize Test 2 to multi-dimensional signals.

Test 2. *If Assumption 1 holds, rational expectations in* (1) *imply that the difference between the two regression coefficients in* (2) *is bounded by*

$$\left|\tilde{\beta}_1^X - \beta_1^X\right| \leq \frac{\sqrt{Var\left(X\right)Var\left(Y\right)}}{Var\left(X_i\right)} + \frac{|\gamma|\,Var\left(Y\right)}{Var\left(X_i\right)}, \tag{3}$$

where $X = \int X_i di$ *is the aggregate component of* X_i.

We provide three examples of how Assumption 1 incorporates relevant information assumptions when X_i is household (log nominal) income changes and Y is the inflation rate in decimal form (e.g., $Y = 0.02$ when inflation is 2%). In the first example, the person's information is given by a noisy signal about household income changes, i.e., $s_i = X_i + \delta_i$. This is nested by Assumption 1 when $\gamma = \nu_i = 0$. The bound in equation (3) then becomes $\frac{\sqrt{Var(X)Var(Y)}}{Var(X_i)}$.

In the second example, a person's information consists of inflation-adjusted income changes $s_i = Z_i = X_i - Y$, where $\delta_i = \nu_i = 0$ and $\gamma = 1$. This case might arise because a rationally inattentive person might focus on implications for feasible consumption bundles rather than on nominal income changes. In this case, the bound is $\left|\tilde{\beta}_1^X - \beta_1^X\right| \leq \frac{\sqrt{Var(X)Var(Y)}}{Var(X_i)} + \frac{Var(Y)}{Var(X_i)}$.

In the third example, consider the case where household income changes are the sum of an observable component and an unobservable component. That is, $X_i = X_{i,1} + X_{i,2}$, where $X_{i,1} = \gamma_1 Y + \omega_i$ is the observable component of income changes and $X_{i,2} = \gamma_2 Y + \nu_i$ is the unobservable component of income changes. The scalars γ_1 and γ_2 have the same sign. This is nested within Assumption 1, with $s_i = Z_i = X_{i,1}$, $\delta_i = 0$, and $\gamma = \gamma_2$. One can prove that in this case, we must have $\frac{|\gamma|Var(Y)}{Var(X_i)} \leq \frac{\sqrt{Var(X)Var(Y)}}{Var(X_i)}$, and thus the bound in (3) implies $\left|\tilde{\beta}_1^X - \beta_1^X\right| \leq \frac{2\sqrt{Var(X)Var(Y)}}{Var(X_i)}$ (see Appendix C.2.2 for details).

[17] By mean-zero, we mean that $\int \nu_i di = \int \delta_i di = \int \omega_i di = 0$.

In sum, in all three examples, the bound in equation (3) implies

$$\left|\tilde{\beta}_1^X - \beta_1^X\right| \leq \max\left\{2\frac{\sqrt{Var\left(X\right)Var\left(Y\right)}}{Var\left(X_i\right)}, \frac{\sqrt{Var\left(X\right)Var\left(Y\right)}}{Var\left(X_i\right)} + \frac{Var\left(Y\right)}{Var\left(X_i\right)}\right\}. \tag{4}$$

We will show that the bound is small in our setting because most of the variation in household income changes is idiosyncratic (i.e., $Var\left(X\right)$ is small relative to $Var\left(X_i\right)$) and because the variance of inflation, $Var\left(Y\right)$, is also small relative to $Var\left(X_i\right)$. The version of the test we utilize in our empirical work generalizes these three examples:

Test 2′. *If Assumption 1 holds, and either (i)* $|\gamma| \leq 1$ *(the unobservable component of the household variable has limited aggregate exposure) or (ii)* $Cov\left(Z, \gamma Y\right) \geq 0$ *(the aggregate observable and unobservable components of the household variable positively co-move), rational expectations imply the bound* (4)*.*

Violations of the bound (4) in Test 2′ therefore rule out rational expectations as an explanation for the difference between $\tilde{\beta}_1^X$ and β_1^X. This includes our examples of a rationally inattentive person who tracks only inflation-adjusted income changes, as well as a person who observes only a single component of income changes.

Without Assumption 1, the bound (3) (and thus (4)) need not always be satisfied. Consider a variant of the third example in which the income change is still given by $X_i = X_{i,1} + X_{i,2}$, but the observable component $X_{i,1} = Y + \omega_i$ and the unobservable component $X_{i,2} = -Y + \omega_i$ have perfectly correlated idiosyncratic components and opposite-signed loadings on inflation. This example violates Assumption 1, which requires that the idiosyncratic components are uncorrelated. Appendix C.2.3 shows that this can lead to $\left|\tilde{\beta}_1^X - \beta_1^X\right|$ being larger than the bound in (3) under rational expectations. That said, we do not believe that examples such as this one are economically plausible.

We run two separate regressions in (2), instead of a single forecast-error regression, to gain additional insights into people's perceived relationship between inflation and household-level income changes, and to compare it to the actual relationship between inflation and household-level income changes. This approach also helps to address a potential concern about the length of our sample. Specifically, the variable X_i is related to Y through time-series variation and to $\mathbb{F}_i[Y|I_i]$ through both time-series variation and household-level (informational) differences in the cross-section. (As discussed above, we omit the time subscripts from these variables to simplify notation and exposition.) One concern is that if our sample does not include sufficiently many years, our estimate of the relationship between Y and X_i, which are related to each other only through time-series variation, could be biased. In particular, this could generate a downward bias in our estimate of $\left|\beta_1^X\right|$, as illustrated by considering the extreme case where we have survey data from only a single month. In this case, the macroeconomic variable Y is constant in this sample, while X_i still varies across households in this sample, and thus the estimates of β_1^X are mechanically zero.[18] Fortunately, in our subsequent analysis, we can utilize full-population data—available over a significantly longer period starting from 1991—to provide an additional estimate of β_1^X. Reassuringly, we show below that the estimate of β_1^X is essentially unaltered when we use the full population data starting from 1991.

Importantly, Test 1 and Test 2 are tests on the joint distribution of $(X_i, Y, \mathbb{F}_i[Y|I_i])$. A particular causal interpretation, such as changes in household income X_i *causing* changes in beliefs $\mathbb{F}_i[Y|I_i]$, is not necessary. Our test still applies, for example, if the direction of causality is in "reverse"; e.g., if exogenous changes in I_i cause changes in X_i, but not the other way around.

3 Inflation Forecasts and Changes in Household Income

In this section, we study the association between inflation forecasts and both recent changes in household income and measures of expected future household income changes. The analysis is guided by the formal tests of rational expectations introduced in Section 2.

For the remainder of the paper, we increase the readability of the regression results by expressing realized and forecasted inflation in percentage points. Relative to Section 2, where the inflation rate was in decimal form, this means that we scale the regression coefficients β_1^X and $\tilde{\beta}_1^X$ (and the corresponding bounds) by 100. The regression coefficients thus represent the percentage-point change in inflation forecasts per unit change in X.

3.1 Inflation Forecasts and Recent Changes in Household Income

We start by studying how recent changes in household income are associated with forecasted versus realized inflation. Recent changes in household income are constructed as the log nominal income of year $t-1$ minus that of year $t-2$, where t denotes the year that includes the survey response month (see Section 1).

Table 1 and Figure 1 present our main results. Column 1 of Table 1 presents a regression of realized inflation on recent changes in household income for individuals in our main survey sample. Column 2 of Table 1 presents an analogous regression, except we utilize the full population sample, and for the years 1991 to 2019. In both columns, the coefficients on recent income changes are close to zero, $\beta_1^X \approx 0$. Reassuringly, the estimates in Columns 1 and 2 are not significantly different from each other, which mitigates concerns that arise from relying on a relatively short time series, the smaller survey sample, or the specific time period.

Columns 3-6 of Table 1 present regressions of inflation forecasts on recent changes in household income, using varying sets of controls. Column 3 presents the regression without controls. Column

[18] In Appendix C.2.4, we further elaborate on the interpretation of β_1^X.

4 includes demographic controls: age, highest level of education, gender, number of children, and deciles of income level.[19] The proxy for income level is constructed as the average logarithm of nominal incomes from $t-3$ to $t-5$, where t is the year of the interview. We use those three years so that there is no overlap with the years we use to construct our measure of recent income changes. Column 5 additionally includes calendar-month fixed effects, as it is done in some related work (e.g., Gennaioli et al., 2016; Kuchler and Zafar, 2019).[20] Column 6 examines robustness to utilizing the longest available series of inflation forecasts in our survey data, starting in calendar year 2008 and encompassing the Great Recession.

Across all four regressions, we find robustly large and negative associations between inflation forecasts and recent changes in household income, $\tilde{\beta}_1^X \ll 0$.[21] Moreover, the coefficient of inflation forecasts on recent income changes is an order of magnitude larger than the coefficient of realized inflation on recent income changes, $\left|\tilde{\beta}_1^X\right| \gg \left|\beta_1^X\right|$. Figure 1 provides a binned scatterplot of the relationship between inflation forecasts and recent income changes, based on the Column 4 specification.[22]

Under the assumption of Test 1, rational expectations require that $\beta_1^X = \tilde{\beta}_1^X$, which is clearly rejected by our empirical evidence. This assumption could be plausible because changes in household income are consequential and salient household-level events. Even without requiring the household-level variable to be within the person's information set, Test 2′ shows that rational expectations imply the bound $|\beta_1^X - \tilde{\beta}_1^X| \leq 0.02$ under our preferred specifications in Columns 1 and 4. This is again rejected by our empirical evidence.[23]

The deviations from rational expectations that we document in Table 1 can in principle arise from either excessive sensitivity to recent changes in household income or prior bias (Patton and Timmermann, 2010; Das et al., 2020; Farmer et al., 2024). That is, another possible explanation for our evidence is that households with higher income growth trajectories simply have lower prior

[19]We control for age linearly, and include fixed effects for the other variables. Including demographic controls in a regression of actual inflation on recent income changes has almost no impact on the coefficient of interest. This is unsurprising, as demographics have no relation to actual inflation realizations.

[20]Because calendar-month fixed effects contain information about Y that is not necessarily in the survey respondents' information sets, this regression cannot be used to provide a formal test of rational expectations. However, this regression is informative in reduced form, as the comparison between the Column 4 and 5 coefficients is informative about how much of the relationship between inflation forecasts and recent income changes is attributable to cross-sectional versus time-series variation. The modest impact of the calendar-month fixed effects implies that most of the association is attributable to cross-sectional variation. This also alleviates concerns about any potential bias in the estimates of $\tilde{\beta}_1^X$ from having a relatively short time series.

[21]The magnitudes in the associations between inflation forecasts and recent changes in household income are comparable to known associations between inflation forecasts and income level, education level, or gender. See Appendix Table B.4 for a replication in our data.

[22]To produce the binned scatterplot and absorb controls, we implement the procedure and programs outlined in Cattaneo et al. (2024).

[23]The standard deviations of the inflation rate (in decimal form), recent nominal income changes, and aggregate nominal income changes are $\sqrt{Var(Y)} = 0.00361$, $\sqrt{Var(X_i)} = 0.577$, and $\sqrt{Var(X)} = 0.009$ respectively. The bound in equation (4) is thus 0.0002. We then multiply it by 100 and arrive at $|\beta_1^X - \tilde{\beta}_1^X| \leq 0.02$, aligning with the units of inflation (in percentage points) used in our regression tables. Extending the data to the longest available time series in Column 2 yields a bound of 0.07.

beliefs about inflation. For example, inflation forecasts are known to differ with demographics such as income level, gender, and education (e.g., Das et al., 2020, D'Acunto et al., 2021a and D'Acunto et al., 2023a), and income growth trajectories may differ along those demographics as well. We find no evidence of this, because when we move from Column 3 to Column 4 and include demographic controls, the coefficient on recent income changes increases rather than decreases in magnitude. Moreover, in Appendix Table B.5 we include regressions analogous to those in Table 1, except instead of recent income changes we consider income changes between (i) years $t-6$ and $t-7$, (ii) years $t-6$ and $t-8$, (iii) years $t-6$ and $t-9$, and (iv) years $t-6$ and $t-10$. All four measures are proxies of income growth trajectories, but rely on income changes further in the past. Conditional on demographic controls, we find no association between inflation forecasts and these past income changes, which again suggests that prior bias is not associated with income growth trajectories.

Table 2 examines the robustness of our main result to various subsamples. Panel (a) presents regressions where actual inflation is the dependent variable, while panel (b) presents regressions where inflation forecasts are the dependent variable. The first column restricts to respondents whose recent household income change is no larger than 20 log points, in absolute value. This restriction allows us to consider robustness to excluding more extreme realizations of income changes. The second column considers respondents who have not experienced any changes in employment status in years $t-1$ and $t-2$, while the third column considers respondents who have experienced a transition in employment status between years $t-1$ and $t-2$. Because employment transitions are often modeled as separate from other types of income shocks in the literature (e.g., Guvenen et al., 2021), these two columns provide insight into the types of household income changes that drive our results. Column 4 considers respondents who experience neither a transition into retirement nor a transition into or out of marriage in years $t-1$ and $t-2$, as these transitions represent another distinct source of changes in household incomes. Columns 5 and 6 consider respondents with above-median versus below-median household income, as measured by the average log nominal income in years $t-3$ through $t-5$. Columns 7 and 8 consider respondents with and without a college degree, respectively. Column 9 restricts to respondents with particularly simple incomes, in the sense that at least ninety percent of their household income is labor income in the years $t-2$ to $t+1$. Columns 10 and 11 consider respondents with positive and negative household net wealth in year t, respectively. Column 12 considers respondents who are public employees. As public employees' incomes are set by the Danish Ministry of Finance, their income changes are independent of, for example, local shocks that can drive differences between individually experienced and national inflation.

Overall, Table 2 shows that our results are robust to various sample restrictions, and the coefficient on recent income changes is meaningfully lower than our baseline estimate in only a few cases. The first case is respondents with some unemployment or leave in years $t-1$ or $t-2$. This regression suggests that employment transitions do not contribute to our main result because respondents who experience those transitions exhibit less of an association between inflation forecasts and recent income changes. Second, the association between inflation forecasts and recent income changes is also lower among the college-educated. This could be related to findings that higher financial literacy leads to more accurate inflation forecasts (e.g., Burke and Manz, 2014; Comerford, 2025).

Appendix B.3.2 studies associations with labor income, rather than total income. Analogous to our results for total income, changes in labor income do not predict realized inflation but are strongly negatively associated with forecasted inflation. Appendix Table B.8 further extends Table 1 by considering other ways in which the household financial situation changed in the recent past: changes in liquid assets and changes in total net wealth. Columns 1 through 3 present regressions where actual inflation is the dependent variable, while Columns 4 through 6 present regressions where inflation forecasts are the dependent variable. We find that recent changes in liquid assets and total net wealth are not strongly associated with either actual or forecasted inflation, consistent with the hypothesis that these changes are not as salient as income changes.[24]

We consider several other robustness checks. We study real income changes rather than nominal income changes in Table B.24, which further helps rule out explanations where people are rationally inattentive and only track real income changes. We also consider changes in net-of-tax income rather than gross income in Table B.27.

3.2 Inflation Forecasts and Expected Future Changes in Household Income

So far, we have documented that people's inflation forecasts are excessively sensitive to recent changes in household income. Are people's inflation forecasts also excessively sensitive to expected future changes in household income? To investigate this question, we consider two proxies of expected future changes in household income. First, we consider how inflation forecasts relate to qualitative survey-forecasted changes in household financial situation, which are shown to be highly informative of realized changes in future household income. Second, we consider how inflation forecasts relate to *realized* changes in future household income that we measure in administrative tax data.

Forecastability of changes in future household income. We first show that people possess information about changes in future household income, and that this information is reflected in people's survey-forecasted changes in household financial situation. This paves the way for the analysis of how forecasted changes in household finances relate to inflation forecasts. The survey question we use is "*How do you expect the financial position of your household to change over the next 12 months?*", which allows possible responses on a 1 to 5 scale, with 1 corresponding to

[24]Due to our high statistical power, the coefficients are statistically different from zero in several cases, but their magnitudes are always small.

the most pessimistic forecast and 5 to the most optimistic forecast (see Appendix A.3). Figure 2 shows that responses to this question are highly informative of future household income changes, constructed as the log nominal income of year $t+1$ minus that of year $t-1$, where t denotes the year that includes the survey response month. Panel (a) presents the distributions of future changes in household income by the five possible survey responses. The distributions are ordered almost perfectly by first-order stochastic dominance. Panel (b) quantifies the means of future changes in household income, for each of the five possible survey responses. The difference in income changes between respondents answering 5 ("will be a lot better") and respondents answering 1 ("will be a lot worse") is 13 log points, which is 0.77 of the standard deviation of changes in household income. Appendix Table B.9 presents regressions, with various sets of controls, that quantify the patterns in Figure 2. Importantly, Appendix Table B.9 shows that recent changes in household income are negatively autocorrelated with future changes in household income, and that the predictive power of the survey proxy for future income changes remains unaltered when recent income changes are included as a control. Appendix Table B.25 shows that these results are robust to using real income.

Inflation forecasts and forecasted changes in household financial situation. We now study how forecasted and realized inflation covary with survey responses about changes in household financial situation. As discussed in Section 2, because any survey response is a function of the household information set plus an idiosyncratic survey response noise, we can deploy Test 1.

Figure 3 and Table 3 present our main results. Figure 3 plots forecasted and actual inflation for each of the five values that the survey responses about changes in household financial situation can take. Table 3 presents regressions of actual and forecasted inflation on the five different integer values of the survey response.[25] Both Figure 3 and Table 3 show that while actual inflation is effectively not associated with forecasted changes in household financial situation, inflation forecasts are nevertheless significantly negatively associated with these responses. Table 3 shows that this is robust to the inclusion of different sets of controls, including controlling for the recent income change measure that we utilized in our first test. Based on Test 1, this empirical evidence rejects rational expectations.

Similar to the discussion in the previous subsection, the deviations from rational expectations can in principle be explained by differences in prior bias. People who are a priori more optimistic about lower inflation may also be more optimistic about changes in their financial situation, and vice versa. To investigate this possibility, we utilize the Michigan Survey of Consumers, where most respondents are sampled twice, approximately six months apart, and which contains a similar

[25]In principle, Test 1 permits us to regress on any transformation of survey responses X_i, as well as on dummy variables for each of the possible values of X_i (analogous to Figure 3). Despite the clear nonlinear relationship between $\mathbb{F}_i[Y|I_i]$ and X_i shown in Figure 3, we regress directly on X_i for the sake of simplicity—to reduce dimensionality and to ease comparability of coefficients across different regressions.

survey question about future household financial situation changes.[26] The question in the Michigan survey is, *"Do you think that a year from now you will be better off financially, or worse off, or just about the same as now?."* Appendix Figure B.1 and Appendix Table B.13 present results for this analogous question, finding similar results. Moreover, because respondents are sampled twice in the Michigan survey, we are able to include respondent fixed effects in Columns 5 and 6 of Appendix Table B.13. The relationship between inflation forecasts and the survey responses is dampened, but still remains highly significant when respondent fixed effects are included. This implies that inflation forecasts are indeed excessively sensitive to news about future income changes.

Inflation forecasts and realized future changes in household income. An alternative proxy for expected future changes in household income is the actual realization of future income changes. This non-survey-based variable has several key advantages. First, any strong associations between inflation forecasts and this variable cannot be attributed to prior bias. This is because we have already established that any potential prior bias in inflation forecasts is not associated with income growth trajectories (see Section 3.1 and Appendix Table B.5). Second, while forecasted changes in household financial situation are informative about future income changes, the somewhat vague phrasing of "financial position of your household" leaves open the possibility that responses to this question reflect beliefs about variables other than future income changes. By contrast, when X_i corresponds to realized future changes in household income, an association between inflation forecasts and X_i would imply that inflation forecasts are associated with actual news about the future household income changes.

To implement (2), we regress realized inflation (Y) and forecasted inflation ($\mathbb{F}_i[Y|I_i]$) on the difference in household log nominal income between the years $t+1$ and $t-1$, where t denotes the year of survey response. Because realized future income changes are not plausibly fully contained in the person's current information set, we deploy Test $2'$.

Table 4 and Figure 4 present our main results. Again, there is no association between realized inflation and realized future household income changes, but there is a strong negative association between inflation forecasts and such changes. This is robust to the inclusion of different sets of controls, including recent changes in log nominal income. In fact, the coefficient on realized future income changes increases in magnitude when recent income changes are included as a covariate, consistent with the fact that recent income changes are negatively related to both realized future income changes and inflation forecasts. In all specifications, $\left|\tilde{\beta}_1^X - \beta_1^X\right|$ far exceeds the bound of 0.042 provided by Test $2'$ under our preferred specifications in Columns 1 and 4.[27]

[26] In our sample of the Michigan Survey of Consumers, 90.2 percent of respondents complete the follow up survey.

[27] The standard deviations of inflation rate (in decimal form), future nominal income changes, and aggregate future nominal income changes are of 0.00361, 0.538 and 0.017, respectively. The bound in equation (4) is 0.00042. We then multiply it by 100 and arrive at $|\beta_1^X - \tilde{\beta}_1^X| \leq 0.042$, aligning with the units of inflation (in percentage points) used in our regression tables. Extending the data to encompass the longest possible time series in Column 2 yields a bound of 0.087.

Additional results and robustness. We provide additional analyses, analogous to those described in the previous subsection, but for forecasted changes in household financial situation and for realized future changes in household income. Appendix Table B.10 presents subsample analysis for forecasted changes in household financial situation, while Appendix Table B.11 presents results for realized future income changes. Appendix Table B.12 studies realized future *labor* income changes. The results are again analogous to those for recent labor income changes (Appendix Table B.6). Appendix Table B.24 shows that using real rather than nominal future income changes does not alter our results. Appendix Table B.27 demonstrates that results are also robust when considering net-of-tax income changes.

4 The Role of Imperfect Recall and Affect

In this section, we study the role that imperfect memory and affect may play in the excessive sensitivity of inflation forecasts to household-level events. The first set of results is facilitated by a unique feature of the Danish Consumer Expectations Survey: the elicitation of survey participants' recollections of inflation over the past 12 months ("backcasts").[28] The second set of results is facilitated by establishing a novel link between the survey and data on emergency room (ER) visits. These results motivate the theory and additional mechanism tests we present in Section 5.

4.1 The Role of Imperfect Recall

Figure 5(a) shows that inflation backcasts are strongly associated with inflation forecast errors, where we define an error as the difference between the actual realization and the respondent's report. Figure 5(b) shows the converse to Figure 5(a): inflation forecasts are strongly associated with backcast errors. By Test 1, neither panel is consistent with rational expectations. In particular, panel (a) suggests that the imperfections in memory may explain some of the forecasting errors. Panel (b), on the other hand, suggests that memory is imperfect and that perceptions of the past are biased.

Analogously to Section 3, we now examine how inflation backcasts—as opposed to forecasts—covary with our household income-change variables. Table 5, panels (a) through (c), presents regression analyses that are analogous to those in Tables 1, 3, 4, respectively. Figure 6 presents corresponding binned scatterplots. The results for backcasts are similar to those for forecasts. As with realized inflation over the next twelve months, realized inflation over the past twelve months does not covary with recent income changes, the survey proxy for expected changes in future income, and realized future income changes. However, inflation backcasts covary strongly and negatively with these household-level measures of income changes.

[28]Such quantitative inflation backcasts are not available in the NY Fed Survey of Consumer Expectations and are only available in the University of Michigan Survey of Consumers starting from 2016.

The results in Table 5 and Figure 6 reject several hypotheses. First, they reject the strong, but standard assumption in macroeconomics that people have full knowledge of recent inflation—consistent with Figure 5(b) above. If this assumption were true, all people would know what past inflation was, and their reports of past inflation, even if reflecting some random noise, would not be related to our income-change measures.

Second, the results reject the hypothesis that people have imperfect memory, but utilize their recalled information in a Bayesian manner when forming predictions about past events. Such "sophistication" is assumed in a variety of theoretical work on imperfect memory (e.g., Bénabou and Tirole, 2002, 2004; Gottlieb, 2014; Azeredo da Silveira et al., 2024), and Tests 1 and 2′ characterize its implications for predictions about past events.

Third, the Table 5(b),(c) results on the association between inflation backcasts and expected changes in future income reject the possibility that people do not understand the meaning of inflation and interpret the inflation questions as questions about their purchasing power. Because positive future income changes correspond to more purchasing power in the future but do not affect it in the past, this possibility cannot explain the association in Table 5(b),(c).

Furthermore, a comparison of Table 5 with Tables 1, 3, and 4 suggests that backcasts covary more strongly with our household-level income change measures than do forecasts. Figure 7 formalizes this comparison. We pool backcast and forecast elicitations and regress them on each income-change measure interacted with indicators for forecast and backcast observations. We then compute the ratio of the coefficient on the backcast interaction to the forecast interaction.[29] We find that the ratio is above one for regressions corresponding to each of our three income change measures, indicating that backcasts are more sensitive than forecasts to household-level income changes.[30]

While the greater sensitivity of backcasts is consistent with memory playing a key mediating role, it does not by itself rule out alternative explanations. Consider the alternative case in which the relationship between forecasts and income changes is not mediated by backcasts, but recent income changes receive more weight when updating beliefs about past rather than future inflation. Formally, this means that inflation forecasts are given by $\mathbb{F}_i[Y|I_i] = aX_i + \epsilon_{i,1}$, and backcasts are given by $\mathbb{F}_i[Y_-|I_i] = bX_i + \epsilon_{i,2}$, where X_i is household income changes, a and b have the same sign, $|b| > |a|$, and $\epsilon_{i,1}$ and $\epsilon_{i,2}$ are random variables independent of X_i and of each other. In this case, a regression of $\mathbb{F}_i[Y|I_i]$ on $\mathbb{F}_i[Y_-|I_i]$ and X_i will lead to $\mathbb{F}_i[Y_-|I_i]$ and X_i having coefficients of 0 and a, respectively.

To test this alternative explanation, we construct Table 6. The table shows that the relationship

[29] When estimated on the same sample, the interacted coefficients are numerically equivalent to those reported in previous backcast regressions (Table 5, panels (a), (b), (c), respectively) and forecast regressions (Tables 1, 3, and 4, respectively). Pooling allows us to cluster by survey response and thus delivers correct standard errors on the backcast-to-forecast ratio.

[30] Appendix Table B.20 presents the coefficients used to compute the ratios in table form.

between our income change measures and forecasts is significantly dampened, or even statistically indistinguishable from zero, when controlling for backcasts. Columns 1, 3, and 5 repeat the regressions of forecasts on recent income change, forecasted family finances change, and future income change, respectively, as studied in Tables 1, 3, and 4. Columns 2, 4, and 6 also include inflation backcasts. The key finding—obtained by comparing Columns 1, 3, 5 to Columns 2, 4, and 6—is that the coefficients on our income change measures are significantly attenuated toward zero when backcasts are included in the regressions. The difference in coefficients on our income change measures is significant at $p < 0.01$ in each pair of regressions. These results are strongly consistent with memory playing a mediating role in how income changes relate to forecasts.[31] Appendix Table B.26 shows that the results are robust when using real income changes. This rules out that our results are driven by a model in which people use realized real income changes to form inflation backcasts and forecasts but misjudge the relative volatility of income changes and inflation, but is consistent with memory playing a mediating role.

4.2 The Role of Affect

What is the channel through which our household-level income changes influence people's backcasts and forecasts? One plausible hypothesis is *affective association*, consistent with the affect heuristic in psychology (e.g., Finucane et al., 2000; Slovic et al., 2007). For example, a realized or expected negative income change generates negative affect, leading to pessimistic, and hence higher, inflation backcasts and forecasts.

If affect is an important channel for how household-level events influence inflation backcasts and forecasts, other household-level events that meaningfully influence people's affect should also influence inflation backcasts and forecasts. We test this prediction using data on family health shocks. Specifically, we focus on Emergency Room (ER) visits by the survey respondent or by members of their immediate family (spouse or children) during the month of the survey. The basic idea of our analysis is to compare two survey respondents with the same number of family ER visits and the same demographics, but with the difference being that one respondent was asked to take the survey right around the family ER visit, while the other respondent was asked to take the survey further away from the visit. Because the sample of people who are approached by Statistics Denmark to take the survey is randomly generated each month, it is random that one respondent was approached to take the survey near the family ER visit while the other one was not.

There are several key properties of family ER visits that make them well-suited for our analysis.

[31] One can also rule out that household income changes impact inflation backcasts only indirectly through their impact on forecasted inflation. Formally, suppose that backcasts $\mathbb{F}_i[Y_-|I_i]$ are related to forecasts $\mathbb{F}_i[Y|I_i]$ via the model $\mathbb{F}_i[Y_-|I_i] = \alpha_0 + \alpha_1 \mathbb{F}_i[Y|I_i] + \epsilon_i$, where $\epsilon_i \perp \mathbb{F}_i[Y|I_i]$ and $\epsilon_i \perp X_i$. Because empirically $\alpha_1 < 1$, this model makes the following two counterfactual predictions. First, it predicts that when regressing forecasts and backcasts, respectively, on X_i, the coefficient of X_i would be larger in the forecast regression, inconsistent with Figure 7. Second, it predicts that in regressions of forecasts on backcasts and the income change measure X_i, the coefficient of X_i will always remain significantly negative, contrary to the results in Column 6 of Table 6.

First, family ER visits plausibly proxy for negative events that lead to negative affect. At the same time, family ER visits are plainly not related to inflation. Second, family ER visits are sufficiently common that we have enough statistical power to examine the impact of a family ER visit in the survey month, while controlling for a household's general propensity to visit the ER. Finally, because ER visits, like most other medical services, are free for Danish residents, visiting the ER does not provide respondents with information about prices. The main concern about family ER visits is that they might induce meaningful survey non-response, but Appendix Table B.29 shows this is not the case in our sample.[32]

Our analysis utilizes the available data on ER visits over 11 years, ranging from 2008 to 2018.[33] We utilize all years, including those of the Great Recession, because there is no obvious impact of such macroeconomic shocks on the relationship between inflation perceptions and having a family ER visit close to the survey date. Under the null hypothesis of rational expectations, a respondent's inflation forecast or backcast should have no relationship to a proximate ER visit. Similarly, because there is no reason why family ER visits should have a different relationship with inflation predictions for working, retired, or not-yet-working individuals, we do not impose the demographic restrictions from our main analysis and expand our sample to the full adult population. We present summary statistics for the sample used in this analysis in Appendix Table B.3. Column 1 of Appendix Table B.30 shows that our results are robust for subsamples with demographic and/or time restrictions that match our main analysis.

On average, there are 3 visits per household in our sample period, and 0.19 visits in the survey month. 90 percent of households have seven or fewer ER visits in our sample period. We exclude households with eight or more ER visits in our sample period, as for these households an ER visit may be a less unusual and thus less affect-inducing event, and because more extreme numbers of ER visits reduce statistical power in regressions that control for the total number of ER visits. Columns 2 and 3 of Appendix Table B.30 show, respectively, that our results are robust to instead excluding the 17 percent of households with 6 or more ER visits, or the 6 percent of households with 10 or more ER visits.

We estimate the impact of a family ER visit in the survey month, including our standard set

[32]Directionally, the table shows that having an ER visit reduces the likelihood of completing the survey by approximately 0.010, which is not statistically significant. These point estimates are very small economically for the following reasons. Given a monthly response rate of 0.64, and a pooled effect size of approximately 0.2 percentage points in Columns 2-5 of Table 7, the marginal respondents who drop out due to the ER visit would need to have inflation forecasts and backcasts that are on average approximately $(0.2 \times 0.64)/0.010 = 12.8$ percentage points lower than the average (for this calculation, we make the standard monotonicity assumption that if an individual responds during the month of an ER visit, then they would also respond in a month without an ER visit). We find a 12.8 percentage point difference to be implausible. Arguably even more implausible are the conditions that need to hold for attrition to explain the asymmetric effects of ER visits on forecasts and backcasts in columns 6 and 7: attrition would need to have a much higher correlation with backcasts than with forecasts, and we see no plausible mechanism for why this could be the case.

[33]In 2019, the National Patient Registry transitioned to a new reporting system. Since we do not have access to data from the new version of the registry, our sample ends in 2018.

of demographic controls, calendar month fixed effects, and also controlling for total number of family ER visits in our sample period with varying flexibility: linearly, quadratically, and non-parametrically via fixed effects.[34] Table 7 presents the results. Columns 1 through 5 pool inflation backcasts and forecasts.[35] In Columns 6 and 7 we include an interaction term with an indicator for forecasts to assess if family ER visits have larger effects on backcasts than forecasts.

Columns 1 through 5 show a significant and robust effect of a family ER visit in the survey month on inflation backcasts and forecasts. Controlling for total number of family ER visits in the sample period slightly lowers the estimate relative to Column 1, but as Column 2 shows, the association with one additional family ER visit in the sample period is only 0.045, while the impact of a family ER visit in the survey month is approximately five times larger. Controlling more flexibly for the total number of family ER visits, as we do in Columns 3-5, has no impact on the results. Column 5 has the most flexible controls for total family ER visits: we include fixed effects for total number of family ER visits and, to allow for the possibility that these have different implications for respondents of different ages, interact the fixed effects with age. Column 4 of Appendix Table B.30 shows that when controlling for recent and future income changes, the impact of a family ER visit on inflation forecasts and backcasts is, if anything, slightly higher—ruling out the hypothesis that the impact of ER visits on inflation forecasts is mediated by our income change measures.

Columns 6 and 7 of Table 7 study the differential impact of a family ER visit in the survey month on forecasts versus backcasts. Column 6 controls for total number of family ER visits linearly, as in Column 2, while Column 7 controls for total visits flexibly via fixed effects. Both columns are consistent with our findings about household income changes in Figure 7 and Table 6: a family ER visit in the survey month has a larger impact on backcasts than forecasts, consistent with the hypothesis that the affective consequences of a family ER visit in the survey month are mediated by memory.[36]

5 A Unified Explanation

We now provide a unified explanation of our full set of empirical results about biases in forecasts and backcasts. In this explanation, households' inflation forecasts are impacted by what they recall and what they recall is cued by household-level events through affective association. Specifically, negative (positive) household-level events cue negative (positive) recollections, which lead to pes-

[34] Note that including calendar month fixed effects is in contrast to our main analyses, where including calendar month fixed effects would constitute an improper test of rational expectations. In this analysis, however, the null hypothesis of rational expectations is that whether or not a respondent recently visited the ER should have no impact on their inflation expectations, conditional on the calendar month. We include calendar month fixed effects to increase precision. Excluding them has no impact on our results.

[35] Note that we cluster two-way by respondent and calendar month, which accounts for the non-independence between a respondent's paired forecast and backcast as well as for common shocks within a calendar month.

[36] In Appendix Table B.31, we find suggestive evidence that the effect of a family ER visit on inflation backcasts and forecasts is lower among the college-educated, similar to the differences between Columns 7 and 8 in Table 2.

simistic, higher-inflation (optimistic, lower-inflation) backcasts and forecasts. This accounts for why (i) nearly-idiosyncratic events such as household income changes are significantly associated with both inflation forecasts and backcasts, (ii) completely idiosyncratic events such as family health shocks also impact both inflation forecasts and backcasts, (iii) inflation backcasts are more strongly associated with these household-level events than forecasts are, and (iv) inflation backcasts mediate the association between inflation forecasts and the household-level events. We first discuss the cognitive foundations, then develop a formal memory-based model of belief formation, and then provide additional survey-experimental evidence of the model's assumptions and predictions.

5.1 Cognitive Foundations

We incorporate three key mechanisms from psychology and neuroscience: (i) memories of past experiences are encoded alongside their affective valence, (ii) current affective states cue the recall of past experiences with similar affective valence, and (iii) recalled memories shape people's forecasts.

First, memory research indicates that past experiences are encoded not in isolation but alongside their associated affective context, consistent with the principles of episodic memory (Tulving, 1972). Consequently, past inflation experiences are encoded not merely in numerical terms but also with their corresponding affective valence—for instance, the anxiety or financial strain felt during times of high inflation. A body of evidence shows that episodic memory integrates factual and affective dimensions, highlighting affective states as intrinsic components of stored experiences (Hassabis and Maguire, 2009; Kahana and Wagner, 2024).

Second, the recall of past experiences is influenced by current affective states, a phenomenon known as mood-congruent recall (Isen et al., 1978; Bower, 1981). According to retrieved-context theory (Kahana, 2012; Cohen and Kahana, 2022), a person's current affective state acts as a retrieval cue, selectively activating memories that share a similar encoded affective valence. This associative recall leads to an overrepresentation of past inflation experiences that align with the individual's current affective state in their retrieved memories.

Third, forecasts about the future are shaped by retrieved memories, particularly through episodic simulation, wherein individuals employ the same cognitive and neural mechanisms involved in memory retrieval to construct future scenarios (Hassabis et al., 2007; Bordalo et al., 2024). This suggests, for example, that recalled prior inflationary episodes lead people to simulate higher-inflation scenarios and produce more pessimistic, higher-inflation forecasts.

5.2 A Memory-based Model of Belief Formation

We now present a memory-based model of belief formation that captures the psychological mechanisms described above, and explains our empirical results. Inflation over the past 12 months is denoted by Y_{-}, and inflation over the next 12 months is denoted by Y. Correspondingly, person

i's inflation backcast and forecast, given information set I_i, are $\mathbb{F}_i[Y_-|I_i]$ and $\mathbb{F}_i[Y|I_i]$, respectively. The information set I_i includes (signals of) household-level events such as changes in household income or family ER visits. We assume $(Y, Y_-)|I_i$ to be jointly normal and use $f(Y_-|I_i)$, $g(Y|Y_-, I_i)$, and $h(Y|I_i) = \int g(Y|Y_-, I_i) f(Y_-|I_i) dY_-$ to denote the objective probability density functions of the relevant conditional distributions. For simplicity, we also assume that the unconditional means of Y and Y_- are zero.

Consistent with the psychological principles described above, we assume that a person's recall of past inflation experiences is impacted by affective association: if information I_i induces negative (positive) affect, then it prompts the recall of episodes of unpleasant (pleasant) price changes. Formally, the similarity between the cue I_i and an inflation state Y_- is inversely related to their difference in affect:

$$\mathcal{S}(Y_-, I_i) = \exp\left(-\frac{(\alpha_Y(Y_-) - \alpha_I(I_i))^2}{2}\right), \tag{5}$$

where $\alpha_Y(Y_-)$ and $\alpha_I(I_i)$ denote the affect induced by Y_- and I_i. Consistent with our survey evidence below, we assume that $\alpha_Y(Y_-)$ decreases with Y_- because people dislike inflation. We normalize such that the unconditional means of $\alpha_Y(Y_-)$ and $\alpha_I(I_i)$ are zero, and $\alpha_Y(Y_-) = -Y_-$. How likely a person is to recall an inflation state Y_- given the information cue I_i is given by the probability density function $f_\theta(Y_-|I_i)$, and increases with the affect-based similarity $\mathcal{S}(Y_-, I_i)$:

$$f_\theta(Y_-|I_i) = \frac{f(Y_-|I_i) \times (\mathcal{S}(Y_-, I_i))^\theta}{\int f(Y_-|I_i) \times (\mathcal{S}(Y_-, I_i))^\theta dY_-}, \tag{6}$$

where $\theta \geq 0$ denotes the importance of associative memory through affect. For $\theta = 0$, $f_\theta(Y_-|I_i)$ corresponds to its Bayesian counterpart $f(Y_-|I_i)$. For $\theta > 0$, $f_\theta(Y_-|I_i)$ inflates the probability of recalling inflation states that have affect similar to the cue, and deflates the probability of recalling inflation states that have affect opposite to the cue.

As in Bordalo et al. (2024) and Gennaioli et al. (2024), the person's belief about past inflation, Y_-, is constructed by sampling infinitely many times from memory. As a result, the probability density function of the person's belief about past inflation, Y_-, is also given by $f_\theta(Y_-|I_i)$, which captures the frequency of recalling a specific inflation state. Their subjective inflation backcast is hence given by

$$\mathbb{F}_i[Y_-|I_i] = \int Y_- f_\theta(Y_-|I_i) dY_- = \mathbb{E}[Y_-|I_i] - \omega_\theta(\alpha_I(I_i) - \mathbb{E}[\alpha_Y(Y_-)|I_i]), \tag{7}$$

where $\mathbb{E}[Y_-|I_i] = \int Y_- f(Y_-|I_i) dY_-$ is the unbiased Bayesian estimate, $\kappa = Var(Y_-|I_i)^{-1} = \left(\int (Y_- - \mathbb{E}[Y_-|I_i])^2 f(Y_- \mid I_i) dY_-\right)^{-1}$ captures its precision, and $\omega_\theta = \frac{\theta}{\kappa+\theta}$ is the sensitivity of backcasts to differences in affect (see Appendix C.3.1 for derivations). The more positive the affect induced by I_i, the greater is $\alpha_I(I_i)$, and thus the lower the backcast $\mathbb{F}_i[Y_-|I_i]$. Note that the weight ω_θ is increasing in θ, the importance of associative memory, and decreasing in κ, the informativeness of the agent's information about past inflation. The limit $\kappa \to \infty$ corresponds to perfect knowledge about past inflation, in which case $\omega_\theta \to 0$ and affect does not influence backcasts.[37] The model thus also makes the prediction that people with more precise information will be less influenced by affect, which is consistent with our results that there is less excess sensitivity among the college-educated.

Recalled experiences influence inflation forecasts as well. Specifically, the person's subjective beliefs about future inflation are given by the probability density function

$$h_\theta (Y|I_i) = \int g (Y|Y_-, I_i) f_\theta (Y_-|I_i) dY_-, \tag{8}$$

where $f_\theta (Y_-|I_i)$ is from (6) and $g (Y|Y_-, I_i)$ captures the conditional probability density of Y given Y_- and I_i.[38] This subjective distribution contrasts with the Bayesian probability density function $h (Y|I_i) = \int g (Y|Y_-, I_i) f (Y_-|I_i) dY_-$. The person's subjective inflation forecast is then given by

$$\mathbb{F}_i [Y|I_i] = \int Y h_\theta (Y|I_i) dY = \mathbb{E} [Y|I_i] - \rho_Y \omega_\theta (\alpha_I (I_i) - \mathbb{E} [\alpha_Y (Y_-) |I_i]), \tag{9}$$

where $\mathbb{E} [Y|I_i] = \int Y h (Y|I_i) dY$ is the unbiased Bayesian estimate and $\rho_Y \equiv \frac{\partial \mathbb{E}[Y|Y_-,I_i]}{\partial Y_-} \in (0, 1)$ captures the extent to which past inflation informs future inflation. In the case where I_i contains no information about future inflation Y conditional on Y_- ($I_i \perp Y|Y_-$), $\rho_Y = \frac{\partial \mathbb{E}[Y|Y_-]}{\partial Y_-}$ is simply the persistence of inflation. Analogous to (7), (9) shows that the more positive the affect induced by information I_i, the lower will be inflation forecasts.

Under the assumptions of Tests 1 or 2′, the Bayesian forecasts $\mathbb{E} [Y|I_i]$ and $\mathbb{E} [Y_-|I_i]$ co-move very little with the household-level variable X_i in our settings. As a result, the model implies that the regression coefficients of inflation backcasts and forecasts on the household-level variable X_i are mostly driven by affect and are given by

$$\tilde{\beta}_1^{X,-} \equiv \frac{Cov (\mathbb{F}_i [Y_-|I_i], X_i)}{Var (X_i)} \approx -\omega_\theta a \tag{10}$$

$$\tilde{\beta}_1^{X} \equiv \frac{Cov (\mathbb{F}_i [Y|I_i], X_i)}{Var (X_i)} \approx -\rho_Y \omega_\theta a, \tag{11}$$

where $a = \frac{Cov(\alpha_I(I_i),X_i)}{Var(X_i)}$ quantifies the impact of the household variable X_i on affect (see Appendix C.3.1 for details).

Equations (10) and (11) show that the model provides a unified explanation of our empirical evidence. It predicts that (i) approximately or fully idiosyncratic household-level events can influence both inflation forecasts and backcasts through affect, (ii) events with positive (negative) affect covary negatively (positively) with inflation forecasts and backcasts, and (iii) the forecast

[37] The importance of associative memory θ is thus not identified without an estimate of the precision of the person's information. For instance, ω_θ could be zero either because $\theta = 0$ (no similarity weighting) or because $\kappa \to \infty$ (perfect knowledge of the past).

[38] To minimize the deviation from the Bayesian forecast, we assume that the person correctly understands the conditional distribution of future inflation $g (Y|Y_-, I_i)$ given Y_- and I_i. But this assumption is not essential to explain the empirical facts and can be relaxed. If we deviate from this assumption, the relevant ρ_Y in (9) is the perceived value.

regression coefficients will be smaller in magnitude than the backcast coefficients.

The model structure largely follows the memory-based model of belief formation in (Bordalo et al., 2018, 2020; Bianchi et al., 2023; Bordalo et al., 2023, 2024), with the key difference being that the similarity function $\mathcal{S}(Y_{-}, I_i)$ depends on affect instead of representativeness. While association through affect is crucial for explaining our results, our model could be further generalized to incorporate representativeness and other forms of association. It is also important to note that an implicit assumption of our model, consistent with prior work, is that when forming beliefs, the person does not (fully) account for how affective association distorts the likelihood of recall, $f_\theta\left(Y_{-}|I_i\right)$. A person fully accounting for affect-cued recall during belief formation would not violate tests of rational expectations.

5.3 Supporting Survey Evidence

Survey Design Appendix A.4 presents the full survey questionnaire. Our survey began with an initial elicitation of inflation forecasts, closely replicating the approach used in the Danish Consumer Expectations Survey. We then asked respondents what factors influenced their forecast: *"You previously wrote that you thought that prices will [increase/decrease] by XX% or stay the same over the next 12 months. Did you consider any of the factors below when coming up with your answer?"* Participants were then asked to rate the influence of various factors on their forecasts on a scale of: not at all (1), a little (2), or a lot (3). Each respondent was randomly assigned to rate a list of ten factors. Five factors were randomly selected from a list of fifteen "textbook macroeconomic" factors, such as "changes in the money supply by the Central Bank." The remaining five were randomly selected from a list of fifteen household-level factors, such as "recent changes in the prices of my usual groceries."[39] The objective of this first elicitation was to investigate how likely respondents are to use traditional macroeconomic factors versus recalled household-level experiences in forming inflation forecasts.

The next question tested the affect-cued recall mechanism with the following prompt: *"Sometimes people recall [negative/positive] experiences from the past. This has probably happened to you before. Can you tell us what kinds of situations, events, or mindsets in the list below lead you to recall [negative/positive experiences] from the past?"* Participants were randomly assigned to recall either "negative" or "positive" experiences. They then rated the importance of each cue in a randomized list of ten cues using a 3-point Likert scale. We randomly selected the ten cues for each respondent by drawing five from a pool of eight financial cues and the remaining five from a pool of ten non-financial cues; these cues were always presented in random order. Examples of financial cues include "When I anticipate that my household income will go up" and "When I feel confident about my job security." Examples of non-financial cues include "When I am in a

[39] The order of factors was fully randomized to eliminate potential order effects. The selection of macroeconomic factors follows the approach of Binetti et al. (2024).

bad mood." Each cue was *independently* assigned either positive or negative affective valence. For example, if the cue about job security was randomized to have negative valence, the respondent would instead see "When I worry about my job security"; or if the mood cue was assigned positive valence, the respondent would see "When I am in a good mood." If a person's recall of past experiences is impacted by affective association, positive (negative) cues should lead to the recall of positive (negative) experiences more than negative (positive) experiences.

Because we are primarily concerned with experiences in the financial domain (e.g., inflation), we slightly modified the elicitation for half of our participants by asking them specifically about the recall of positive/negative financial events, rather than just generic experiences. The elicitation was modified as follows: *"Sometimes people recall [negative/positive] events from the past that directly impacted their financial situation. This has probably happened to you before. Can you tell us what kinds of situations, events, or mindsets in the list below lead you to recall such [negative/positive] events from the past?"*

Finally, to connect directly with our central results about inflation perceptions, in a separate question we specifically tested affect-cued recall of inflation experiences*: "How much do each of the following influence your tendency to remember and focus on periods in your life when there was very [high/low] inflation in the prices of things you need?"* The valence of the two recall questions was the same for each respondent: respondents were asked about high inflation if they were also asked about negative experiences from the past, and vice-versa. For the inflation recall question, respondents were presented with a new set of ten cues (5 financial, 5 non-financial), and again rated them with a 3-point Likert scale. The valence of each cue was again independently randomized between positive and negative.[40]

After these main questions, we also directly tested if inflation carries a negative affective valence by asking respondents to rate how they feel about price increases. Responses were on a 3 point Likert scale: (1) unpleasant, (2) neutral, and (3) pleasant.

The survey also included an attention check, placed between our two recall questions, where participants had to leave the answer blank to demonstrate attention (see Appendix A.4 for details).

Samples We fielded the same survey questionnaire in both Denmark and the US. The Danish survey sample was randomly drawn from the Danish population registry. Invitations were sent via DigitalPost, the official electronic mail system used by all Danes, and the survey was conducted in May and June 2025. We invited 22521 participants and obtained 3744 complete submissions. Each Danish participant who completed the survey was entered into a raffle for ten lottery prizes

[40]Note that cues were never shown twice, independently of their valence. For example if the cue "When I worry about my job security" was presented in the first recall question, neither "When I worry about my job security" nor its positive counterpart "When I feel confident about my job security" was shown in the second recall question. Furthermore, the two additional financial cues "When I expect my household income to [increase/decrease]" and "When my wealth has recently [increased/decreased]" are always shown for the inflation recall elicitation.

worth 1,000 Danish Kroner each. We fielded the US survey on Prolific Academic in October 2024, collecting 1600 submissions from participants sampled to be representative of the U.S. Census along age, gender, and ethnicity. US participants received \$2 for completing the survey. In the US sample, we dropped 77 participants who responded incorrectly to our attention check, and obtained a final sample of 1523 respondents. We present summary statistics for both samples in Appendix Table B.32.

Results Our first finding is that past household-level experiences, particularly ones involving recent price changes, shape inflation forecasts as much as macroeconomic factors. Since past experiences can only influence forecasts if they are recalled, this provides direct evidence that inflation forecasts are shaped by recalled household-level experiences, consistent with our assumptions in equation (8). We summarize the results in Figure 8, and provide additional summary statistics in Appendix Table B.34. Figure 8 shows that respondents rely on macroeconomic factors slightly less than household-level experiences in shaping their inflation forecasts. On average, the probability that a macroeconomic factor is rated as mattering "A Lot" is 0.16 in the Danish sample and 0.24 in the US sample. For household-level factors, these probabilities are 0.18 and 0.27, respectively. When we recode the responses as "Not at all" = 1, "A little" = 2, and "A lot" = 3, macroeconomic factors average 1.71 in the Danish sample and 1.86 in the US sample, while household-level factors average 1.72 and 1.89, respectively. For instance, "Change in price of groceries" receives the highest mean Likert score among all factors in both samples, consistent with D'Acunto et al. (2021b), who find that households update significantly based on the prices of their grocery baskets. Moreover, the second and third most important personal experiences in Denmark are changes in utility prices and consumer good prices, and in the US, changes in consumer goods prices and eating-out prices. By contrast, factors related to money supply and monetary policy rank lowest among macroeconomic options.

The data are also consistent with the household financial situation being a key determinant of inflation forecasts. For both Danish and US respondents "Feeling financially strained" ranks 4th among household-level factors, with an average score of 1.93 in the Danish sample and 2.11 in the US sample, indicating that respondents consider it as important as key macroeconomic factors such as "Household spending" (average scores of 2.06 in Denmark and 2.16 in the US), "Oil and energy prices" (average scores of 1.98 and 2.09), and "Supply chain conditions" (average scores of 2.04 and 2.04).

Our second finding is that all else equal, positive cues facilitate recall of positive experiences more than negative experiences, and vice-versa. This provides direct evidence that the affective context influences what people recall, as postulated in equations (5) and (6) of the model. Columns 1 and 2 of Table 8 report on a linear probability model that analyzes how the affective valence of cues influences whether people recall positive or negative experiences. The dependent variable is an indicator for whether a cue was chosen to influence recall "a lot" (Column 1) or "a little or a lot" (Column 2). The right-hand-side variables include indicators for cue type (financial or non-financial), interacted with an indicator that equals one when the cue matches the affective valence of the experience. We find that cues whose valence is congruent with the valence of the experience in the question are significantly more likely to be selected. When the cue and recall question share the same affective valence, the probability of selecting a cue as "Influencing recall a lot" increases by 94% for financial cues and by 137% for non-financial cues in the Danish sample. In the US sample, these probabilities increase by 188% for financial cues and by 267% for non-financial cues, respectively. Appendix Figure B.2 breaks down these results for each individual cue. Appendix Table B.35 shows that affect-cued recall matters both when we ask about financial experiences specifically and experiences in general.

Our third finding is that all else equal, positive cues facilitate recall of lower inflation than negative cues, and vice versa. To begin, we verify that 66% and 87% of respondents considered inflation a negative experience in the Danish and US samples respectively. Columns 3 and 4 in Table 8 present the results of a linear probability model analogous to Columns 1 and 2. Again, the positive and statistically significant coefficients in the third and fourth rows support our hypothesis. When the cue and recall question share the same affective valence, the probability of selecting a cue as "Influencing recall a lot" increases by 33% for financial cues and by 52% for non-financial cues in the Danish sample. In the US sample, these probabilities increase by 74% for financial cues and by 74% for non-financial cues. Appendix Figure B.3 provides a graphical summary of these results for each of the different cues. Appendix Table B.36 shows that the effects are concentrated on those who perceive inflation negatively, consistent with our theory.

In Appendix B.10.3, we present complementary results that inflation forecasts also covary negatively with people's reported wellbeing changes, even when conditioning on reported changes in household finances. These results are also broadly consistent with the affect-cued recall hypothesis.

5.4 Other Potential Explanations

Here we consider other alternative theories that could explain some of our results. While our main empirical results in Section 3 rule out the possibility that our results are due to prior bias, there are other prominent theories that could explain some of our results. Models of overconfidence and over-precision bias are natural candidates for explaining our results about excess sensitivity. Models in which people have incorrect mental models of what causes inflation, or in which people report moments of their beliefs other than the mean, are also natural candidates for explaining some of the systematic errors in inflation forecasts. We show, however, that none of these possibilities can explain all four key empirical regularities summarized at the beginning of Section 5.

Overconfidence, over-precision bias, and other theories of over-reaction. Overconfidence or over-precision bias (e.g., Scheinkman and Xiong, 2003; Broer and Kohlhas, 2024), where the person's perceived variance of the noise in their signal is lower than its actual variance, can lead to excess sensitivity to the signal. However, such theories cannot explain the even greater excess sensitivity of backcasts. These theories also cannot explain why inflation forecasts are sensitive to household-level events that are completely idiosyncratic to inflation, such as family ER visits.

In fact, standard parameterizations of these models also cannot explain our findings that variables that are nearly idiosyncratic to inflation, such as household-level income changes, covary strongly with inflation forecasts. For instance, the lower bound of the 95% confidence interval in Column 1 of Table 1 is a coefficient of approximately -0.04 on household income changes, while the upper bound of the 95% confidence interval in Column 4 of Table 1 is approximately -0.40. This implies that people would have to overweight the informational content of household-level income changes by at least a factor of 10, a degree of overreaction far larger than is typically estimated or assumed in these models.

"Supply-side" view of inflation. One potential explanation for the negative relationship between inflation forecasts and household income changes is people's "supply-side" view of inflation (Candia et al., 2020; Kamdar and Ray, 2025). That is, people perceive inflation as being driven by negative supply shocks (e.g., supply chain shortages) that decrease economic activity and household income.[41] Clearly, this does not explain our results about the impact of family health shocks on inflation forecasts, or our results about the mediating role of memory.

In Appendix C.3.2, we show that this also cannot account for our results about excess sensitivity to income changes. Although this mechanism can explain the sign of $\tilde{\beta}_1^X$, it cannot explain the large absolute difference between β_1^X and $\tilde{\beta}_1^X$. We show in the appendix that if people simply misperceive the sign of the correlation between income changes and inflation, then the bound on $\left|\tilde{\beta}_1^X - \beta_1^X\right|$ in our Tests 2 and $2'$ can increase by at most $2\left|\beta_1^X\right|$, which is negligible. The result illustrates the robustness of our tests due to the focus on absolute differences rather than signs.

Affective association without memory. Can alternative psychological foundations of affective association (beyond associative memory) explain our empirical results? For example, affective association could, in principle, arise from Kahneman (2011)'s "what you see is all there is" (WYSIATI) bias. In our context, this means that people simply place both household-level events and macroeconomic experiences into a binary good/bad category and make inflation forecasts accordingly. However, this does not explain our results on why our backcasts are even more excessively sensitive to household-level events than our forecasts, nor our results on the mediating role of memory (e.g.,

[41] Candia et al. (2020) study people's perceived relationship between macroeconomic variables, but do not study perceived relationships between inflation and household-level variables.

in Table 6).

Survey beliefs reflecting other moments. People may not necessarily state their conditional expectation and may instead report another quantile of the posterior distribution of beliefs (e.g., Bhandari et al., 2024). This by itself cannot explain our ER visits results, or our results about the mediating role of imperfect recall. This also cannot plausibly explain the magnitudes of our excess sensitivity results. To see this, suppose that what people report can be approximated as $\theta_0 + \theta_1 \mathbb{E}[Y|I_i]$. For example, if posterior beliefs are normally distributed and people report the n-th quantile of their beliefs, then $\theta_1 = 1$ and $\theta_0 = \sigma\Phi^{-1}(n/100)$, where σ is the standard deviation of the posterior and Φ^{-1} is the inverse function of the standard normal CDF. In our empirical results, we generally find that people's reports covary with their income changes by an order of magnitude more than realized inflation does, which implies that we would need $\theta_1 > 10$ to rationalize our results. We are not aware of any natural assumptions about the information process—and the types of moments that people might be plausibly reporting—that could rationalize reports being an order of magnitude more sensitive to information than the mean.

6 Conclusion

This paper finds that people's forecasts are influenced by largely idiosyncratic household-level events. Additional tests suggest that affect-cued recall is a key mechanism.

Our findings have aggregate implications. First, the mechanism we document can amplify the macroeconomic impact of aggregate shocks. Consider accommodative monetary or fiscal shocks. They increase household income, which makes people more optimistic about the economy, and thus leads people to further increase spending. This increase in spending further amplifies the macroeconomic impact of aggregate shocks and, in turn, reinforces confidence. This is the "confidence multiplier" envisioned by Akerlof and Shiller (2010) and Angeletos and Lian (2022). Second, as Broer et al. (2025) show, differences in beliefs about the economy driven by idiosyncratic shocks lead to differences in consumption and saving decisions, which shape the wealth distribution in the economy. Our findings show how affect-cued recall contributes to differences in beliefs.

Our findings challenge not only theories of rational expectations but also a variety of "quasi-Bayesian" models in behavioral economics. Our findings also suggest that existing findings of "experience effects" may be a manifestation of a broader and deeper psychology, as such effects are not limited to within-domain extrapolation or to realized past experiences. For instance, our model of affect-cued recall can also help explain why stress, anxiety, and other negative mental states can influence financial decision making and why interventions designed to improve mental wellbeing can improve financial decision making (e.g., Hirshleifer and Shumway, 2003; Edmans et al., 2007; Cohn et al., 2015; Ridley et al., 2020; Sergeyev et al., 2025). This differs from standard models of overreaction, and suggests that policies that improve people's wellbeing may generate economic spillovers through the affect channel. In future work, it will be important to study these additional implications, as well as to directly document how affect-cued recall impacts people's decisions.

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Table 1: Inflation Forecasts and Recent Changes in Household Income

	Realized Inflation next 12m		Inflation Forecast next 12m			
	(1)	(2)	(3)	(4)	(5)	(6)
Recent Log Nominal Income Change	0.008 (0.022)	0.034** (0.016)	-0.655*** (0.140)	-0.674*** (0.140)	-0.563*** (0.137)	-0.499*** (0.130)
Demog. Controls	No	No	No	Yes	Yes	Yes
Month FE	No	No	No	No	Yes	No
Sample	Respondents 2012 - 2019	Population 1991 - 2019	Respondents 2012 - 2019	Respondents 2012 - 2019	Respondents 2012 - 2019	Respondents 2008 - 2019
Longest Possible Series		✓				✓
Observations	35050	62449159	35050	35050	35050	53367

Notes: This table presents regressions of realized and forecasted inflation over the 12 months following the survey response on recent log nominal income change. The units of inflation and inflation forecasts are expressed in percentage points. Recent changes in households' log nominal income are calculated based on the log nominal income of the year $t-1$ minus the log nominal income in the year $t-2$, with t denoting the year of the survey response. "Respondents" denotes the set of survey respondents satisfying the restriction outlined in Section 1. "Population" refers to everyone in the Danish population who in a given year meets our survey sample demographic restrictions. To make this comparable to the survey sample analysis, for each individual in a given year we randomly assign a month within each calendar year, and compute the inflation in the 12 months following that randomly assigned month. "Longest Possible Series" checkmarks denote the longest sample we can construct given the available data. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. The specification "Month FE" includes a fixed effect dummy for each calendar month. These regressions are based on data from 2012-2019, except for Column 2, where we use years 1991-2019, and Column 6, where we use years 2008-2019. Robust standard errors are clustered two ways: by calendar month and by unique respondent. Since only 467 respondents answer the survey more than once, this is essentially numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 2: Inflation Forecasts and Recent Changes in Household Income: Subsamples

(a) Realized inflation

	Realized Inflation next 12m											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Recent Log Nominal Income Change	0.014 (0.024)	0.006 (0.023)	0.017 (0.041)	0.001 (0.024)	-0.004 (0.029)	0.011 (0.024)	-0.009 (0.030)	0.022 (0.021)	-0.009 (0.035)	0.011 (0.027)	0.006 (0.025)	-0.033 (0.038)
Demog. Controls	No	No	No	No	No	No	No	No	No	No	No	No
Sample Restriction	Income Change Restricted	No Unemp. or Leave	Some Unemp. or Leave	No Marriage or Retirement Transitions	> Median Avg Past Income	< Median Avg Past Income	College Educated	Non-College Educated	Simple Income	Net Saver	Net Borrower	Public Employee
Observations	32486	32264	2786	31841	18447	16603	15489	19561	17843	19849	15200	9791

(b) Forecasted inflation

	Inflation Forecast next 12m											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Recent Log Nominal Income Change	-0.725*** (0.185)	-0.688*** (0.153)	-0.423 (0.341)	-0.755*** (0.157)	-0.555*** (0.205)	-0.741*** (0.193)	-0.308 (0.202)	-0.899*** (0.185)	-0.843*** (0.248)	-0.842*** (0.189)	-0.500** (0.236)	-0.570** (0.287)
Demog. Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample Restriction	Income Change Restricted	No Unemp. or Leave	Some Unemp. or Leave	No Marriage or Retirement Transitions	> Median Avg Past Income	< Median Avg Past Income	College Educated	Non-College Educated	Simple Income	Net Saver	Net Borrower	Public Employee
Observations	32486	32264	2786	31841	18447	16603	15489	19561	17843	19849	15200	9791

Notes: This table presents regressions of realized (panel a) and forecasted (panel b) inflation over the 12 months following the survey response on recent log nominal income change for various subsamples. The units of inflation and inflation forecasts are expressed in percentage points. Recent changes in households' log nominal income are calculated based on the log nominal income of the year $t-1$ minus the log nominal income in the year $t-2$, with t denoting the year of the survey response. "Income change restricted" refers to a recent log nominal income change whose absolute value is smaller than 0.2. "No Unemp. or Leave", "Some Unemp. or Leave", and "No Marriage or Retirement Transitions" refer to the samples of respondents that do not experience unemployment, are unemployed for some or all of the time, and do not transition in or out of marriage or retirement for the period $t-1$ to $t-2$, respectively. "> Median Avg Past Income" is the sample for which the average past log income from $t-3$ to $t-5$ is above the median. "< Median Avg Past Income" is the sample for which the average past log income from $t-3$ to $t-5$ is below or equal to the median. "College Educated" and "Non-College Educated" restrict to respondents with and without a college degree, respectively. The "Simple Income" sample restricts to individuals for whom at least ninety percent of income is labor income in the years $t-2$ to $t+1$. "Net Saver" restricts to the subsamples with positive total net assets in year t. "Net Borrower" restricts to the subsamples with negative total net assets in year t. "Public Employee" denotes individuals who are employed in the public sector in the month of interview. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. These regressions are based on data from 2012-2019. Robust standard errors are clustered two ways: by calendar month and by unique respondent. Since only 467 respondents answer the survey more than once, this is essentially numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 3: Inflation Forecasts and Forecasted Family Finances Changes

	Realized Inflation next 12m		Forecasted Inflation next 12m				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Family Finances Change Forecast	-0.009* (0.005)	-0.036*** (0.009)	-0.341*** (0.027)	-0.320*** (0.027)	-0.318*** (0.027)	-0.285*** (0.024)	-0.359*** (0.023)
Recent Log Nominal Income Change					-0.638*** (0.137)		
Demog. Controls	No	Yes	No	Yes	Yes	Yes	Yes
Month FE	No	No	No	No	No	Yes	No
Sample	Respondents 2012 - 2019	Respondents 2008 - 2019	Respondents 2012 - 2019	Respondents 2012 - 2019	Respondents 2012 - 2019	Respondents 2012 - 2019	Respondents 2008 - 2019
Longest Possible Series		✓					✓
Observations	35050	53367	35050	35050	35050	35050	53367

Notes: This table presents regressions of realized and forecasted inflation over the 12 months following the survey response on the forecasted family finances changes. The units of inflation and inflation forecasts are expressed in percentage points. Forecasted family finances changes are elicited on a 5-point Likert scale. Recent changes in households' log nominal income are calculated based on the log nominal income of the year $t-1$ minus the log nominal income in the year $t-2$, with t denoting the year of the survey response. "Longest Possible Series" checkmarks denote the longest sample we can construct given the available data. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. The specification "Month FE" includes a fixed effect dummy for each calendar month. These regressions are based on data from 2012-2019, except for Columns (2) and (7), where we use years 2008-2019. Robust standard errors are clustered two ways: by calendar month and by unique respondent. Since only 467 respondents answer the survey more than once, this is essentially numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 4: Inflation Forecasts and Realized Future Changes in Household Income

	Realized Inflation next 12m		Inflation Forecast next 12m				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Future Log Nominal Income Change	-0.027	0.062^{***}	-0.405^{***}	-0.358^{***}	-0.445^{***}	-0.268^{**}	-0.214^{**}
	(0.020)	(0.018)	(0.106)	(0.104)	(0.107)	(0.105)	(0.096)
Recent Log Nominal Income Change					-0.762^{***}		
					(0.144)		
Demog. Controls	No	No	No	Yes	Yes	Yes	Yes
Month FE	No	No	No	No	Yes	Yes	No
Sample	Respondents 2012 - 2019	Population 1991 - 2019	Respondents 2012 - 2019	Respondents 2012 - 2019	Respondents 2012 - 2019	Respondents 2012 - 2019	Respondents 2008 - 2019
Longest Possible Series		✓					✓
Observations	35050	62449159	35050	35050	35050	35050	53367

Notes: This table presents regressions of realized and forecasted inflation over the 12 months following the survey response on future log nominal income change. The units of inflation and inflation forecasts are expressed in percentage points. Future changes in households' log nominal income are calculated based on the log nominal income of the year $t+1$ minus the log nominal income in the year $t-1$, with t denoting the year of the survey response. Recent changes in households' log nominal income are calculated based on the log nominal income of the year $t-1$ minus log nominal income in the year $t-2$. "Respondents" denotes the set of survey respondents satisfying the restriction outlined in Section 1. "Population" refers to everyone in the Danish population who in a given year meets our survey sample demographic restrictions. To make this comparable to the survey sample analysis, for each individual in a given year we randomly assign a month within each calendar year, and compute the inflation in the 12 months following that randomly assigned month. "Longest Possible Series" checkmarks denote the longest sample we can construct given the available data. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. The specification "Month FE" includes a fixed effect dummy for each calendar month. These regressions are based on data from 2012-2019, except for Column 2, where we use years 1991-2019, and Column 7, where we use years 2008-2019. Robust standard errors are clustered two ways: by calendar month and by unique respondent. Since only 467 respondents answer the survey more than once, this is essentially numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 5: Inflation Backcasts and Household-Level Income Changes

(a) Inflation Backcasts and Recent Changes in Household Income

	Realized Inflation past 12m		Inflation Backcast past 12m			
	(1)	(2)	(3)	(4)	(5)	(6)
Recent Log Nominal Income Change	-0.011	0.039**	-0.858***	-0.862***	-0.725***	-0.756***
	(0.022)	(0.015)	(0.209)	(0.201)	(0.188)	(0.165)
Demog. Controls	No	No	No	Yes	Yes	Yes
Month FE	No	No	No	No	Yes	No
Sample	Respondents 2013 - 2019	Population 1991 - 2019	Respondents 2013 - 2019	Respondents 2013 - 2019	Respondents 2013 - 2019	Respondents 2009 - 2019
Longest Possible Series		✓				✓
Observations	30752	62449159	30752	30752	30752	48783

(b) Inflation Backcasts and Forecasted Family Finances Changes

	Realized Inflation past 12m		Backcasted Inflation past 12m				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Family Finances Change Forecast	0.002	-0.074***	-0.337***	-0.312***	-0.310***	-0.277***	-0.384***
	(0.004)	(0.010)	(0.035)	(0.034)	(0.034)	(0.031)	(0.033)
Recent Log Nominal Income Change					-0.831***		
					(0.200)		
Demog. Controls	No	Yes	No	Yes	Yes	Yes	Yes
Month FE	No	No	No	No	No	Yes	No
Sample	Respondents 2013 - 2019	Respondents 2009 - 2019	Respondents 2013 - 2019	Respondents 2013 - 2019	Respondents 2013 - 2019	Respondents 2013 - 2019	Respondents 2009 - 2019
Longest Possible Series		✓					✓
Observations	30752	48783	30752	30752	30752	30752	48783

(c) Inflation Backcasts and Realized Future Changes in Household Income

	Realized Inflation past 12m		Inflation Backcast past 12m				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Future Log Nominal Income Change	0.014	-0.026*	-0.563***	-0.510***	-0.624***	-0.413***	-0.653***
	(0.020)	(0.014)	(0.128)	(0.131)	(0.132)	(0.135)	(0.142)
Recent Log Nominal Income Change					-0.985***		
					(0.203)		
Demog. Controls	No	No	No	Yes	Yes	Yes	Yes
Month FE	No	No	No	No	Yes	Yes	No
Sample	Respondents 2013 - 2019	Population 1991 - 2019	Respondents 2013 - 2019	Respondents 2013 - 2019	Respondents 2013 - 2019	Respondents 2013 - 2019	Respondents 2009 - 2019
Longest Possible Series		✓					✓
Observations	30752	62449159	30752	30752	30752	30752	48783

Notes: Panel (a) presents regressions of inflation backcasts and realized inflation over the 12 months preceding the survey response on recent log nominal income change. Panel (b) presents regressions of inflation backcasts and realized past inflation on forecasted family finances change. Panel (c) presents regressions of inflation backcasts and realized past inflation on future log nominal income change. The units of inflation and inflation backcasts are expressed in percentage points. Recent changes in households' log nominal income are calculated based on the log nominal income of the year $t-1$ minus the log nominal income in the year $t-2$, with t denoting the year of the survey response. Forecasted family finances changes are elicited on a 5-point Likert scale. Future changes in households' log nominal income are calculated based on the log nominal income of the year $t+1$ minus log nominal income in the year $t-1$. For panels (a) and (c), "Respondents" denotes the set of survey respondents satisfying the restriction outlined in Section 1. "Population" refers to everyone in the Danish population who in a given year meets our survey sample demographic restrictions. To make this comparable to the survey sample analysis, for each individual in a given year we randomly assign a month within each calendar year, and compute the inflation in the 12 months preceding that randomly assigned month. "Longest Possible Series" checkmarks denote the longest sample we can construct given the available data. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. The specification "Month FE" includes a fixed effect dummy for each calendar month. All regressions are based on data from 2013-2019, except for Column 2 in panels (a) and (c), where we use years 1991-2019, Column 2 in panel (b), where we use years 2009-2019, and the "Longest Possible Series" columns (Column 6 in panel (a) and Column 7 in panels (b) and (c)), where we use years 2009-2019. Robust standard errors are clustered two ways: by calendar month and by unique respondent. Since only 467 respondents answer the survey more than once, this is essentially numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 6: Association Between Inflation Forecasts and Income Change Measures when Controlling for Backcasts

	Inflation next 12m Forecast					
	(1)	(2)	(3)	(4)	(5)	(6)
Recent Log Nominal Income Change	-0.674*** (0.139)	-0.195* (0.108)				
Family Finances Change Forecast			-0.320*** (0.027)	-0.122*** (0.019)		
Future Log Nominal Income Change					-0.358*** (0.103)	0.073 (0.082)
Inflation past 12m Backcast		0.493*** (0.011)		0.491*** (0.011)		0.493*** (0.011)
Demog. Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	35050	35050	35050	35050	35050	35050

Notes: This table presents regressions of forecasted inflation on recent log nominal income change (Columns 1 and 2), forecasted family finances change (Columns 3 and 4), and future log nominal income change (Columns 5 and 6). Columns (2), (4), and (6) also control for inflation backcasts. Inflation forecasts and backcasts are measured in percentage points and refer, respectively, to the inflation in the 12 months after and 12 months before the interview. Recent changes in households' log nominal income are calculated based on the log nominal income of the year $t-1$ minus the log nominal income in the year $t-2$, with t denoting the year of the survey response. Forecasted family finances changes are elicited on a 5-point Likert scale. Future changes in households' log nominal income are calculated based on the log nominal income of the year $t+1$ minus the log nominal income in the year $t-1$. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. The data covers years 2012-2019. Robust standard errors are clustered two ways: by calendar month and by unique respondent. Since only 467 respondents answer the survey more than once, this is essentially numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 7: Impact of Family ER Visit in Survey Month on Inflation Forecasts and Backcasts

	Inflation Forecasts and Backcasts						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
I(Fam. ER visit in survey month)	0.265***	0.204**	0.204**	0.204**	0.204**	0.343***	0.344***
	(0.083)	(0.084)	(0.083)	(0.083)	(0.083)	(0.109)	(0.108)
# of ER visits		0.045***	0.042**			0.045***	
		(0.006)	(0.019)			(0.006)	
# of ER visits sq.			0.001				
			(0.003)				
I(Forecast)						-0.901***	-0.901***
						(0.101)	(0.101)
I(Forecast) x I(Fam. ER visit)						-0.279**	-0.279**
						(0.108)	(0.108)
Demog. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of ER visits FE	No	No	No	Yes	Yes	No	Yes
Age × # of ER FE	No	No	No	No	Yes	No	No
Sample	2008-2018	2008-2018	2008-2018	2008-2018	2008-2018	2008-2018	2008-2018
Survey Responses	95637	95637	95637	95637	95637	95637	95637
Observations	177091	177091	177091	177091	177091	177091	177091

Notes: This table pools elicitations of inflation forecasts and backcasts and regresses them on the indicator I(Fam. ER visit in survey month). This indicator equals one if any member of the household visited the emergency room in the calendar month of the interview. An observation denotes an elicitation. Thus, we have up to two observations for each survey respondent. Inflation forecasts and backcasts are expressed in percentage points. The control variables "# of ER visits" and "# of ER Visits sq." denote the total number of family ER visits in the sample period, and its square, respectively. "# of ER visits FE" indicates that we include fixed effects for the total number of ER visits. "Age × # of ER FE" indicates that we also control for age interacted with these fixed effects. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. Respondents with more than 7 emergency room visits in the sample period are dropped. The specification "Month FE" includes a fixed effect dummy for each calendar month. These regressions use monthly data from 2008-2018. Robust standard errors are clustered two ways: by calendar month and by unique respondent. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 8: Affective Association: Importance of Cues in Recall

(a) Danish Sample

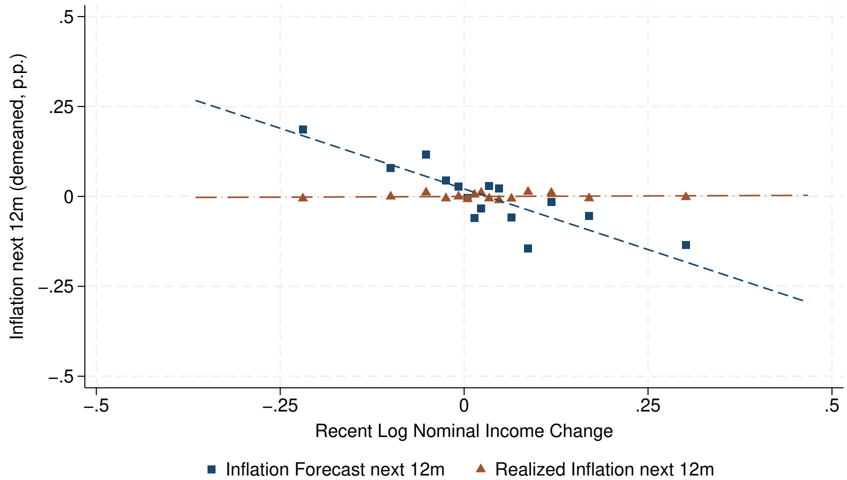
	Recall Experience		Recall Inflation	
	(1) Influence a lot	(2) Influence a little or a lot	(3) Influence a lot	(4) Influence a little or a lot
I(financial cue)	0.146***	0.454***	0.150***	0.495***
	(0.014)	(0.023)	(0.013)	(0.019)
I(non-financial cue)	0.127***	0.429***	0.094***	0.311***
	(0.012)	(0.025)	(0.010)	(0.025)
I(financial cue) x I(same valence as event)	0.138***	0.197***	0.050***	0.066***
	(0.019)	(0.018)	(0.008)	(0.011)
I(non-financial cue) x I(same valence as event)	0.175***	0.260***	0.049***	0.094***
	(0.024)	(0.028)	(0.008)	(0.010)
Observations	37440	37440	37440	37440
Respondents	3744	3744	3744	3744

(b) US Sample

	Recall Experience		Recall Inflation	
	(1) Influence a lot	(2) Influence a little or a lot	(3) Influence a lot	(4) Influence a little or a lot
I(financial cue)	0.129***	0.404***	0.196***	0.544***
	(0.013)	(0.020)	(0.022)	(0.027)
I(non-financial cue)	0.098***	0.360***	0.120***	0.380***
	(0.010)	(0.018)	(0.014)	(0.030)
I(financial cue) x I(same valence as event)	0.242***	0.365***	0.145***	0.190***
	(0.023)	(0.023)	(0.017)	(0.013)
I(non-financial cue) x I(same valence as event)	0.262***	0.446***	0.089***	0.192***
	(0.018)	(0.020)	(0.013)	(0.018)
Observations	15230	15230	15230	15230
Respondents	1523	1523	1523	1523

Notes: Columns 1 and 2 of each table present analysis based on survey responses to the question eliciting which cues affect recall of an experience. We pool across the baseline and financial framing of the elicitation. Section 5.3 reports the wording for both for both framings (baseline and financial). Columns 3 and 4 present a similar analysis based on responses to the question: "How much do each of the following influence your tendency to remember and focus on periods in your life when there was [very low/very high] inflation in the prices of things you need?" In the reported results, we regress indicators for respondents selecting "a lot" (Columns 1 and 3) and "a lot" or "a little" (Columns 2 and 4) on indicators for financial and non-financial cues, as well as interactions between these indicators and an indicator for the cues having the same valence as the event. Panel (a) presents results for the Danish survey sample. Panel (b) presents results for the US survey sample. Robust standard errors, clustered two ways (Cameron et al., 2011) at the respondent and cue level, are in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

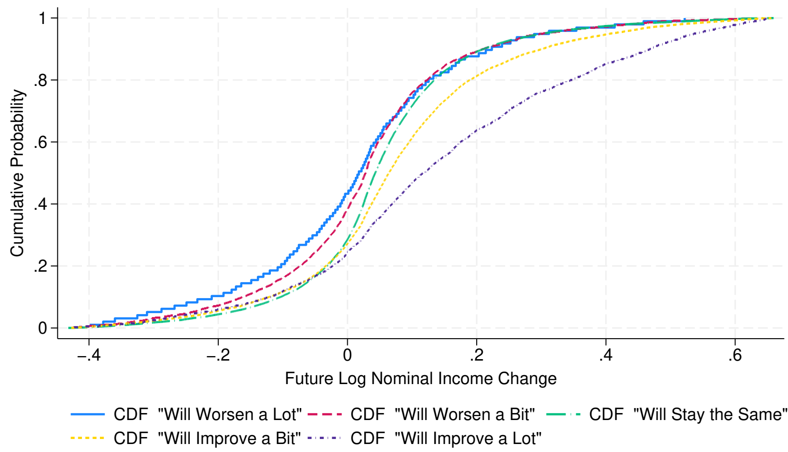
Figure 1: Realized and Forecasted Inflation and Recent Changes in Household Income



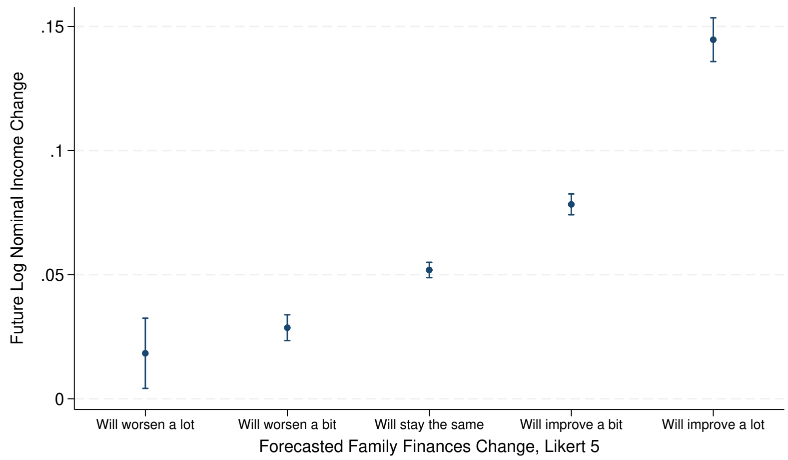
Notes: This figure presents the relationship between realized future and forecasted inflation over the 12 months following the survey response and recent log nominal income change. The relationship is plotted after partialling out demographic controls. The units of inflation and inflation forecasts are expressed in percentage points. Recent changes in households' log nominal income are calculated based on the log nominal income of the year $t-1$ minus the log nominal income in the year $t-2$, with t denoting the year of the survey response. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. This figure is based on data from 2012-2019.

Figure 2: Informativeness of Forecasted Family Finances Change

(a) Cumulative Density Functions (CDFs) of Future Log Nominal Income Changes, by Survey Response

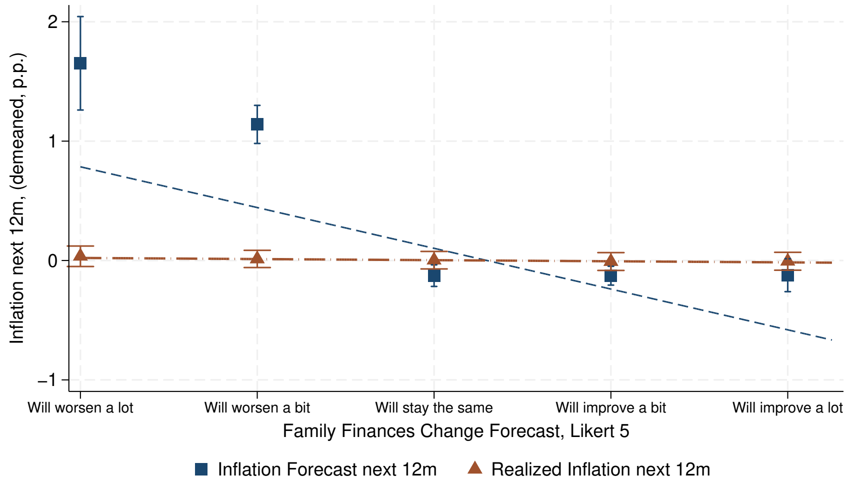


(b) Mean Future Log Nominal Income Change, by Survey Response



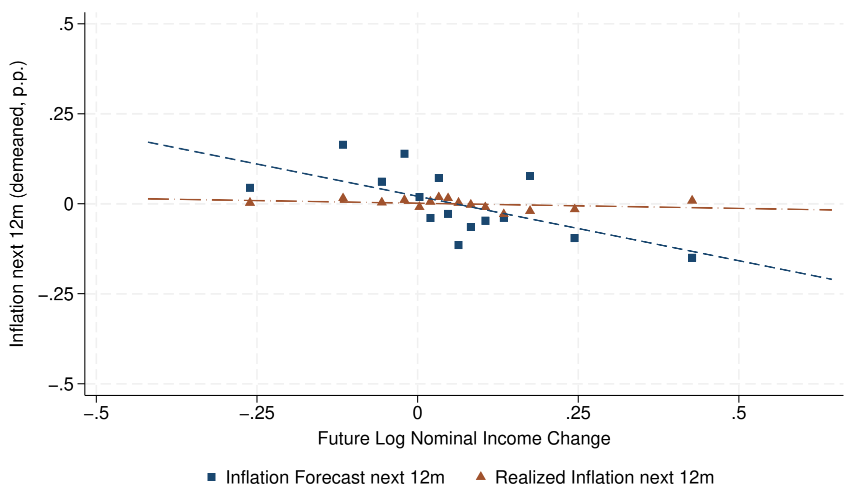
Notes: Panel (a) presents empirical CDFs of future log nominal income changes by responses to the survey question about forecasts of the future family financial situation. Panel (b) presents average future log nominal income change by responses to the same survey question. We do not add any demographic controls for this analysis. Future changes in households' log nominal income are calculated based on the log nominal income of the year $t + 1$ minus the log nominal income in the year $t - 1$, with t denoting the year of the survey response. Forecasted family finances changes are elicited on a 5-point Likert scale. The confidence intervals in panel (b) are based on robust standard errors clustered two ways: by calendar month and by unique respondent. Since only 467 respondents answer the survey more than once, this is essentially numerically equivalent to clustering by calendar month alone for the survey sample. Both figures are based on data from 2012-2019. For Panel (a), we plot the empirical distribution after aggregating the data in groups of ten respondents to preserve the anonymity of our respondents. The details of our procedure are described in Appendix A.1.4.

Figure 3: Inflation Forecasts and Forecasted Family Finances Changes



Notes: This figure presents the relationship between realized future and forecasted inflation over the 12 months following the survey response and forecasted family finances change. The units of inflation and inflation forecasts are expressed in percentage points. Forecasted family finances changes are elicited on a 5-point Likert scale. We do not add any demographic controls for this analysis. This figure is based on data from 2012-2019.

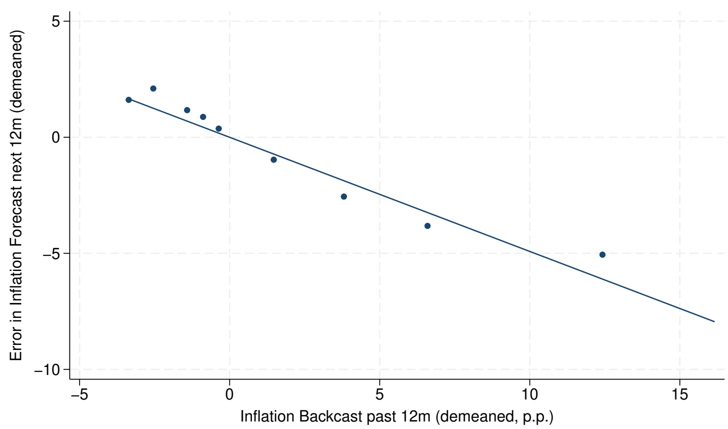
Figure 4: Realized and Forecasted Inflation and Realized Future Income Changes



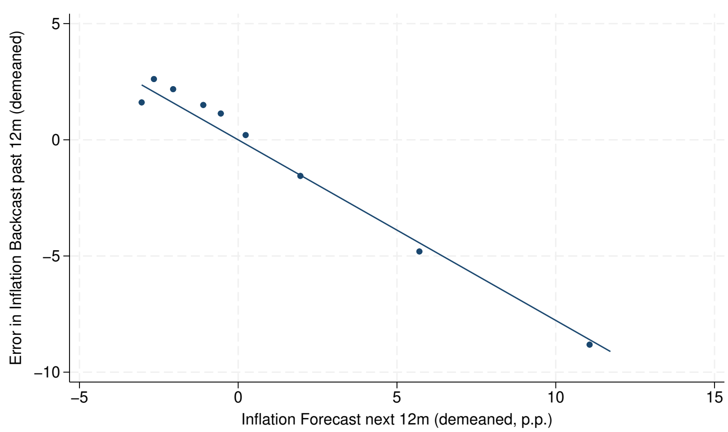
Notes: This figure presents the relationship between realized future and forecasted inflation over the 12 months following the survey response and future realized log nominal income change. The relationship is plotted after partialling out demographic controls. The units of inflation and inflation forecasts are expressed in percentage points. Future changes in households' log nominal income are calculated based on the log nominal income of the year $t+1$ minus the log nominal income in the year $t-1$, with t denoting the year of the survey response. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. This figure is based on data from 2012-2019.

Figure 5: Relationship between forecasts (errors) and backcasts (errors)

(a) Inflation Backcasts and Inflation Forecast Errors



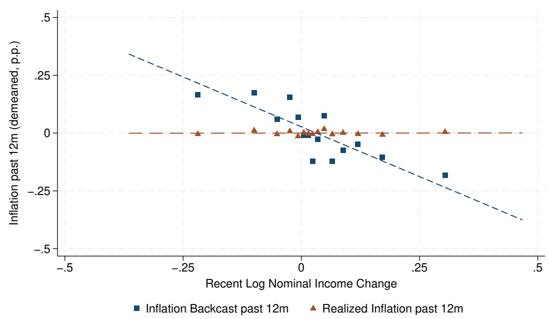
(b) Inflation Forecasts and Inflation Backcast Errors



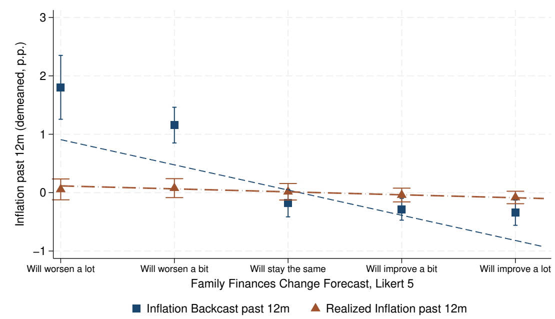
Notes: Panel (a) presents the relationship between the error in inflation forecasts over the 12 months following the survey response and inflation backcasts over the 12 months before the survey response. Forecast errors in inflation are calculated by subtracting the inflation forecasts over the same horizon from the realized inflation over the 12 months following the survey response. Panel (b) presents the relationship between errors in inflation backcasts and forecasted inflation. Backcast errors in inflation are calculated by subtracting the inflation backcasts over the same time horizon from the realized inflation over the 12 months preceding the survey response. The units of all figures are expressed in percentage points. All relationships are plotted after residualizing by demographic controls, which include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. Figures are based on data from 2012-2019. Table B.14 presents the coefficient estimates from analogous regressions.

Figure 6: Inflation Backcasts

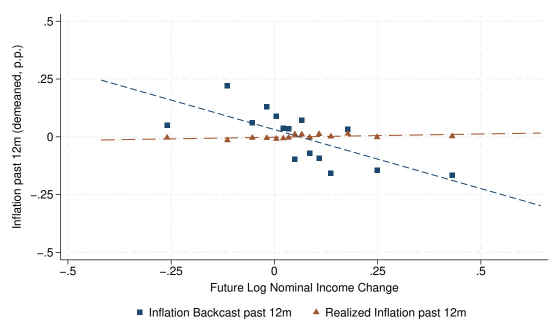
(a) Inflation Backcasts and Recent Changes in Household Income



(b) Inflation Backcasts and Forecasted Family Finances Changes

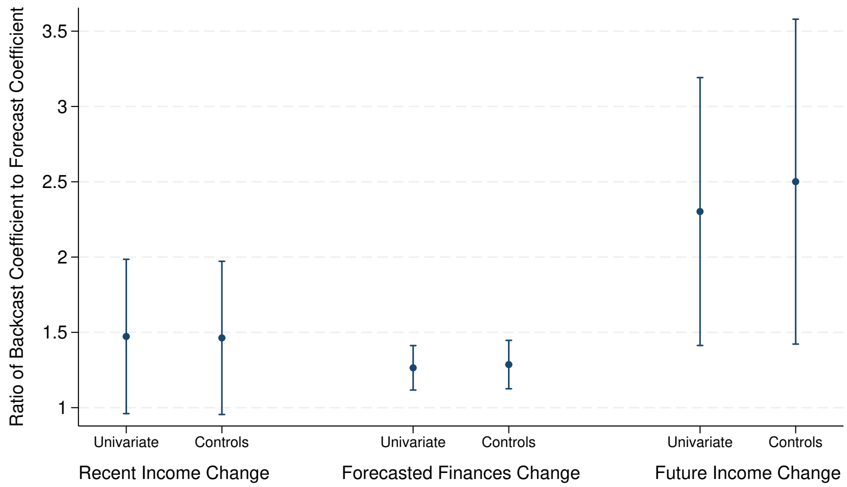


(c) Inflation Backcasts and Future Changes in Household Income



Notes: Panel (a) presents the relationship between backcast and realized inflation over the 12 months preceding the survey response and recent log nominal income change. This figure includes demographic controls: age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. The units of inflation and inflation backcasts are expressed in percentage points. Recent changes in households' log nominal income are calculated based on the log nominal income of the year $t-1$ minus the log nominal income in the year $t-2$, with t denoting the year of the survey response. Panel (b) presents the relationship between realized and backcast inflation over the 12 months preceding the survey response and forecasted family finances change. We do not add any demographic controls for this analysis to make the means for each of the five possible survey responses interpretable. Bars denote 95% confidence intervals, calculated using robust standard errors clustered two ways: by calendar month and by unique respondent. Since only 467 respondents answer the survey more than once, this is essentially numerically equivalent to clustering by calendar month alone for the survey sample. Panel (c) is analogous to panel (a), but studies future realized changes in log nominal income. Future changes in households' log nominal income are calculated based on the log nominal income of the year $t+1$ minus the log nominal income in the year $t-1$. All figures use data from years 2013-2019.

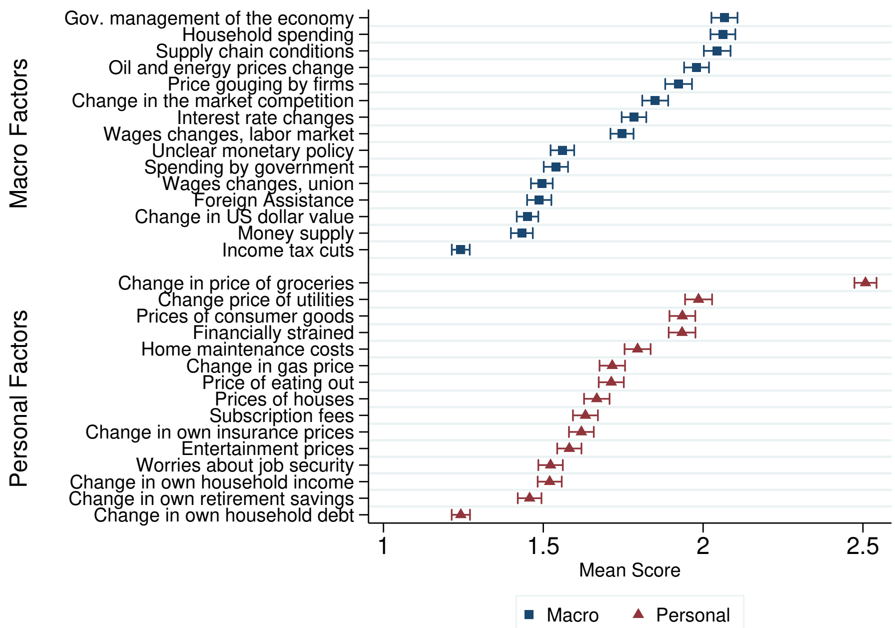
Figure 7: Ratio of Backcast to Forecast Coefficients for Three Measures of Income Change - Coefficient Plot



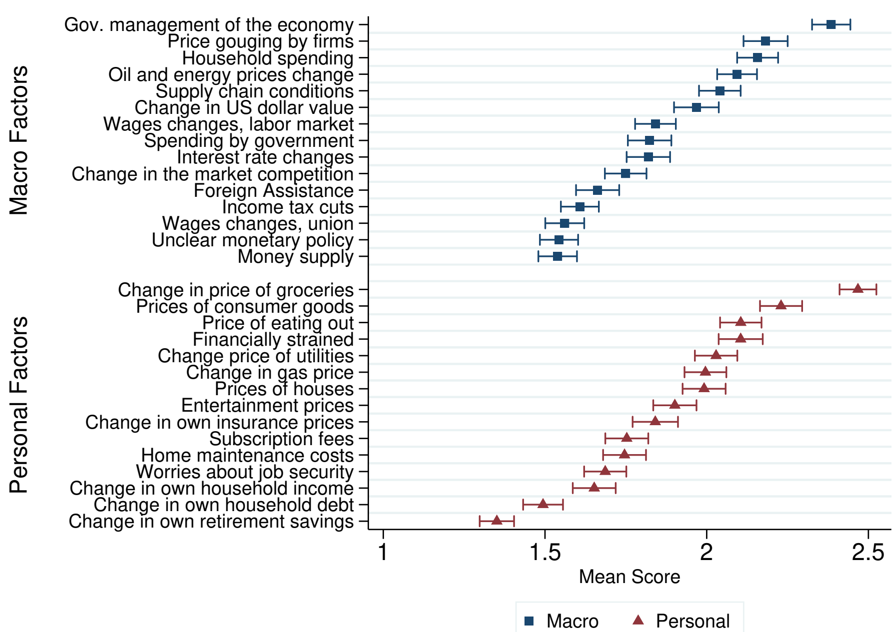
Notes: This figure presents ratios computed from coefficients from regressions of pooled inflation backcasts and forecasts on different independent variables interacted with an indicator for forecast and backcast observations. Dots represent the point estimates of the ratio of the coefficient on the independent variable interacted with the backcast indicator to the coefficient on the same variable interacted with the forecast indicator. “Recent Income Changes” uses recent log nominal income change as the main independent variable. Recent changes in households’ log nominal income are calculated based on the log nominal income of the year $t-1$ minus the log nominal income in the year $t-2$, with t denoting the year of the survey response. “Forecasted Finances Change ” uses the family finances change forecast elicitations on a Likert 5 scale as the primary independent variable. “Future Income Changes” leverages realized future changes in households’ log nominal income. Future changes in households’ log nominal income are calculated based on the log nominal income of the year $t+1$ minus the log nominal income in the year $t-1$. The "controls" coefficient plots use coefficients from regressions that partial out the following demographic controls: age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. Bars denote 95% robust confidence intervals, calculated using the delta method, with standard errors clustered two ways by calendar month and unique respondent. All dots use data for the years 2012-2019.

Figure 8: Importance of Different Factors in Shaping Inflation Forecasts

(a) Danish Sample



(b) US Sample



Notes: This figure summarizes survey responses on factors influencing inflation forecasts. Markers represent mean scores (1 = Not at all, 2 = A little, 3 = A lot) for each cue. Squares indicate macroeconomic factors, while triangles indicate personal factors. Bars denote 95% robust confidence intervals. Panel (a) presents results for the Danish survey sample. Panel (b) presents results for the US survey sample.

Online Appendix

Table of Contents

A Data Appendix

A.1 Registries Used and Documentation

Our data encompasses three main data sources. First, we obtain survey data from the Danish Consumer Expectations Survey. Second, we merge the survey data with individual-level information on respondents using Danish registry data. Third, to increase the robustness and external validity of our findings, we also run supplementary analyses using data from the Michigan Survey of Consumers. In the remainder of this appendix, we detail how we obtain and polish each raw data source.

A.1.1 Survey data

Main survey data As noted in the main text, the Danish Consumer Expectations Survey utilizes a repeated cross-sectional approach. The survey targets Danish residents aged 16 to 74. Monthly, Statistics Denmark draws a fresh sample of 1,500 individuals via simple random sampling from the Danish Civil Registration System (CPR Registret). This Consumer Expectations Survey is conducted as a component of Statistics Denmark's Omnibus Survey and adheres closely to the European Commission's Consumer Confidence Survey framework. Beyond the survey responses themselves, Statistics Denmark collects CPR codes for all individuals contacted. These codes allow Statistics Denmark to link survey and registry data, enabling us to examine potential selection issues among survey participants following invitation. Our dataset covers the period from 2008 through 2020. The main survey data are available to us in digital format for the years 2008 to 2020.

Our analysis compares individuals' inflation forecasts and backcasts with actual inflation over corresponding periods. We obtain monthly consumer price index (CPI) data from StatBank, Statistics Denmark's publicly accessible database of economic indicators, to construct our inflation measure. Following standard national accounting practices, the CPI reflects changes in the cost of a representative household's consumption basket relative to a base period. For Danish monthly CPI, this base period is January 2015. We calculate 12-month forward and backward inflation rates by computing the CPI growth rate over these respective timeframes. Monthly Danish CPI data are available spanning 1980 to 2023.

We complete our dataset by incorporating additional covariates from registry data as outlined in Section 1.

Michigan Survey of Consumers The Michigan Consumer Survey is conducted by the Survey Research Center at the University of Michigan. The survey is designed to represent all American households, excluding Alaska and Hawaii. Michigan enumerators conduct a minimum of 600 telephone interviews each month. Researchers invite all individuals who participated exactly six months prior to take a second survey in addition to contacting new waves of participants. Since 1978, researchers have achieved random sampling by randomly generating U.S. telephone numbers for each new wave of contacted individuals. For details on the sampling frame and the randomization process, we refer readers to the excellent official documentation. Each questionnaire contains about fifty core questions tracking various aspects of consumer attitudes and expectations. To compare elicited expectations with realized inflation, we obtain the true CPI inflation from FRED. Specifically, we use the Consumer Price Index for All Urban Consumers from FRED, available each month since 1980.

A.1.2 Emergency Room Visits Data

We obtain data on emergency room visits from the Danish National Patient Registry (NPR). The NPR contains information about all hospital patients at Danish hospitals, both public and private. The NPR is maintained by the Danish Health Data Authority for administrative purposes, such as monitoring public health and hospital activity. It is made available for researchers by Statistics Denmark. Each time an individual is examined or treated at a Danish hospital, the hospital must register and report information about the patient, the nature of the hospital visit, any injuries or illnesses, treatment, time stamps, etc. We use the second version of the NPR, which covers the years 1977-2018. Emergency room visits and ambulatory care (i.e. health care that does not involve hospitalization) have been recorded since 1994. The NPR defines a patient's hospital visit as an emergency room visit if the patient's health situation is acute (i.e. requires urgent care) and the patient is an "outpatient" (i.e. they are not hospitalized). The patient may be hospitalized after the emergency room visit, but once they are hospitalized they are considered an "inpatient" and the emergency room visit has ended. The labeling of emergency room visits in NPR changed slightly in 2014. In the years prior, emergency room visits were recorded as a separate type of patient, e.g. "patient type = ER". From 2014 on, this category no longer exists, and such visits are instead recorded as "acute outpatients". There are no acute outpatients that are not emergency room visits, so emergency room visits are still well-defined in the NPR from 2014. This change in labeling did not lead to a break in the number of emergency room visits in our data, and our point estimates are not sensitive to using only pre- or post-2014 data.

A.1.3 Final Datasets

Main data The construction of our main dataset is described in Section 1.

Long panel data In this paragraph, we detail the construction of the longer panel used in regressions presented in Column 2 of Table 1 and similar analyses. We start by obtaining the yearly lists of all Danish residents and their baseline demographics from the Danish CPR-Registret. Then, we merge the CPR data with yearly individualized tax records from the Danish Tax and Custom Authority (SKAT). Next, we aggregate income and wealth measures at the household level using a procedure identical to the one outlined in Section 1. Namely, household income in year t is the average income between spouses for married couples and the individual income otherwise. Finally, we simulate survey assignment by randomly assigning each observation to a month and merge in CPI inflation as described in Section A.1.1. To make this sample comparable to our main sample, we apply similar restrictions to those outlined in Section 1. Specifically, we (i) drop individuals younger than 25 or older than 60, (ii) drop individuals whose income is derived from self-employment and (iii) drop individuals whose demographic records are incomplete. We also trim income changes at 2.5 and 97.5 percentiles.

Final Emergency Room Dataset The dataset we use for our regressions with emergency room visits is constructed as follows. First, we create a monthly dataset of all emergency room visits in Denmark 2008-2018. We merge this with the Population Registry (BEF) to obtain the household identifier for each individual. Next, we join the emergency room data with the survey data to get a list of household emergency room visits for each survey respondent. We use this dataset to count the number of emergency room visits that each survey respondent experiences and to determine whether a survey respondent experienced an emergency room visit in the month they were surveyed. Finally, we merge in demographic variables. The final dataset contains survey responses from 2008-2018, along with information on emergency room visits and demographics.

Michigan data The Michigan Consumer Survey was started in 1946, however early survey waves have known issues.[42] Due to the data limitations and to avoid including years during the COVID-19 pandemic, we only use data from 1980 to 2019. Further, we impose the following restriction to make the sample comparable to our main Danish sample described in Section 1. Namely, we drop (i) respondents younger than 25 or older than 60, (ii) individuals who refuse to provide baseline demographics (age, sex, income, marriage status, family composition) and (iii) those who do not provide usable answers to all the most important questions for our analysis (inflation expectation, family financial situation elicitations, and general economic situation elicitations). Finally, since the main objective of our exercise is to introduce respondent fixed effects in our regressions, we drop individuals who attrited before completing the second round of surveys.

A.1.4 A Note on Empirical Cumulative Distribution of Continuous Variables

Our data agreement with Statistics Denmark allows us to only export statistics computed in samples of at least five individuals. This restriction is only binding when we plot empirical cumulative distribution functions (CDF) of continuous variables where each pixel represents information of a single individual. To comply with the data provider, we adopt the following procedure whenever we plot a CDF. First we order the data in increasing order with respect to the variable we are studying. Then, we collapse the data in ordered bins of ten observations and substitute individual values with bin averages. We then plot the empirical CDF of this collapsed data.

[42] See the appendix to Malmendier and Nagel (2016) for a detailed explanation on the issues with early waves.

A.1.5 Data Citations

- Statistics Denmark, Consumers Expectations Survey, 2008-2020. https://www.dst.dk/en/Statistik/emner/oekonomi/forbrug/forbrugerforventninger#:~:text=The%20survey%20of%20consumer%20expectations,in%20assessing%20the%20economic%20situation.
- Statistics Denmark, Befolkningen (BEF, Population Demographics), 1992-2022. https://www.dst.dk/extra/ForskningVariabellister/BEF%20-%20Befolkningen.html
- Statistics Denmark, Indkomst (IND, Income from returns), 1989-2022. https://www.dst.dk/extra/ForskningVariabellister/IND%20-%20Indkomst.html
- Statistics Denmark, Uddannelser (UDDA, Education), 2007-2019 http://www.dst.dk/extra/forskningvariabellister/Oversigt%20over%20registre.html
- Statistics Denmark, Detaljeret lonmodtagerdata fra e-Indkomst (BFL, Detailed employee data), 2012-2020. https://www.dst.dk/extra/ForskningVariabellister/BFL%20-%20Detaljeret%20l%C3%B8nmodtagerdata%20fra%20e-Indkomst.html
- Statistics Denmark, Landspatientregistret (LPR, Registry of Patients), 2008-2020. https://www.esundhed.dk/Dokumentation/DocumentationExtended?id=5
- Statistics Denmark, Consumer price Index (PRIS 113), 1947-2023. https://www.statbank.dk/20072
- University of Michigan, Michigan Consumer Survey, 1980-2023. https://data.sca.isr.umich.edu/
- FRED, Consumer Price Index for All Urban Consumers (CPIAUCSL), 1980-2023. https://fred.stlouisfed.org/series/CPIAUCSL

A.2 Non response and sample restrictions in the Danish Survey of Consumers Expectations

In this section, we describe how we process the Danish Survey of Consumer Expectations data to construct our main analysis sample. Table A1 shows the impact of each sample restriction on the number of observations. The column labeled “Dropped” indicates the number of observations that would be removed if the restriction were applied on its own, while the “Sample Size” column reports the remaining sample size after applying restrictions sequentially.

As noted in the main text, the high-quality survey data span the years 2012 to 2019, yielding an initial total of 92,397 responses. We then impose the following sample restrictions. First, we limit the age of respondents to between 25 and 60 years. This helps avoid large income changes driven by very young individuals entering the labor force or older individuals exiting it.

Next, we exclude observations with potentially problematic self-employment income. Specifically, we classify a household as problematic if more than one-fourth of its income comes from self-employment in any year from the four years prior to the interview up to the year following it. We exclude such income because it is not subject to third-party reporting and is therefore more prone to misreporting in tax data (see, e.g., Kleven et al. (2011)).

Non-response rates are generally low: fewer than two percent of respondents answer “Do not know” on our main Likert-scale questions. Overall, 9.2 percent of responses to the numeric inflation forecast elicitation and 8.1 percent of responses to the backcast elicitation are unusable due to non-response. Table A2 details non-response rates across all key survey questions.

We also drop respondents for whom we cannot obtain all main registry variables. Finally, we trim all income changes at the 2.5th and 97.5th percentiles to mitigate the influence of outliers.

Table A1: Sample Restrictions and Sample Size

	Dropped	Sample Size
Total	-	92397
Age Restriction	37226	55171
High Self-Employment Income	8730	49075
Missing Surv. Resp.	13054	43180
Missing Registry Var.	6847	40922
Trimming	-	35050

Notes: This table presents the effect of sample restrictions on total sample size for the main analysis sample using the Danish Survey of Consumers Expectations. The first column presents the number of observations we would drop by applying only the restriction in the current row. The second displays the effective sample size after applying all restrictions up to the current row. Sample restrictions are defined as follows: *Age Restriction* limits age of respondents to the interval between 25 and 60 years; *Self-Employment* drops respondents whose income comes in large part from self-employment; *Missing Survey Responses* omits respondents who did not answer or provided unusable responses for any of the main survey questions. *Missing Registry Variable* drops individuals with imperfect records of key variables in the registry data. Finally, *Trimming* shows the effective sample size after the application of trimming at 2.5 and 97.5 percentiles of recent and future log nominal income changes for the remaining observations. The data covers the years 2012-2019.

Table A2: Survey Data: Fraction of Missing Responses

	Fraction Missing Responses
Forecasted Inflation, Likert 5	0.017
Backcast Inflation, Likert 5	0.009
Forecasted Inflation next 12m, Numeric	0.092
Backcast Inflation past 12m, Numeric	0.081
Family Finances Change Forecast, Likert 5	0.008
Family Finances Change Backcast, Likert 5	0.003

Notes: This table presents the fraction of unusable responses for each of the main survey questions required to construct our main variables. We define an answer as unusable if either (i) the respondent answered "do not know" to the given question (ii) the respondent refused to answer (iii) the answer is coded as missing by the enumerator or (iv) the enumerator reports implausibly high (absolute value greater than 100) inflation backcasts or forecasts. The data covers the years 2012-2019.

A.3 Danish Survey of Consumers Expectations: Questionnaire

In this section we outline all survey questions asked in all months in the Danish Survey of Consumers Expectations. The survey starts by informing individuals that the purpose is to construct measures of consumer confidence and that individuals may refuse participation and further contact. If an individual chooses to participate, they are first asked a set of demographic questions regarding their current living and working situation. The survey then proceeds with the elicitation of perceptions of economic variables.

Economic Situation Past 12m

Text: *How do you think the general economic situation in the country changed over the past 12 months? It has...*

Labels:

100: Gotten a lot better
50: Gotten a little better
0: Stayed the same
-50: Gotten a little worse
-100: Gotten a lot worse
N: Don't know

Notes: Variable is recoded to be on a Likert 5 scale: (100 = 1) (50 = 2) (0 = 3) (-50 = 4) (-100 = 5).

Economic Situation Next 12m

Text: *How do you think the general economic situation in this country will develop over the next 12 months? It will...*

Labels:

100: Get a lot better
50: Get a little better
0: Stay the same
-50: Get a little worse
-100: Get a lot worse
N: Don't know

Notes: Variable is recoded to be on a Likert 5 scale: (100 = 1) (50 = 2) (0 = 3) (-50 = 4) (-100 = 5).

Present Purchases of Consumer Durables

Text: In view of the general economic situation, do you think that now is the right moment for people to make purchases such as furniture, electrical/electronic devices, etc?

Labels:

100: Yes, it is the right moment now
0: It is neither the right nor the wrong moment
-100: No it is not the right moment now
N: Don't know

Notes: Variable is recoded such that: (100 = 1) (0 = 2) (-100 = 3).

Family Financial Situation Past 12m

Text: *How has the financial situation of your household changed over the last 12 months? It has...*

Labels:

100: Gotten a lot better
50: Gotten a little better
0: Stayed the same
-50: Gotten a little worse
-100: Gotten a lot worse
N: Don't know

Notes: Variable is recoded to be on a Likert 5 scale: (100 = 5) (50 = 4) (0 = 3) (-50 = 2) (-100 = 1).

Family Financial Situation Next 12m

Text: *How do you expect the financial position of your household to change over the next 12 months? It will...*

Labels:

100: Get a lot better
50: Get a little better
0: Stay the same
-50: Get a little worse
-100: Get a lot worse
N: Don't know

Notes: Variable is recoded to be on a Likert 5 scale: (100 = 5) (50 = 4) (0 = 3) (-50 = 2) (-100 = 1).

Prices Next 12m

Text: *By comparison with the past 12 months, how do you expect that consumer prices will develop in the next 12 months? They will...*

Labels:

100: Increase more rapidly
50: Increase at the same rate
0: Increase at a slower rate
-50: Stay about the same
-100: Fall
N: Don't know

Notes: Variable is recoded such that (100 = 1) (50 = 2) (0 = 3) (-50 = 4) (-100 = 5).

Prices Percent Change Next 12m

Text: *By what percentage do you expect consumer prices to go up/down in the next 12 months?*

Prices Past 12m

Text: *How do you think consumer prices have developed over the last 12 months? They have...*

Labels:

100: Risen a lot
50: Risen moderately
0: Risen slightly
-50: Stayed about the same
-100: Fallen
N: Don't know

Notes: Variable is recoded such that (100 = 1) (50 = 2) (0 = 3) (-50 = 4) (-100 = 5).

prispro1: Prices Percent Change Past 12m

Text: *By what percentage do you think prices have gone up/down in the past 12 months?*

Present Family Financial Situation

Text: *Which of these statements best describes the current financial situation of your household?*

Labels:

100: We are saving a lot
50: We are saving a little
0: We are just able to make ends meet on our income
-50: We are having to draw on our savings
-100: We are running into debt
N: Don't know

Notes: Variable is recoded to be on a Likert 5 scale: (100 = 1) (50 = 2) (0 = 3) (-50 = 4) (-100 = 5).

Unemployment Forecast

Text: *How do you expect the number of people unemployed in the country to change over the next 12 months? The number will...*

Labels:

100: Increase sharply
50: Increase slightly
0: Remain the same
-50: Fall slightly
-100: Fall sharply
N: Don't know

Notes: Variable is recoded to be on a Likert 5 scale: (100 = 1) (50 = 2) (0 = 3) (-50 = 4) (-100 = 5).

Consumer Durables Next 12m

Text: *Compared to the past 12 months, do you expect to spend more or less money on major purchases (furniture, electrical/electronic devices, etc.) over the next 12 months? I will spend...*

Labels:

100: Much more
50: A little more
0: About the same
-50: A little less
-100: Much less
N: Don't know

Notes: Variable is recoded to be on a Likert 5 scale: (100 = 1) (50 = 2) (0 = 3) (-50 = 4) (-100 = 5).

Present Saving

Text: *In view of the general economic situation, do you think that now is...?*

Labels:

100: A very good moment to save
50: A fairly good moment to save
-50: Not a good moment to save
-100: A very bad moment to save
N: Don't know

Variable is recoded to be on a Likert 4 scale: (100 = 1) (50 = 2) (-50 = 3) (-100 = 4). **Saving Next 12m**

Text: *Over the next 12 months, how likely is it that you will save any money?*

Labels:

100: Very likely
50: Fairly likely
-50: Not likely
-100: Not at all likely
N: Don't know

Notes: Variable is recoded to be on a Likert 4 scale: (100 = 1) (50 = 2) (-50 = 3) (-100 = 4).

A.4 Additional Surveys: Questionnaire

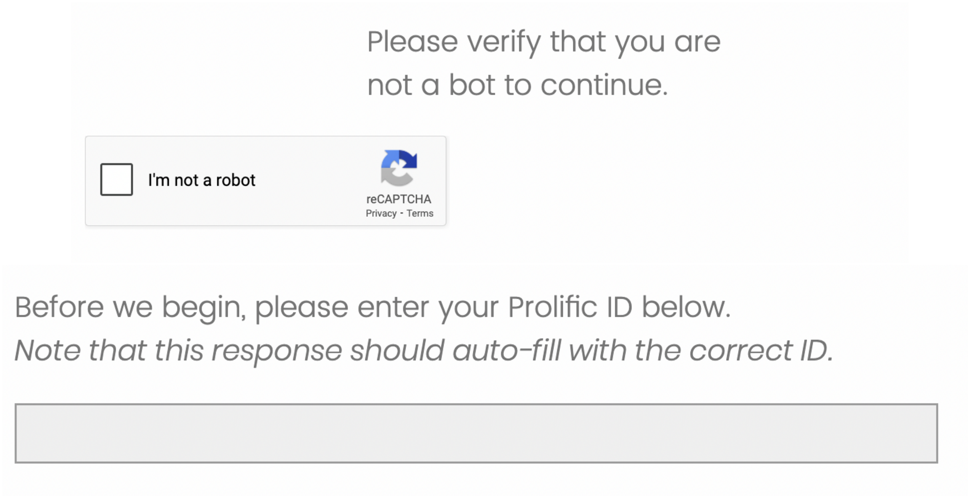
In this section, we outline the questions from the surveys conducted through Prolific for the U.S. sample and through the survey firm Epinion in Denmark. To ensure comparability of results, the survey questionnaires were virtually identical. For brevity, we mainly present screenshots from the U.S. survey and highlight any differences with the Danish questionnaire.

A.4.1 Introduction and Consent

The introduction and consent slightly differ across the two surveys. Individuals 18 years or older and living in the U.S. were recruited through Prolific to participate in a study that involved "Making

Forecasts About the Future". A web link to the study opened the Qualtrics survey. Respondents were first asked to complete CAPTCHA identification and fill in their unique Prolific ID.

Figure A1: CAPTCHA Identification and Prolific ID Entry



They were then presented with the following consent screen.

Figure A2: Consent Page

Thank you for your interest in this study! This is a consent form. Please read and click below to continue.

Study Background and Purpose: We are interested in what individuals remember and how they make forecasts about the future. Your participation in this research will take approximately 10 minutes.

Procedure: If you agree to be in this study, you will be asked to answer survey questions about your inflation expectations and personal experiences.

Confidentiality: Your data will be anonymous and will not be linked to your identity.

Voluntary Participation: Participating in this research is voluntary. You can withdraw from the study at any time.

Contact: If you have questions, concerns, or complaints regarding this research, please contact the researchers at sdewees@berkeley.edu.

Agreement to Participate: By clicking to continue, you are indicating that you have read this consent form and that you voluntarily agree to participate in the study.

In Denmark, respondents aged between 18 and 65 were contacted by the survey firm Epinion. Invitations were sent via DigitalPost, the official electronic mail system used by all Danish residents. Before beginning the survey, respondents were asked to choose their preferred language, Danish or English. The survey then began with the following welcome screen

Thank you for your interest in this study!

We are a team of researchers from Copenhagen Business School conducting a research project about how people recall past events to form expectations about the future.

Press 'Next' to start the survey.

A.4.2 Inflation Elicitations

Participants were then asked to predict how much they thought prices would change over the next 12 months.

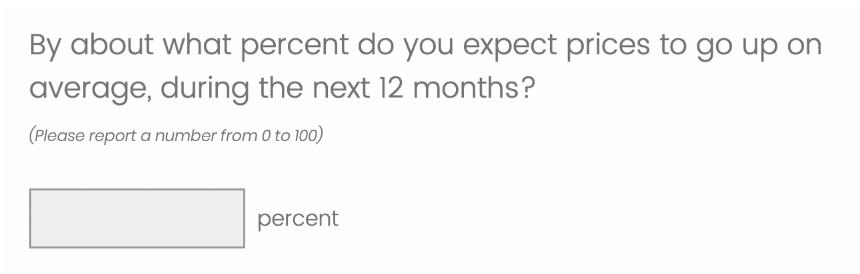
Figure A3: Inflation Forecast

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

- ◯ Prices will go up a lot in the next 12 months
- ◯ Prices will go up moderately in the next 12 months
- ◯ Prices will go up a bit in the next 12 months
- ◯ Prices will be unchanged
- ◯ Prices will go down in the next 12 months

If they selected “Prices will go up a lot in the next 12 months”, “Prices will go up moderately in the next 12 months”, or “Prices will go up a bit in the next 12 months”, they were asked to provide the percent they expected prices to increase.

Figure A4: Price Increase



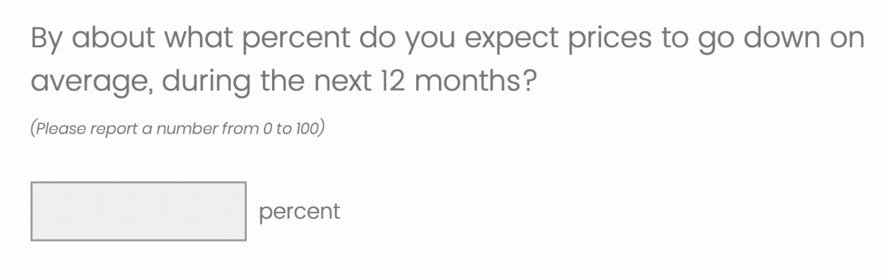
By about what percent do you expect prices to go up on average, during the next 12 months?

(Please report a number from 0 to 100)

percent

If they selected “Prices will go down in the next 12 months”, they were asked to provide the percent they expected prices to decrease.

Figure A5: Price Decrease


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

(Please report a number from 0 to 100)

percent

Next, participants were asked to indicate how much each of the provided factors influenced their inflation forecast. We asked participants “You previously wrote that you thought that prices will [increase by X%/decrease by X%/stay the same]. Did you consider any of the factors below in coming up with your answer?”.

The factors displayed to participants were randomized such that participants saw 5 “Macro” and 5 “Personal” factors from a list of 15 Macro and 15 Personal factors.

The complete list of factors is provided below. In some cases, the Danish version of the survey slightly adapts the factors to make them more relevant to the Danish context. In such cases, the Danish wording is reported in square brackets.

Macroeconomic Factors:

- Income tax cuts by the government
- Changes in government debt because of foreign assistance
- Debt-financed changes in spending by the government
- Interest rate changes by the Central Bank
- Changes in money supply by the Central Bank
- Unclear announcement of future central bank policy
- Oil and energy price changes in the United States [DK: Oil and energy price changes in Denmark]
- Supply chain conditions
- Firms wanting to increase profits, even when costs have not changed
- Change in the degree of competition in the market
- Workers’ wages changing due to union activity in the United States [DK: Workers’ wages changing due to union activity in Denmark]

- Workers' wages changing due to labor market conditions in the United States [DK: Workers' wages changing due to labor market conditions in Denmark]
- Politicians' management of the economy
- Household spending in the United States [DK: Household spending in Denmark]
- Change in the value of the U.S. dollar [DK: Change in the value of the Danish Krone]

Household factors:

- Recent changes in the prices of my usual groceries
- Recent changes in my utility bills, such as electricity, water, and garbage
- Recent changes in the price I pay for gasoline and/or diesel
- Recent changes in the prices of houses in the area around me
- Recent changes in the prices of eating out
- Recent changes in the prices of clothing, electronics, and other consumer goods that I regularly purchase
- Recent changes in my household income
- Recent worries about my own or my friends' job security
- Recent changes in the service fees of my subscriptions, such as magazines, newspapers, or streaming platforms
- Feeling financially strained
- Recent changes in the price of entertainment, such as movie theaters, amusement parks, or music concerts
- Recent changes in my retirement savings
- Recent changes in how much debt I have
- Recent changes in the price of my health, auto, or homeowner's insurance
- Recent changes in home maintenance costs

Figure A6 provides an example of what respondents might have seen when taking the survey.

Figure A6: Factors Influencing Inflation Forecast

You previously wrote that you thought that prices will decrease by 2% over the next 12 months.

Did you consider any of the factors below when coming up with your answer?

	Not at all	A little	A lot
Unclear announcement of future central bank policy	○	○	○
Politicians' management of the economy	○	○	○
Change in the value of the U.S. dollar	○	○	○
Oil and energy price changes in the United States	○	○	○
Changes in money supply by the Central Bank	○	○	○
Recent changes in my utility bills, such as electricity, water, and garbage	○	○	○
Recent changes in the service fees of my subscriptions, such as magazines, newspapers, or streaming platforms	○	○	○
Recent changes in home maintenance costs	○	○	○
Recent changes in my household income	○	○	○
Recent changes in the prices of clothing, electronics, and other consumer goods that I regularly purchase	○	○	○

Are there any other factors that you would like to mention?

A.4.3 Recall Elicitations

Participants were then asked about the kinds of situations/events that have influenced their recall of positive or negative experiences. They were shown one of the four following versions of this question:

- Sometimes people recall **negative experiences** from the past. This has probably happened to you before. Can you tell us what kinds of situations, events, or mindsets in the list below lead you to recall negative experiences from the past?
- Sometimes people recall **positive experiences** from the past. This has probably happened to you before. Can you tell us what kinds of situations, events, or mindsets in the list below lead you to recall positive experiences from the past?
- Sometimes people recall **negative events from the past that directly impacted their financial situation**. This has probably happened to you before. Can you tell us what kinds of situations, events, or mindsets in the list below lead you to recall such negative events from the past?
- Sometimes people recall **positive events from the past that directly impacted their financial situation**. This has probably happened to you before. Can you tell us what kinds of situations, events, or mindsets in the list below lead you to recall such positive events from the past?

The options for this question were randomized such that participants were shown 5 "Non-financial" and 5 "Financial" options from a list of 10 non-financial and 8 financial options. For each of these options, both positive and negative variants existed, with the framing independently randomized for every option presented. All available options are listed below.

Financial Cues:

- **Positive:** When I feel good about my family's financial situation \ **Negative:** When I feel pressured by my family's financial situation
- **Positive:** When I feel secure about my job stability \ **Negative:** When I am worried about my job stability
- **Positive:** When my household income has recently increased \ **Negative:** When my household income has recently decreased
- **Positive:** When I feel good about my household budget due to lower-than-normal expenses \ **Negative:** When I feel pressured by my household budget due to unexpectedly high expenses

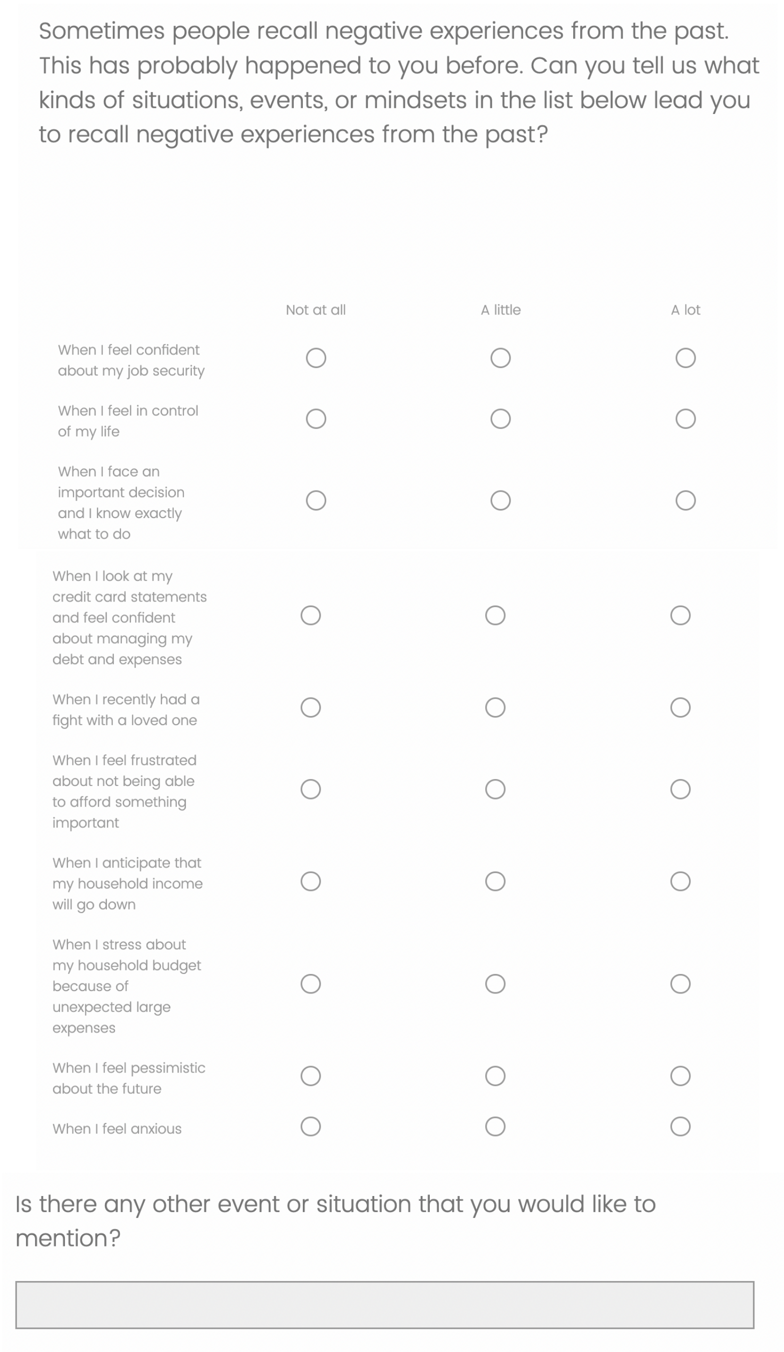
- **Positive:** When I look at my bank statements and feel confident that I can manage my debt and expenses \ **Negative:** When I look at my bank statements and worry whether I can manage my debt and expenses
- **Positive:** When I feel grateful for being able to afford something important \ **Negative:** When I feel frustrated about not being able to afford something important
- **Positive:** When I scroll through social media and see that I am doing better than my peers \ **Negative:** When I scroll through social media and see that I am doing worse than my peers
- **Positive:** When I expect my wealth to increase significantly \ **Negative:** When I expect my wealth to decrease significantly

Non-financial cues:

- **Positive:** When I am in a good mood \ **Negative:** When I am in a bad mood
- **Positive:** When I feel calm and relaxed \ **Negative:** When I feel uneasy
- **Positive:** When I feel good about myself \ **Negative:** When I feel bad about myself
- **Positive:** When I feel in control of my life \ **Negative:** When I feel like I have no control over my life
- **Positive:** When I feel optimistic about the future \ **Negative:** When I feel pessimistic about the future
- **Positive:** When I recently had a pleasant moment with someone close to me \ **Negative:** When I recently had an argument with someone close to me
- **Positive:** When everyone in my family has been healthy for a while \ **Negative:** When someone in my family has a serious illness
- **Positive:** When other people treat me with respect \ **Negative:** When other people treat me disrespectfully
- **Positive:** When I feel proud \ **Negative:** When I feel embarrassed
- **Positive:** When I face an important decision and know exactly what to do \ **Negative:** When I face an important decision and don't know what to do

Figure A7 provides an example of what a respondent might have seen while answering the recall elicitations.

Figure A7: Recall of Past Experiences



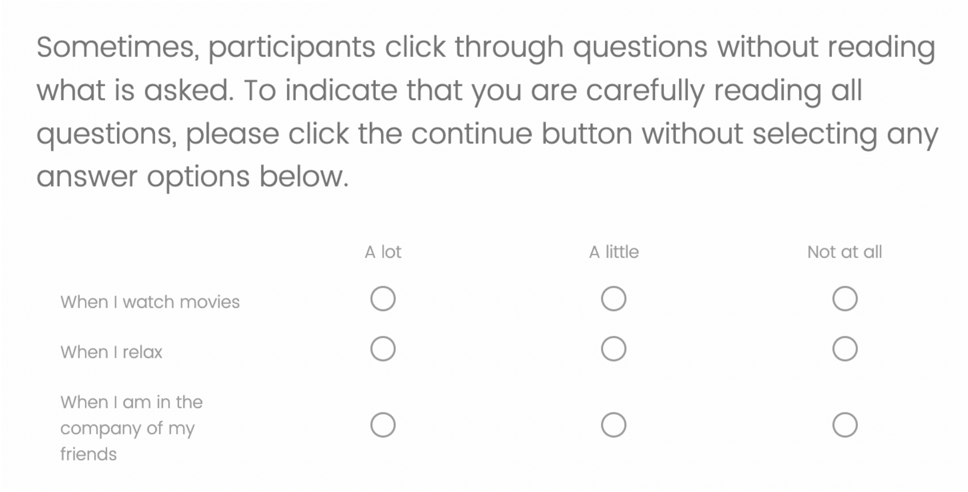
Sometimes people recall negative experiences from the past. This has probably happened to you before. Can you tell us what kinds of situations, events, or mindsets in the list below lead you to recall negative experiences from the past?

	Not at all	A little	A lot
When I feel confident about my job security	○	○	○
When I feel in control of my life	○	○	○
When I face an important decision and I know exactly what to do	○	○	○
When I look at my credit card statements and feel confident about managing my debt and expenses	○	○	○
When I recently had a fight with a loved one	○	○	○
When I feel frustrated about not being able to afford something important	○	○	○
When I anticipate that my household income will go down	○	○	○
When I stress about my household budget because of unexpected large expenses	○	○	○
When I feel pessimistic about the future	○	○	○
When I feel anxious	○	○	○

Is there any other event or situation that you would like to mention?

Next, to ensure that respondents were reading each question carefully, we included the following attention check.

Figure A8: Attention Check


Sometimes, participants click through questions without reading what is asked. To indicate that you are carefully reading all questions, please click the continue button without selecting any answer options below.

	A lot	A little	Not at all
When I watch movies	○	○	○
When I relax	○	○	○
When I am in the company of my friends	○	○	○

Participants were next asked to determine how much each of the provided factors influenced their tendency to focus on periods when there was either high or low inflation.

If the question in Figure A7 included the word "negative", then participants were shown the following version of the question:

- How much do each of the following influence your tendency to remember and focus on periods in your life when there was **very high inflation** in the prices of things you need?

If the question in Figure A7 included the word "positive", then participants were shown the following version of the question:

- How much do each of the following influence your tendency to remember and focus on periods in your life when there was **very low inflation** in the prices of things you need?

Note: The options displayed for this question are those that were not displayed in the question in Figure A7 plus two additional financial cues

- **Positive:** When I expect my household income to increase \ **Negative:** When I expect my household income to decrease

- **Positive:** When my wealth has recently increased \ **Negative:** When my wealth has recently decreased

Figure A9 displays an example of what participants might have seen when taking the survey.

Figure A9: Price Fluctuations

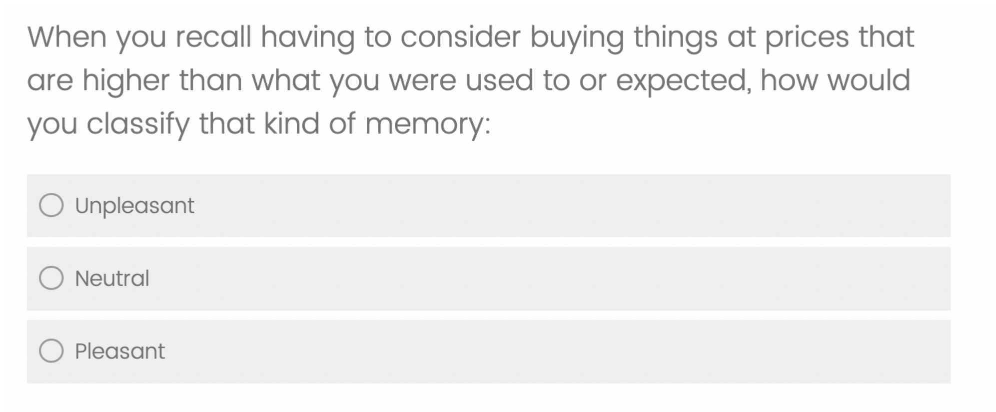

How much do each of the following influence your tendency to remember and focus on periods in your life when there was very high inflation in the prices of things you need?

	Not at all	A little	A lot
When someone in my family has a scary medical emergency	○	○	○
When my household income has gone down in the recent past	○	○	○
When I am in a bad mood	○	○	○
When I feel good about myself	○	○	○
When I feel embarrassed	○	○	○
When other people treat me with disrespect	○	○	○
When I anticipate that my wealth will significantly increase	○	○	○
When I scroll through social media and I see that I am doing worse than my peers	○	○	○
When I stress about my family's financial situation	○	○	○
When my wealth has increased in the recent past	○	○	○

Is there any other event or situation that you would like to mention?

Participants were next asked how they would classify a memory of buying things at higher prices.

Figure A10: Memory of Buying Things at Higher Prices

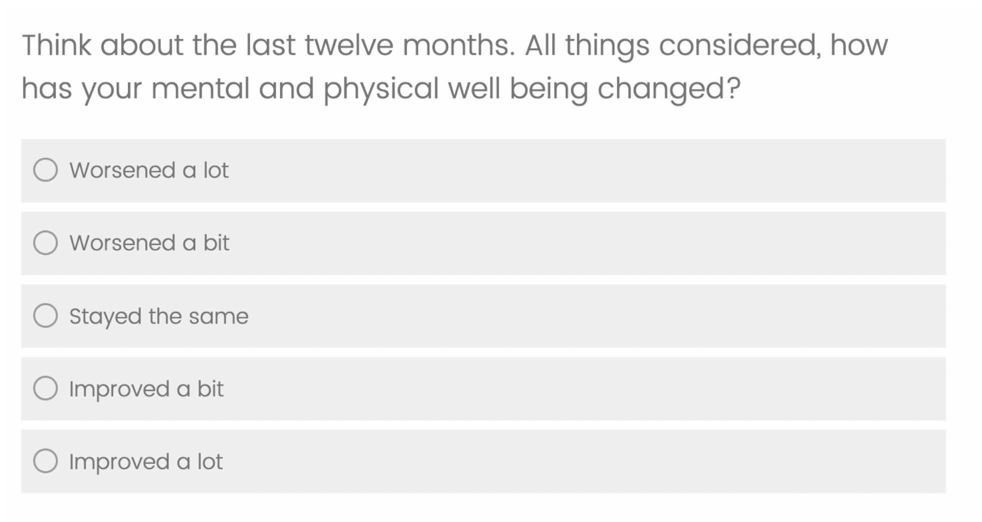

When you recall having to consider buying things at prices that are higher than what you were used to or expected, how would you classify that kind of memory:

- ◯ Unpleasant
- ◯ Neutral
- ◯ Pleasant

A.4.4 Wellbeing Elicitations

They then were asked how their mental and physical wellbeing changed over the past 12 months.

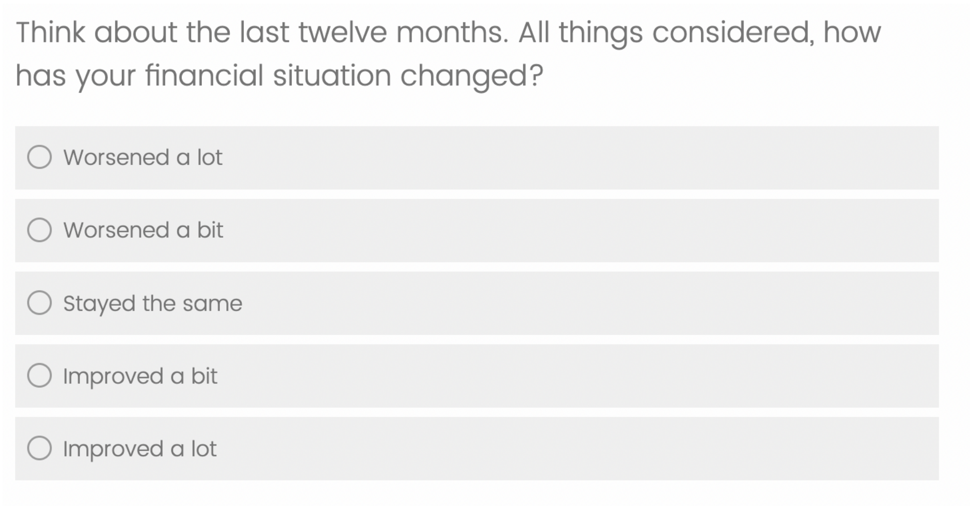
Figure A11: Mental and Physical Wellbeing Last 12 Months


Think about the last twelve months. All things considered, how has your mental and physical well being changed?

- ◯ Worsened a lot
- ◯ Worsened a bit
- ◯ Stayed the same
- ◯ Improved a bit
- ◯ Improved a lot

They then were asked how their financial situation changed over the past 12 months.

Figure A12: Financial Situation Last 12 Months


Think about the last twelve months. All things considered, how has your financial situation changed?

- Worsened a lot
- Worsened a bit
- Stayed the same
- Improved a bit
- Improved a lot

A.4.5 Demographic Questions

Finally, participants were asked to provide demographic information.

In the US sample we added the full battery of demographic questions reported below. In the Danish sample, we only elicited marital status and income.

Figure A13: Demographics Introduction


Last, we just have a few demographics questions to ask you before you complete the survey.

Figure A14: Age

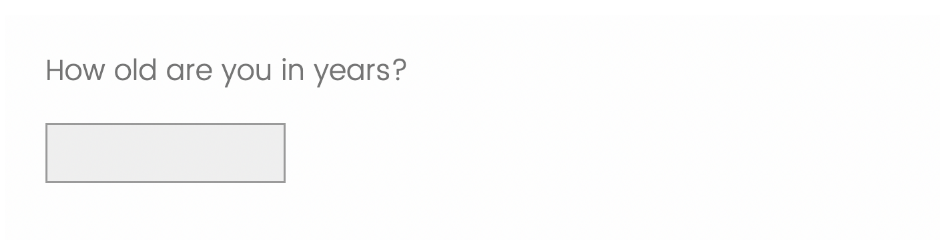

How old are you in years?

Figure A15: Gender

What is your gender?

- ○ Male
- ○ Female
- ○ Non binary
- ○ Other
- ○ Prefer not to respond

Figure A16: Highest Level of Education

Please select the highest level of education that you have completed.

- ○ High School Diploma
- ○ Secondary education (e.g. GED/GCSE)
- ○ Technical/community college
- ○ Bachelors degree or equivalent level
- ○ Masters degree or equivalent
- ○ Doctoral Degree or Higher
- ○ Other

Figure A17: Marital Status

What is your marital status?

- ○ Single
- ○ Living with a partner
- ○ Married
- ○ Divorced/Separated/Widowed
- ○ Other
- ○ Prefer not to say

Figure A18: Employment Status

Which of the following best describes your current employment status?

- ○ Working full-time
- ○ Working part-time
- ○ Not working

Figure A19: Income

What was your household income in 2023?

- ◯ Less than $10,000
- ◯ $10,000 to $14,999
- ◯ $15,000 to $24,999
- ◯ $25,000 to $34,999
- ◯ $35,000 to $49,999
- ◯ $50,000 to $74,999
- ◯ $75,000 to $99,999
- ◯ $100,000 to $149,999
- ◯ $150,000 to $199,999
- ◯ $200,000 or more

B Supplementary Empirical Results

B.1 Summary Statistics and Representativeness of Survey Respondents

Table B.1 summarizes the characteristics of our survey-respondent sample and compares them to those of all contacted individuals and the Danish population. The characteristics of our survey respondents broadly align with those of the Danish population, although there are slightly fewer single individuals, and the respondents tend to be slightly more educated and wealthier. Changes in log nominal income are roughly the same for our sample, the set of contacted individuals, and the population. Table B.2 provides summary statistics of our survey responses. Average inflation forecasts and backcasts are higher than the average realized inflation, consistent with findings in the literature (e.g., Weber et al., 2022). We instead focus on how people's inflation forecasts covary too strongly with recently realized income changes and measures of expected future income changes.

Table B.1: Sample Characteristics: Income and Demographics

	Population	Contacted	Respondents
Demographics			
Age	43.5	43.9	45.3
Female (%)	50.7	50.5	50.2
Single (%)	30.8	29.7	23.1
No. of Children in Household	1.03	0.99	1.03
Highest Education			
Primary or Lower Secondary (%)	19.4	18.8	12.7
Upper Secondary (%)	43.7	43.6	43.1
Bachelor or Higher (%)	36.9	37.7	44.2
Household Income			
Household Income (in 2015 level)	371,683	376,219	405,925
Recent Log Nominal Income Change	0.037	0.037	0.031
Observations	16,212,954	73,348	35,050
Unique Individuals	2,779,410	72,204	34,655

Notes: This table presents statistics related to demographics, education, and income for the Danish population and survey respondents. These statistics are calculated using data from 2012-2019 and only consider Danish residents between 25 and 60 years old. Household income levels are measured in 2015 Danish Kroner. *Population* indicates the pooled panel of all Danish residents who satisfy our age and data quality restrictions. *Contacted* indicates individuals who received an invitation to participate in the Consumer Expectations Survey and satisfy the same set of restrictions. Finally, the *Respondents* column presents statistics for our baseline sample, which includes all survey respondents who provided usable answers to key elicitations.

Table B.2: Summary Statistics: Survey Responses

	Mean	Std. Dev.
Likert Questions:		
Family Finances Change Backcast, Likert 5	3.15	0.83
Family Finances Change Forecast, Likert 5	3.28	0.75
G.E.S. Change Backcast, Likert 5	3.21	0.83
G.E.S. Change Forecast, Likert 5	3.20	0.82
Unemployment Change Forecast, Likert 5	2.90	0.81
Quantitative Questions:		
Inflation Backcast, past 12m (p.p.)	3.36	3.94
Inflation Forecast, next 12m (p.p.)	3.04	3.08
Realized Inflation:		
Realized Inflation, past 12m (p.p.)	0.89	0.67
Realized Inflation, next 12m (p.p.)	0.66	0.36
Observations	35050	

Notes: This table presents summary statistics for key survey variables. These statistics are calculated using data from 2012-2019 and the *Respondents* sample, which includes all survey respondents who provided usable answers to key elicitations, satisfy our age and self-employment restrictions, and have usable records in the registry data.

Table B.3: Emergency Room Sample: Income and Demographics

	2008-2018 Health Sample
Demographics	
Age	48.5
Female (%)	50.9
Single (%)	26.3
No. of Children in Household	0.76
Highest Education	
Primary or Lower Secondary (%)	23.6
Upper Secondary (%)	43.4
Bachelor or Higher (%)	33.0
Household Income	
Household Income (in 2015 level)	328,295
Observations	114099

Notes: This table presents statistics related to demographics, education, and income for the survey respondents in the emergency room exercise. These statistics are calculated using data from 2008-2018 and only consider Danish residents between 18 and 75 years old. Household income levels are measured in 2015 Danish Kroner.

B.2 Demographic Correlates of Inflation Forecasts

Table B.4: Correlations between Inflation Forecasts and Demographics

	Inflation Forecast next 12m			
	(1)	(2)	(3)	(4)
Log Nominal Income Level	-0.867***			-0.740***
	(0.046)			(0.046)
Female Indicator		0.201***		0.239***
		(0.032)		(0.033)
College Educated			-0.473***	-0.317***
			(0.038)	(0.039)
Year FE	Yes	Yes	Yes	Yes
Observations	35050	35050	35050	35050

Notes: This table presents regressions of forecasted inflation over the 12 months following the survey response on log nominal income in the year of the survey response, t, and indicators for female and college-educated survey respondents. The specification "Year FE" includes a fixed effect dummy for each year. These regressions are based on data from 2012-2019. Robust standard errors are clustered two ways: by calendar month and by unique respondent. Since only 467 respondents answer the survey more than once, this is essentially numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

B.3 Additional Results for Section 3.1

B.3.1 Inflation Forecasts and Placebo Income Changes

Table B.5: Inflation Forecasts and Different Timings of Placebo Changes in Household Income

(a) Realized Inflation

	Realized Inflation next 12m			
	(1)	(2)	(3)	(4)
Placebo Income Change	0.017 (0.019)	-0.039** (0.016)	-0.025* (0.014)	-0.032** (0.013)
Placebo Timing	t-6 vs t-7	t-6 vs t-8	t-6 vs t-9	t-6 vs t-10
Observations	33309	32688	32158	31584

(b) Forecasted Inflation

	Inflation Forecast next 12m			
	(1)	(2)	(3)	(4)
Placebo Income Change	0.007 (0.107)	0.143* (0.080)	-0.065 (0.069)	0.025 (0.064)
Demog. Controls	Yes	Yes	Yes	Yes
Placebo Timing	t-6 vs t-7	t-6 vs t-8	t-6 vs t-9	t-6 vs t-10
Observations	33309	32688	32158	31584

Notes: These tables present regressions of realized (panel a) and forecasted (panel b) inflation over the 12 months following the survey response on different definitions of placebo income change. Panel (b) includes demographic controls, while panel (a) does not include them. The units of inflation and inflation forecasts are expressed in percentage points. Placebo income change is defined as the difference in the log nominal income in the year $t-6$ minus the log nominal income in the year indicated in the "Placebo Timing" row, with t denoting the year of the survey response. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. These regressions are based on data from 2012-2019. Robust standard errors are clustered two ways: by calendar month and by unique respondent. Since only 467 respondents answer the survey more than once, this is essentially numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

B.3.2 Recent Labor Income Changes

Appendix Table B.6 investigates how inflation forecasts and realized inflation relate to labor income specifically, rather than total income. Analogous to our results for total income, changes in labor income do not predict realized inflation but are strongly negatively associated with forecasted inflation. However, the point estimates in Columns 3 and 4 are smaller than their counterparts in Table 1. We hypothesize that this is because beliefs are impacted by changes in total income, which are only partly accounted for by changes in labor income. That is, a ten percent change in labor income leads to a smaller percent change in total income, and thus impacts beliefs by less than a ten percent change in total income. To test our hypothesis, we run a two-stage least squares regression where we rescale the labor income changes by the inverse of the coefficient from a regression of total income changes on labor income changes. This regression answers the following question: when changes in labor income change total income by X%, by how much do inflation forecasts change?[43] The rescaled coefficient, presented in Column 5 of Table B.6, is similar to the one in Column 4 of Table 1. Furthermore, when in Column 6 we restrict to households most of whose income consists of labor income, we again obtain a coefficient of similar magnitude to Column 9 of Table 2.[44]

Table B.6: Inflation Forecasts and Recent Changes in Household Labor Income

	Realized Inflation next 12m		Inflation Forecast next 12m			
	(1)	(2)	(3)	(4)	(5)	(6)
Recent Log Nominal Labor Income Change	0.010	-0.011	-0.204**	-0.230**	-0.520**	-0.872***
	(0.014)	(0.031)	(0.094)	(0.096)	(0.217)	(0.255)
Demog. Controls	No	No	No	Yes	Yes	Yes
Sample	Respondents	Simple Income	Respondents	Respondents	Respondents	Simple Income
Observations	33479	17843	33479	33479	33479	17843
Rescaled by $\frac{\Delta\text{Log Total Income}}{\Delta\text{Log Labor Income}}$	No	No	No	No	Yes	No

Notes: This table presents regressions of realized and forecasted inflation over the 12 months following the survey response on recent log nominal labor income change. The units of inflation and inflation forecasts are expressed in percentage points. Recent changes in households' log nominal labor income are calculated based on the log nominal labor income of the year $t-1$ minus the log nominal labor income in the year $t-2$, with t denoting the year of the survey response. In the "Rescaled" column, we divide the log nominal labor income changes coefficient by the coefficient obtained from a regression of log nominal total income changes on log nominal labor income changes. To obtain correct standard errors, we implement the rescaling with a 2SLS estimator where log nominal total income changes are instrumented with log nominal labor income changes. The "Simple Income" sample restricts to individuals for whom at least ninety percent of income is labor income in the years $t-2$ to $t+1$. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. These regressions are based on data from 2012-2019. Robust standard errors are clustered two ways: by calendar month and by unique respondent. Since only 467 respondents answer the survey more than once, this is essentially numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

[43] To accurately compute standard errors, we use the standard 2SLS estimator, where labor income is treated as the "instrument" for total income.

[44] In fact, the coefficient is larger in magnitude (though not statistically-significantly so). The larger magnitude might result from the fact that income changes are particularly salient for individuals who have relatively simple finances.

Table B.7: First Stage: Total Log Nominal Income and Log Nominal Labor Income Changes

	Recent Log Nominal Income Change		Future Log Nominal Income Change	
	(1)	(2)	(3)	(4)
Recent Log Nominal Labor Income Change	0.449*** (0.005)	0.442*** (0.005)		
Future Log Nominal Labor Income Change			0.448*** (0.006)	0.436*** (0.005)
Demog. Controls	No	Yes	No	Yes
Observations	33479	33479	33479	33479

Notes: This table presents regressions of recent total log nominal income changes and realized future total log nominal income changes onto, respectively, recent log nominal labor income changes and realized future log nominal labor income changes. Recent changes in households' log nominal labor income are calculated based on the log nominal labor income of the year $t-1$ minus log nominal labor income in the year $t-2$, with t denoting the year of the survey response. Recent changes in total log nominal income is calculated analogously. Future changes in households' log nominal labor income are calculated based on the log nominal labor income of the year $t+1$ minus log nominal labor income in the year $t-1$. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal incomes from year $t-3$ to $t-5$. These regressions are based on data from 2012-2019. Robust standard errors are clustered two ways: by calendar month and by unique respondent. Since only 467 respondents answer the survey more than once, this is essentially numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

B.3.3 Recent Liquid Assets and Total Net Wealth Changes

Appendix Table B.8 investigates how inflation forecasts covary with changes in wealth, rather than income. Because net wealth can be negative, we use inverse hyperbolic sine transformations, rather than logarithmic transformations, to construct changes in liquid assets and total net wealth.

Table B.8: Inflation Forecasts and Recent Changes in Liquid Assets and Total Net Wealth

	Realized Inflation next 12m			Inflation Forecast next 12m		
	(1)	(2)	(3)	(4)	(5)	(6)
Recent Asinh Liquid Assets (000's DKK) Change	-0.007		-0.009*	-0.023		0.002
	(0.005)		(0.005)	(0.030)		(0.031)
Recent Asinh Total Net Wealth (000's DKK) Change		0.001	0.002		-0.026**	-0.025*
		(0.002)	(0.002)		(0.013)	(0.013)
Recent Log Nominal Income Change			0.014			-0.513***
			(0.023)			(0.166)
Demog. Controls	No	No	No	Yes	Yes	Yes
Observations	29769	29769	29769	29769	29769	29769

Notes: This table presents regressions of realized and forecasted inflation over the 12 months following the survey response on recent total income, liquid assets, and total net wealth changes. Recent changes in households' asinh liquid assets and total net wealth are calculated by taking the inverse hyperbolic sine of the given independent variable in the year $t-1$ minus the inverse hyperbolic sine of the given variable in the year $t-2$, with t denoting the year of the survey response. Recent changes in households' log nominal income are calculated analogously using logarithms instead of inverse hyperbolic sine. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. These regressions are based on data from 2012-2019. Robust standard errors are clustered two ways: by calendar month and by unique respondent. Since only 467 respondents answer the survey more than once, this is essentially numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

B.4 Additional Results for Section 3.2

B.4.1 Forecastability of Future Income Changes

Table B.9: Informativeness of Forecasted Family Finances Change

	Future Log Nominal Income Change				
	(1)	(2)	(3)	(4)	(5)
Will Worsen a Lot	-0.039***	-0.044***	-0.046***	-0.045***	
	(0.009)	(0.008)	(0.008)	(0.008)	
Will Worsen a Bit	-0.025***	-0.028***	-0.028***	-0.028***	
	(0.003)	(0.003)	(0.003)	(0.003)	
Will stay the same	-	-	-	-	
Will Improve a Bit	0.023***	0.011***	0.012***	0.011***	
	(0.002)	(0.002)	(0.002)	(0.002)	
Will Improve a Lot	0.091***	0.058***	0.058***	0.057***	
	(0.005)	(0.005)	(0.005)	(0.005)	
Recent Log Nominal Income Change			-0.199***	-0.201***	-0.197***
			(0.010)	(0.010)	(0.010)
Demog. Controls	No	Yes	Yes	Yes	Yes
Month FE	No	No	No	Yes	No
Observations	35050	35050	35050	35050	35050

Notes: This table presents regressions of future log nominal income change on forecasted family finances change. Forecasted family finances changes are elicited on a 5-point Likert scale. Future changes in households' log nominal income are calculated based on the log nominal income of the year $t+1$ minus log nominal income in the year $t-1$, with t denoting the year of the survey response. We regress the dependent variable onto dummies for each possible categorical survey response and the intercept. The answer "Will stay the same" is set as the reference category. Columns 3-5 additionally control for the recent log nominal income change, and Column 5 reports the specification with this control alone, omitting the categorical dummies. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. The specification "Month FE" includes a fixed effect dummy for each calendar month. These regressions are based on data from 2012-2019. Robust standard errors are clustered two ways: by calendar month and by unique respondent. Since only 467 respondents answer the survey more than once, this is essentially numerically equivalent to clustering by calendar month alone for the survey sample. $^*p < 0.10$ $^{**}p < 0.05$ $^{***}p < 0.01$.

B.4.2 Inflation Forecast, Forecasted Family Finances Changes and Future Income Changes: Sub-sample analysis

Table B.10: Inflation Forecasts and Forecasted Family Finances Change: Subsamples

(a) Realized inflation

	Realized Inflation next 12m											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Family Finances Change Forecast	-0.011** (0.005)	-0.009* (0.005)	-0.019* (0.011)	-0.010* (0.005)	-0.009 (0.006)	-0.010* (0.005)	-0.004 (0.005)	-0.014*** (0.005)	-0.011 (0.007)	-0.009 (0.006)	-0.010** (0.005)	-0.001 (0.007)
Demog. Controls	No	No	No	No	No	No	No	No	No	No	No	No
Sample Restriction	Income Change Restricted	No Unemp. or Leave	Some Unemp. or Leave	No Marriage or Retirement Transitions	> Median Avg Past Income	< Median Avg Past Income	College Educated	Non-College Educated	Simple Income	Net Saver	Net Borrower	Public Employee
Observations	30307	33434	1616	30971	18447	16603	15489	19561	17843	19849	15200	9791

(b) Forecasted inflation

	Inflation Forecast next 12m											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Family Finances Change Forecast	-0.340*** (0.028)	-0.324*** (0.027)	-0.274*** (0.084)	-0.341*** (0.027)	-0.281*** (0.036)	-0.348*** (0.034)	-0.268*** (0.030)	-0.351*** (0.036)	-0.308*** (0.041)	-0.351*** (0.033)	-0.312*** (0.036)	-0.350*** (0.055)
Demog. Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample Restriction	Income Change Restricted	No Unemp. or Leave	Some Unemp. or Leave	No Marriage or Retirement Transitions	> Median Avg Past Income	< Median Avg Past Income	College Educated	Non-College Educated	Simple Income	Net Saver	Net Borrower	Public Employee
Observations	30307	33434	1616	30971	18447	16603	15489	19561	17843	19849	15200	9791

Notes: These tables present regressions of realized (panel a) and forecasted (panel b) inflation over the 12 months following the survey response on forecasted family finances change for various subsamples. Forecasted family finances changes are elicited on a 5-point Likert scale. “Income change restricted” refers to future log nominal income change whose absolute value is smaller than 0.2. “No Unemp. or Leave”, “Some Unemp. or Leave”, and “No Marriage or Retirement Transitions” refer to the samples of respondents that do not experience unemployment, are unemployed for some or all of the time, and do not transition in or out of marriage or retirement for the period $t-1$ to $t+1$, respectively with t denoting the year of the survey response. “> Median Avg Past Income” is the sample for which the average past log income from $t-3$ to $t-5$ is above the median. “< Median Avg Past Income” is the sample for which the average past log income from $t-3$ to $t-5$ is below or equal to the median. ”College Educated” and ”Non-College Educated” restrict to respondents with and without a college degree, respectively. The “Simple Income” sample restricts to individuals for whom at least ninety percent of income is labor income in the years $t-2$ to $t+1$. “Net Saver” restricts to the subsamples with positive total net assets in year t. “Net Borrower” restricts to the subsamples with negative total net assets in year t. “Public Employee” denotes individuals who are employed in the public sector in the month of interview. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. These regressions are based on data from 2012-2019. Robust standard errors are clustered two ways: by calendar month and by unique respondent. Since only 467 respondents answer the survey more than once, this is essentially numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.11: Inflation Forecasts and Future Changes in Household Income: Subsamples

(a) Realized inflation

	Realized Inflation next 12m											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Future Log Nominal Income Change	-0.067** (0.030)	-0.032 (0.020)	0.021 (0.035)	-0.036* (0.021)	-0.041 (0.028)	-0.021 (0.024)	-0.037 (0.027)	-0.019 (0.020)	-0.072* (0.041)	-0.019 (0.023)	-0.035 (0.024)	-0.024 (0.040)
Demog. Controls	No	No	No	No	No	No	No	No	No	No	No	No
Sample Restriction	Income Change Restricted	No Unemp. or Leave	Some Unemp. or Leave	No Marriage or Retirement Transitions	> Median Avg Past Income	< Median Avg Past Income	College Educated	Non-College Educated	Simple Income	Net Saver	Net Borrower	Public Employee
Observations	30307	33434	1616	30971	18447	16603	15489	19561	17843	19849	15200	9791

(b) Forecasted inflation

	Inflation Forecast next 12m											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Future Log Nominal Income Change	-0.290** (0.138)	-0.322*** (0.106)	-0.552 (0.345)	-0.341*** (0.113)	0.004 (0.146)	-0.602*** (0.151)	-0.297** (0.145)	-0.335** (0.143)	-0.283 (0.185)	-0.183 (0.152)	-0.568*** (0.149)	-0.425** (0.207)
Demog. Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample Restriction	Income Change Restricted	No Unemp. or Leave	Some Unemp. or Leave	No Marriage or Retirement Transitions	> Median Avg Past Income	< Median Avg Past Income	College Educated	Non-College Educated	Simple Income	Net Saver	Net Borrower	Public Employee
Observations	30307	33434	1616	30971	18447	16603	15489	19561	17843	19849	15200	9791

Notes: These tables present regressions of realized (panel a) and forecasted (panel b) inflation over the 12 months following the survey response on future log nominal income change for various subsamples. Future changes in households' log nominal income are calculated based on the log nominal income of the year $t+1$ minus log nominal income in the year $t-1$, with t denoting the year of the survey response. "Income change restricted" refers to future log nominal income change whose absolute value is smaller than 0.2. "No Unemp. or Leave", "Some Unemp. or Leave", and "No Marriage or Retirement Transitions" refer to the samples of respondents that do not experience unemployment, are unemployed for some or all of the time, and do not transition in or out of marriage or retirement for the period $t-1$ to $t+1$, respectively. "> Median Avg Past Income" is the sample for which the average past log income from $t-3$ to $t-5$ is above the median. "< Median Avg Past Income" is the sample for which the average past log income from $t-3$ to $t-5$ is below or equal to the median. "College Educated" and "Non-College Educated" restrict to respondents with and without a college degree, respectively. The "Simple Income" sample restricts to individuals for whom at least ninety percent of income is labor income in the years $t-2$ to $t+1$. "Net Saver" restricts to the subsamples with positive total net assets in year t. "Net Borrower" restricts to the subsamples with negative total net assets in year t. "Public Employee" denotes individuals who are employed in the public sector in the month of interview. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. These regressions are based on data from 2012-2019. Robust standard errors are clustered two ways: by calendar month and by unique respondent. Since only 467 respondents answer the survey more than once, this is essentially numerically equivalent to clustering by calendar month alone for the survey sample. * $p<0.10$ ** $p<0.05$ *** $p<0.01$.

B.4.3 Inflation Forecast and Future Labor Income Changes

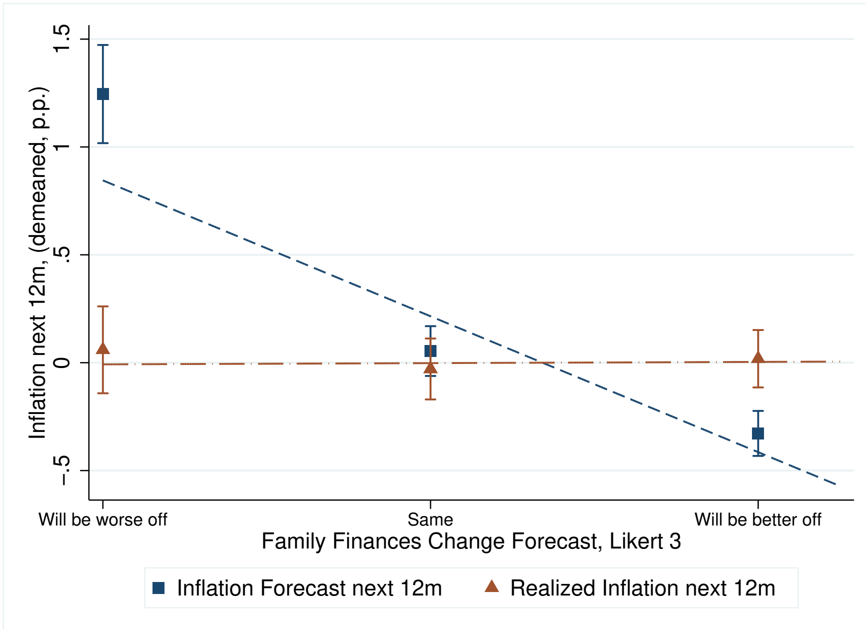
Table B.12: Inflation Forecasts and Realized Future Changes in Household Labor Income

	Realized Inflation next 12m		Inflation Forecast next 12m			
	(1)	(2)	(3)	(4)	(5)	(6)
Future Log Nominal Labor Income Change	-0.011	-0.064	-0.262***	-0.206***	-0.471***	-0.223
	(0.009)	(0.040)	(0.073)	(0.073)	(0.169)	(0.184)
Demog. Controls	No	No	No	Yes	Yes	Yes
Sample	Respondents	Simple Income	Respondents	Respondents	Respondents	Simple Income
Observations	33479	17843	33479	33479	33479	17843
Rescaled by $\frac{\Delta\text{Log Total Income}}{\Delta\text{Log Labor Income}}$	No	No	No	No	Yes	No

Notes: This table presents regressions of realized and forecasted inflation over the 12 months following the survey response on future log nominal labor income change. The units of inflation and inflation forecasts are expressed in percentage points. Future changes in households' log nominal labor income are calculated based on the log nominal labor income of the year $t+1$ minus log nominal labor income in the year $t-1$, with t denoting the year of the survey response. In the "Rescaled" column, we divide the log nominal labor income changes coefficient by the coefficient obtained from a regression of log nominal total income changes on labor income changes. To obtain correct standard errors, we implement the rescaling with a 2SLS estimator where log nominal total income changes are instrumented with log nominal labor income changes. The "Simple Income" sample restricts to individuals for whom at least ninety percent of income is labor income in the years $t-2$ to $t+1$. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. These regressions are based on data from 2012-2019. Robust standard errors are clustered two ways: by calendar month and by unique respondent. Since only 467 respondents answer the survey more than once, this is essentially numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

B.4.4 Results from Michigan Survey of Consumers: Inflation Forecasts and Expected Future Changes in Household Income

Figure B.1: Inflation Forecasts and Forecasted Family Finances Change: Michigan



Notes: This figure presents the relationship between realized and forecasted inflation over the 12 months following the survey response and forecasted family finances change. The units of inflation and inflation forecasts are expressed in percentage points. Forecasted family finances changes are elicited on a 3-point Likert scale. We do not add any demographic controls for this analysis. This figure is based on data from 1980-2019. Dots denote mean conditional on survey response. Bars denote 95% confidence intervals constructed with robust standard errors clustered two ways: by calendar month and by unique respondent.

Table B.13: Inflation Forecasts and Forecasted Family Finances Change: Michigan

	Realized Inflation next 12m	Inflation Forecast next 12m				
	(1)	(2)	(3)	(4)	(5)	(6)
Family Finances Change Forecast	0.006 (0.023)	-0.630*** (0.033)	-0.601*** (0.032)	-0.491*** (0.025)	-0.257*** (0.031)	-0.188*** (0.029)
Demog. Controls	No	No	Yes	Yes	No	No
Month FE	No	No	No	Yes	No	Yes
Resp. FE	No	No	No	No	Yes	Yes
Observations	104134	104134	104134	104134	104134	104134

Notes: This table presents regressions of realized and forecasted inflation over the 12 months following the survey response on forecasted family finances change, excluding those who respond to the survey once. The units of inflation and inflation forecasts are expressed in percentage points. Forecasted family finances changes are elicited on a 3-point Likert scale. Demographic controls include age, highest education, gender, number of children, marital status, and log income. "Resp. FE" denotes fixed effects for each respondent. These regressions are based on data from 1980-2019. Robust standard errors are clustered two ways: by calendar month and by unique respondent. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

B.5 Additional Results for Section 4.1

This appendix section presents additional results supporting the analyses presented in section 4.1. Appendix B.5.1 presents the results from Figure 5 in table form. In Appendix B.5.2, we examine how recent income changes, expected family finances, and future income changes relate to inflation backcasts separately for each of the subsamples studied in Table 2. Appendix B.5.3 studies how recent and future log labor income changes correlate with inflation backcasts. Finally, Appendix B.5.4 presents an analysis in the same spirit as Figure 7, but displayed in table format.

B.5.1 Relationship between forecasts (errors) and backcasts (errors)

Table B.14: Relationship between forecasts (errors) and backcasts (errors)

(a) Inflation Backcasts and Inflation Forecast Errors

	Error in Inflation Forecast next 12m		
	(1)	(2)	(3)
Inflation Backcast past 12m	-0.494***	-0.492***	-0.505***
	(0.012)	(0.012)	(0.010)
Demog. Controls	No	Yes	Yes
Month FE	No	No	Yes
Observations	35050	35050	35050

(b) Inflation Forecasts and Inflation Backcast Errors

	Error in Inflation Backcast past 12m		
	(1)	(2)	(3)
Inflation Forecast next 12m	-0.790***	-0.777***	-0.770***
	(0.010)	(0.010)	(0.011)
Demog. Controls	No	Yes	Yes
Month FE	No	No	Yes
Observations	35050	35050	35050

Notes: Panel (a) presents the relationship between the error in inflation forecasts over the 12 months following the survey response and inflation backcasts over the 12 months before the survey response. Forecast errors in inflation are calculated by subtracting the inflation forecasts over the same horizon from the realized inflation over the 12 months following the survey response. Panel (b) presents the relationship between errors in inflation backcasts and forecasted inflation. Backcast errors in inflation are calculated by subtracting the inflation backcasts over the same time horizon from the realized inflation over the 12 months preceding the survey response. The units of all variables are expressed in percentage points. These regressions are based on data from 2012-2019. Robust standard errors are clustered two ways: by calendar month and by unique respondent. Since only 467 respondents answer the survey more than once, this is essentially numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

B.5.2 Inflation Backcasts: Subsample Analysis for Recent Income changes, Forecasted Family Finances Changes, and Future Income Changes

Table B.15: Inflation Backcasts and Recent Changes in Household Income: Subsamples

(a) Realized Inflation

	Realized Inflation past 12m											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Recent Log Nominal Income Change	-0.010 (0.026)	-0.007 (0.022)	-0.020 (0.049)	0.000 (0.024)	-0.021 (0.025)	0.008 (0.030)	-0.017 (0.027)	-0.009 (0.026)	0.005 (0.031)	-0.019 (0.027)	-0.001 (0.030)	-0.029 (0.045)
Demog. Controls	No	No	No	No	No	No	No	No	No	No	No	No
Sample Restriction	Income Change Restricted	No Unemp. or Leave	Some Unemp. or Leave	No Marriage or Retirement Transitions	> Median Avg Past Income	< Median Avg Past Income	College Educated	Non-College Educated	Simple Income	Net Saver	Net Borrower	Public Employee
Observations	28457	28231	2521	27940	16530	14222	13698	17054	15649	17360	13391	8587

(b) Inflation Backcast

	Inflation Backcast past 12m											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Recent Log Nominal Income Change	-0.846*** (0.236)	-0.853*** (0.201)	-0.725 (0.504)	-0.980*** (0.218)	-0.502* (0.273)	-1.104*** (0.254)	-0.548** (0.252)	-1.028*** (0.276)	-0.739** (0.314)	-1.007*** (0.256)	-0.697** (0.271)	-1.105** (0.436)
Demog. Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample Restriction	Income Change Restricted	No Unemp. or Leave	Some Unemp. or Leave	No Marriage or Retirement Transitions	> Median Avg Past Income	< Median Avg Past Income	College Educated	Non-College Educated	Simple Income	Net Saver	Net Borrower	Public Employee
Observations	28457	28231	2521	27940	16530	14222	13698	17054	15649	17360	13391	8587

Notes: These tables present regressions of realized (panel a) and backcasted (panel b) inflation over the 12 months preceding the survey response on recent log nominal income change for various subsamples. Recent changes in households' log nominal income are calculated based on the log nominal income of the year $t-1$ minus log nominal income in the year $t-2$, with t denoting the year of the survey response. "Income change restricted" refers to recent log nominal income change whose absolute value is smaller than 0.2. "No Unemp. or Leave", "Some Unemp. or Leave", and "No Marriage or Retirement Transitions" refer to the samples of respondents that do not experience unemployment, are unemployed for some or all of the time, and do not transition in or out of marriage or retirement for the period $t-1$ to $t-2$, respectively. "> Median Avg Past Income" is the sample for which the average past log income from $t-3$ to $t-5$ is above the median. "< Median Avg Past Income" is the sample for which the average past log income from $t-3$ to $t-5$ is below or equal to the median. "College Educated" and "Non-College Educated" restrict to respondents with and without a college degree, respectively. The "Simple Income" sample restricts to individuals for whom at least ninety percent of income is labor income in the years $t-2$ to $t+1$. "Net Saver" restricts to the subsamples with positive total net assets in year t. "Net Borrower" restricts to the subsamples with negative total net assets in year t. "Public Employee" denotes individuals who are employed in the public sector in the month of interview. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. These regressions are based on data from 2013-2019. Robust standard errors are clustered two ways: by calendar month and by unique respondent. Since only 467 respondents answer the survey more than once, this is essentially numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.16: Inflation Backcasts and Forecasted Family Finances Change: Subsamples

(a) Realized Inflation

	Realized Inflation past 12m											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Family Finances Change Forecast	0.003 (0.005)	0.003 (0.004)	0.004 (0.011)	0.004 (0.004)	0.003 (0.005)	0.003 (0.004)	0.005 (0.005)	-0.000 (0.004)	0.005 (0.006)	0.004 (0.005)	0.002 (0.004)	0.004 (0.006)
Demog. Controls	No	No	No	No	No	No	No	No	No	No	No	No
Sample Restriction	Income Change Restricted	No Unemp. or Leave	Some Unemp. or Leave	No Marriage or Retirement Transitions	> Median Avg Past Income	< Median Avg Past Income	College Educated	Non-College Educated	Simple Income	Net Saver	Net Borrower	Public Employee
Observations	26485	29350	1402	27224	16530	14222	13698	17054	15649	17360	13391	8587

(b) Inflation Backcast

	Inflation Backcast past 12m											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Family Finances Change Forecast	-0.297*** (0.039)	-0.315*** (0.034)	-0.325*** (0.110)	-0.342*** (0.037)	-0.309*** (0.045)	-0.310*** (0.044)	-0.282*** (0.041)	-0.326*** (0.046)	-0.281*** (0.048)	-0.384*** (0.045)	-0.277*** (0.049)	-0.348*** (0.069)
Demog. Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample Restriction	Income Change Restricted	No Unemp. or Leave	Some Unemp. or Leave	No Marriage or Retirement Transitions	> Median Avg Past Income	< Median Avg Past Income	College Educated	Non-College Educated	Simple Income	Net Saver	Net Borrower	Public Employee
Observations	26485	29350	1402	27224	16530	14222	13698	17054	15649	17360	13391	8587

Notes: These tables present regressions of realized (panel a) and backcast (panel b) inflation over the 12 months preceding the survey response on forecasted family finances change for various subsamples. Forecasted family finances changes are elicited on a 5-point Likert scale. "Income change restricted" refers to future log nominal income change whose absolute value is smaller than 0.2. "No Unemp. or Leave", "Some Unemp. or Leave", and "No Marriage or Retirement Transitions" refer to the samples of respondents that do not experience unemployment, are unemployed for some or all of the time, and do not transition in or out of marriage or retirement for the period $t-1$ to $t+1$, respectively, with t denoting the year of the survey response. "> Median Avg Past Income" is the sample for which the average past log income from $t-3$ to $t-5$ is above the median. "< Median Avg Past Income" is the sample for which the average past log income from $t-3$ to $t-5$ is below or equal to the median. "College Educated" and "Non-College Educated" restrict to respondents with and without a college degree, respectively. The "Simple Income" sample restricts to individuals for whom at least ninety percent of income is labor income in the years $t-2$ to $t+1$. "Net Saver" restricts to the subsamples with positive total net assets in year t. "Net Borrower" restricts to the subsamples with negative total net assets in year t. "Public Employee" denotes individuals who are employed in the public sector in the month of interview. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. These regressions are based on data from 2013-2019. Robust standard errors are clustered two ways: by calendar month and by unique respondent. Since only 467 respondents answer the survey more than once, this is essentially numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.17: Inflation Backcasts and Future Changes in Household Income: Subsamples

(a) Realized Inflation

	Realized Inflation past 12m											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Future Log Nominal Income Change	0.038 (0.029)	0.011 (0.021)	0.039 (0.040)	0.013 (0.024)	0.009 (0.029)	0.028 (0.022)	0.018 (0.027)	0.008 (0.021)	0.051 (0.041)	-0.013 (0.024)	0.047* (0.024)	0.024 (0.040)
Demog. Controls	No	No	No	No	No	No	No	No	No	No	No	No
Sample Restriction	Income Change Restricted	No Unemp. or Leave	Some Unemp. or Leave	No Marriage or Retirement Transitions	> Median Avg Past Income	< Median Avg Past Income	College Educated	Non-College Educated	Simple Income	Net Saver	Net Borrower	Public Employee
Observations	26485	29350	1402	27224	16530	14222	13698	17054	15649	17360	13391	8587

(b) Inflation Backcast

	Inflation Backcast past 12m											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Future Log Nominal Income Change	-0.468** (0.191)	-0.490*** (0.138)	-0.561 (0.450)	-0.487*** (0.156)	-0.019 (0.189)	-0.854*** (0.201)	-0.181 (0.193)	-0.680*** (0.175)	-0.331 (0.215)	-0.325* (0.180)	-0.728*** (0.196)	-0.071 (0.285)
Demog. Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample Restriction	Income Change Restricted	No Unemp. or Leave	Some Unemp. or Leave	No Marriage or Retirement Transitions	> Median Avg Past Income	< Median Avg Past Income	College Educated	Non-College Educated	Simple Income	Net Saver	Net Borrower	Public Employee
Observations	26485	29350	1402	27224	16530	14222	13698	17054	15649	17360	13391	8587

Notes: These tables present regressions of realized (panel a) and backcast (panel b) inflation over the 12 months preceding the survey response on future log nominal income change for various subsamples. Future changes in households' log nominal income are calculated based on the log nominal income of the year $t+1$ minus log nominal income in the year $t-1$, with t denoting the year of the survey response. "Income change restricted" refers to future log nominal income change whose absolute value is smaller than 0.2. "No Unemp. or Leave", "Some Unemp. or Leave", and "No Marriage or Retirement Transitions" refer to the samples of respondents that do not experience unemployment, are unemployed for some or all of the time, and do not transition in or out of marriage or retirement for the period $t-1$ to $t+1$, respectively. "> Median Avg Past Income" is the sample for which the average past log income from $t-3$ to $t-5$ is above the median. "< Median Avg Past Income" is the sample for which the average past log income from $t-3$ to $t-5$ is below or equal to the median. "College Educated" and "Non-College Educated" restrict to respondents with and without a college degree, respectively. The "Simple Income" sample restricts to individuals for whom at least ninety percent of income is labor income in the years $t-2$ to $t+1$. "Net Saver" restricts to the subsamples with positive total net assets in year t. "Net Borrower" restricts to the subsamples with negative total net assets in year t. "Public Employee" denotes individuals who are employed in the public sector in the month of interview. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. These regressions are based on data from 2013-2019. Robust standard errors are clustered two ways: by calendar month and by unique respondent. Since only 467 respondents answer the survey more than once, this is essentially numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

B.5.3 Inflation Backcasts: Labor Income Analysis for Recent Income Changes and Future Income Changes

Table B.18: Inflation Backcasts and Recent Changes in Household Labor Income

	Realized Inflation past 12m		Inflation Backcast past 12m			
	(1)	(2)	(3)	(4)	(5)	(6)
Recent Log Nominal Labor Income Change	-0.008	0.004	-0.322**	-0.342***	-0.770***	-0.770**
	(0.014)	(0.030)	(0.132)	(0.132)	(0.297)	(0.308)
Demog. Controls	No	No	No	Yes	Yes	Yes
Sample	Respondents	Simple Income	Respondents	Respondents	Respondents	Simple Income
Observations	29392	15649	29392	29392	29392	15649
Rescaled by $\frac{\Delta\text{Log Total Income}}{\Delta\text{Log Labor Income}}$	No	No	No	No	Yes	No

Notes: This table presents regressions of realized and backcasted inflation over the past twelve months on the recent changes in labor income. The units of inflation and inflation backcasts are expressed in percentage points. Recent changes in households' log nominal labor income are calculated based on the log nominal labor income of the year $t-1$ minus the log nominal labor income in the year $t-2$, with t denoting the year of the survey response. "Respondents" denotes the set of survey respondents satisfying the restriction outlined in Section 1. In the "Rescaled" column, we divide the log nominal labor income changes coefficient by the coefficient obtained from a regression of log nominal total income changes on log nominal labor income changes. To obtain correct standard errors, we implement the rescaling with a 2SLS estimator where log nominal total income changes are instrumented with log nominal labor income changes. "Simple Income" is the sample of respondents for which 90 percent of their income comes from labor in years $t-2$ to $t+1$. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. These regressions are based on data from 2013-2019. Robust standard errors are clustered two ways: by calendar month and by unique respondent. Since only 467 respondents answer the survey more than once, this is essentially numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.19: Inflation Backcasts and Future Changes in Household Labor Income

	Realized Inflation past 12m		Inflation Backcast past 12m			
	(1)	(2)	(3)	(4)	(5)	(6)
Future Log Nominal Labor Income Change	0.003	0.045	-0.283***	-0.226**	-0.512**	-0.284
	(0.008)	(0.041)	(0.089)	(0.090)	(0.205)	(0.208)
Demog. Controls	No	No	No	Yes	Yes	Yes
Sample	Respondents	Simple Income	Respondents	Respondents	Respondents	Simple Income
Observations	29392	15649	29392	29392	29392	15649
Rescaled by $\frac{\Delta\text{Log Total Income}}{\Delta\text{Log Labor Income}}$	No	No	No	No	Yes	No

Notes: This table presents regressions of realized and backcasted inflation over the past twelve months on the future changes in labor income. The units of inflation and inflation backcasts are expressed in percentage points. Future changes in households' log nominal labor income are calculated based on the log nominal labor income of the year $t+1$ minus the log nominal labor income in the year $t-1$, with t denoting the year of the survey response. "Respondents" denotes the set of survey respondents satisfying the restriction outlined in Section 1. In the "Rescaled" column, we divide the log nominal labor income changes coefficient by the coefficient obtained from a regression of log nominal total income changes on log nominal labor income changes. To obtain correct standard errors, we implement the rescaling with a 2SLS estimator where log nominal total income changes are instrumented with log nominal labor income changes. "Simple Income" is the sample of respondents for which 90 percent of their income comes from labor in years $t-2$ to $t+1$. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. These regressions are based on data from 2013-2019. Robust standard errors are clustered two ways: by calendar month and by unique respondent. Since only 467 respondents answer the survey more than once, this is essentially numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

B.5.4 Forecasts and Backcasts Coefficient Comparison: Table

Table B.20: Inflation Beliefs Correlate with Income Changes and Forecasted Family Finances Changes – Forecasts and Backcasts Coefficient Comparison

	Inflation Forecast/Backcast					
	(1)	(2)	(3)	(4)	(5)	(6)
Recent Log Nominal Income Change	-0.964***	-0.978***				
	(0.192)	(0.186)				
I(Forecast) × Recent Log Nominal Income Change	0.310**	0.310**				
	(0.150)	(0.150)				
Family Finances Change Forecast			-0.432***	-0.406***		
			(0.038)	(0.038)		
I(Forecast) × Family Finances Change Forecast			0.090***	0.090***		
			(0.025)	(0.025)		
Future Log Nominal Income Change					-0.934***	-0.880***
					(0.151)	(0.152)
I(Forecast) × Future Log Nominal Income Change					0.528***	0.528***
					(0.114)	(0.114)
I(Forecast)	-0.333***	-0.333***	-0.619***	-0.619***	-0.354***	-0.354***
	(0.076)	(0.076)	(0.133)	(0.133)	(0.077)	(0.077)
Demog. Controls	No	Yes	No	Yes	No	Yes
Survey Responses	35050	35050	35050	35050	35050	35050
Observations	70100	70100	70100	70100	70100	70100

Notes: This table pools elicitations of inflation forecasts and backcasts and regresses them on the indicator I(Forecast) interacted with various measures of income change. I(Forecast) is one if the observation refers to a forecast elicitation and zero if it refers to backcasts. As income change measures we use recent log nominal income change, forecasted family finances change and future log nominal income change. Inflation forecasts and backcasts are measured in percentage points and refer, respectively, to the inflation in the 12 months after and 12 months before the interview. Recent changes in households' log nominal income are calculated based on the log nominal income of the year $t-1$ minus log nominal income in the year $t-2$, with t denoting the year of the survey response. Forecasted family finances change is elicited on a 5-point Likert scale. Future changes in households' log nominal income are calculated based on the log nominal income of the year $t+1$ minus log nominal income in the year $t-1$. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. Danish data covers years 2012-2019. Robust standard errors are clustered two ways: by calendar month and by unique respondent. * $p<0.10$ ** $p<0.05$ *** $p<0.01$.

B.6 Additional Robustness: Extending Sample to 2008-2019

Table B.21: Inflation and Recent Changes in Household Income, Sample Starting in 2008

	Inflation Forecast next 12m			Inflation Backcast past 12m		
	(1)	(2)	(3)	(4)	(5)	(6)
Recent Log Nominal Income Change	-0.523***	-0.499***	-0.538***	-0.797***	-0.756***	-0.668***
	(0.133)	(0.130)	(0.119)	(0.166)	(0.165)	(0.149)
Demog. Controls	No	Yes	Yes	No	Yes	Yes
Month FE	No	No	Yes	No	No	Yes
Sample	Respondents 2008 - 2019	Respondents 2008 - 2019	Respondents 2008 - 2019	Respondents 2009 - 2019	Respondents 2009 - 2019	Respondents 2009 - 2019
Observations	53367	53367	53367	48783	48783	48783

Notes: This table presents regressions of inflation forecasts and backcasts over the 12 months following or preceding the survey response on recent log nominal income changes. The units of inflation and inflation forecasts and backcasts are expressed in percentage points. Recent changes in log nominal income are calculated based on the log nominal income of the year $t-1$ minus log nominal income in the year $t-2$. "Respondents" denotes the set of survey respondents satisfying the restriction outlined in Section 1. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. The specification "Month FE" includes a fixed effect dummy for each calendar month. These regressions are based on data from 2008-2019, except that the inflation backcast columns begin in 2009. Robust standard errors are clustered two ways: by calendar month and by unique respondent. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.22: Inflation and Forecasted Family Finances Changes, Sample Starting in 2008

	Inflation Forecast next 12m			Inflation Backcast past 12m		
	(1)	(2)	(3)	(4)	(5)	(6)
Family Finances Change Forecast	-0.390***	-0.359***	-0.315***	-0.422***	-0.384***	-0.273***
	(0.023)	(0.023)	(0.021)	(0.032)	(0.033)	(0.027)
Demog. Controls	No	Yes	Yes	No	Yes	Yes
Month FE	No	No	Yes	No	No	Yes
Sample	Respondents 2008 - 2019	Respondents 2008 - 2019	Respondents 2008 - 2019	Respondents 2009 - 2019	Respondents 2009 - 2019	Respondents 2009 - 2019
Observations	53367	53367	53367	48783	48783	48783

Notes: This table presents regressions of inflation forecasts and backcasts over the 12 months following or preceding the survey response on forecasted family finances change. The units of inflation and inflation forecasts and backcasts are expressed in percentage points. Forecasted family finances changes are elicited on a 5-point Likert scale. "Respondents" denotes the set of survey respondents satisfying the restriction outlined in Section 1. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. The specification "Month FE" includes a fixed effect dummy for each calendar month. These regressions are based on data from 2008-2019, except that the inflation backcast columns begin in 2009. Robust standard errors are clustered two ways: by calendar month and by unique respondent. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.23: Inflation and Realized Future Income Changes, Sample Starting in 2008

	Inflation Forecast next 12m			Inflation Backcast past 12m		
	(1)	(2)	(3)	(4)	(5)	(6)
Future Log Nominal Income Change	-0.345***	-0.214**	-0.183**	-0.805***	-0.653***	-0.367***
	(0.095)	(0.096)	(0.091)	(0.140)	(0.142)	(0.127)
Demog. Controls	No	Yes	Yes	No	Yes	Yes
Month FE	No	No	Yes	No	No	Yes
Sample	Respondents 2008 - 2019	Respondents 2008 - 2019	Respondents 2008 - 2019	Respondents 2009 - 2019	Respondents 2009 - 2019	Respondents 2009 - 2019
Observations	53367	53367	53367	48783	48783	48783

Notes: This table presents regressions of inflation forecasts and backcasts over the 12 months following or preceding the survey response on future realized log nominal income changes. The units of inflation and inflation forecasts and backcasts are expressed in percentage points. Future changes in log nominal income are calculated based on the log nominal income of the year $t + 1$ minus log nominal income in the year $t - 1$. "Respondents" denotes the set of survey respondents satisfying the restriction outlined in Section 1. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t - 3$ to $t - 5$. The specification "Month FE" includes a fixed effect dummy for each calendar month. These regressions are based on data from 2008-2019, except that the inflation backcast columns begin in 2009. Robust standard errors are clustered two ways: by calendar month and by unique respondent. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

B.7 Additional Robustness: Real Income Changes

Table B.24: Inflation and Real Changes in Household Income

	Realized Inflation next 12m		Inflation Forecast next 12m		Realized Inflation past 12m		Inflation Backcast past 12m	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Recent Log Real Income Change	0.010 (0.036)		-0.864*** (0.148)		-0.028 (0.035)		-1.100*** (0.226)	
Future Log Real Income Change		-0.065*** (0.023)		-0.417*** (0.107)		-0.012 (0.021)		-0.504*** (0.132)
Demog. Controls	No	No	Yes	Yes	No	No	Yes	Yes
Sample	Respondents 2012 - 2019	Respondents 2012 - 2019	Respondents 2012 - 2019	Respondents 2012 - 2019	Respondents 2013 - 2019	Respondents 2013 - 2019	Respondents 2013 - 2019	Respondents 2013 - 2019
Observations	35014	35014	35014	35014	30734	30734	30734	30734

Notes: This table presents regressions of realized inflation, forecasted inflation, and backcasted inflation over the 12 months following or preceding the survey response on recent and future log real income changes. The units of inflation and inflation forecasts are expressed in percentage points. Recent changes in households' log real income are calculated based on the log real income of the year $t-1$ minus log real income in the year $t-2$, with t denoting the year of the survey response. Future changes in households' log real income are calculated based on the log real income of the year $t+1$ minus log real income in the year $t-1$. To compute real income levels in years $t+1$, $t-1$, and $t-2$ we deflate nominal values using the monthly level consumer price index data provided by Statistics Denmark. "Respondents" denotes the set of survey respondents satisfying the restriction outlined in Section 1. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. These regressions are based on data from 2012-2019 for Columns (1) to (4) and 2013-2019 for Columns (5) to (8). Robust standard errors are clustered two ways: by calendar month and by unique respondent. Since only 467 respondents answer the survey more than once, this is essentially numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.25: Informativeness of Forecasted Family Finances Changes (Real Income)

	Future Log Real Income Change				
	(1)	(2)	(3)	(4)	(5)
Will Worsen a Lot	-0.039***	-0.044***	-0.047***	-0.045***	
	(0.009)	(0.008)	(0.008)	(0.008)	
Will Worsen a Bit	-0.026***	-0.028***	-0.029***	-0.028***	
	(0.003)	(0.003)	(0.003)	(0.003)	
Will stay the same	-	-	-	-	
Will Improve a Bit	0.024***	0.012***	0.013***	0.011***	
	(0.002)	(0.002)	(0.002)	(0.002)	
Will Improve a Lot	0.092***	0.059***	0.060***	0.057***	
	(0.005)	(0.005)	(0.005)	(0.005)	
Recent Log Real Income Change			-0.191***	-0.202***	-0.188***
			(0.010)	(0.010)	(0.010)
Demog. Controls	No	Yes	Yes	Yes	Yes
Month FE	No	No	No	Yes	No
Observations	35014	35014	35014	35014	35014

Notes: This table presents regressions of future log real income change on the discrete forecasted family finances change variable. Future changes in households' log real income are calculated based on the log real income of the year $t+1$ minus log real income in the year $t-1$, with t denoting the year of the survey response. To compute real income levels in years $t+1$ and $t-1$, we deflate nominal values using the monthly level consumer price index data provided by Statistics Denmark. Forecasted family finances changes are elicited on a 5-point Likert scale. Columns 3-5 additionally control for the recent log real income change, and Column 5 reports the specification with this control alone, omitting the categorical dummies. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. The specification "Month FE" includes a fixed effect dummy for each calendar month. These regressions are based on data from 2012-2019. Robust standard errors are clustered two ways: by calendar month and by unique respondent. Since only 467 respondents answer the survey more than once, this is essentially numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.26: Association Between Inflation Forecasts and Income Change Measures when Controlling for Backcasts

	Inflation next 12m Forecast			
	(1)	(2)	(3)	(4)
Recent Log Real Income Change	-0.854***	-0.091		
	(0.147)	(0.109)		
Future Log Real Income Change			-0.416***	0.113
			(0.107)	(0.082)
Inflation past 12m Backcast		0.493***		0.493***
		(0.011)		(0.011)
Demog. Controls	Yes	Yes	Yes	Yes
Observations	35029	35029	35035	35035

Notes: This table presents regressions of forecasted inflation on recent log real income change (Columns 1 and 2) and future log real income change (Columns 3 and 4). Columns (2) and (4) also control for inflation backcasts. Inflation forecasts and backcasts are measured in percentage points and refer, respectively, to the inflation in the 12 months after and 12 months before the interview. Recent changes in households' log real income are calculated based on the log real income of the year $t-1$ minus the log real income in the year $t-2$, with t denoting the year of the survey response. Future changes in households' log real income are calculated based on the log real income of the year $t+1$ minus the log real income in the year $t-1$. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. The data covers years 2012-2019. Robust standard errors are clustered two ways: by calendar month and by unique respondent. Since only 467 respondents answer the survey more than once, this is essentially numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

B.8 Additional Robustness: Net of Tax Income Changes

Table B.27: Inflation and Net of Tax Changes in Household Income

	Realized Inflation next 12m		Inflation Forecast next 12m		Realized Inflation past 12m		Inflation Backcast past 12m	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Recent Log Nominal Net-of-Tax Income Change	-0.061** (0.025)		-0.744*** (0.153)		-0.010 (0.023)		-0.955*** (0.237)	
Future Log Nominal Net-of-Tax Income Change		-0.013 (0.026)		-0.423*** (0.121)		0.080*** (0.024)		-0.527*** (0.151)
Demog. Controls	No	No	Yes	Yes	No	No	Yes	Yes
Sample	Respondents 2012 - 2019	Respondents 2012 - 2019	Respondents 2012 - 2019	Respondents 2012 - 2019	Respondents 2013 - 2019	Respondents 2013 - 2019	Respondents 2013 - 2019	Respondents 2013 - 2019
Observations	35048	35048	35048	35048	30750	30750	30750	30750

Notes: This table presents regressions of realized inflation, forecasted inflation, and backcasted inflation over the 12 months following or preceding the survey response on recent and future log net-of-tax income changes. The units of inflation and inflation forecasts are expressed in percentage points. Recent changes in households' log income are calculated based on the log net of tax income of the year $t-1$ minus log net of tax income in the year $t-2$, with t denoting the year of the survey response. Future changes in households' log income are calculated based on the log net of tax income of the year $t+1$ minus log net of tax income in the year $t-1$. To compute net of tax income changes we subtract the total income tax due in each fiscal year using tax returns provided from the Danish Tax Authority. "Respondents" denotes the set of survey respondents satisfying the restriction outlined in Section 1. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. These regressions are based on data from 2012-2019 for Columns (1) to (4) and 2013-2019 for Columns (5) to (8). Robust standard errors are clustered two ways: by calendar month and by unique respondent. Since only 467 respondents answer the survey more than once, this is essentially numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

B.9 Additional Results for Section 4.2

Table B.28: Empirical Distribution of Household ER Events

	Freq.	Percent
0	27443	24.05
1	22515	19.73
2	17197	15.07
3	12079	10.59
4	8692	7.62
5	6436	5.64
6	4549	3.99
7	3542	3.10
8	2640	2.31
9	1972	1.73
=10 or more	7034	6.16
Total	114099	100.00

Notes: This table shows the frequency and empirical probability for the number of emergency room events that a survey respondent experiences in the sample period 2008-2018. An ER event is defined as any member of the household visiting the emergency room.

Table B.29: Family ER Visits and Survey Participation

	Survey Participation				
	(1)	(2)	(3)	(4)	(5)
Fam. ER visit this month	-0.010	-0.009	-0.010	-0.010	-0.010
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
# of ER visits		-0.001	0.008***		
		(0.001)	(0.002)		
# of ER visits sq.			-0.001***		
			(0.000)		
Demog. controls	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
# of ER visits FE	No	No	No	Yes	Yes
Age × # of ER FE	No	No	No	No	Yes
Sample	2008-2018	2008-2018	2008-2018	2008-2018	2008-2018
Observations	161158	161158	161158	161158	161158

Notes: This table uses data on contacted individuals, i.e. both survey respondents and non-respondents. The dependent variable I(Survey Participation) is an indicator variable that equals one if the contacted individual participated in the survey. The indicator I(Fam. ER visit in survey month) is one if any member of the household visited the emergency room in the month of interview. The control variables "# of ER visits" and "# of ER Visits sq." denote the total number of family ER visits in the sample period, and its square, respectively. "# of ER visits FE" indicates that we include fixed effects for the total number of ER visits. "Age × # of ER FE" indicates that we also control for age interacted with these fixed effects. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. Contacted individuals with more than 7 emergency room visits in the sample period are dropped. The specification "Month FE" includes a fixed effect dummy for each calendar month. These regressions use monthly data from 2008-2018. Robust standard errors are clustered by calendar month. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.30: Impact of Family ER Visit in Survey Month on Inflation Forecasts and Backcasts (Robustness)

	Inflation Forecasts and Backcasts			
	(1)	(2)	(3)	(4)
I(Fam. ER visit in survey month)	0.444**	0.391***	0.237**	0.359***
	(0.172)	(0.120)	(0.099)	(0.110)
I(Forecast) x I(Fam. ER visit)	-0.308*	-0.302**	-0.224**	-0.256**
	(0.159)	(0.125)	(0.105)	(0.110)
Recent Log Nominal Income Changes				-0.307***
				(0.071)
Future Log Nominal Income Changes				-0.267***
				(0.055)
Demog. controls	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
# of ER visits FE	Yes	Yes	Yes	Yes
Sample	2012-2018	2008-2018	2008-2018	2008-2018
Survey Responses	24820	88059	99940	95637
Observations	49640	163025	185131	162619
Robustness	Baseline Sample	Max 5 ER visits	Max 9 ER visits	Control Income Changes

Notes: This table pools elicitations of inflation forecasts and backcasts and regresses them on the indicator I(Fam. ER visit in survey month). This indicator equals one if any member of the household visited the emergency room in the calendar month of the interview. We present results for our preferred specification across multiple subsamples to illustrate robustness of our findings. Inflation forecasts and backcasts are expressed in percentage points. The control variable "# of ER visits" denotes the total number of family ER visits in the sample period. "# of ER visits FE" indicates that we include fixed effects for the total number of ER visits. "Age × # of ER FE" indicates that we also control for age interacted with these fixed effects. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. Except for columns 2 and 3, respondents with more than 7 emergency room visits in the sample period are dropped. The specification "Month FE" includes a fixed effect dummy for each calendar month. These regressions use monthly data from 2008-2018, except for column 1. Robust standard errors are clustered two ways: by calendar month and by unique respondent. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.31: Impact of Family ER Visit in Survey Month on Inflation Forecasts and Backcasts (Education Subsamples)

	Inflation Forecasts and Backcasts			
	(1)	(2)	(3)	(4)
I(Fam. ER visit in survey month)	0.282** (0.111)	0.210* (0.125)	0.202* (0.112)	0.186 (0.126)
Demog. controls	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Age × # of ER FE	No	No	Yes	Yes
Sample	2008-2018	2008-2018	2008-2018	2008-2018
Sample Restriction	Non-College Educated	College Educated	Non-College Educated	College Educated
Survey Responses	63576	32061	63576	32061
Observations	117356	59735	117356	59735

Notes: This table pools elicitations of inflation forecasts and backcasts and regresses them on the indicator I(Fam. ER visit in survey month). This indicator equals one if any member of the household visited the emergency room in the calendar month of the interview. We split the analysis sample by educational attainment of the main respondent. Inflation forecasts and backcasts are expressed in percentage points. "College Educated" and "Non-College Educated" restrict to respondents with and without a college degree, respectively. The variable "# of ER visits" denotes the total number of family ER visits in the sample period. "# of ER visits FE" indicates that we include fixed effects for the total number of ER visits. "Age × # of ER FE" indicates that we also control for age interacted with these fixed effects. Demographic controls include age, highest education, gender, number of children, and average past income level deciles. Average past income level is constructed based on the average log nominal income from year $t-3$ to $t-5$. The specification "Month FE" includes a fixed effect dummy for each calendar month. These regressions use monthly data from 2008-2018. Respondents with more than 7 emergency room visits in the sample period are dropped. Robust standard errors are clustered two ways: by calendar month and by unique respondent. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

B.10 Additional Results for Section 5.3

B.10.1 Summary Statistics

For the Danish survey sample median completion time was 6 minutes and 59 seconds.

For the US survey sample median completion time was 4 minutes and 48 seconds. In the US sample we discard 77 participants for failing to pass attention checks.

Table B.32: Survey: Summary Statistics

(a) Danish Sample

	Mean	SD
Price Percent Change Next 12m	7.80	10.09
Age - Survey	45.23	13.72
Married (%)	48.26	49.98
Bachelors or Higher (%)	47.36	49.94
Respondents	3744	

(b) US Sample

	Mean	SD
Price Percent Change Next 12m	4.05	10.90
Age	38.95	12.32
Married (%)	41.04	49.21
Bachelors or Higher (%)	57.91	49.39
Respondents	1523	

Notes: This table displays summary statistics for our Danish and US survey samples in panels (a) and (b) respectively. "Price Percent Change Next 12m" refers to responses to 12 months ahead inflation forecast elicitation, units in percentage point. "Age", "married", and "bachelor or higher" refer to self-reported demographic information in our survey.

Table B.33: Danish Survey: Comparison to Registry Data

	Respondents	Population
Age	46.3	42.1
Female (%)	51.7	49.6
Single (%)	36.5	44.2
No. of Children in Household	0.94	1.01
Household Income (in 2015 level)	386,199	332,641
Highest Education		
Primary or Lower Secondary (%)	16.9	25.4
Upper Secondary (%)	36.1	34.1
Bachelor or Higher (%)	38.6	26.5
Observations	3,703	3,720,924

Notes: This table reports statistics on demographics, education, and income for both the Danish population and respondents to our Danish survey experiment. Age reflects the individual's age in December 2025. Demographic characteristics are based on registry data from 2023, while educational attainment is measured using 2019 data. We restrict the sample to individuals aged 18 to 65 in 2025. The *Respondents* column summarizes characteristics of participants in our Danish survey experiment, whereas the *Population* column provides corresponding statistics for the entire Danish population. Household income is reported in 2015 Danish Kroner.

B.10.2 Additional Survey Results: Main Elicitations

Table B.34: Factors Influencing Inflation Expectations — Summary Statistics by Factor

(a) Danish Sample

	Percent a Lot	Percent a Little	Average Score
Gov. mgmt of the economy (Macro)	31.08	44.53	2.07
Price gouging by firms (Macro)	25.06	42.22	1.92
Household spending (Macro)	28.39	49.41	2.06
Oil and energy prices (Macro)	22.99	51.97	1.98
Supply chain conditions (Macro)	30.69	43.03	2.04
US dollar value (Macro)	5.67	33.74	1.45
Wages, labor market (Macro)	11.34	51.96	1.75
Spending by government (Macro)	11.63	30.68	1.54
Interest rate changes (Macro)	15.64	47.09	1.78
Market competition (Macro)	20.48	44.06	1.85
Foreign Assistance (Macro)	11.36	26.03	1.49
Income tax cuts (Macro)	3.34	17.51	1.24
Wages, union (Macro)	5.78	37.99	1.50
Unclear monetary policy (Macro)	9.89	36.20	1.56
Money supply (Macro)	6.98	29.34	1.43
Price of groceries (Pers.)	57.83	35.14	2.51
Consumer goods prices (Pers.)	23.52	46.48	1.94
Price of eating out (Pers.)	15.38	40.52	1.71
Financially strained (Pers.)	25.69	42.03	1.93
Change price of utilities (Pers.)	27.15	44.28	1.99
Change in gas price (Pers.)	16.10	39.38	1.72
Prices of houses (Pers.)	15.04	36.66	1.67
Entertainment prices (Pers.)	11.26	35.62	1.58
Own insurance prices (Pers.)	12.37	37.18	1.62
Subscription fees (Pers.)	12.94	37.30	1.63
Home maintenance costs (Pers.)	18.37	42.78	1.80
Worries about job security (Pers.)	11.37	29.54	1.52
Own household income (Pers.)	11.38	29.26	1.52
Own household debt (Pers.)	4.40	15.41	1.24
Own retirement savings (Pers.)	8.96	27.81	1.46

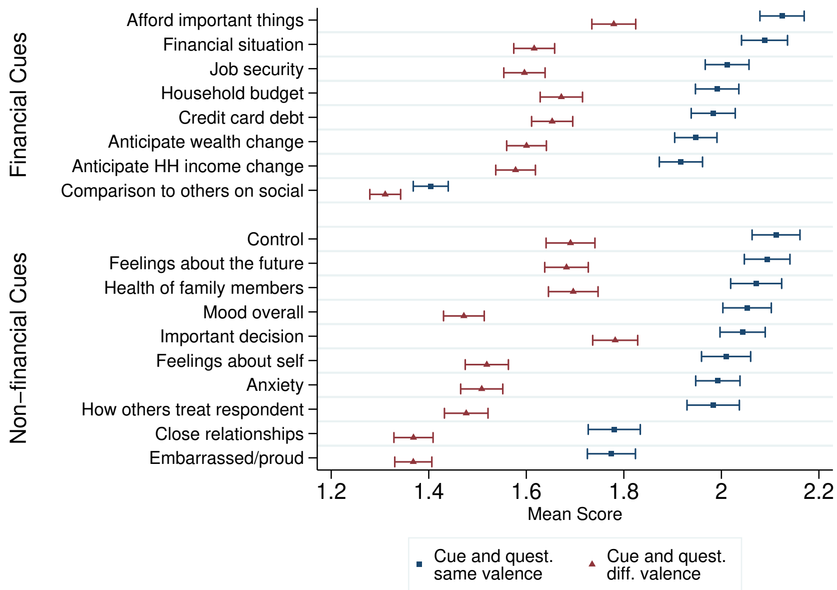
(b) US Sample

	Percent a Lot	Percent a Little	Average Score
Gov. mgmt of the economy (Macro)	49.90	38.70	2.39
Price gouging by firms (Macro)	41.39	35.45	2.18
Household spending (Macro)	35.63	44.49	2.16
Oil and energy prices (Macro)	30.33	48.73	2.09
Supply chain conditions (Macro)	28.66	46.75	2.04
US dollar value (Macro)	29.82	37.18	1.97
Wages, labor market (Macro)	19.41	45.35	1.84
Spending by government (Macro)	22.75	36.86	1.82
Interest rate changes (Macro)	22.55	36.86	1.82
Market competition (Macro)	17.95	39.05	1.75
Foreign Assistance (Macro)	18.06	30.16	1.66
Income tax cuts (Macro)	10.98	38.82	1.61
Wages, union (Macro)	11.22	33.67	1.56
Unclear monetary policy (Macro)	11.18	31.98	1.54
Money supply (Macro)	11.85	30.21	1.54
Price of groceries (Pers.)	56.63	33.52	2.47
Consumer goods prices (Pers.)	42.50	38.01	2.23
Price of eating out (Pers.)	33.20	44.14	2.11
Financially strained (Pers.)	36.31	37.90	2.11
Change price of utilities (Pers.)	30.43	42.05	2.03
Change in gas price (Pers.)	27.82	43.97	2.00
Prices of houses (Pers.)	28.40	42.40	1.99
Entertainment prices (Pers.)	24.50	41.16	1.90
Own insurance prices (Pers.)	25.15	33.80	1.84
Subscription fees (Pers.)	20.00	35.29	1.75
Home maintenance costs (Pers.)	19.20	36.20	1.75
Worries about job security (Pers.)	17.45	33.73	1.69
Own household income (Pers.)	17.88	29.47	1.65
Own household debt (Pers.)	12.20	25.00	1.49
Own retirement savings (Pers.)	7.14	20.83	1.35

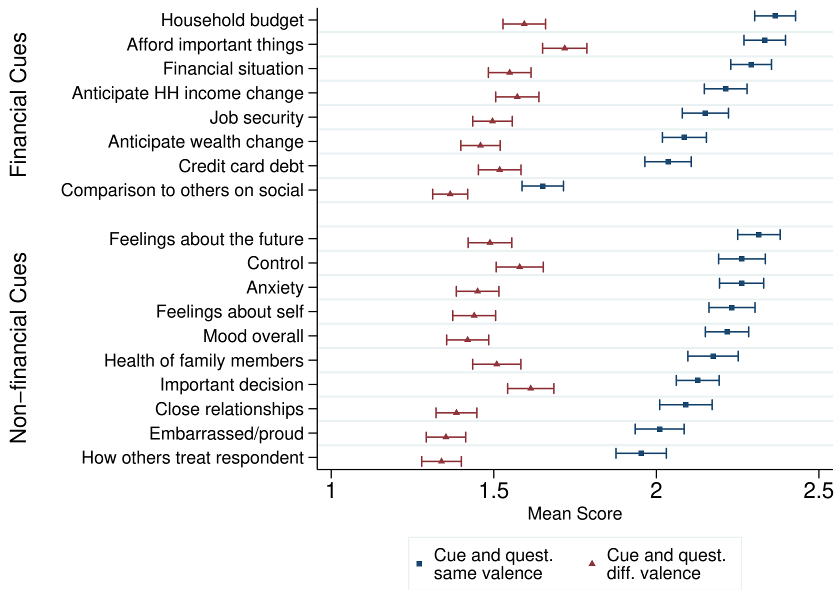
Notes: This table summarizes survey responses to the survey elicitation "You previously wrote that you thought that prices will [increase/decrease] by XX% over the next 12 months. Did your thinking about the answer involve any of the factors below?". We display the percent of participants who selected "a lot" (Column 1) and "a little" (Column 2) for each factor, as well as the average Likert score assigned to each factor on a scale of 1 "Not at all" to 3 "A lot" (Column 3). Panel (a) presents results for the Danish sample, while Panel (b) presents results for the US sample.

Figure B.2: Affective Association: What leads you to recall negative/positive experiences?

(a) Danish Sample



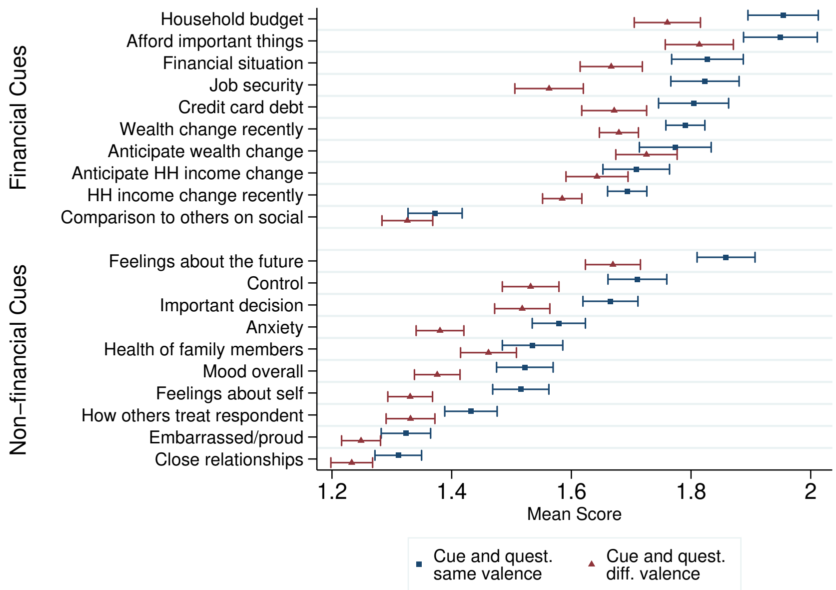
(b) US Sample



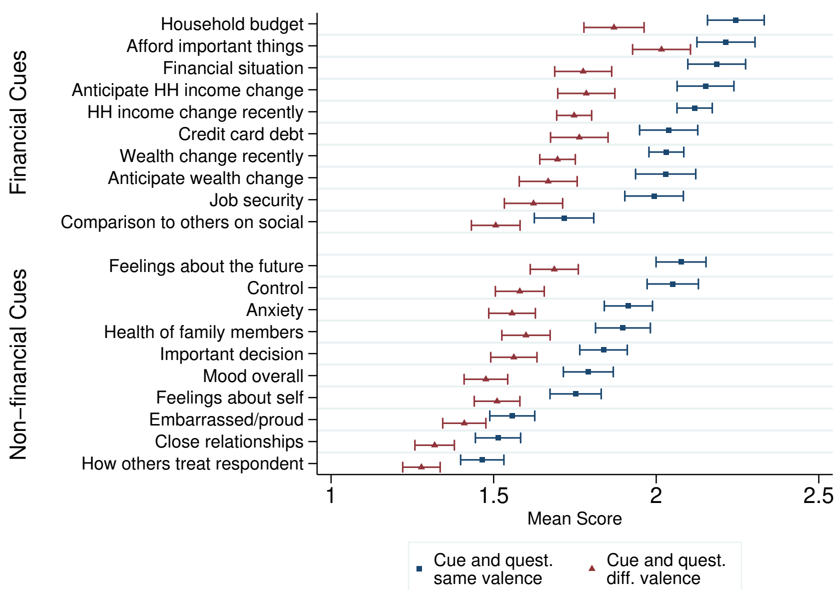
Notes: This figure illustrates how respondents rate the importance of different cues in recalling positive or negative past experiences. We pool across the baseline and financial framing of the elicitation. Section 5.3 reports the wording for both for both framings (baseline and financial). Markers represent mean Likert scores (1 = "Not at all," 2 = "A little," 3 = "A lot") for each possible cue under two experimental conditions: Squares denote cases where the cue and question have congruent affective valence, while triangles represent cases where they have different affective valence. Bars indicate 95% confidence intervals, constructed using robust standard errors. Panel (a) presents results for the Danish sample, while Panel (b) presents results for the US sample.

Figure B.3: Affective Association: What leads you to recall high/low inflation?

(a) Danish Sample



(b) US Sample



Notes: This figure illustrates how respondents rate the importance of different cues in recalling low or high past inflation experiences. Responses are based on the question:
"How much do each of the following influence your tendency to remember and focus on periods in your life when there was [very low/very high] inflation in the prices of things you need?"
Markers represent mean Likert scores (1 = "Not at all," 2 = "A little," 3 = "A lot") for each possible cue under two experimental conditions: squares denote cases where the cue and question have congruent affective valence, while triangles represent cases where they have different affective valence. Bars indicate 95% confidence intervals, constructed using robust standard errors. Panel (a) presents results for the Danish sample, while Panel (b) presents results for the US sample.

Table B.35: Factors Influencing Recall of Positive/Negative Events and Framing of the Recall — Regression Table

(a) Danish Sample

	Non-financial Event		Financial Event	
	(1) Influence a lot	(2) Influence a little or a lot	(3) Influence a lot	(4) Influence a little or a lot
I(financial cue)	0.138***	0.425***	0.154***	0.485***
	(0.012)	(0.023)	(0.016)	(0.026)
I(non-financial cue)	0.135***	0.444***	0.120***	0.414***
	(0.013)	(0.024)	(0.012)	(0.027)
I(financial cue) x I(same valence as event)	0.127***	0.211***	0.151***	0.183***
	(0.021)	(0.019)	(0.019)	(0.019)
I(non-financial cue) x I(same valence as event)	0.229***	0.309***	0.115***	0.205***
	(0.029)	(0.034)	(0.021)	(0.025)
Observations	19540	19540	17900	17900
Respondents	1954	1954	1790	1790

(b) US Sample

	Non-financial Event		Financial Event	
	(1) Influence a lot	(2) Influence a little or a lot	(3) Influence a lot	(4) Influence a little or a lot
I(financial cue)	0.099***	0.339***	0.161***	0.474***
	(0.009)	(0.020)	(0.020)	(0.029)
I(non-financial cue)	0.092***	0.354***	0.105***	0.366***
	(0.009)	(0.019)	(0.014)	(0.026)
I(financial cue) x I(same valence as event)	0.255***	0.415***	0.229***	0.312***
	(0.027)	(0.035)	(0.024)	(0.020)
I(non-financial cue) x I(same valence as event)	0.339***	0.503***	0.181***	0.385***
	(0.023)	(0.024)	(0.021)	(0.024)
Observations	7910	7910	7320	7320
Respondents	791	791	732	732

Notes: This table analyzes responses to survey question eliciting which cues influence recall of positive/negative experiences. We break down responses by the sub-variants of the elicitation. Column 1 and 2 present results for the baseline elicitation “Sometimes people recall [negative/positive] experiences from the past. This has probably happened to you before. Can you tell us what kinds of situations, events, or mindsets in the list below lead you to recall [negative/positive] experiences from the past?”. Column 3 and 4 present results for the financial framing elicitation “Sometimes people recall [negative/positive] events from the past that directly impacted their financial situation. This has probably happened to you before. Can you tell us what kinds of situations, events, or mindsets in the list below lead you to recall such [negative/positive] events from the past?”. In the reported results, we regress indicators for respondents selecting “a lot” (Columns 1 and 3) and “a lot” or “a little” (Columns 2 and 4) on indicators for financial and non-financial cues, as well as interactions between these indicators and an indicator for the cues having the same valence as the event. Panel (a) presents results for the Danish survey sample. Panel (b) presents results for the US survey sample. Robust standard errors, clustered two ways (Cameron et al., 2011) at the respondent and cue level, are in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.36: Factors Influencing Recall of High/Low Inflation (By Perceived Valence of Inflation) — Regression Table

(a) Danish Sample

	Inflation is unpleasant		Inflation not unpleasant	
	(1) Influence a lot	(2) Influence a little or a lot	(3) Influence a lot	(4) Influence a little or a lot
I(financial cue)	0.174***	0.535***	0.102***	0.417***
	(0.016)	(0.020)	(0.010)	(0.022)
I(non-financial cue)	0.104***	0.331***	0.075***	0.274***
	(0.012)	(0.028)	(0.009)	(0.021)
I(financial cue) x I(same valence as event)	0.064***	0.078***	0.023	0.042*
	(0.009)	(0.012)	(0.013)	(0.019)
I(non-financial cue) x I(same valence as event)	0.062***	0.108***	0.025*	0.065***
	(0.009)	(0.011)	(0.010)	(0.014)
Observations	24670	24670	12770	12770
Respondents	2467	2467	1277	1277

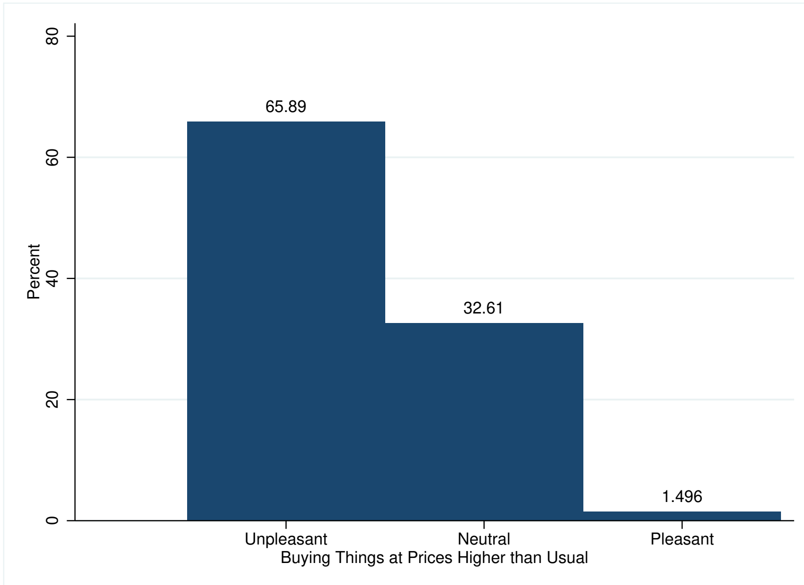
(b) US Sample

	Inflation is unpleasant		Inflation not unpleasant	
	(1) Influence a lot	(2) Influence a little or a lot	(3) Influence a lot	(4) Influence a little or a lot
I(financial cue)	0.200***	0.543***	0.168***	0.551***
	(0.024)	(0.029)	(0.027)	(0.032)
I(non-financial cue)	0.119***	0.375***	0.129***	0.415***
	(0.016)	(0.032)	(0.017)	(0.035)
I(financial cue) x I(same valence as event)	0.160***	0.208***	0.030	0.063
	(0.020)	(0.014)	(0.031)	(0.037)
I(non-financial cue) x I(same valence as event)	0.096***	0.204***	0.038	0.109**
	(0.015)	(0.019)	(0.029)	(0.040)
Observations	13280	13280	1950	1950
Respondents	1328	1328	195	195

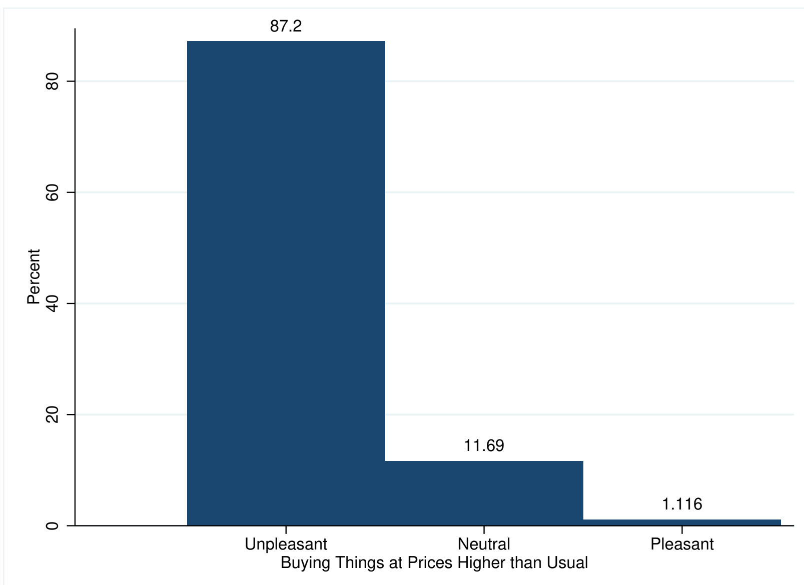
Notes: This table analyzes responses to survey question "How much do each of the following influence your tendency to remember and focus on periods in your life when there was [very low/very high] inflation in the prices of things you need?". We break down responses by the affective valence respondents assign to price increases. In the reported results, we regress indicators for respondents selecting "a lot" (Columns 1 and 3) and "a lot" or "a little" (Columns 2 and 4) on indicators for financial and non-financial cues, as well as interactions between these indicators and an indicator for the cues having the same valence as the event. Panel (a) presents results for the Danish survey sample. Panel (b) presents results for the US survey sample. Robust standard errors, clustered two ways (Cameron et al., 2011) at the respondent and cue level, are in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Figure B.4: Affective Valence of Price Increase — Histogram

(a) Danish Sample



(b) US Sample



Notes: The figure presents the empirical distribution of responses to the survey question "When you recall having to consider buying things at prices that are higher than what you were used to or expected, how would you classify that kind of memory:". We show the percent of respondents who classify the memory of buying things at higher prices as "unpleasant", "neutral", and "pleasant". Panel (a) presents results for the Danish sample, while Panel (b) presents results for the US sample.

B.10.3 Additional Survey Results: Self-Reported Mood and Inflation Forecasts

Table B.37: Inflation Forecasts and Wellbeing Change Backcast– Regression Table

(a) Danish Sample

	Inflation Forecast next 12m					
	(1)	(2)	(3)	(4)	(5)	(6)
Personal Wellbeing Backcast, Likert 5	-1.593*** (0.206)	-1.493*** (0.200)			-1.136*** (0.204)	-1.139*** (0.200)
Backcast Family Finances Changes, Likert 5			-1.588*** (0.188)	-1.351*** (0.189)	-1.203*** (0.184)	-0.971*** (0.188)
Demog. Controls	No	Yes	No	Yes	No	Yes
Respondents	3744	3744	3744	3744	3744	3744

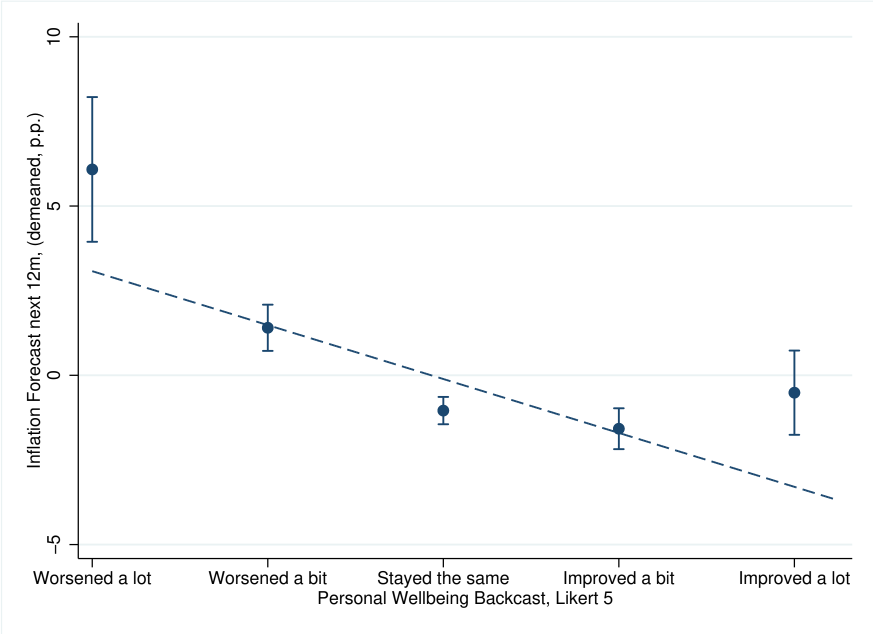
(b) US Sample

	Inflation Forecast next 12m					
	(1)	(2)	(3)	(4)	(5)	(6)
Personal Wellbeing Backcast, Likert 5	-0.941** (0.300)	-0.785** (0.303)			-0.721* (0.326)	-0.647* (0.327)
Backcast Family Finances Changes, Likert 5			-0.738** (0.271)	-0.563* (0.281)	-0.403 (0.292)	-0.270 (0.301)
Demog. Controls	No	Yes	No	Yes	No	Yes
Respondents	1523	1523	1523	1523	1523	1523

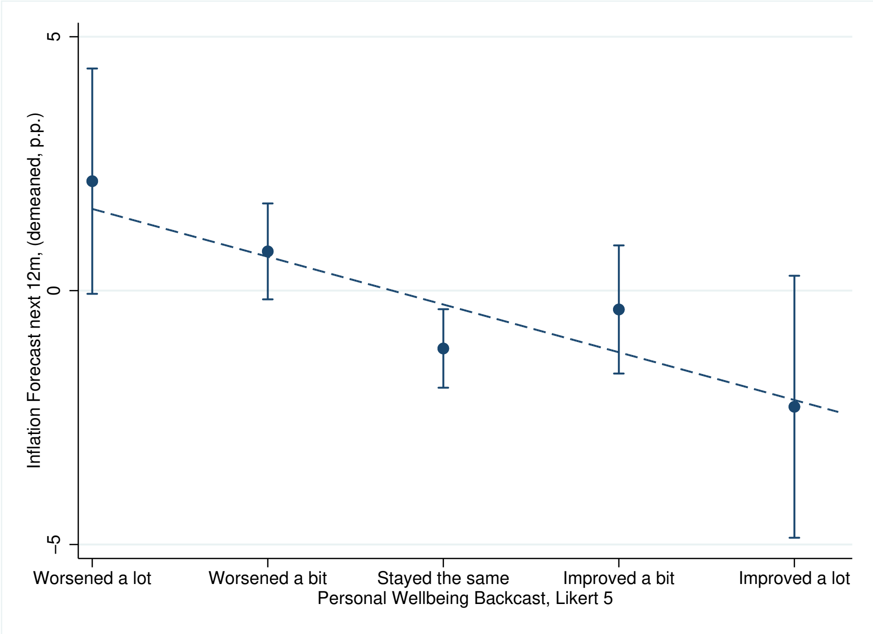
Notes: This table displays a regression of inflation expectations over the 12 months following the survey response on personal wellbeing backcast and financial family situation change backcast. We measure personal wellbeing backcast by asking respondents to select how their mental and physical wellbeing has changed over the 12 months preceding the survey response on a 5-point Likert scale from 1 ("Worsened a lot") to 5 ("Improved a lot"). We measure financial family situation backcast change by asking respondents how their financial situation has changed over the 12 months preceding the survey response, using a similar 5-point Likert scale from 1 ("Worsened a lot") to 5 ("Improved a lot"). Demographic controls include age, gender, an indicator for being married, and income. Robust standard errors are in parentheses. Panel (a) presents results for the Danish sample, while Panel (b) presents results for the US sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Figure B.5: Inflation Forecasts and Wellbeing Change Backcast

(a) Danish Sample



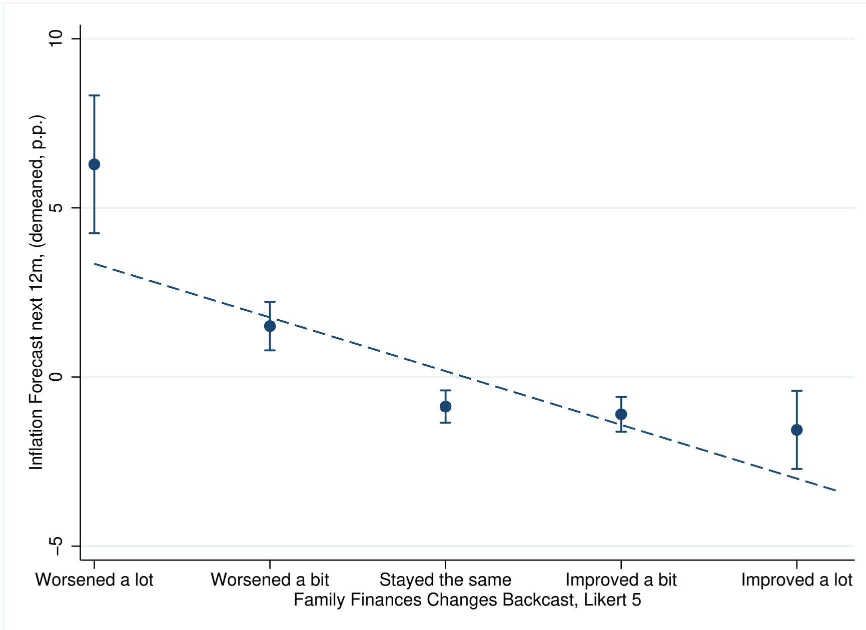
(b) US Sample



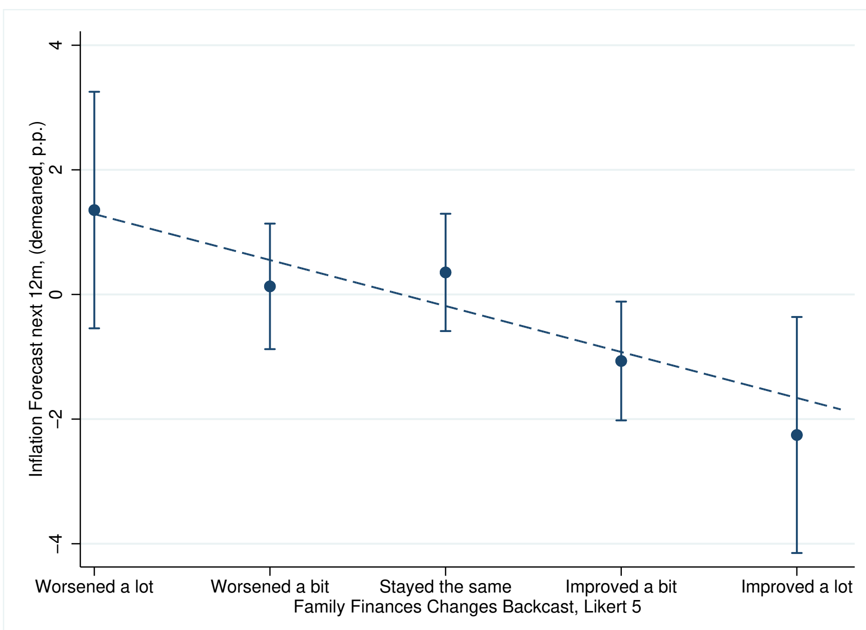
Notes: This figure presents the relationship between inflation forecast over the 12 months following the survey response and personal wellbeing backcast. We measure personal wellbeing backcast by asking respondents to assess how their mental and physical wellbeing has changed over the 12 months preceding the survey response, using a 5-point Likert scale from 1 ("Worsened a lot") to 5 ("Improved a lot"). We do not include demographic controls in this analysis to ensure that the means for each of the five possible survey responses remain interpretable. Dots represent means conditional on survey responses to the Self-Reported Personal Wellbeing Backcast elicitation. Bars denote 95% confidence intervals, constructed using robust standard errors. The fitted line is derived from a regression of forecasted inflation on personal wellbeing backcast. Panel (a) presents results for the Danish sample, while Panel (b) presents results for the US sample.

Figure B.6: Inflation Forecasts and Family Finances Changes Backcast

(a) Danish Sample



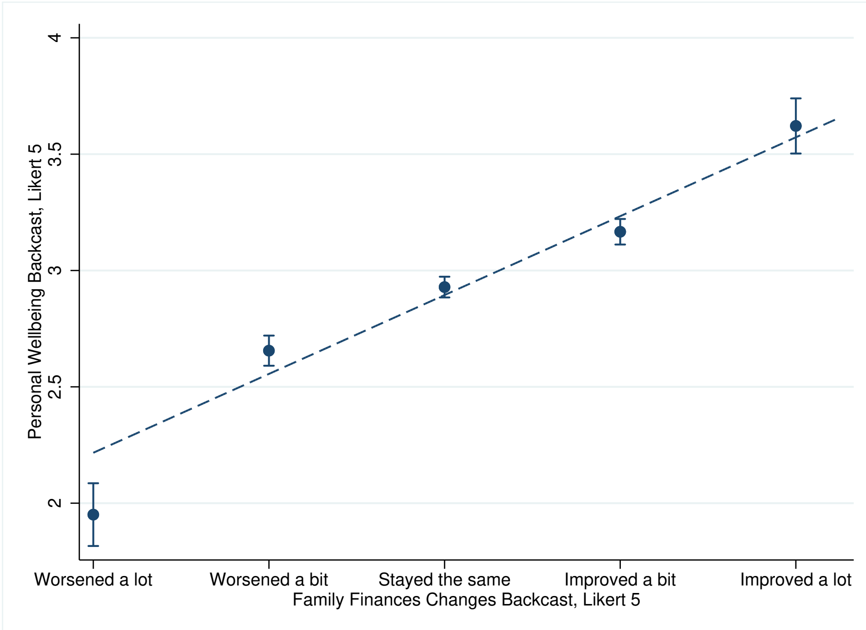
(b) US Sample



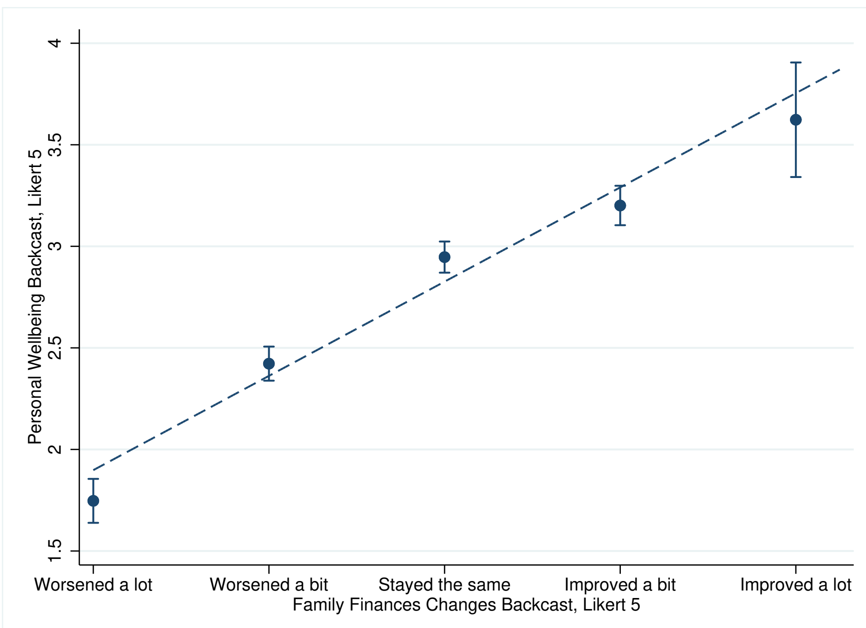
Notes: This figure presents the relationship between inflation forecast over the 12 months following the survey response and financial family situation change backcast. We measure financial family situation backcast change by asking respondents to assess how their family financial situation has changed over the 12 months preceding the survey response, using a 5-point Likert scale from 1 ("Worsened a lot") to 5 ("Improved a lot"). We do not include demographic controls in this analysis to ensure that the means for each of the five possible survey responses remain interpretable. Dots represent means conditional on survey responses to the Self-Reported Financial Situation Change Backcast elicitation. Bars denote 95% confidence intervals, constructed using robust standard errors. The fitted line is derived from a regression of forecasted inflation on financial family situation change backcast. Panel (a) presents results for the Danish sample, while Panel (b) presents results for the US sample.

Figure B.7: Wellbeing Change Backcast and Family Finances Changes Backcast

(a) Danish Sample



(b) US Sample



Notes: This figure presents the relationship between personal wellbeing backcast and financial family situation change backcast. We measure personal wellbeing backcast by asking respondents to assess how their mental and physical wellbeing has changed over the 12 months preceding the survey response, using a 5-point Likert scale from 1 ("Worsened a lot") to 5 ("Improved a lot"). Similarly, we measure financial family situation change backcast by asking respondents how their financial situation has changed over the same period, using an identical 5-point Likert scale. We do not include demographic controls in this analysis to ensure that the means for each of the five possible survey responses remain interpretable. Dots represent means conditional on survey responses to the Family Finance Changes Backcast elicitation. Bars denote 95% confidence intervals, constructed using robust standard errors. The fitted line is derived from a regression of personal wellbeing backcast on financial family situation change backcast. Panel (a) presents results for the Danish sample, while Panel (b) presents results for the US sample.

C Mathematical Results

C.1 Proofs

Proof of Test 1. By the definition of the regression equations in (2):

$$\beta_1^X = \frac{Cov\,(Y, X_i)}{Var\,(X_i)} \quad \text{and} \quad \tilde{\beta}_1^X = \frac{Cov\,(\mathbb{F}_i[Y|I_i], X_i)}{Var\,(X_i)}.$$

Using the definition of rational expectations in (1), including the fact that $\eta_i \perp X_i$, we can replace $\mathbb{F}_i[Y|I_i]$ with $\mathbb{E}[Y|I_i]$:

$$\tilde{\beta}_1^X = \frac{Cov\,(\mathbb{E}[Y|I_i], X_i)}{Var\,(X_i)} = \frac{Cov\,(Y, X_i)}{Var\,(X_i)} = \beta_1^X$$

where we use $X_i \perp Y|I_i$ and the law of total covariance for the second equality.

Proof of Test 2. By Assumption 1,

$$\beta_1^X = \frac{Cov\,(X_i, Y)}{Var\,(X_i)} = \frac{Cov\,(Z + \gamma Y, Y)}{Var\,(X_i)}.$$

From the definition of rational expectations in (1), including the fact that $\eta_i \perp X_i$,

$$\tilde{\beta}_1^X = \frac{Cov\,(\mathbb{F}_i[Y|I_i], X_i)}{Var\,(X_i)} = \frac{Cov\,(\mathbb{E}[Y|I_i], X_i)}{Var\,(X_i)}.$$

Because Assumption 1 guarantees that $\mathbb{E}\,[Y|s_i]$ is linear in the signal s_i, it follows that[45]

$$\mathbb{E}\,[Y|s_i] = a_0 + \frac{Cov\,(s_i, Y)}{Var\,(s_i)} s_i,$$

where a_0 is a constant. Thus

$$\begin{aligned} \frac{Cov\,(\mathbb{E}[Y|I_i], X_i)}{Var\,(X_i)} &= \frac{Cov\,(s_i, Y)\,Cov\,(s_i, X_i)}{Var\,(s_i)\,Var\,(X_i)} \\ &= \frac{Cov\,(Z_i, Y)\,Cov\,(Z_i + \gamma Y, Z_i)}{(Var\,(Z_i) + Var\,(\delta_i))\,Var\,(X_i)} \\ &= \frac{Cov\,(Z, Y)\,(Cov\,(Z + \gamma Y, Z) + Var\,(\omega_i))}{(Var\,(Z) + Var\,(\omega_i) + Var\,(\delta_i))\,Var\,(X_i)}, \end{aligned} \tag{12}$$

[45]Note that Assumption 1, specifically the assumption that information $I_i = \{s_i\}$ is one-dimensional, implies that ν_i, δ_i, and ω_i are identically distributed across people (and time), in addition to being mutually independent and independent of Y and Z. Otherwise person i's own distribution would itself be additional information, and I_i would no longer be one-dimensional.

where we use the forms of X_i, s_i, and Z_i from Assumption 1 for the final equality. Together, we have

$$\begin{aligned}
\left|\beta_1^X-\tilde{\beta}_1^X\right| &= \left|\frac{Cov\left(Z+\gamma Y,Y\right)}{Var\left(X_i\right)}-\frac{Cov\left(Z,Y\right)}{Var\left(Z\right)+Var\left(\omega_i\right)+Var\left(\delta_i\right)}\frac{Cov\left(Z+\gamma Y,Z\right)+Var\left(\omega_i\right)}{Var\left(X_i\right)}\right| \\
&= \frac{1}{Var\left(X_i\right)}\left|Cov\left(Z+\gamma Y,Y\right)-\frac{\left(Cov\left(Z+\gamma Y,Y\right)-Cov\left(\gamma Y,Y\right)\right)\left(Cov\left(\gamma Y,Z\right)+Var\left(Z\right)+Var\left(\omega_i\right)\right)}{Var\left(Z\right)+Var\left(\omega_i\right)+Var\left(\delta_i\right)}\right| \\
&= \frac{1}{Var\left(X_i\right)}\left|\frac{Cov\left(Z+\gamma Y,Y\right)Var\left(\delta_i\right)}{Var\left(Z\right)+Var\left(\omega_i\right)+Var\left(\delta_i\right)}+\gamma\frac{Var\left(Y\right)\left(Var\left(Z\right)+Var\left(\omega_i\right)\right)-Cov^2\left(Y,Z\right)}{Var\left(Z\right)+Var\left(\omega_i\right)+Var\left(\delta_i\right)}\right| \\
&= \frac{1}{Var\left(X_i\right)}\left|\frac{Cov\left(X,Y\right)Var\left(\delta_i\right)}{Var\left(Z\right)+Var\left(\omega_i\right)+Var\left(\delta_i\right)}+\gamma\frac{Var\left(Y\right)\left(Var\left(Z\right)+Var\left(\omega_i\right)\right)-Cov^2\left(Y,Z\right)}{Var\left(Z\right)+Var\left(\omega_i\right)+Var\left(\delta_i\right)}\right| \\
&\leq \frac{\left|Cov\left(X,Y\right)\right|}{Var\left(X_i\right)}+\frac{|\gamma|}{Var\left(X_i\right)}\left|\frac{Var\left(Y\right)\left(Var\left(Z\right)+Var\left(\omega_i\right)\right)-Cov^2\left(Y,Z\right)}{Var\left(Z\right)+Var\left(\omega_i\right)+Var\left(\delta_i\right)}\right| \\
&\leq \frac{\sqrt{Var\left(X\right)Var\left(Y\right)}}{Var\left(X_i\right)}+\frac{|\gamma|}{Var\left(X_i\right)}\left|\frac{Var\left(Y\right)\left(Var\left(Z\right)+Var\left(\omega_i\right)\right)-Cov^2\left(Y,Z\right)}{Var\left(Z\right)+Var\left(\omega_i\right)+Var\left(\delta_i\right)}\right| \\
&\leq \frac{\sqrt{Var\left(X\right)Var\left(Y\right)}}{Var\left(X_i\right)}+\frac{|\gamma|}{Var\left(X_i\right)}\frac{Var\left(Y\right)\left(Var\left(Z\right)+Var\left(\omega_i\right)\right)}{Var\left(Z\right)+Var\left(\omega_i\right)+Var\left(\delta_i\right)} \\
&\leq \frac{\sqrt{Var\left(X\right)Var\left(Y\right)}}{Var\left(X_i\right)}+\frac{|\gamma|\,Var\left(Y\right)}{Var\left(X_i\right)}
\end{aligned}$$

Proof of Test 2′. Assume that Assumption 1 holds. If $|\gamma|\leq 1$, then the bound in equation (3) implies that

$$\left|\tilde{\beta}_1^X-\beta_1^X\right|\leq\frac{\sqrt{Var\left(X\right)Var\left(Y\right)}}{Var\left(X_i\right)}+\frac{Var\left(Y\right)}{Var\left(X_i\right)}.$$

If $Cov\left(Z,\gamma Y\right)\geq 0$, then

$$Var\left(X\right)=Var\left(Z+\gamma Y\right)\geq\gamma^2 Var\left(Y\right).$$

From the bound in equation (3), we have

$$\left|\tilde{\beta}_1^X-\beta_1^X\right|\leq\frac{\sqrt{Var\left(X\right)Var\left(Y\right)}}{Var\left(X_i\right)}+\frac{|\gamma|\,Var\left(Y\right)}{Var\left(X_i\right)}\leq 2\frac{\sqrt{Var\left(X\right)Var\left(Y\right)}}{Var\left(X_i\right)}.$$

Together, this proves Test 2′.

C.2 Additional results related to Tests 1 and 2.

C.2.1 Version of Test 2 allowing noise in signal s_i to depend on aggregate Y

Assumption 2. *Person i's information is given by $I_i=\{s_i\}$, where $\mathbb{E}\left[Y|s_i\right]$ is linear in the signal s_i. Furthermore, the household-level variable X_i and the signal s_i are given by: $X_i=Z_i+\gamma Y+\nu_i$, $s_i=Z_i+\alpha Y+\delta_i$, and $Z_i=Z+\omega_i$, where ν_i,δ_i,ω_i are mean-zero, mutually independent, and* *independent of both Y and Z.*[46]

Here, we generalize Assumption 1 to allow the noise in signal s_i to also depend on the aggregate Y, captured by the term αY. We now extend Test 2.

Test 3. *If Assumption 2 holds, rational expectations in* (1) *imply that the difference between the two regression coefficients in* (2) *is bounded by*

$$\left|\tilde{\beta}_1^X - \beta_1^X\right| \leq \frac{\sqrt{Var\,(X)\,Var\,(Y)}}{Var\,(X_i)} + \frac{|\gamma - \alpha|\,Var\,(Y)}{Var\,(X_i)}, \tag{13}$$

where $X = \int X_i di$ is the aggregate component of X_i.

Proof of Test 3. By Assumption 2,

$$\beta_1^X = \frac{Cov\,(X_i, Y)}{Var\,(X_i)} = \frac{Cov\,(Z + \gamma Y, Y)}{Var\,(X_i)}.$$

From the definition of rational expectations in (1), including the fact that $\eta_i \perp X_i$,

$$\tilde{\beta}_1^X = \frac{Cov\,(\mathbb{F}_i[Y|I_i], X_i)}{Var\,(X_i)} = \frac{Cov\,(\mathbb{E}[Y|I_i], X_i)}{Var\,(X_i)}.$$

Because Assumption 2 guarantees that $\mathbb{E}\,[Y|s_i]$ is linear in the signal s_i, it follows that[47]

$$\mathbb{E}\,[Y|s_i] = a_0 + \frac{Cov\,(s_i, Y)}{Var\,(s_i)} s_i,$$

where a_0 is a constant. Thus,

$$\begin{aligned}\frac{Cov\,(\mathbb{E}[Y|I_i], X_i)}{Var\,(X_i)} &= \frac{Cov\,(s_i, Y)\,Cov\,(s_i, X_i)}{Var\,(s_i)\,Var\,(X_i)} \\ &= \frac{Cov\,(Z_i + \alpha Y, Y)\,Cov\,(Z_i + \gamma Y, Z_i + \alpha Y)}{(Var\,(Z_i + \alpha Y) + Var\,(\delta_i))\,Var\,(X_i)} \\ &= \frac{Cov\,(Z + \alpha Y, Y)\,(Cov\,(Z + \gamma Y, Z + \alpha Y) + Var\,(\omega_i))}{(Var\,(Z + \alpha Y) + Var\,(\omega_i) + Var\,(\delta_i))\,Var\,(X_i)},\end{aligned} \tag{14}$$

[46] By mean-zero, we mean that $\int \nu_i di = \int \delta_i di = \int \omega_i di = 0$.

[47] Note that Assumption 2, specifically the assumption that information $I_i = \{s_i\}$ is one-dimensional, implies that ν_i, δ_i, and ω_i are identically distributed across people (and time), in addition to being mutually independent and independent of Y and Z. Otherwise person i's own distribution would itself be additional information, and I_i would no longer be one-dimensional.

where we use the forms of X_i, s_i, and Z_i from Assumption 2 for the final equality. Together, we have

$$\begin{aligned}
\left|\beta_1^X - \tilde{\beta}_1^X\right| &= \left|\frac{Cov\left(Z+\gamma Y, Y\right)}{Var\left(X_i\right)} - \frac{Cov\left(Z+\alpha Y, Y\right)}{Var\left(Z+\alpha Y\right)+Var\left(\omega_i\right)+Var\left(\delta_i\right)}\frac{Cov\left(Z+\gamma Y, Z+\alpha Y\right)+Var\left(\omega_i\right)}{Var\left(X_i\right)}\right| \\
&= \frac{1}{Var\left(X_i\right)}\left|Cov\left(Z+\gamma Y, Y\right)\right. \\
&\left. - \frac{\left(Cov\left(Z+\gamma Y, Y\right)-Cov\left(\left(\gamma-\alpha\right)Y, Y\right)\right)\left(Cov\left(\left(\gamma-\alpha\right)Y, Z+\alpha Y\right)+Var\left(Z+\alpha Y\right)+Var\left(\omega_i\right)\right)}{Var\left(Z+\alpha Y\right)+Var\left(\omega_i\right)+Var\left(\delta_i\right)}\right| \\
&= \frac{1}{Var\left(X_i\right)}\left|Cov\left(Z+\gamma Y, Y\right)\left(\frac{Var\left(\delta_i\right)}{Var\left(Z+\alpha Y\right)+Var\left(\omega_i\right)+Var\left(\delta_i\right)}\right)\right. \\
&\left. + \left(\gamma-\alpha\right)\frac{Var\left(Y\right)\left(Var\left(Z+\alpha Y\right)+Var\left(\omega_i\right)\right)-Cov^2\left(Y, Z+\alpha Y\right)}{Var\left(Z+\alpha Y\right)+Var\left(\omega_i\right)+Var\left(\delta_i\right)}\right| \\
&= \frac{1}{Var\left(X_i\right)}\left|Cov\left(X, Y\right)\left(\frac{Var\left(\delta_i\right)}{Var\left(Z+\alpha Y\right)+Var\left(\omega_i\right)+Var\left(\delta_i\right)}\right)\right. \\
&\left. + \left(\gamma-\alpha\right)\frac{Var\left(Y\right)\left(Var\left(Z+\alpha Y\right)+Var\left(\omega_i\right)\right)-Cov^2\left(Y, Z+\alpha Y\right)}{Var\left(Z+\alpha Y\right)+Var\left(\omega_i\right)+Var\left(\delta_i\right)}\right| \\
&\leq \frac{\left|Cov\left(X, Y\right)\right|}{Var\left(X_i\right)} + \frac{\left|\gamma-\alpha\right|}{Var\left(X_i\right)}\left|\frac{Var\left(Y\right)\left(Var\left(Z+\alpha Y\right)+Var\left(\omega_i\right)\right)-Cov^2\left(Y, Z+\alpha Y\right)}{Var\left(Z+\alpha Y\right)+Var\left(\omega_i\right)+Var\left(\delta_i\right)}\right| \\
&\leq \frac{\sqrt{Var\left(X\right)Var\left(Y\right)}}{Var\left(X_i\right)} + \frac{\mid\gamma-\alpha\mid}{Var\left(X_i\right)}\left|\frac{Var\left(Y\right)\left(Var\left(Z+\alpha Y\right)+Var\left(\omega_i\right)\right)-Cov^2\left(Y, Z+\alpha Y\right)}{Var\left(Z+\alpha Y\right)+Var\left(\omega_i\right)+Var\left(\delta_i\right)}\right| \\
&\leq \frac{\sqrt{Var\left(X\right)Var\left(Y\right)}}{Var\left(X_i\right)} + \frac{\mid\gamma-\alpha\mid}{Var\left(X_i\right)}\frac{Var\left(Y\right)\left(Var\left(Z+\alpha Y\right)+Var\left(\omega_i\right)\right)}{Var\left(Z+\alpha Y\right)+Var\left(\omega_i\right)+Var\left(\delta_i\right)} \\
&\leq \frac{\sqrt{Var\left(X\right)Var\left(Y\right)}}{Var\left(X_i\right)} + \frac{\mid\gamma-\alpha\mid Var\left(Y\right)}{Var\left(X_i\right)}
\end{aligned}$$

C.2.2 Bound in (3) for the third example of Test 2′ in the main text.

Consider the case where household income changes, $X_i = X_{i,1} + X_{i,2}$, can be decomposed into two components: $X_{i,1} = \gamma_1 Y + \omega_i$, the observable component of income changes, and $X_{i,2} = \gamma_2 Y + \nu_i$, the unobservable component of income changes, where the loadings on inflation, γ_1 and γ_2, have the same sign and are not both zero and ν_i, ω_i are mean-zero, mutually independent, and independent of Y. This case can be nested within Assumption 1 with $s_i = Z_i = X_{i,1}$, $\delta_i = 0$, and $\gamma = \gamma_2$. The bound in (3) implies

$$\left|\tilde{\beta}_1^X - \beta_1^X\right| \leq \frac{\sqrt{Var\left(X\right)Var\left(Y\right)}}{Var\left(X_i\right)} + \frac{\left|\gamma_2\right| Var\left(Y\right)}{Var\left(X_i\right)}.$$

Because $X = \int X_i di = (\gamma_1 + \gamma_2) Y$, we have $Var(X) = (\gamma_1 + \gamma_2)^2 Var(Y)$, or $\sqrt{Var(Y)} = \sqrt{Var(X)}/|\gamma_1 + \gamma_2|$, and thus

$$|\gamma_2| \, Var(Y) = |\gamma_2| \sqrt{Var(Y)} \cdot \sqrt{Var(Y)} = \frac{|\gamma_2|}{|\gamma_1 + \gamma_2|} \sqrt{Var(Y)} \cdot \sqrt{Var(X)},$$

from which it follows that

$$\left| \tilde{\beta}_1^X - \beta_1^X \right| \leq \left(1 + \frac{|\gamma_2|}{|\gamma_1 + \gamma_2|} \right) \frac{\sqrt{Var(X) \, Var(Y)}}{Var(X_i)} \leq 2 \frac{\sqrt{Var(X) \, Var(Y)}}{Var(X_i)},$$

where we use the fact that because γ_1 and γ_2 have the same sign and are not both zero, $\frac{|\gamma_2|}{|\gamma_1 + \gamma_2|} \leq 1$.

C.2.3 An example violating assumption 1

Consider a variant of the third example in which the income change is still given by $X_i = X_{i,1} + X_{i,2}$, but the observable component $X_{i,1} = Y + \omega_i$ and the unobservable component $X_{i,2} = -Y + \omega_i$ have perfectly correlated idiosyncratic components (ω_i is mean-zero and independent of Y) and opposite-signed loadings on inflation. Person i's information is given by $I_i = \{s_i = X_{i,1}\}$ and we continue to assume that $\mathbb{E}[Y|s_i]$ is linear. This example violates Assumption 1, which requires that the idiosyncratic components are uncorrelated.

In this case, $X_i = 2\omega_i$ is completely idiosyncratic, so that

$$\beta_1^X = \frac{Cov(X_i, Y)}{Var(X_i)} = 0.$$

Moreover,

$$\mathbb{E}[Y|I_i] = \mathbb{E}[Y|X_{i,1}] = a_0 + \frac{Var(Y)}{Var(Y) + Var(\omega_i)} X_{i,1},$$

where a_0 is a constant. Thus,

$$Cov(\mathbb{E}[Y|X_{i,1}], X_i) = \frac{Var(Y)}{Var(Y) + Var(\omega_i)} Cov(X_{i,1}, X_i) = \frac{Var(Y)}{Var(Y) + Var(\omega_i)} 2Var(\omega_i),$$

and

$$\tilde{\beta}_1^X = \frac{Cov(\mathbb{E}[Y|X_{i,1}], X_i)}{Var(X_i)} = \frac{Var(Y)}{Var(Y) + Var(\omega_i)} \frac{Cov(X_{i,1}, X_i)}{Var(X_i)} = \frac{1}{2} \frac{Var(Y)}{Var(Y) + Var(\omega_i)}.$$

On the other hand, note that $Var(X) = 0$, and $Var(X_i) = 4Var(\omega_i)$. Thus the bound in Test 2, (3), is simply

$$\frac{Var(Y)}{Var(X_i)} = \frac{Var(Y)}{4Var(\omega_i)}$$

Consequently, as long as $Var(Y) < Var(\omega_i)$, rational expectations imply that $\left| \tilde{\beta}_1^X - \beta_1^X \right|$ is larger than the bound in Test 2, (3):

$$\left| \tilde{\beta}_1^X - \beta_1^X \right| > \frac{Var(Y)}{Var(X_i)}.$$

C.2.4 Understanding coefficients β_1^X in estimated regressions

Here we further elaborate on the interpretation of β_1^X, the regression coefficient of Y on X_i in (2). Consider an example akin to Assumption 1. That is, $X_i = Z_i + \gamma Y + \nu_i$ and $Z_i = Z + \omega_i$, where ν_i, ω_i are mean-zero, mutually independent, and independent of both Y and Z. In this case,

$$\beta_1^X = \frac{Cov\left(X, Y\right)}{Var\left(X_i\right)} = \frac{Cov\left(X, Y\right)}{Var\left(X\right) + Var\left(X_i - X\right)}, \tag{15}$$

where $X = Z + \gamma Y$. The numerator of (15) is given by the covariance of X (the aggregate component of X_i) and Y. This is related to the discussion in the main text: Y and X_i are related to each other through time-series variation, and a time series that is too short could generate a downward bias in the estimate of $\left|\beta_1^X\right|$. The denominator of (15) is instead given by the total variance of X_i, which can be decomposed into the variance of its idiosyncratic component and aggregate component. When most of the variation in X_i is idiosyncratic—i.e., when $Var\left(X\right)$ and $Cov\left(X, Y\right)$ are small relative to $Var\left(X_i\right)$, $\left|\beta_1^X\right|$ is necessarily small, connecting to the intuition behind Test 2.

C.2.5 Multidimensional version of Test 2

Assumption 3. *Person i's information is given by* $I_i = I_i' \cup \{s_i\}$, *where* $\mathbb{E}\left[Y | I_i', s_i\right]$ *is linear in the signal* s_i. *Furthermore, the household-level variable* X_i *and the signal* s_i *are given by:* $X_i = Z_i + \gamma Y + \nu_i$, $s_i = Z_i + \alpha Y + \delta_i$, *and* $Z_i = Z + \omega_i$, *where* $\nu_i, \delta_i, \omega_i$ *are mean-zero, mutually independent, and independent of both* Y *and* Z. *Furthermore, conditional on* I_i', $\nu_i, \delta_i, \omega_i$ *are mutually independent and independent of both* Y *and* Z.[48]

In words, we consider an information structure where we allow additional information ($I_i^{'}$), for example, capturing additional signals about macroeconomic variables. The key assumption, which guarantees that the bound (13) continues to hold, is that the idiosyncratic components of X_i and s_i ($\nu_i, \delta_i, \omega_i$) are independent of aggregates (Y and Z) conditional on $I_i^{'}$. This prevents the complication that the association between X_i and $\mathbb{E}\left[Y | I_i', s_i\right]$ arises because the person reacts to s_i for the reason that s_i helps the person better use $I_i^{'}$ to forecast Y. Further below, we show that Assumption 3 covers a variety of dynamic models that jointly consider the evolution of the macroeconomic variable, the household's income process, and the person's information sets.

Test 4. *If Assumption 3 holds, rational expectations in* (1) *imply that the difference between the two regression coefficients in* (2) *is bounded by*

$$\left|\tilde{\beta}_1^X - \beta_1^X\right| \leq \frac{\sqrt{Var\left(X\right) Var\left(Y\right)}}{Var\left(X_i\right)} + \frac{\left|\gamma - \alpha\right| Var\left(Y\right)}{Var\left(X_i\right)}, \tag{16}$$

where $X = \int X_i di$ *is the aggregate component of* X_i.

[48] By mean-zero, we mean that $\int \nu_i di = \int \delta_i di = \int \omega_i di = 0$.

Proof of Test 4. From (2) and Assumption 3, we have:

$$\begin{aligned}\beta_1^X &= \frac{Cov\left(X_i, Y\right)}{Var\left(X_i\right)} = \frac{Cov\left(X, Y\right)}{Var\left(X_i\right)} \\ &= \frac{\mathbb{E}_{I_i'}\left[Cov\left(X, Y|I_i'\right)\right]}{Var\left(X_i\right)} + \frac{Cov\left(\mathbb{E}\left[X|I_i'\right], \mathbb{E}\left[Y|I_i'\right]\right)}{Var\left(X_i\right)},\end{aligned}$$

where $X = \int X_i di = Z + \gamma Y$ and we use the law of total covariance for the last equality. From the definition of rational expectations in (1), we have

$$\tilde{\beta}_1^X = \frac{Cov\left(\mathbb{F}_i\left[Y|I_i\right], X_i\right)}{Var\left(X_i\right)} = \frac{Cov\left(\mathbb{E}\left[Y|I_i\right], X_i\right)}{Var\left(X_i\right)}.$$

By Assumption 3,

$$\begin{aligned}\mathbb{E}\left[Y|I_i', s_i\right] &= \mathbb{E}\left[Y|I_i'\right] + \frac{Cov\left(s_i, Y|I_i'\right)}{Var\left(s_i|I_i'\right)}\left(s_i - \mathbb{E}\left[s_i|I_i'\right]\right) \\ &= \mathbb{E}\left[Y|I_i'\right] + \frac{Cov\left(Z + \alpha Y, Y|I_i'\right)}{Var\left(Z + \alpha Y|I_i'\right) + Var\left(\omega_i|I_i'\right) + Var\left(\delta_i|I_i'\right)}\left(s_i - \mathbb{E}\left[s_i|I_i'\right]\right),\end{aligned}$$

where we use the fact that, conditional on I_i', $\nu_i, \delta_i, \omega_i$ are mutually independent and independent of both Y and Z. Repeated application of the law of total covariance thus yields

$$\begin{aligned}\tilde{\beta}_1^X &= \frac{Cov\left(\mathbb{E}\left[Y|I_i'\right], X_i\right)}{Var\left(X_i\right)} + \frac{Cov\left(\frac{Cov\left(Z+\alpha Y, Y|I_i'\right)}{Var\left(Z+\alpha Y|I_i'\right)+Var\left(\omega_i|I_i'\right)+Var\left(\delta_i|I_i'\right)}\left(s_i - \mathbb{E}\left[s_i|I_i'\right]\right), X_i\right)}{Var\left(X_i\right)} \\ &= \frac{Cov\left(Y, X_i\right)}{Var\left(X_i\right)} - \mathbb{E}_{I_i'}\left[\frac{Cov\left(Y, X_i|I_i'\right)}{Var\left(X_i\right)}\right] + \frac{1}{Var\left(X_i\right)}\mathbb{E}_{I_i'}\left[\frac{Cov\left(Z + \alpha Y, Y|I_i'\right)Cov\left(s_i, X_i|I_i'\right)}{Var\left(Z + \alpha Y|I_i'\right) + Var\left(\omega_i|I_i'\right) + Var\left(\delta_i|I_i'\right)}\right] \\ &= \frac{Cov\left(Y, X\right)}{Var\left(X_i\right)} - \mathbb{E}_{I_i'}\left[\frac{Cov\left(Y, X|I_i'\right)}{Var\left(X_i\right)}\right] + \frac{1}{Var\left(X_i\right)}\mathbb{E}_{I_i'}\left[\frac{Cov\left(Z + \alpha Y, Y|I_i'\right)Cov\left(s_i, X_i|I_i'\right)}{Var\left(Z + \alpha Y|I_i'\right) + Var\left(\omega_i|I_i'\right) + Var\left(\delta_i|I_i'\right)}\right] \\ &= \frac{Cov\left(\mathbb{E}\left[Y|I_i'\right], \mathbb{E}\left[X|I_i'\right]\right)}{Var\left(X_i\right)} + \frac{1}{Var\left(X_i\right)}\mathbb{E}_{I_i'}\left[\frac{Cov\left(Z + \alpha Y, Y|I_i'\right)\left(Cov\left(Z + \gamma Y, Z + \alpha Y|I_i'\right) + Var\left(\omega_i|I_i'\right)\right)}{Var\left(Z + \alpha Y|I_i'\right) + Var\left(\omega_i|I_i'\right) + Var\left(\delta_i|I_i'\right)}\right],\end{aligned}$$

where we again use the fact that, conditional on I_i', $\nu_i, \delta_i, \omega_i$ are mutually independent, and independent of both Y and Z. Following calculations similar to the one-dimensional version of Test 3, we have

$$
\begin{aligned}
\left|\beta_1^X-\tilde{\beta}_1^X\right| &= \left|\frac{\mathbb{E}_{I_i'}\left[Cov\left(Y,X|I_i'\right)-\frac{Cov\left(Z+\alpha Y,Y|I_i'\right)\left(Cov\left(Z+\gamma Y,Z+\alpha Y|I_i'\right)+Var\left(\omega_i|I_i'\right)\right)}{Var\left(Z+\alpha Y|I_i'\right)+Var\left(\omega_i|I_i'\right)+Var\left(\delta_i|I_i'\right)}\right]}{Var\left(X_i\right)}\right| \\
&= \frac{1}{Var\left(X_i\right)}\left|\mathbb{E}_{I_i'}\left[Cov\left(Y,X|I_i'\right)\left(\frac{Var\left(\delta_i|I_i'\right)}{Var\left(Z+\alpha Y|I_i'\right)+Var\left(\omega_i|I_i'\right)+Var\left(\delta_i|I_i'\right)}\right)\right]\right. \\
&\quad \left.+\mathbb{E}_{I_i'}\left[\left(\gamma-\alpha\right)\frac{Var\left(Y|I_i'\right)\left(Var\left(Z+\alpha Y|I_i'\right)+Var\left(\omega_i|I_i'\right)\right)-Cov^2\left(Y,Z+\alpha Y|I_i'\right)}{Var\left(Z+\alpha Y|I_i'\right)+Var\left(\omega_i|I_i'\right)+Var\left(\delta_i|I_i'\right)}\right]\right| \\
&\le \frac{\mathbb{E}_{I_i'}\left[\sqrt{Var\left(X|I_i'\right)Var\left(Y|I_i'\right)}\right]}{Var\left(X_i\right)} \\
&\quad +\frac{|\gamma-\alpha|}{Var\left(X_i\right)}\left|\mathbb{E}_{I_i'}\left[\frac{Var\left(Y|I_i'\right)\left(Var\left(Z+\alpha Y|I_i'\right)+Var\left(\omega_i|I_i'\right)\right)-Cov^2\left(Y,Z+\alpha Y|I_i'\right)}{Var\left(Z+\alpha Y|I_i'\right)+Var\left(\omega_i|I_i'\right)+Var\left(\delta_i|I_i'\right)}\right]\right| \\
&\le \frac{\mathbb{E}_{I_i'}\left[\sqrt{Var\left(X|I_i'\right)Var\left(Y|I_i'\right)}\right]}{Var\left(X_i\right)}+\frac{|\gamma-\alpha|\,\mathbb{E}_{I_i'}\left[Var\left(Y|I_i'\right)\right]}{Var\left(X_i\right)} \\
&\le \frac{\sqrt{\mathbb{E}_{I_i'}\left[Var\left(X|I_i'\right)\right]\mathbb{E}_{I_i'}\left[Var\left(Y|I_i'\right)\right]}}{Var\left(X_i\right)}+\frac{|\gamma-\alpha|\,\mathbb{E}_{I_i'}\left[Var\left(Y|I_i'\right)\right]}{Var\left(X_i\right)} \qquad (17) \\
&\le \frac{\sqrt{Var\left(X\right)Var\left(Y\right)}}{Var\left(X_i\right)}+\frac{|\gamma-\alpha|\,Var\left(Y\right)}{Var\left(X_i\right)} \qquad (18)
\end{aligned}
$$

where (17) follows from the Cauchy–Schwarz inequality and (18) follows from the law of total variance.

Processes satisfying Assumption 3. Here we show how Assumption 3 covers several dynamic models commonly used in the literature that jointly consider the evolution of macroeconomic variable, the household's income process, and the person's information sets.

Example 1: Let $X_{i,t}^{\text{level}}$ denote household i's (log) income level at period t. It has an aggregate component X_t^{level}, a persistent idiosyncratic component $\eta_{i,t}^{\text{level}}$, and a transitory idiosyncratic component $\xi_{i,t}$.[49] $X_t^{\text{level}}, \eta_{i,t}^{\text{level}}$, and the macro variable (e.g., inflation) Y_t all follow an AR(1) process:

$$X_{i,t}^{\text{level}} = X_t^{\text{level}} + \eta_{i,t}^{\text{level}} + \xi_{i,t}, \qquad (19)$$

$$X_t^{\text{level}} = \rho_x X_{t-1}^{\text{level}} + \varepsilon_t^x, \qquad (20)$$

$$\eta_{i,t}^{\text{level}} = \rho_\eta \eta_{i,t-1}^{\text{level}} + \varepsilon_{i,t}^\eta, \qquad (21)$$

$$Y_t = \rho_y Y_{t-1} + \varepsilon_t^y, \qquad (22)$$

where $\rho_x, \rho_\eta, \rho_y \in [-1,1]$, $\xi_{i,t}$ and $\varepsilon_{i,t}^\eta$ are i.i.d. across i,t, and ε_t^x and ε_t^y are i.i.d. across t. Moreover, the processes $\{\xi_{i,t}\}$, $\left\{\varepsilon_{i,t}^\eta\right\}$, $\{\varepsilon_t^x\}$, and $\{\varepsilon_t^y\}$ are jointly Normal, have mean zero, and are independent. This income process is akin to the one in Guvenen and Smith (2014), abstracting

[49] The transitory idiosyncratic component $\xi_{i,t}$ in the income level introduces a force that leads to negative autocorrelation in income changes, consistent with our empirical evidence.

from deterministic life-cycle components.

The agent possesses perfect knowledge of past household income levels and their transitory components (e.g. one-time lottery income) and past macro variables, up to finite or infinite lags ($L, L_\xi, L_{agg} \in \{0, 1, 2, \cdots, \infty\}$). They also receive a signal $s_{i,t}^{\text{level}}$ about its future income level $X_{i,t+1}^{\text{level}}$. That is, agent i's information $I_{i,t}$ is given by

$$\begin{aligned} I_{i,t} &= \left\{ s_{i,t}^{\text{level}} = X_{i,t+1}^{\text{level}} + \delta_{i,t}, \left\{ X_{i,t-l}^{\text{level}} \right\}_{l=0}^{L}, \left\{ X_{t-l}^{\text{level}}, Y_{t-l} \right\}_{l=0}^{L_{agg}}, \{\xi_{i,t-l}\}_{l=0}^{L_\xi} \right\} \\ &= \left\{ s_{i,t} = X_{i,t+1}^{\text{level}} - X_{i,t}^{\text{level}} + \delta_{i,t}, \left\{ X_{i,t-l}^{\text{level}} \right\}_{l=0}^{L}, \left\{ X_{t-l}^{\text{level}}, Y_{t-l} \right\}_{l=0}^{L_{agg}}, \{\xi_{i,t-l}\}_{l=0}^{L_\xi} \right\}, \end{aligned} \tag{23}$$

where $\delta_{i,t}$ is i.i.d. across i, t, has mean zero, and is independent of $\left\{ \varepsilon_t^x, \varepsilon_t^y, \xi_{i,t}, \varepsilon_{i,t}^\eta \right\}$. Note that we use the fact that $X_{i,t}^{\text{level}}$ is part of $I_{i,t}$ for the second step.

We now map the environment to Test 4. The household's realized future income change, its aggregate component, and the macro variable can then be written as

$$X_i = X_{i,t+1}^{\text{level}} - X_{i,t}^{\text{level}} \quad \text{and} \quad X = X_{t+1}^{\text{level}} - X_t^{\text{level}} \quad \text{and} \quad Y = Y_{t+1}.$$

The household's information can be written as $I_i = I_{i,t} = \left\{ s_i, I_i' \right\}$, where

$$s_i = s_{i,t} = X_i + \delta_{i,t} \quad \text{and} \quad I_i' = \left\{ \left\{ X_{i,t-l}^{\text{level}} \right\}_{l=0}^{L}, \left\{ X_{t-l}^{\text{level}}, Y_{t-l} \right\}_{l=0}^{L_{agg}}, \{\xi_{i,t-l}\}_{l=0}^{L_\xi} \right\}.$$

This satisfies Assumption 3 with

$$Z = X, \quad \omega_i = \eta_{i,t+1}^{\text{level}} + \xi_{i,t+1} - \eta_{i,t}^{\text{level}} - \xi_{i,t}, \quad \delta_i = \delta_{i,t} \quad \text{and} \quad \gamma = \alpha = \nu_i = 0.$$

Because $\varepsilon_{i,t+1}^\eta$, $\xi_{i,t+1}$, and $\delta_{i,t}$ are independent of $\left(I_i', X, Y \right)$, we know that, conditional on I_i' (which contains perfect information about $\xi_{i,t}$ and $\eta_{i,t}^{\text{level}} = X_{i,t}^{\text{level}} - X_t^{\text{level}} - \xi_{i,t}$), ω_i and δ_i are mutually independent and independent of both Y and Z.

One may argue that the assumption that the person perfectly knows about past macro variables, despite being standard, is too strong. This assumption is also inconsistent with our results on inflation backcasts in Section 4.1. Now we consider an alternative example where the person only perfectly knows about past household income levels (but not past macro variables) and Assumption 3 still holds.

Example 2: Now consider the case that the persistent idiosyncratic component $\eta_{i,t}^{\text{level}}$ follows a random walk. That is, consider the process in (19) – (22) with $\rho_\eta = 1$. This is akin to the income process in Blundell et al. (2008).

The agent possesses perfect knowledge of past household income levels and their transitory components (e.g. one-time lottery income), up to finite or infinite lags ($L, L_\xi \in \{0, 1, 2, \cdots, \infty\}$). They also receive a signal $s_{i,t}$ about future household income level $X_{i,t+1}^{\text{level}}$. That is, the agent's information I_i is given by

$$\begin{aligned} I_{i,t} &= \left\{ s_{i,t}^{\text{level}} = X_{i,t+1}^{\text{level}} + \delta_{i,t}, \left\{ X_{i,t-l}^{\text{level}} \right\}_{l=0}^{L}, \{\xi_{i,t-l}\}_{l=0}^{L_\xi} \right\} \\ &= \left\{ s_{i,t} = X_{i,t+1}^{\text{level}} - X_{i,t}^{\text{level}} + \delta_{i,t}, \left\{ X_{i,t-l}^{\text{level}} \right\}_{l=0}^{L}, \{\xi_{i,t-l}\}_{l=0}^{L_\xi} \right\}, \end{aligned} \tag{24}$$

where $\delta_{i,t}$ is i.i.d. across i, t and independent of $\left\{ \varepsilon_t^x, \varepsilon_t^y, \xi_{i,t}, \varepsilon_{i,t}^\eta \right\}$ and we use the fact that $X_{i,t}^{\text{level}}$ is part of $I_{i,t}$ for the second step.

We now map the environment to Test 4. The household's realized future income change, its aggregate component, and the macro variable can then be written as

$$X_i = X_{i,t+1}^{\text{level}} - X_{i,t}^{\text{level}} \quad \text{and} \quad X = X_{t+1}^{\text{level}} - X_t^{\text{level}} \quad \text{and} \quad Y = Y_{t+1}.$$

The household's information can be written as $I_i = I_{i,t} = \left\{ s_i, I_i' \right\}$, where

$$s_i = s_{i,t} = X_i + \delta_{i,t} \quad \text{and} \quad I_i' = \left\{ \left\{ X_{i,t-l}^{\text{level}} \right\}_{l=0}^{L}, \{\xi_{i,t-l}\}_{l=0}^{L_\xi} \right\}.$$

This satisfies Assumption 3 with

$$Z = X, \quad \omega_i = \varepsilon_{i,t+1}^\eta + \xi_{i,t+1} - \xi_{i,t}, \quad \delta_i = \delta_{i,t} \quad \text{and} \quad \gamma = \alpha = \nu_i = 0.$$

Because $\varepsilon_{i,t+1}^\eta$, $\xi_{i,t+1}$, and $\delta_{i,t}$ are independent of $\left(I_i', X, Y\right)$, we know that, conditional on I_i' (which contains perfect information about $\xi_{i,t}$), ω_i and δ_i are mutually independent and independent of both Y and Z.

C.3 Additional results related to Section 5.2.

C.3.1 Derivations of key equations in Section 5.2

(7) **and** (9). As $Y_-|I_i$ is Normally distributed, its probability density function can be written as

$$f\left(Y_-|I_i\right) = \frac{\sqrt{\kappa}}{\sqrt{2\pi}} \exp\left(-\frac{\kappa \left(Y_- - \mathbb{E}\left[Y_-|I_i\right]\right)^2}{2} \right),$$

where $\kappa = Var\left(Y_-|I_i\right)^{-1}$ and we assume that it is a constant for simplicity. Based on the formula of the similarity function $\mathcal{S}\left(Y_-, I_i\right)$ in (5), and the definition of subjective probability density function $f_\theta\left(Y_-|I_i\right)$ in (6), we have

$$f\left(Y_-|I_i\right) \times \left(\mathcal{S}\left(Y_-, I_i\right)\right)^\theta = \frac{\sqrt{\kappa}}{\sqrt{2\pi}} \exp\left(-\tfrac{1}{2} \left(\kappa \left(Y_- - \mathbb{E}\left[Y_-|I_i\right]\right)^2 + \theta \left(\alpha_Y\left(Y_-\right) - \alpha_I\left(I_i\right)\right)^2 \right) \right).$$

$$f_\theta\left(Y_-|I_i\right) = \frac{\sqrt{\kappa+\theta}}{\sqrt{2\pi}} \exp\left(-\frac{(\kappa+\theta)\left(Y_- - \mathbb{F}_i\left[Y_-|I_i\right]\right)^2}{2} \right),$$

where we use $\alpha_Y\left(Y_-\right) = -Y_-$ and

$$\mathbb{F}_i\left[Y_-|I_i\right] = \mathbb{E}\left[Y_-|I_i\right] - \frac{\theta}{\kappa+\theta}\left(\alpha_I\left(I_i\right) - \mathbb{E}\left[\alpha_Y\left(Y_-\right)|I_i\right]\right)$$

is the subjective inflation backcast in (7).

Because $Y|Y_-, I_i$ is Normally distributed, its probability density function can be written as

$$g(Y|Y_-, I_i) = \frac{\sqrt{\kappa_+}}{\sqrt{2\pi}} \exp\left(-\frac{\kappa_+ (Y - \mathbb{E}[Y|Y_-, I_i])^2}{2}\right),$$

where $\kappa_+ = Var(Y|Y_-, I_i)^{-1}$ (constant for simplicity) and

$$\mathbb{E}[Y|Y_-, I_i] = \mathbb{E}[Y|I_i] + \rho_Y \big(Y_- - \mathbb{E}[Y_-|I_i]\big),$$

which comes from the fact that $(Y, Y_-)|I_i$ is joint Normally distributed and $\rho_Y \equiv \frac{\partial \mathbb{E}[Y|Y_-, I_i]}{\partial Y_-}$ (constant for simplicity).

Based on the formula of $f_\theta(Y_-|I_i)$ above and the definition of subjective probability density function $h_\theta(Y|I_i)$ in (8), we have

$$h_\theta(Y|I_i) = \sqrt{\frac{\kappa_+(\kappa+\theta)}{2\pi\left(\kappa_+\rho_Y^2 + (\kappa+\theta)\right)}} \exp\left(-\frac{\frac{\kappa_+(\kappa+\theta)}{\kappa_+\rho_Y^2+(\kappa+\theta)}(Y - \mathbb{F}_i[Y|I_i])^2}{2}\right),$$

where

$$\mathbb{F}_i[Y|I_i] = \mathbb{E}[Y|I_i] - \rho_Y \frac{\theta}{\kappa+\theta}(\alpha_I(I_i) - \mathbb{E}[\alpha_Y(Y_-)|I_i]),$$

which is the subjective inflation forecast in (9).

(10) **and** (11)**.** We can always write

$$\alpha_I(I_i) = a_0 + aX_i + \varepsilon_i^a,$$

where $a = \frac{Cov(\alpha_I(I_i), X_i)}{Var(X_i)}$ and $Cov(\varepsilon_i^a, X_i) = 0$. (7) and (9) together with the fact that $\alpha_Y(Y_-) = -Y_-$ then imply

$$\mathbb{F}_i[Y_-|I_i] = (1-\omega_\theta)\mathbb{E}[Y_-|I_i] - \omega_\theta(a_0 + aX_i + \varepsilon_i^a)$$
$$\mathbb{F}_i[Y|I_i] = \mathbb{E}[Y|I_i] - \omega_\theta\rho_Y\mathbb{E}[Y_-|I_i] - \rho_Y\omega_\theta(a_0 + aX_i + \varepsilon_i^a).$$

We then study the model's implications for the regression coefficients of inflation backcasts and forecasts on the household-level variable X_i:

$$\tilde{\beta}_1^{X,-} = \frac{Cov(\mathbb{F}_i[Y_-|I_i], X_i)}{Var(X_i)} = (1-\omega_\theta)\frac{Cov(\mathbb{E}[Y_-|I_i], X_i)}{Var(X_i)} - \omega_\theta a$$
$$\tilde{\beta}_1^{X} = \frac{Cov(\mathbb{F}_i[Y|I_i], X_i)}{Var(X_i)} = \frac{Cov(\mathbb{E}[Y|I_i], X_i)}{Var(X_i)} - \rho_Y\omega_\theta\frac{Cov(\mathbb{E}[Y_-|I_i], X_i)}{Var(X_i)} - \rho_Y\omega_\theta a$$

Under the assumption of Test 1, we have

$$\tilde{\beta}_1^{X,-} = (1-\omega_\theta)\beta_1^{X,-} - \omega_\theta a$$
$$\tilde{\beta}_1^{X} = \beta_1^{X} - \rho_Y\omega_\theta\beta_1^{X,-} - \rho_Y\omega_\theta a,$$

where we use

$$\beta_1^{X,-} \equiv \frac{Cov\left(Y_-, X_i\right)}{Var\left(X_i\right)} = \frac{Cov\left(\mathbb{E}[Y_-|I_i], X_i\right)}{Var\left(X_i\right)}$$
$$\beta_1^{X} \equiv \frac{Cov\left(Y, X_i\right)}{Var\left(X_i\right)} = \frac{Cov\left(\mathbb{E}[Y|I_i], X_i\right)}{Var\left(X_i\right)}$$

as in the proof of Test 1. Because $\beta_1^{X,-}, \beta_1^X \approx 0$ in our setting, we have (10) and (11) in the main text.

Under the assumptions of Test 2′, as in its proof, we have

$$\left|\frac{Cov\left(\mathbb{E}\left[Y|I_i\right], X_i\right)}{Var\left(X_i\right)} - \beta_1^X\right| \leq \max\left\{2\frac{\sqrt{Var\left(X\right)Var\left(Y\right)}}{Var\left(X_i\right)}, \frac{\sqrt{Var\left(X\right)Var\left(Y\right)}}{Var\left(X_i\right)} + \frac{Var\left(Y\right)}{Var\left(X_i\right)}\right\} \equiv B$$
$$\left|\frac{Cov\left(\mathbb{E}\left[Y_-|I_i\right], X_i\right)}{Var\left(X_i\right)} - \beta_1^{X,-}\right| \leq \max\left\{2\frac{\sqrt{Var\left(X\right)Var\left(Y_-\right)}}{Var\left(X_i\right)}, \frac{\sqrt{Var\left(X\right)Var\left(Y_-\right)}}{Var\left(X_i\right)} + \frac{Var\left(Y_-\right)}{Var\left(X_i\right)}\right\} \equiv B_-$$

Because $\beta_1^{X,-}, \beta_1^X, B, B_- \approx 0$ in our setting, we have (10) and (11) in the main text.

C.3.2 Supply-side view of inflation

To investigate whether this can explain our findings, suppose that people's mental models have the wrong sign on the relationship between different types of information bundles and inflation: $\mathbb{F}_i[Y|I_i] - \mathbb{F}_i[Y|I_i'] = -\left(\mathbb{E}[Y|I_i] - \mathbb{E}[Y|I_i']\right)$ for any two information sets I_i and I_i'. This implies that $\mathbb{F}_i[Y|I_i] = -\mathbb{E}[Y|I_i] + C$ for a constant C.

As a concrete example, suppose that the person's information is given by $I_i = \{X_i\}$, where the household income change X_i is given by $X_i = X + \nu_i$, where X captures its aggregate component and ν_i captures its idiosyncratic component that is independent of X and Y. If all variables are jointly normally distributed, and people think that the correlation between Y and X has the opposite sign of what it is in reality, then $\mathbb{F}_i[Y|I_i] - \mathbb{F}_i[Y|I_i'] = -\left(\mathbb{E}[Y|I_i] - \mathbb{E}[Y|I_i']\right)$. In words, even if inflation and household income changes positively co-move in our sample because they are mostly driven by positive demand shocks, the person perceives them as negatively co-moving, as if they are driven mostly by supply shocks.

Let $\tilde{\beta}_1^X$ denote the coefficient on X_i from the forecast regression (2) based on the subjective forecast $\mathbb{F}_i[Y|I_i]$ and let $\tilde{\beta}_1^{X,RE}$ denote the coefficient that would result if people had rational expectations $\mathbb{E}[Y|I_i]$. Our assumptions imply that $\tilde{\beta}_1^X = -\tilde{\beta}_1^{X,RE}$, and thus that

$$\begin{aligned}\left|\tilde{\beta}_1^X - \beta_1^X\right| &= \left|\tilde{\beta}_1^{X,RE} + \beta_1^X\right| \\ &\leq \left|\tilde{\beta}_1^{X,RE} - \beta_1^X\right| + 2\left|\beta_1^X\right|\end{aligned}$$

Thus, the bounds derived in our Test 2 can increase by at most $2\left|\beta_1^X\right|$, even if people completely misinterpret the sign of the relationship between income changes and inflation. Given that we estimate $\left|\beta_1^X\right|$ to be much smaller than $\left|\tilde{\beta}_1^X - \beta_1^X\right|$, simply having "wrong-sign" cannot explain our excess sensitivity results. Additionally, this cannot explain our ER visit evidence, which suggests a more general mechanism (outlined above) whereby negative affective experiences lead to more pessimistic forecasts.