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 selective recall cued by affective association. 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 violates general tests of 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).

We focus on household income changes for several reasons. First, these events are salient and consequential for households' economic decisions and welfare. Second, establishing that these largely idiosyncratic events nevertheless influence people's forecasts constitutes a particularly important challenge for theories of belief formation. Third, income changes can be measured well with appropriate administrative data from tax authorities, which facilitates robust empirical analysis.

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 other macroeconomic and 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 and other variables which we use later to explore mechanisms related to memory. The link to the Danish administrative registry data provides detailed data on households' past, present, and future income and assets from the Danish Tax and Customs Authority (SKAT), adverse health events, which we use in an extension of our analysis, and a rich set of demographics. The linkage between the consumer expectations survey and the rich administrative registry data makes Denmark an ideal laboratory; to our knowledge, such linkages are not yet feasible, for example, with commonly used US surveys.[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

[1]For example, the University of Michigan Survey of Consumers, the NY Fed Survey of Consumer Expectations, the Survey of Professional Forecasters, and the Blue Chip Survey.

rational expectations encompasses both the standard benchmark of full information rational expectations (FIRE), as well as a broad class of models in which people form Bayesian forecasts using limited information, including rational inattention or memory constraints (e.g., da Silveira et al., 2020). The tests involve regressing both actual and forecasted inflation on a household-level variable and comparing the coefficients of 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 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 of actual inflation and the inflation forecast on the household-level variable should be equal. 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. This implication holds if inflation forecasts are reported with noise, and does not require additional assumptions about functional form or the direction of causality between the household-level variables and the inflation forecast.

The second test generalizes the first and focuses on cases where the household-level variable is not fully in the respondent's information set, such as realized 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 difference between these coefficients is bounded, with the bound inversely proportional to the extent to which household-level income changes are idiosyncratic rather than correlated.

We start by investigating how actual inflation and the inflation forecast covary with recent changes in total household income, as well as related variables such as labor 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 implied by the second test, largely due to the idiosyncratic nature of household income changes.

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 (though remains marginally significant) 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 (Patton and Timmermann, 2010; Das et al., 2020; Farmer et al., 2023)—which we refer to as *prior bias*: an association between people's prior biases about inflation and income growth trajectories cannot explain this set of regression results; instead, people's inflation forecasts appear to be excessively sensitive to changes in their income.

A natural next question is whether inflation forecasts covary with *expected* future income changes in a manner similar to recent income changes. Our next set of tests thus examines 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. Responses were on a 1 to 5 scale, ranging from "will be a lot worse" to "will be a lot better." To validate our analysis, we first show that responses to this question contain significant information about future income changes. The changes in households' log nominal income between the year after the survey response versus the year before increases significantly, on average, with each value on the scale. Because survey responses, by definition, do not contain information not in a respondent's information set, our first test implies that, under rational expectations, regressing actual and forecasted inflation, respectively, on the survey proxy for expected future income changes will yield identical coefficients. Instead, and analogous to our first result, we find that the coefficient in the actual inflation regression is tightly estimated to be effectively zero, while the coefficient in the inflation forecast regression is significantly negative. We complement this result with a replication in the Michigan Survey of Consumers, where many respondents are sampled twice. This allows us to use fixed effects regressions to rule out the possibility that the relationship between inflation forecasts and forecasted finances changes is entirely driven by some people being persistently more optimistic (pessimistic) about both the economy and their own finances.

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 of 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, people's inflation forecasts also appear to comove excessively negatively with news about their future income changes.

In the second part of the paper, we investigate mechanisms behind 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 forecasts 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 study 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 of 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 an important channel through which household-level events influence backcasts and forecasts is through *affective association*: negative (positive) household-level events generate negative (positive) affect, which, in turn, lead 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 role 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 selective recall cued by affective association. 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. The recalled inflation experience is then used to form inflation backcasts and forecasts. We provide additional survey evidence supporting the model's assumptions and predictions. First, personal experiences shape inflation expectations as much as macroeconomic factors. Second, positive (negative) cues are more likely to trigger the recall of positive (negative) events. Third, positive (negative) cues are more likely to trigger the recall of high (low) inflation.

Our paper contributes to the literature that studies how economic forecasts deviate from Bayesian updating.[2] Bordalo et al. (2020) show that, at the household level, revisions in fore-

[2]There is a large literature rejecting 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

casts 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 (2022) show that forecasts initially underreact but then overreact to macroeconomic shocks. This paper identifies excess sensitivity to household-level shocks as contributing to rational expectations violations. Andrade et al. (2022) document that French manufacturing firms' macroeconomic forecasts respond persistently to industry-level shocks that have no aggregate effects. They explain the findings through the lens of a limited-information rational expectations model motivated by Lucas (1972), where firms rationally confuse industry-level and macroeconomic shocks in a manner consistent with Bayesian updating.

Our paper also complements studies of how personal experiences affect economic decisions and macroeconomic expectations (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) by focusing on different, but universally experienced household-level events—household income changes and health shocks, (iii) leveraging a link to detailed and rich administrative panel data on household experiences, rather than relying on less-detailed survey-reported outcomes or macroeconomic trends,[3] and (iv) studying how experiences in one domain affect economic expectations in a different domain.[4]

Methodologically, our paper contributes to a recent set of papers that exploits links between consumer expectations surveys and the administrative data. Caplin et al. (2023) and Lee and Sæverud (2023) study subjective earnings expectations and compare them with actual realizations. Vellekoop and Wiederholt (2019) find that higher inflation expectations are associated with reduced saving and increased expenditure. Caplin et al. (2024) and Briggs et al. (2024) develop novel methodology for combining survey and administrative data.

Our paper also contributes to theories of belief formation and overreaction, which include the papers that we summarize above; see Barberis (2018) and Benjamin (2019) for further reviews. In particular, we contribute to the line of work that links forecasting biases to imperfect memory (e.g., Bénabou and Tirole, 2002, 2004; Mullainathan, 2002; da Silveira et al., 2020; Zimmermann,

due to limited information or systematic deviations from Bayesian updating.

[3]We also directly address potential noise in survey data, which can cause bias in regression analysis (Gillen et al., 2019; Kučinskas and Peters, 2022; Juodis and Kučinskas, 2023). We do this both by developing rational expectations tests that are robust to potential noise and by leveraging administrative tax data where any potential reporting error is minimal.

[4]In recent work on cross-domain extrapolation, Binder and Makridis (2022) and Cenzon (2025) find that rising gas prices and personal credit rejections, respectively, lead to pessimism about the macroeconomy. Tsiaplias (2021) finds that inflation forecasts are negatively related to self-reported household income changes over the past twelves 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.

2020; Gagnon-Bartsch et al., 2021; Huffman et al., 2022; Afrouzi et al., 2023; Sial et al., 2023). Within this line of work, studies particularly related to ours examine how associative memory influences forecasts (Bordalo et al., 2018, 2020, 2024, 2023; Enke et al., 2024); these papers focus on associations formed through representativeness rather than affect. D'Acunto and Weber (2024), Gennaioli et al. (2024), Link et al. (2024), and Salle et al. (2024) also 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. (2024) document that a rising market prompts investors to recall past experiences more positively, leading to more optimistic expectations of future stock returns. Finally, our paper contributes more generally to work on bounded rationality in macroeconomics (e.g., Ameriks et al., 2003; Woodford, 2013; Gabaix, 2014, 2019, 2023).

The rest of the paper is organized as follows. Section 1 describes the data. Section 2 sets up a template for analysis. Sections 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 4 provides a unified explanation of empirical results and additional supporting survey evidence. Section 6 concludes.

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

[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.

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.

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. 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 with the question:

Q: How do you think prices will be in a year compared to today?

Respondents can 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 implied a price change. If the answer implies a price increase (that is, answers 1, 2, or 3), the respondent is then asked to quantify it in percentage points with the following question:

Q: By what percentage do you think prices will go up in the next 12 months?

Responses are recorded through a number box. If the response implies that prices remained unchanged, the response to the quantitative percentage change question is automatically attributed to be 0 and the survey skips to the next question. Finally, if the answer implies a reduction in prices, the respondent is asked to quantify the price decrease in the number box.[6] For all Likert questions, a *Do not know* option is available only if the respondent attempts to skip the question. In this case, an error message appears, and the option is added to the list of possible responses.[7]

Perceptions of past inflation (backcasts) are elicited in a similar way, starting with

Q: How do you think prices are today compared to a year ago?

Possible answers are: *1-Much Higher*, *2-Somewhat Higher, 3-A bit higher*, *4-Unchanged,* and *5-A little lower.* If the answer implies a price increase (that is, answers 1, 2, or 3), the respondent is then asked to quantify it in percentage points with the following question:

[6] If the answer to the Likert question is *"A little lower",* the quantitative elicitation changes to *"By what percentage do you think prices will fall in the next 12 months?".*

[7] The fraction of *Do not know* answers is below two percent for all our main Likert questions. Overall, 9.2 percent and 8.1 percent of the responses to the numeric inflation forecast and backcast elicitations, respectively, are unusable due to non-response. In Table A1, we document the fraction of missing answers for all key survey questions.

Q: By what percentage do you think prices have gone up in the last 12 months?

If the respondent instead answers *4-Unchanged,* the quantitative percentage change question is automatically attributed to be 0 and the survey skips to the next question. If the answer is *5-A little lower*, the respondent is asked to quantify the price decrease in the number box.[8]

The Consumer Expectations Survey also includes questions about changes in household financial situation:

Q: How has the financial situation of your household changed over the last 12 months?

Q: How do you expect the financial position of your household to change over the next 12 months?

Possible responses lie in a 5-point Likert scale ranging from *1-Much Better* to *5-Much worse.* The Consumer Expectations module also includes several other Likert questions about beliefs about the general economic situation of the Danish economy and about future unemployment, plans to save, and plans for large consumption (housing, renovations, cars, and other big purchases). Since these questions are not the focus of our analysis, we describe them in Appendix A.3.

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). Both wage income and household-level balance sheet data are subject to third-party reporting. Further, tax evasion is very low in Denmark (Kleven et al., 2011). For these reasons, the data are considered to be of very high quality. We construct yearly measures at the household level of total income, labor income, liquid assets, and net wealth. Total income is measured before taxes and labor market contributions, and it 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.[9] 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 assets capture the net value of total financial assets, excluding cash and foreign assets.[10] 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

[8] If the answer to the Likert question is *"A little lower",* the quantitative elicitation changes to *"By what percentage do you think prices have fallen in the last 12 months?".*

[9] 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.

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

SKAT at the end of each fiscal year.[11] All economic quantities are reported at the individual level using unique anonymized CPR codes (i.e. the Danish correspondent of Social Security Numbers). To aggregate the economic variables at the household level, we look for the presence of a spouse in the Danish Civil Registration System (CPR Registeret). 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.[12]

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.[13]

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. The registry is maintained by the Danish Health Data Authority for administrative purposes such as monitoring public health and hospital activity. 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.[14] In Appendices B.3.4 and B.4.7, 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;[15] (ii) if they declined to answer any of

[11] 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.

[12] 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 16% respondents experience marriage transitions in years around survey response. Second we show robustness of all our main results by excluding all respondents who did experience marriage transitions in the years around survey response (See Column 4 for Table 2 and Column 4 in all tables in Appendix B.4.2).

[13] We use the 2011 revision of ISCED codes with nine possible values ranging from "less than primary schooling" to "doctoral studies".

[14] 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.

[15] 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

the key survey forecast or backcast questions mentioned above;[16] (iii) if there is missing income or demographic information. Overall, we have 55171 survey responses satisfying our age restrictions between 2012 and 2019. After imposing the additional restrictions and trimming income changes, we are left with 35050 usable responses. We evaluate the effect of each sample restriction in Table A2.

For our analysis, a key household-level variable is recent changes in households' log nominal income. 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 that occurred before the interview.[17] Similarly, we measure future log nominal income changes by comparing log nominal incomes in years $t+1$ versus $t-1$.[18] In the appendix, we show that our findings remain valid when focusing on recent and future changes in households' log real income, as well as on changes in net-of-tax income.

We construct similar measures of income changes using only labor income. Because net assets are potentially negative, we use hyperbolic sine transformations, rather than logarithmic transformations, to construct changes in total liquid assets and net wealth. We use these additional household-level changes to study which specific changes in households' economic situation affect inflation expectations. Finally, we trim all income changes at the 2.5 and 97.5 percentiles.[19]

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.

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

more prone to misreporting in our tax data (Kleven et al., 2011).

[16] 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).

[17] Because income at time t is measured at the end of the year, we opt to compare income at years $t-1$ and $t-2$ to make sure that recent income changes are fully observed by respondents. If we were to compare income at t and $t-1$, respondents interviewed towards the end of the year would already know the realization of their income for year t, while respondents contacted at the start of the year would not have had a chance to observe their year t earnings. This is consequential for the rational expectations test developed in Section 2.

[18] 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, the past income, $t-1$, is already fully realized at interview while the future income, $t+1$, lies fully in the future.

[19] 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 that are in the 2.5 and 97.5 percentiles (relative to the full sample before trimming the income changes). For analyses studying wealth changes, we trim the changes analogously.

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 both our sample, the set of contacted individuals, and the population.

Table B.2 provides summary statistics for 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.

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 the tests employed for testing rational expectations.

In our empirical analysis, our 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, as we explain further below. 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 formal rational expectations tests, 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 define the null hypothesis of rational expectations as the survey elicitation of subjective belief of person i about Y 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, and η_i captures idiosyncratic noise or measurement

error in the survey elicitation. The Bayesian forecast $\mathbb{E}[Y|I_i]$ restricts that households update their beliefs in a Bayesian fashion based on the information in I_i given a correct prior. Deviations from rational expectations can arise from both excessive sensitivity to information I_i and prior bias (Patton and Timmermann, 2010; Das et al., 2020; Farmer et al., 2023), meaning that persistent over-pessimism or over-optimism, independent of available information.

This definition generalizes full-information rational-expectations (FIRE), which is the special case in which the information set I_i incorporates all available information in the economy. It also allows the possibility that 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 Bayesian updating with memory constraints (e.g., da Silveira et al., 2020).

We provide two formal tests of rational expectations in (1). 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 two 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 in* (1) *imply that the two regression coefficients in* (2) *are equal $\beta_1^X = \tilde{\beta}_1^X$.*

This test applies to recent, salient household-level variables plausibly in the person's information set, such as recent changes in household income and household health events. It also applies to any survey response, such as household forecasts about their financial situation changes. By design, any survey response is a function of the household information set I_i plus an idiosyncratic survey response noise, satisfying the assumption that $X_i \perp Y|I_i$.

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 implies the coefficient on X_i, $\beta_1^X - \tilde{\beta}_1^X = 0$ or, equivalently, 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 recent changes in household income but we consider an alternative information assumption, where X_i is not fully in the household's information.

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., $s_i = X_i + \varepsilon_i$, where $\varepsilon_i \perp X_i, Y$. When $E[Y|s_i]$ is linear in the signal s_i (which holds if Y and s_i are Normally distributed), the two regression coefficients in (2) are given by

$$\tilde{\beta}_1^X = \frac{Cov\left(\mathbb{E}[Y|s_i], X_i\right)}{Var\left(X_i\right)} = \frac{Cov\left(s_i, Y\right) Cov\left(s_i, X_i\right)}{Var\left(s_i\right) Var\left(X_i\right)} = \frac{Cov\left(X_i, Y\right)}{Var\left(X_i\right) + Var\left(\varepsilon_i\right)} \neq \frac{Cov\left(X_i, Y\right)}{Var\left(X_i\right)} = \beta_1^X.$$

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

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

which is small when most of the variation in X_i is idiosyncratic—i.e., when $Var\left(X\right)$ is small relative to $Var\left(X_i\right)$, where $X = \int X_i di$ is the aggregate component of X_i. This is true in our data for household income changes. Test 2 generalizes this example and encompasses several relevant cases of information about household-level income changes.

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: $X_i = Z_i + \beta Y + \nu_i$, $s_i = Z_i + \alpha Y + \delta_i$, 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.*[20]

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

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

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

We provide three examples of how Assumption 1 incorporates relevant information assumption when X_i is household income changes. The first example is the previous case that the person's

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

information is given by a noisy signal about household income changes, i.e., $s_i = X_i + \delta_i$ where $\alpha = \beta = \nu_i = 0$. The bound in equation (3) becomes $\frac{\sqrt{Var(X)Var(Y)}}{Var(X_i)}$, which is small when most of the variation in X_i is idiosyncratic—i.e., when $Var(X)$ is small relative to $Var(X_i)$. In our data, the standard deviations of Y, X, and X_i are 0.361, 0.017, and 0.538 respectively, which implies a bound of 0.021.[21]

Second, while X_i represents nominal household income changes in our baseline analysis, a person's information could instead be given by real household income changes, i.e., $s_i = X_i - 1/100 \cdot Y$, where $\alpha = 1/100$ and $\beta = \delta_i = \nu_i = 0$. This case arises because a rationally inattentive person might focus on economically relevant real income changes rather than nominal income changes. In our data, the bound in (3) in this case is 0.01, similar to the first case because $\alpha \approx 0$.

Third, 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 $\gamma_1 + \gamma_2 \neq 0$. This case can be nested within Assumption 1 with $s_i = Z_i = X_{i,1}$, $\alpha = \delta_i = 0$, and $\beta = \gamma_2$. One can prove that 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 for details), which implies a bound of 2×0.021 in our data.

For simplicity, Assumption 1 restricts the signal to be single-dimensional. In Appendix C.3, we extend Test 2 to a more general version of Assumption 1 where the signal is allowed to be multi-dimensional. Finally, despite (3) being a tight bound without further assumptions, it can be further tightened under the additional assumption that the household-level variable X_i is purely idiosyncratic. Under this additional assumption—which arguably well-approximates our setting—we establish a tighter bound in Appendix C.2. In that case, the coefficient of actual inflation β_1^X is necessarily zero, but the coefficient of inflation forecast (backcast) $\tilde{\beta}_1^X$ is not, and its magnitude decreases with $Var(X_i)$, as in (3).

Note that we run two separate regressions, 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

[21] These standard deviations are calculated when X_i represents future changes in household income. When X_i represents recent changes in household income, , the standard deviations of X_i and$X$are , 0.577 and 0.009 respectively, implying a bound of 0.01.

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 in this sample. Fortunately, in our subsequent analysis, we can utilize full-population data—available over a significantly longer period starting from 1991—to provide an 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 above.

3.1 Inflation Forecasts Recent Changes in Household Income

We start with the association between inflation forecasts and recent changes in household income. As discussed in Section 1, 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 of survey response. Following (2), we regress realized inflation (Y) and forecasted inflation ($\mathbb{F}_i[Y|I_i]$) over the 12 months following the survey response on recent changes in household's log nominal income (X_i).

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. Column 2 of Table 1 presents an analogous regression, except we utilize the full population sample, for the years 1991 to 2019. In both columns, the coefficients of 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. Specifically, Column 3 presents the regression without controls. Column 4 includes demographic controls: age, highest level of education, gender, number

of children, and deciles of income level.[22,23] 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 include calendar-month fixed effects, as it is done in some related work (e.g., Gennaioli et al., 2016; Kuchler and Zafar, 2019).[24] Column 6 uses the longest available series of inflation forecasts in our survey data, starting in calendar year 2008 and encompassing the Great Recession.

All four regressions find large and negative associations between inflation forecasts and recent changes in household income, $\tilde{\beta}_1^X \ll 0$. Moreover, the coefficient of inflation forecasts on recent income changes is an order of magnitude larger than the coefficient of inflation forecasts on recent income changes, $\left|\tilde{\beta}_1^X\right| \gg \left|\beta_1^X\right|$. Figure 1 provides a binned scatter plot of the relationship between inflation forecasts and recent income changes, based on the Column 4 specification.[25] The magnitudes in the associations between inflation forecasts and recent changes in household income are comparable to known associations between recent changes in household income and inflation forecasts, education level, or gender—see Appendix Table B.4 for a replication in our data. The estimates in Columns 4 and 6 are very similar, suggesting that extending the sample to include major macroeconomic events, such as the Great Recession, does not significantly affect our results.

Recent changes in households' income are salient household-level events, plausibly within the household's information set. From the perspective of Test 1, rational expectations then imply that $\beta_1^X = \tilde{\beta}_1^X$, clearly rejected by our empirical evidence. Even without requiring the household-level variable to be within the person's information set, Test 2 shows that rational expectations imply the bound $|\beta_1^X - \tilde{\beta}_1^X| \leq 0.01$, again rejected by our empirical evidence. Intuitively, because most of the variation in X_i is idiosyncratic ($Var(X) \ll Var(X_i)$), X_i cannot have significant predictive power for Y under rational expectations.

Deviations from rational expectations document in Table 1 can arise from both excessive sensitivity to recent changes in household income or prior bias. Specifically, the latter could, in principle, explain our empirical evidence if households with higher income growth trajectories have a biased lower prior in their inflation forecasts. 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.,

[22] We control for age linearly, and include fixed effects for the other variables.

[23] 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.

[24] 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-year 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.

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

2021a and D'acunto et al., 2023a; see Appendix Table B.4 for replication in our data), and income growth trajectories may differ along those demographics as well. But further investigation does not support this explanation based on prior bias. Comparing the uncontrolled regression in Column 3 with the regression in column 4, which includes demographic controls, the coefficient of recent income changes increases rather than decreases in magnitude when such controls are included. 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 $t-10$.[26] 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. Together, we find that excessive sensitivity to recent changes in household income better explains 1, paving the way for our affective association hypothesis later.

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 individuals whose recent 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 individuals who have not experienced any changes in employment status in years $t-1$ and $t-2$, while the third column considers individuals who have experienced a transition in employment status in years $t-1$ and $t-2$. These two columns provide insight into the types of household income changes that drive our results. We focus on employment transitions because these are often modeled as separate from other types of income shocks in the literature (e.g., Guvenen et al., 2021). Column 4 considers individuals without transitions to retirement, or without transitions in 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 individuals with above-median versus below-median 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 the at least ninety percent of their household income is labor income in the years $t+1$ to $t-2$. Columns 10 and Columns 11 consider individuals with positive and negative net wealth in year t, respectively. Column 12 considers respondents who are public employees, and whose incomes are not subject to local economic shocks. This last subsample is of interest because if some respondents answer the survey with forecasts of local rather than national inflation, then we

[26] Again, we avoid having the years in our income changes measure overlap with the years we use to construct a measure of income levels. Thus, the most recent "past" income change we can consider starts in year $t-6$.

might see a different association for respondents whose incomes are not subject to local shocks.[27] Alternatively, public employees' inflation forecasts might be more sensitive to their income changes if they believe that their incomes better reflect national conditions.

Overall, Table 2 shows that our results are robust to various sample restrictions, and the coefficient of recent income changes is meaningfully lower than our baseline estimate in only a few cases.[28] The first case is individuals with some unemployment leave in years $t-1$ or $t-2$. This regressions suggests that employment transitions do not contribute to our main result because individuals 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. Third, the point estimate for net savers is meaningfully larger than for net borrowers. This is consistent with the affective association hypothesis—fleshed out in Section 5—that positive income changes lead to lower inflation forecasts because people perceive inflation as "bad." Inflation is particularly bad for net savers, because it erodes the real value of their savings, while it is potentially helpful to net borrowers, because it reduces the real burden of their debt.

Table 3 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. 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?[29] The rescaled coefficient, presented in Column 5 of Table 3, 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.[30]

Appendix Table B.7 further extends Table 1 by considering other ways in which the household

[27] It is, however, unlikely that there are large difference between local and national inflation in Denmark, given the small size of this country.

[28] For example, Column 12, based on public employees, shows that our results cannot be explained by the possibility that respondents report forecasted local inflation, which they believe is strongly related to their income changes because both are driven by local shocks.

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

[30] 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.

financial situation changed in the recent past: changes in liquid assets and changes in total assets (see Section 1.2 for definitions and construction). 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 assets are not strongly associated with either actual or forecasted inflation, consistent with the hypothesis that these changes are not as salient as income changes.[31]

Appendices B.3.4, B.3.5, and B.3.6 include several other robustness checks, replicating our main results. First, we replicate all specifications in Table 1 after including the years 2008-2011, covering the Great Recession, where inflation was more volatile. Second, we consider real income changes rather than nominal income changes. Third, we consider changes in net-of-tax income rather than gross income.

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? The answer to this question is a priori unclear. There are reasons why inflation forecasts may associate less strongly with expected income changes than with recently realized income changes. First, recently realized income changes may be much more salient and top-of-mind than news about future income changes. Second, results from the literature on experience effects suggest experienced income changes can alter the strength of neural connections in a way that news about future income changes cannot (see, e.g., Malmendier, 2021). As a result, recently realized income changes may have larger effects on people's forecasts. On the other hand, news about future income changes can be salient as well, and people may perceive a closer relationship between future inflation and future rather than past household income changes.

Our analysis here consists of two sets of tests, corresponding to two types of proxies for expected future changes in household income, which are not directly observed. First, we consider how inflation forecasts relate to qualitative survey forecasted changes in household financial situation (which are shown are 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. As a preliminary step, we first show that people possess information about changes in future household income and that this information is reflected in responses to the survey question "*How do you expect the financial position of your household to change over the next 12 months?*" The possible responses to this question were on a 1 to 5 scale (see Section 1.1). Figure 2 shows that responses to this question are

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

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 of survey response. 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 "will be a lot better" and respondents answering "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.11 presents regressions, with various sets of controls, that quantify the patterns in Figure 2. Importantly, Appendix Table B.11 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 Figure B.2 and Appendix Table B.16 show that these results are robust to alternatively using real income.

Inflation forecasts and forecasted changes in household financial situation. We now study the association between inflation forecasts ($\mathbb{F}_i[Y|I_i]$) and forecasted changes in household financial situation (X_i), which have just been documented as a survey proxy for expected future changes in household income, and compare it with the association between actual inflation (Y) and the same survey proxy. 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 4 present our main results. Figure 3 plots forecasted and actual inflation for each of the five values that the survey's forecasted changes in household financial situation (X_i) can take. Table 4 presents regressions of actual and forecasted inflation on X_i.[32] Both Figure 3 and Table 4 show that while actual inflation is effectively not associated with X_i, inflation forecasts are nevertheless significantly negatively associated with it. Table 4 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 2, our empirical evidence rejects rational expectations.

Similar to the discussion in the previous subsection, the deviations from rational expectations can in principle be explained solely by 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 survey question about future household financial situation changes.[33] The question in the Michigan

[32]We simply treat the survey forecast X_i as a variable that takes on the values $1, 2, 3, 4, 5$ (with 1 denoting the worst possible outcome and 5 denoting the best possible outcomes.). In principle, Test 1 permits us to regress on any transformation of 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.

[33]In our sample, 90.2 percent of respondents complete the follow up survey.

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.15 present results for this analogous question, finding similar results. Moreover, because respondents are sampled twice in the Michigan survey, we are able to include survey respondent fixed effects in Columns 5 and 6 of Appendix Table 4. The relationship between inflation forecasts and X_i 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. At the same time, the dampening of the coefficient of X_i implies that some of the relationship between inflation forecasts and X_i is driven by across-respondent differences in how optimistic (pessimistic) they are about both inflation and their household finances 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 is 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. This, in turn, could leave open the possibility that some of the association between inflation forecasts and this survey question is driven by the beliefs about other variables that it reflects. 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 is 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 $t-1$ (X_i), 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 5 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 of 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 bounds 0.021 provided in Test 2.

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 househol income. Appendix Table B.12 presents subsample analysis for forecasted changes in household financial situation while Appendix Table B.13 presents results for realized future income changes. Qualitatively, the results are analogous to the results for recent income changes. Table B.14 studies realized future *labor* income changes. The results are again analogous to those for recent labor income changes, as studied in Table 3. Tables B.19 and B.20 show that the results are robust to starting in 2008 across all specifications. Table B.17 shows that using real rather than nominal future income changes does not alter our results. Appendix Table B.18 demonstrates that results are also robust when considering net-of-tax income changes.

In sum, across two different types of analyses, we again find stark violations of rational expectations for expected future changes in household income. Proxies of expected future income changes are strongly negatively related to inflation forecasts but have effectively no predictive power for realized inflation.

4 The Role of Imperfect Recall and Affect

In this section, we provide additional evidence regarding 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 Survey: the elicitation of survey participants' recollections of inflation over the past 12 months ("backcasts").[34] The next set of results is facilitated by establishing a novel link between the survey and data on emergency room (ER) visits. These results motivate our unified explanations in the next section, where inflation forecasts are shaped by selective recall cued by affective association.

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. Figure 5(b) provides initial, suggestive evidence that memory is imperfect, and Figure 5(a) suggests the imperfections in memory may explain some of the forecasting errors.[35]

We now examine the association with household income changes, as in Section 3, using inflation backcasts, rather than forecasts, as the dependent variable. Table 6, panels (a) through (c), presents regression analyses that are analogous to those in Tables 1, 4, 5, respectively. Figure 6 presents

[34]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.

[35]Results in Figure 5a and Figure 5b can be viewed versions of Test 1 where X_i is a survey response. Results indicate that inflation forecasts are backcasts and are not formed in a Bayesian manner given households' information available at the time of the survey response (which may be limited due to imperfect attention or memory).

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.

The results in Table 6 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 have imperfect memory, but utilize their recalled/available information efficiently and in a Bayesian manner when forming predictions about past events. Such "sophistication" is assumed in a variety of theoretical work on imperfect memory, including Bénabou and Tirole (2002, 2004), Gottlieb (2014), and da Silveira et al. (2020). Under this assumption, the recalled events are just a part of people's information sets, and Tests 1 – 2 characterize the implications of rational expectations for predictions about past events.

Third, the Table 6b,c results on the association between inflation backcasts and expected changes in future income reject the possibility that individuals 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 6(b),(c).

Further more, a comparison of Table 6 with Tables 1, 4, and 5 shows that backcasts covary more strongly with our household-level income change measures than do forecasts. Figure 7 presents the ratio of coefficients of our income change measures from our backcast regressions (Table 6, panels (a), (b), (c), respectively) versus forecast regressions (Tables 1, 4, and 5, respectively), using the specifications with demographic controls but without calendar-month fixed effects. We find that the ratio is above one for regressions corresponding to each of our three tests, indicating that backcasts are more sensitive than forecasts to household-level income changes. Additionally, Table B.31 shows that the relationship between our income change measures and forecasts is significantly dampened, or even statistically indistinguishable from zero, when controlling for backcasts.

Together, Figure 7 and Table B.31 suggest that our income change measures are associated with backcasts not merely because people's backcasts reflect their forecasts.[36] Instead, our results

[36]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 $\epsilon_i \perp X_i$, meaning that the income change measure X_i is related to backcasts only through forecasts. 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 measureX_i, the coefficient of X_i will always remain significantly negative, contrary to the results in Column 6 of Table B.31.

are consistent with the possibility that the relationship between people's forecasts and our income change measures is at least partly shaped by what people recall.

4.2 The Role of Affect

What is the channel through which our household-level income changes influence people's backcasts and hence 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, with an asymmetrically larger impact on backcasts than 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 a family ER visit. Because the sample of people who are approached by DST 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. Thus, this generates a plausibly clean natural experiment.

There are several key properties of family ER visits that make them well-suited for our analysis. 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 selection into survey non-response, but Appendix Table B.34 shows this is not the case in our sample.

Our analysis utilizes the available data on ER visits over 11 years, ranging from 2008 to 2018.[37] 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

[37] 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 registry, our sample ends in 2018.

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. Appendix Table B.35 shows that our results are robust for subsamples with demographic and/or time restrictions that match our main analysis.

On average, there are 2 visits per household in our sample period, and 0.07 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 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. Appendix Table B.37 and B.36 show, respectively, that our results are robust to instead excluding the 6 percent of households with ten or more ER visits, or the 17 percent of households with 6 or more ER visits.

We estimate the impact of a family ER visit in the survey month, including our standard set 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.[38] Table 7 presents the results. Columns (1) through (5) pool inflation backcasts and forecasts.[39] 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 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.

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

[38]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.

[39]Note that, as in all other regressions, we conservatively cluster by calendar month, which accounts for the non-independence between forecasts and backcasts in this analysis.

linearly, as in column (2), while column (7) controls for total visits flexibly via fixed effects and their interactions with age. Both columns are consistent with our findings in Figure 7 and Table B.31: a family ER visit in the survey month has a much larger impact on backcasts than forecasts, consistent with the hypothesis that affective consequences of a family ER visit in the survey month is channeled through associative memory.

Finally, one hypothesis might be that the channel through which family ER visits alter inflation expectations is that negative health shocks reduce household income, and it is the negative income change, rather than the negative health shocks themselves, that alters affect and beliefs. Appendix Tables B.38 and B.39 show that when controlling for our measures of recent or future income changes, the impact of a family ER visit on inflation forecasts and backcasts is, if anything, slightly higher.

5 A Unified Explanation

We now provide a unified explanation of the above empirical results on the excess sensitivity of inflation backcasts and forecasts to largely idiosyncratic household events by combining the roles of imperfect recall and affective association. In this explanation, households' inflation forecasts are impacted by what they recall (and hence their backcasts), which, in turn, are cued by household events through affect. Specifically, negative (positive) household-level events cue negative (positive) recollections, which lead to pessimistic, higher-inflation (optimistic, lower-inflation) backcasts and forecasts. We first discuss the explanation's cognitive foundations, then formalize it using a memory-based model of belief formation. In the next section, we provide additional survey evidence to support it.

5.1 Cognitive Foundations

At its core, our explanation relies on three key mechanisms from psychology and neuroscience: (1) memories of past experiences are encoded alongside their affective valence, (2) current affective states cue the recall of past experiences with similar affective valence, and (3) 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. Neuroscientific evidence further confirms 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 Bower (1981). According to retrieved-context theory (Kahana, 2012; Cohen and Kahana, 2022), people's current affective state, impacted by household-level events, 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.

Finally, forecasts about the future are shaped by these 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 these key psychological mechanisms and explains our empirical results. We explicitly distinguish between inflation over the past 12 months, Y_-, and inflation over the next 12 months, denoted by Y. We denote person i's inflation backcast and forecast, given information set I_i, as $\mathbb{F}_i[Y_-|I_i]$ 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 use $f\left(Y_-|I_i\right)$, $g\left(Y|Y_-,I_i\right)$, and $h(Y|I_i) = \int g\left(Y|Y_-,I_i\right) f\left(Y_-|I_i\right) dY_-$ to denote the objective probability density function of the relevant conditional distributions, which we assume to be Normally distributed. Finally, for simplicity, we also assume that Y and Y_- are demeaned: the unconditional means of Y and Y_- are zero.

Motivated by the evidence from psychology and neuroscience, we assume that the person's recall of past inflation experiences is impacted by affective association: information I_i inducing negative affect prompts the recall of episodes of price increases, which also evoke negative affect. Formally, we define the similarity between the cue I_i and an inflation state Y_- based on their difference in affect:

$$\mathcal{S}(Y_-, I_i) = \exp\left(-\frac{\left(\alpha_Y\left(Y_-\right) - \alpha_I\left(I_i\right)\right)^2}{2}\right), \tag{4}$$

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

$$f_\theta\left(Y_-|I_i\right) = \frac{f\left(Y_-|I_i\right) \times \left(\mathcal{S}\left(Y_-, I_i\right)\right)^\theta}{\int f\left(Y_-|I_i\right) \times \left(\mathcal{S}\left(Y_-, I_i\right)\right)^\theta dY_-}, \tag{5}$$

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 inflation states that have affect similar to the cue, and deflates the probability of inflation states that have affect opposite to the cue. As in Bordalo et al. (2024) and Gennaioli et al. (2024), inflation backcasts are based on experiences sampled from the distribution with density function $f_\theta(Y_-|I_i)$:[40]

$$\mathbb{F}_i[Y_-|I_i] = \int f_\theta(Y_-|I_i)\, dY_- = \mathbb{E}[Y_-|I_i] + \underbrace{\frac{\theta}{\kappa+\theta}\left(-\alpha_I(I_i) - \mathbb{E}[Y_-|I_i]\right)}_{\text{deviation from the Bayesian counterpart}}, \tag{6}$$

where $\mathbb{E}[Y_-|I_i] = \int f(Y_-|I_i)\, dY_-$ is the unbiased Bayesian estimate and $\kappa = Var(Y_-|I_i)^{-1} = \left(\int \left(Y_- - \mathbb{E}[Y_-|I_i]\right)^2 f(Y_- \mid I_i)\, dY_-\right)^{-1}$ captures its precision. (6) captures that, for example, information I_i inducing negative affect ($\alpha_I(I_i) < 0$) prompts the recall of higher inflation states and leads to higher inflation backcasts.

The person uses the recalled experiences cued by information I_i to form inflation forecasts. Specifically, the person's subjective distribution of future inflation is governed by the probability density function

$$h_\theta(Y|I_i) = \int g(Y|Y_-, I_i)\, f_\theta(Y_-|I_i)\, dY_-, \tag{7}$$

where $f_\theta(Y_-|I_i)$ is from (5) and $g(Y|Y_-, I_i)$ captures the conditional probability density of Y given Y_- and I_i.[41] This 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

$$\mathbb{F}_i[Y|I_i] = \int h_\theta(Y|I_i)\, dY = \mathbb{E}[Y|I_i] + \underbrace{\rho_Y \frac{\theta}{\kappa+\theta}\left(-\alpha_I(I_i) - \mathbb{E}[Y|I_i]\right)}_{\text{deviation from the Bayesian counterpart}}, \tag{8}$$

where $\mathbb{E}[Y|I_i] = \int h(Y|I_i)\, dY$ is the unbiased Bayesian estimate and $\rho_Y \equiv \frac{\partial \mathbb{E}[Y|Y_-, I_i]}{\partial Y_-}$ 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. (8) captures that, for example, information I_i inducing negative affect ($\alpha_I(I_i) < 0$) leads to higher inflation forecasts, as it prompts the recall of higher inflation states and higher inflation backcasts from (6).

The model provides a unified explanation of our empirical evidence. From (6) and (8), household-level events inducing positive affect lead to lower inflation backcasts and forecasts, more so with a higher theta θ. Moreover, under the plausible assumption that $\rho_Y \in (0, 1)$, inflation backcasts are more sensitive to household-level events than inflation forecasts. Finally, even cues unrelated

[40] We refer the reader to Appendix C.1 for detailed derivations of formulas in this section.

[41] 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.

to inflation ($I_i \perp Y_-, Y$) can influence subjective inflation backcasts and forecasts ($\mathbb{F}_i[Y_-|I_i]$ and $\mathbb{F}_i[Y|I_i]$) through affective association.

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 $\mathcal{S}(Y_-, s_i)$ depends on affect instead of representativeness. It is also worth noting that the above memory-based model of belief formation posits that the person takes what they recall at face value and does not account for how affective association distorts the likelihood of recall, $f_\theta(Y_-|I_i)$. Otherwise, they will undo affective-based recall and form inflation forecasts and backcasts in a Bayesian fashion.

5.3 Supporting Survey Evidence

Here, we provide additional, direct survey evidence in support of our model ingredients and predictions.

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 asked to rate the influence of various factors on their forecasts using the following 3-point Likert scale: not at all (1), a little (2), or a lot (3). Each respondent was randomly assigned 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."[42]The objective of this first elicitation was to investigate how likely respondents are to use traditional macroeconomic factors versus mostly idiosyncratic household-level experiences in forming inflation forecasts.

The next question tested the affective association hypothesis for selective recall:

> *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?*

[42]Two notes on the design of the inflation list are warranted. First, the order of factors is fully randomized to eliminate potential order effects. Second, the selection of macroeconomic factors follows the approach of Binetti et al. (2024).

Participants were randomly assigned to recall either the "negative" or the "positive" experiences. They then rated the importance of each cue in a randomized list of ten cues using a 3-point Likert scale, similar to the previous question. We randomly selected the ten cues for each respondent by drawing five from a pool of ten 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 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 modify 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 affective association with respect to selectively recalling 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 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 Liker scale. The valence of each cue was again independently randomized between positive and negative.[43]

After these main questions, we also directly tested if inflation carries a negative affective valence by asking Prolific respondents to rate how they feel about price increases.

[43]Note that cues are never shown twice, independently of their valence. For example if the cue "When I worry about my job security" is presented in in the first recall question, neither "When I worry about my job security" or its positive counterpart "When I fell confident about my job security" are shown in the second recall 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:

Responses were on a 3 point Likert sccale: (1) unpleasant, (2) neutral, and (3) pleasant.

The survey also included the following attention check, placed between our two recall questions:

Sometimes, participants do not pay attention to all the questions in the study and click through too quickly. To indicate that you are paying attention to all questions, please click the continue button without filling in any answer options below.

Participants were presented with a list of possible factors and the same 3-point Likert scale response format as in our main elicitations. Submitting any response—other than leaving the answer blank—amounted to failing the check.

Sample We fielded the survey on Prolific in October 2024, collecting 1600 submissions from participants sampled to be representative of the U.S. Census along age, gender, and ethnicity. Participants received $2 for completing the survey. The average completion time was 6 minutes and 4 seconds. We dropped 77 participants who failed our attention check, to obtain a final sample of 1523 respondents. We present summary statics in Appendix Table B.40.

Results Our first finding is that past household-level experiences 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 equations (6) and (7). We summarize the results in figure 8, and provide additional summary statistics in Appendix Table B.41. 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" ("A Little or A Lot") is 0.12 (0.31). For household-level factors, the corresponding probabilities are is 0.13 and 0.31. A similar pattern emerges when examining Likert scores, with macroeconomic factors averaging 1.86 and household-level factors averaging 1.89.[44] For instance, "Change in price of groceries" receives the highest mean Likert score among all factors (consistent with D'Acunto et al. 2021b, who find that households update significantly from the prices of their grocery baskets). By contrast, factors related to money supply and monetary policy rank lowest among macroeconomic options. "Government management of the economy" and "price gouging by firms" emerge as the most influential macroeconomic factors in respondents' assessments.

[44] Average Likert scores are computed by assigning numerical values to responses—"Not at all" = 1, "A little" = 2, "A lot" = 3—and taking the mean across respondents.

The data is also consistent with the household financial situation being a key determinant of inflation forecasts. "Feeling financially strained" ranks 4th among household-level factors, with an average Likert score of 2.11, indicating that respondents consider it as important as key macroeconomic factors such as "Household spending" (average score of 2.16), "Oil and energy prices" (average score of 2.09), and "Supply chain conditions" (average score of 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 (4) and (5) of the model. Table 8(a) reports on a linear probability model that analyzes how the 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 188% and 267% for financial and non-financial cues, respectively. Figure 9(a) provides a graphical summary of these results for each of the different cues. Appendix Table B.42 presents separate analyses for the baseline elicitation and the elicitation regarding the recall of experiences that impacted the financial situation. The results show that affective congruence is highly significant for both versions of the question.

Our third finding is that all else equal, positive cues facilitate recall of lower inflation than negative cues, and vice versa. This shows that equations (4) and (5) apply to how people form perception of inflation. Table 8(b) presents the results of a linear probability model analogous to Panel (a). 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" increase by 74% and 74% for financial and non-financial cues, respectively. Figure 9(a) provides a graphical summary of these results for each of the different cues. Consistent with the negative affective value of inflation, 87% of respondents considered inflation to be a negative experience.

We present additional findings from our Prolific survey in Appendix Section B.6.

6 Conclusion

People's forecasts of the economy are a key ingredient for forward-looking economic behaviors such as consumption, saving, and labor force participation. This paper studies to what extent people use largely idiosyncratic household-level events to guide their forecasts. Our analysis is facilitated by

establishing a previously unexploited link between the Danish Consumer Expectations Survey and administrative tax, health, and other data from the Danish registry. We find that relative to the null hypothesis of rational expectations, people's inflation forecasts covary too strongly and negatively with household recent income changes and measures of their expected changes in future income. We establish additional results that suggest that selective recall cued by affective association plays an important role in how people form their forecasts. Positive (negative) household-level events cue the recall of positive (negative) experiences, which in turn make households optimistic (pessimistic) about macroeconomic outcomes. Even adverse health events, which are unrelated to inflation, influence what people recall and forecast about inflation.

Our findings that events from one domain influence beliefs in other, sometimes completely unrelated domains challenge theories of rational expectations, as well as many behavioral economics theories of deviations from Bayesian updating. 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, and not even limited to realized past experiences—news generate analogous effects. This calls for additional investigation into the prevalence of cross-domain influences on beliefs, and the role of affect and associative memory in explaining such cross-domain influences.

Our findings can have important aggregate implications. First, our findings can help explain the "confidence channel" of the transmission of monetary and fiscal policy, as suggested by Keynes (1936) and Akerlof and Shiller (2010). That is, accommodative monetary and fiscal policy increases household income, which makes people more optimistic about the economy and leads them to further increase spending. This increase in spending could amplify the economic boom and, in turn, further reinforce confidence. This is the "confidence multiplier" envisioned by Akerlof and Shiller (2010) and Angeletos and Lian (2022). Second, as Broer et al. (2021) show, differences in subjective forecasts of the economy driven by idiosyncratic shocks lead to differences in consumption and saving decisions, which shape wealth distribution in the economy. This can have important macroeconomic implications, as shown in recent work (e.g., Kaplan et al., 2018).[45] Third, our findings also motivate the possibility that how workers respond to wage changes reflects not only the direct incentive effects, but also how wage shocks influence beliefs about the whole economy. We leave a full exploration of these implications for future work.

[45]Broer et al. (2021) explore the implications of differences in subjective forecasts due to information frictions in a model of endogenous information choice within rational expectations. Future work should formally explore the implications of non-Bayesian updating accounting for some of the differences in subjective forecasts.

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Table 1: Inflation Forecasts and Recent Changes in Household Income

	Realized Inflation next 12m		Forecasted Inflation next 12m			
	(1)	(2)	(3)	(4)	(5)	(6)
Recent Log Nominal Income Change	0.008	0.034**	-0.655***	-0.674***	-0.563***	-0.499***
	(0.022)	(0.016)	(0.139)	(0.139)	(0.136)	(0.129)
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	53365

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. 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 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	0.007	0.020	0.005	-0.004	0.011	-0.009	0.022	-0.009	0.011	0.006	-0.033
	(0.024)	(0.027)	(0.027)	(0.025)	(0.029)	(0.024)	(0.030)	(0.021)	(0.035)	(0.027)	(0.025)	(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	26108	6468	30796	18447	16603	15489	19561	17843	19849	15200	9791

(b) Forecasted inflation

	Forecasted Inflation next 12m											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Recent Log Nominal Income Change	-0.725***	-0.710***	-0.365*	-0.742***	-0.555***	-0.741***	-0.308	-0.899***	-0.843***	-0.842***	-0.500**	-0.570**
	(0.185)	(0.180)	(0.217)	(0.153)	(0.205)	(0.193)	(0.202)	(0.185)	(0.248)	(0.189)	(0.236)	(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	26108	6468	30796	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 recent log nominal income change less than the absolute value of 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. The "Simple Income" sample restricts to individuals for whom at least ninety percent of income is labor income in the years $t+1$ to $t-2$. "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 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 Recent Changes in Household Labor Income

	Realized Inflation next 12m		Forecasted Inflation 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 $t+1$ to $t-2$. 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 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 Forecasted Family Finances Changes

	Realized Inflation next 12m		Forecasted Inflation next 12m				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Forecasted Family Finances Change	-0.009*	-0.036***	-0.341***	-0.320***	-0.318***	-0.285***	-0.359***
	(0.005)	(0.009)	(0.027)	(0.027)	(0.026)	(0.024)	(0.023)
Recent Log Nominal Income Change					-0.638***		
					(0.137)		
Demog. Controls	No	No	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	53365	35050	35050	35050	35050	53365

Notes: This table presents regressions of realized and forecasted inflation over the 12 months following the survey response on the forecasted family changes variable. 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. 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 numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 5: Inflation Forecasts and Realized Future Changes in Household Income

	Realized Inflation next 12m		Forecasted Inflation 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**
	(0.019)	(0.018)	(0.105)	(0.103)	(0.106)	(0.104)	(0.096)
Recent Log Nominal Income Change					-0.762***		
					(0.143)		
Demog. Controls	No	No	No	Yes	Yes	Yes	Yes
Month FE	No	No	No	No	No	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	53365

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. 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 numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 6: Inflation Backcasts and Household-Level Income Changes

(a) Inflation Backcasts and Recent Changes in Household Income

	Realized Inflation past 12m		Backcasted Inflation 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)	(0.208)	(0.200)	(0.187)	(0.164)
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	48781

(b) Inflation Backcasts and Forecasted Family Finances Changes

	Realized Inflation past 12m		Backcasted Inflation past 12m				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Forecasted Family Finances Change	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***		
					(0.199)		
Demog. Controls	No	No	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	48781	30752	30752	30752	30752	48781

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

	Realized Inflation past 12m		Backcasted Inflation 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)	(0.130)	(0.131)	(0.134)	(0.142)
Recent Log Nominal Income Change					-0.985***		
					(0.202)		
Demog. Controls	No	No	No	Yes	Yes	Yes	Yes
Month FE	No	No	No	No	No	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	48781

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 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. All regressions are based on data from 2013-2019, except for column 2 in panels (a) and (c) where we use data for the years 1991-2019. 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 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)	0.272*** (0.084)	0.210** (0.086)	0.210** (0.086)	0.211** (0.086)	0.211** (0.086)	0.321*** (0.107)	0.321*** (0.107)
# of ER visits		0.045*** (0.007)	0.048*** (0.019)			0.045*** (0.007)	
# of ER visits sq.			-0.001 (0.003)				
I(Forecast) x I(Fam. ER visit)						-0.228** (0.101)	-0.228** (0.101)
I(Forecast)						-0.877*** (0.098)	-0.877*** (0.098)
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
Observations	91688	91688	91688	91688	91688	91688	91688

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 two observations for each survey respondent. Inflation forecasts and backcasts are expressed in percentage points. The control variables "# of ER visits" and "# 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. Since only 467 respondents answer the survey more than once, this is numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 8: Affective Association and Selecive Recall

(a) Importance of Cue in Recalling Positive/Negative Experiences

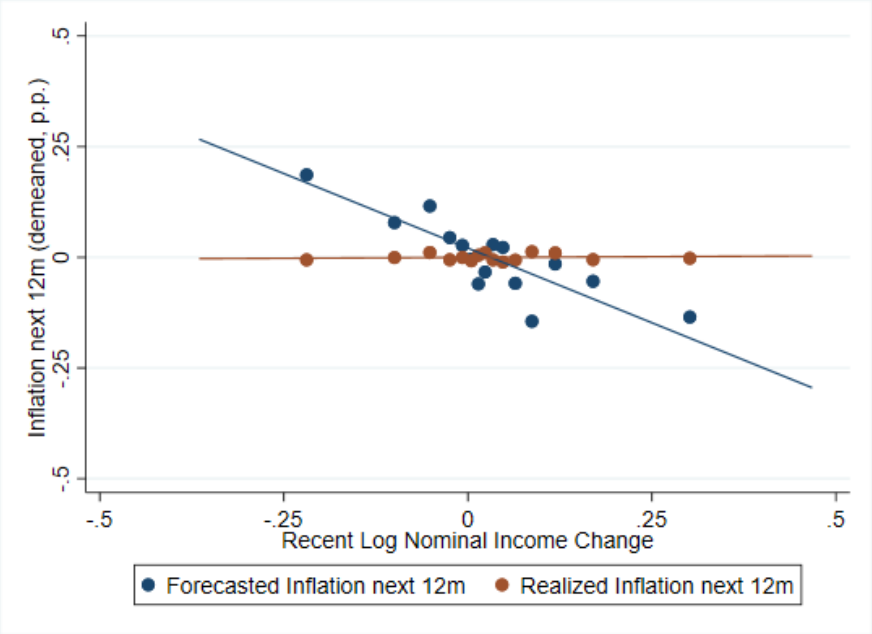
	(1) Influence a lot	(2) Influence a little or a lot
I(financial cue)	0.129***	0.404***
	(0.013)	(0.020)
I(non-financial cue)	0.098***	0.360***
	(0.010)	(0.018)
I(financial cue) x I(same valence as event)	0.242***	0.365***
	(0.023)	(0.023)
I(non-financial cue) x I(same valence as event)	0.262***	0.446***
	(0.018)	(0.020)
Observations	15230	15230
Respondents	1523	1523

(b) Importance of Cue in Recalling Low/High Inflation

	(1) Influence a lot	(2) Influence a little or a lot
I(financial cue)	0.196***	0.544***
	(0.022)	(0.027)
I(non-financial cue)	0.120***	0.380***
	(0.014)	(0.030)
I(financial cue) x I(same valence as event)	0.145***	0.190***
	(0.017)	(0.013)
I(non-financial cue) x I(same valence as event)	0.089***	0.192***
	(0.013)	(0.018)
Observations	15230	15230
Respondents	1523	1523

Notes: Panel (a) of this table presents analysis based on survey responses to the question: "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?"
Panel (b) presents 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?"
The table shows linear regression coefficients for the following analysis. We regress indicators for respondents selecting "a lot" (Column 1) and "a lot" or "a little" (Column 2) 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. Robust standard errors, clustered two ways (Cameron et al., 2011) at the respondent and cue level, are in parentheses. Results are based on the Prolific survey sample, and observations are at cue-response level. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

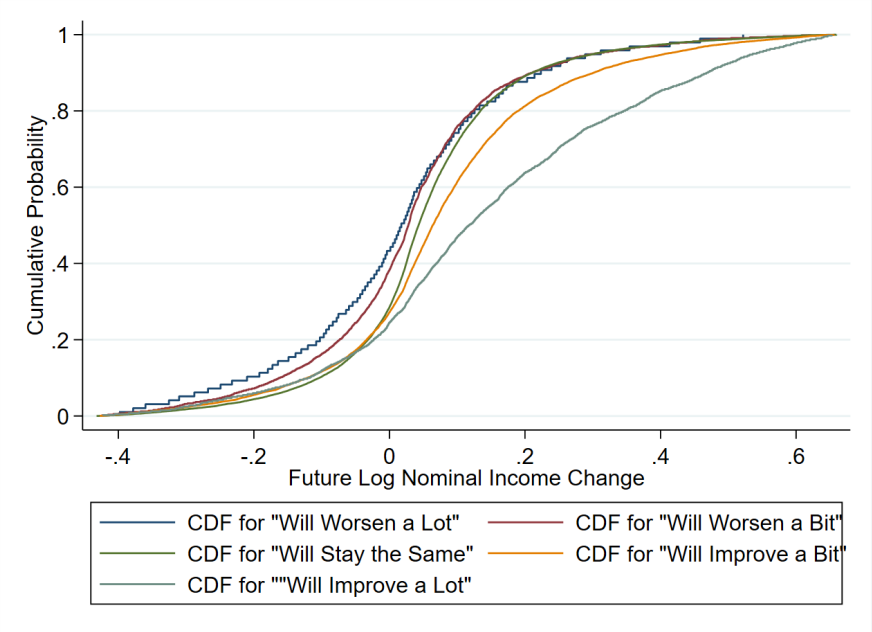
Figure 1: Realized and Forecasted Inflation and Recent Changes in Household Income



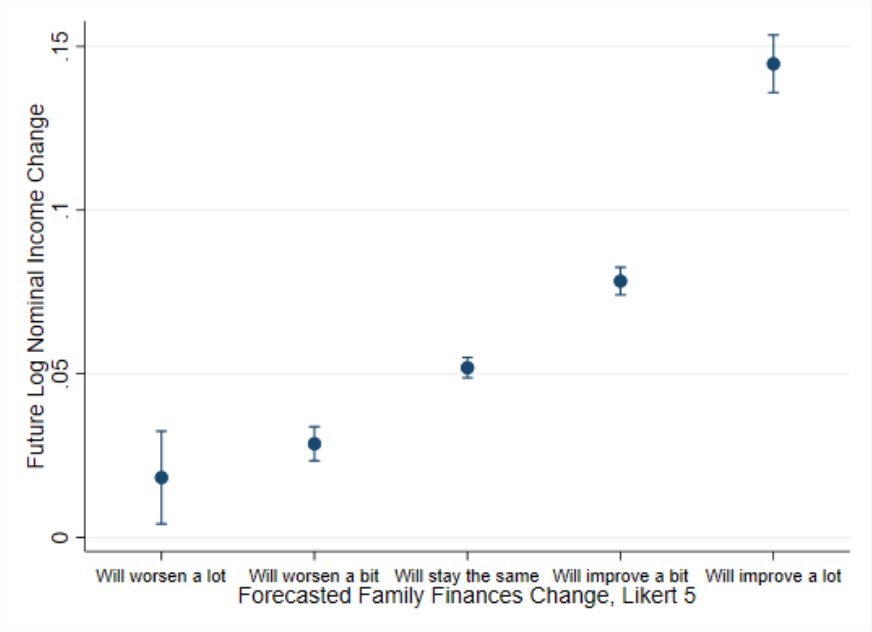
Notes: This figure presents the relationship between realized future and forecasted inflation over the 12 months following the survey response and recent log nominal income change. The relationship is plotted after partialling out demographic controls. The units of inflation and inflation forecasts are 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

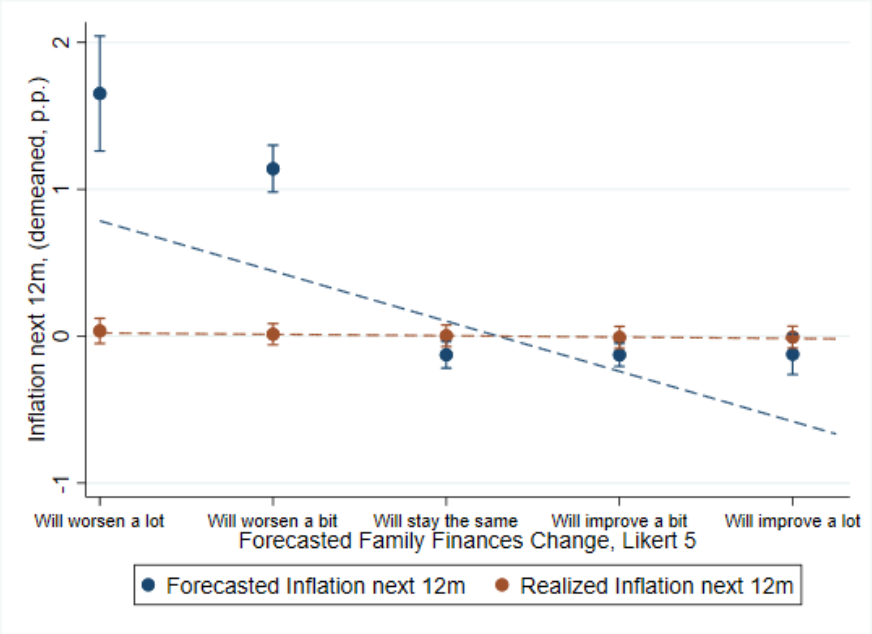


(b) Mean Future Log Nominal Income Change, by Survey Response



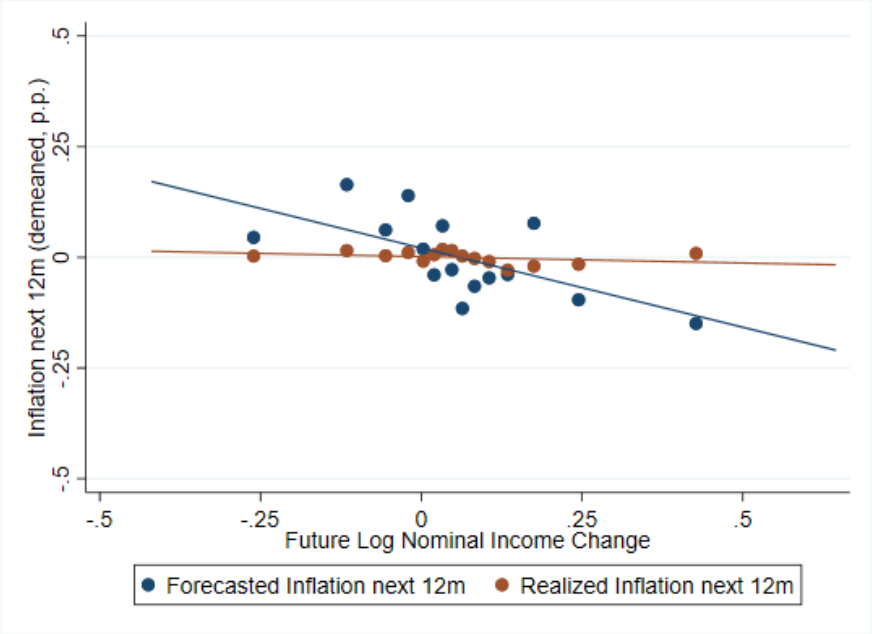
Notes: Panel (a) presents empirical CDFs of future log nominal income changes by responses to the survey question about forecasts of the future family financial situation. Panel (b) presents average future log nominal income change by responses to the same survey question. We do not add any demographic 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 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 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.

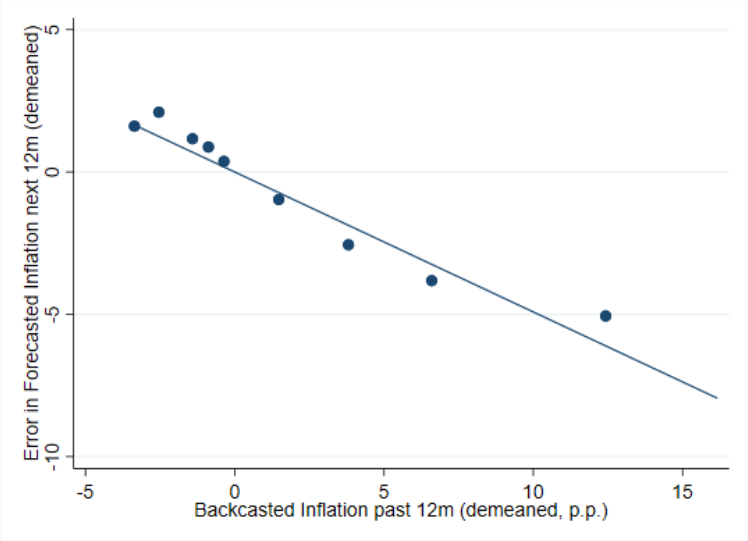
Figure 4: Realized and Forecasted Inflation and Realized Future Income Changes



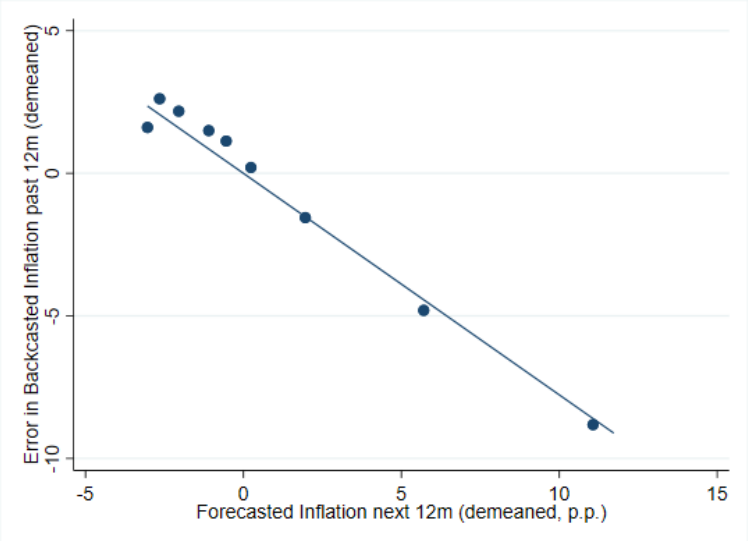
Notes: This figure presents the relationship between realized future and forecasted inflation over the 12 months following the survey response and future realized log nominal income change. The relationship is plotted after partialling out demographic controls. The units of inflation and inflation forecasts 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



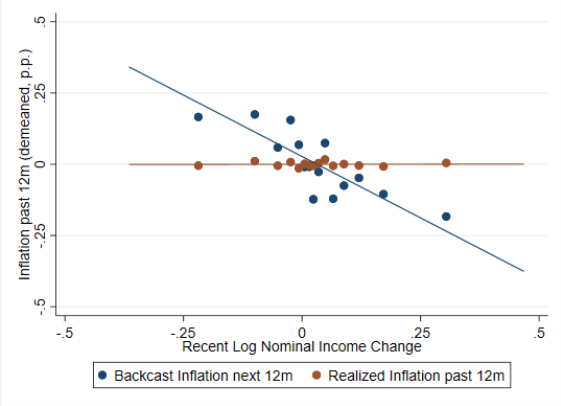
(b) Inflation Forecasts and Inflation Backcast Errors



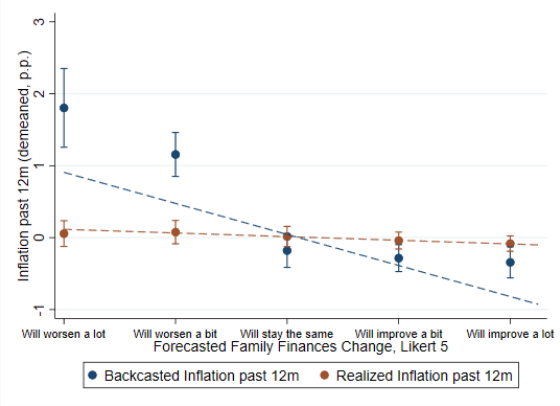
Notes: Panel (a) presents the relationship between the error in backcasted inflation over the 12 months preceding the survey response and forecasted inflation over the 12 months following the survey response. Forecast errors in inflation are calculated by subtracting the realized inflation over the 12 months following the survey response and the inflation forecasts over the same horizon. Panel (b) presents the relationship between errors in backcasted inflation and forecasted inflation. Backcast errors in inflation are calculated by subtracting the realized inflation over the 12 months preceding the survey response and the inflation backcasts over the same time horizon. 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.

Figure 6: Inflation Backcasts

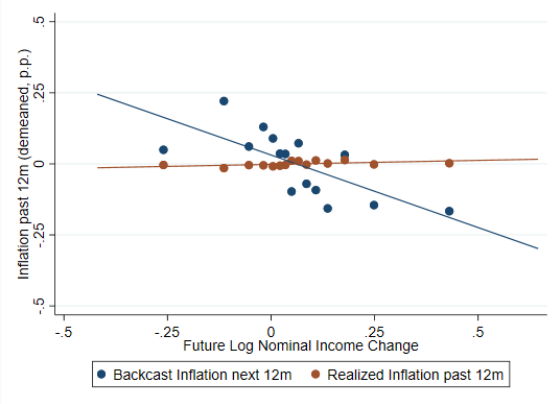
(a) Inflation Backcasts and Recent Changes in Household Income



(b) Inflation Backcasts and Forecasted Family Finances Changes

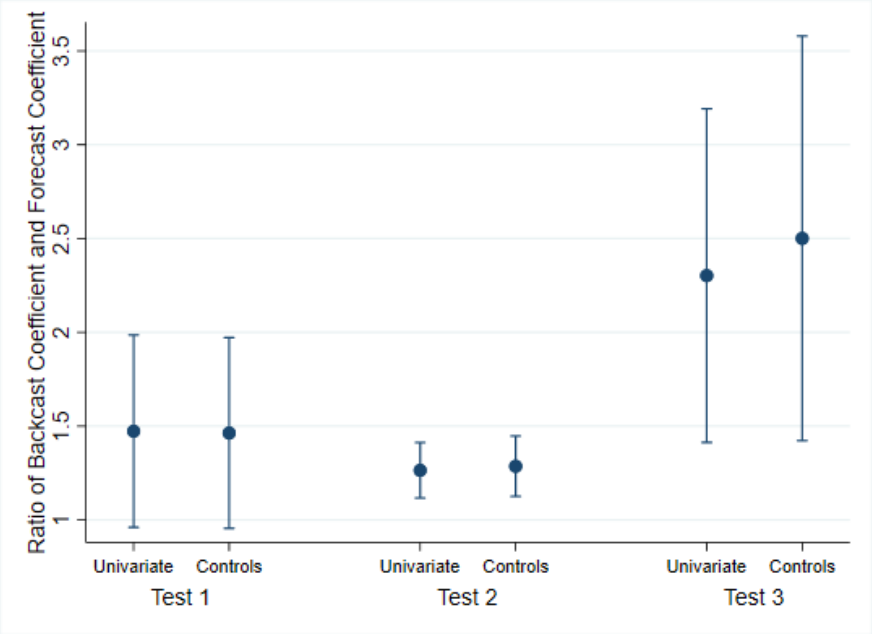


(c) Inflation Backcasts and Future Changes in Household Income



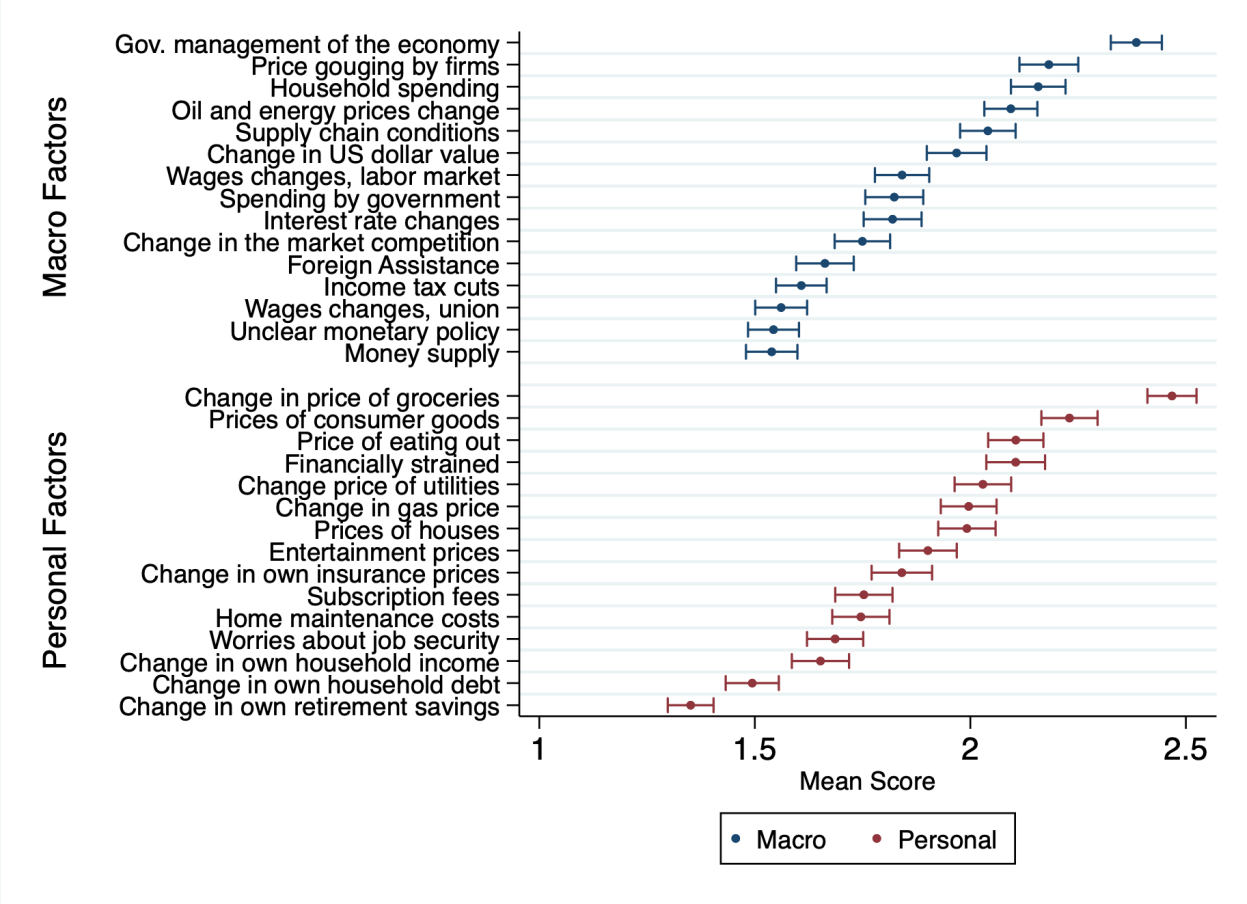
Notes: Panel (a) presents the relationship between backcast and realized inflation over the 12 months preceding the survey response and recent log nominal income change. This figure includes demographic controls: age, highest education, gender, number of children, and average past income level deciles. 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 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 Forecast and Backcast Coefficients for Three Measures of Income Change - Coefficient Plot



Notes: This figure presents plotted coefficients from regressions of pooled inflation forecasts and backcasts on different independent variables interacted with an indicator for forecast and backcast observations. Each blue dot represents the ratio of the coefficient of the dependent variable interacted with the backcast indicator to the coefficient of the same variable interacted with the forecast indicator. "Test 1" 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. "Test 2" uses the forecasted family finances change elicitations on a Likert 5 scale as the primary independent variable. "Test 3" is analogous to "Test 1" but 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 clustered at the calendar month, calculated using the delta method. All dots use data for the years 2012-2019.

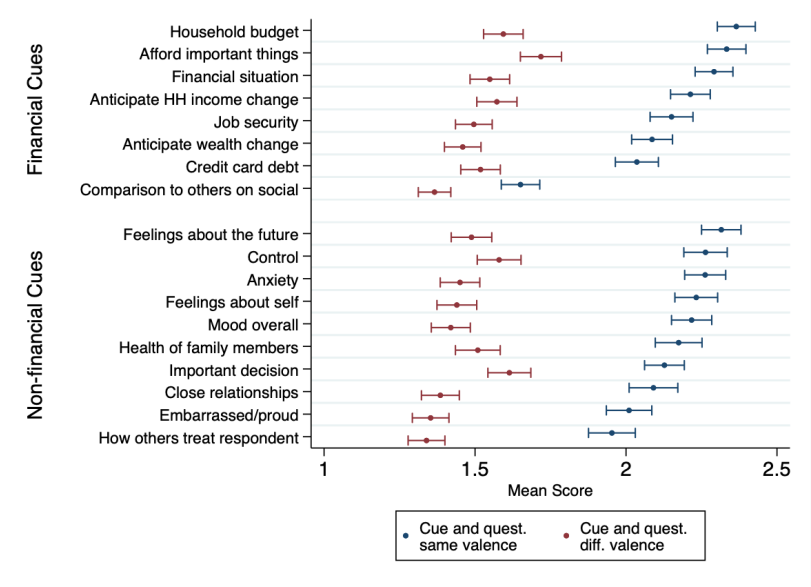
Figure 8: Importance of Different Factors in Shaping Inflation Forecasts



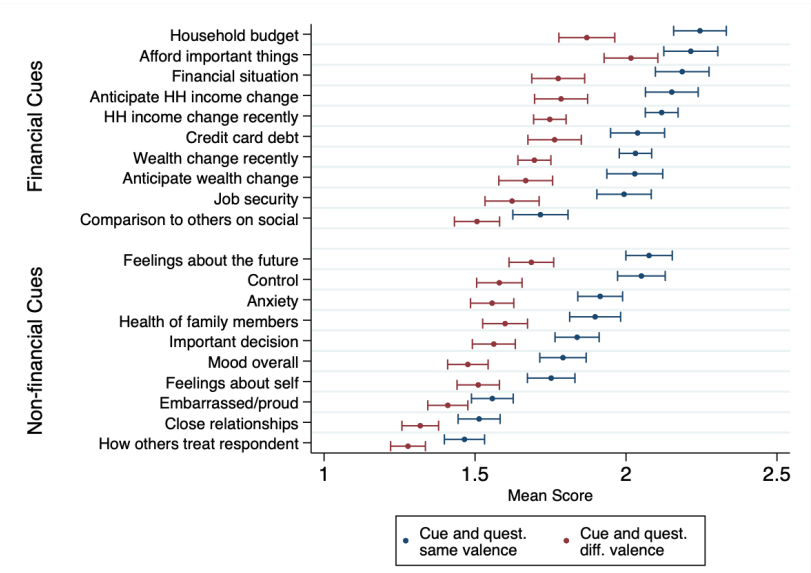
Notes: This figure summarizes survey responses on factors influencing inflation forecasts. Dots represent mean scores (1 = Not at all, 2 = A little, 3 = A lot) for each cue. Blue dots indicate macroeconomic factors, while red dots indicate personal factors. Bars denote 95% robust confidence intervals. Results are based on the Prolific survey sample.

Figure 9: Affective Association and Selective Recall

(a) What leads you to recall negative/positive experiences?



(b) What leads you to recall high/low inflation?



Panel (a) illustrates how respondents rate the importance of different cues in recalling positive or negative past experiences. Responses are based on the question:
"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?"
Panel (b) presents how respondents rate the importance of different cues in recalling periods of high or low inflation. 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?"
Dots represent mean Likert scores (1 = "Not at all," 2 = "A little," 3 = "A lot") for each possible cue under two experimental conditions: blue denotes cases where the cue and question have congruent affective valence, while red represents cases where they have different affective valence. Bars indicate 95% confidence intervals, constructed using robust standard errors. Results are based on the Prolific survey sample.

Online Appendix

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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 mentioned in the main text, the Danish Consumer Expectations Survey employs a repeated cross-section design. The target population is all Danish residents between 16 and 74 years of age. Each month, Statistics Denmark contacts a new wave of 1,500 individuals

selected through simple random sampling from the Danish Civil Registration System (CPR Registret) registry. Statistics Denmark administers the Consumer Expectations Survey as a module in Statistics Denmark's Omnibus Survey. Further, the survey closely follows the European Commission's Consumer Confidence Survey questionnaire. In addition to the main responses, Statistics Denmark also provides us with the CPR codes of all contacted individuals.We use this additional information to address concerns regarding the selection of survey participants, conditional on the survey invitation. This data is available to us for the years 2008 to 2020.

In our analysis, we compare elicited forecasts and backcasts over inflation with realized inflation over the same period. To construct our inflation measure, we source monthly consumer price index (henceforth, CPI) data from StatBank, the public-access database of economic indicators. In line with standard national accounting procedures, the CPI captures the change in cost for a given basket of goods consumed by a representative household relative to the base month.[46] To compute 12 months ahead and 12 months before inflation measures, we compute the growth rate of the CPI index in the same time frame. The Danish CPI data is available each month from 1980 to 2023.

In the final step, we merge in the additional covariates from the registry data as described 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

[46]The base month for Danish monthly CPI is January 2015.

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 rooms 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 rooms 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) whose demographic records are incomplete. We also trim income changes at 2.5 and 97.5 percent.

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 survey was started in 1946, however early survey waves have known issues.[47] 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 functions 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.

[47] 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/extranet/ForskningVariabellister/BEF%20-%20Befolkningen.html
- Statistics Denmark, Indkomst (IND, Income from returns), 1989-2022. https://www.dst.dk/extranet/ForskningVariabellister/IND%20-%20Indkomst.html
- Statistics Denmark, Uddannelser (UDDA, Education), 2007-2019 http://www.dst.dk/extranet/forskningvariabellister/Oversigt%20over%20registre.html
- Statistics Denmark, Detaljeret lønmodtagerdata fra e-Indkomst (BFL, Detailed employee data), 2012-2020. https://www.dst.dk/extranet/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

Table A1: 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.

Table A2: 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. The first column presents the number of observation 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.

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.

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 expect the general economic situation in this country to 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 = 1) (50 = 2) (0 = 3) (-50 = 4) (-100 = 5).

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 = 1) (50 = 2) (0 = 3) (-50 = 4) (-100 = 5).

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 past 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 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).

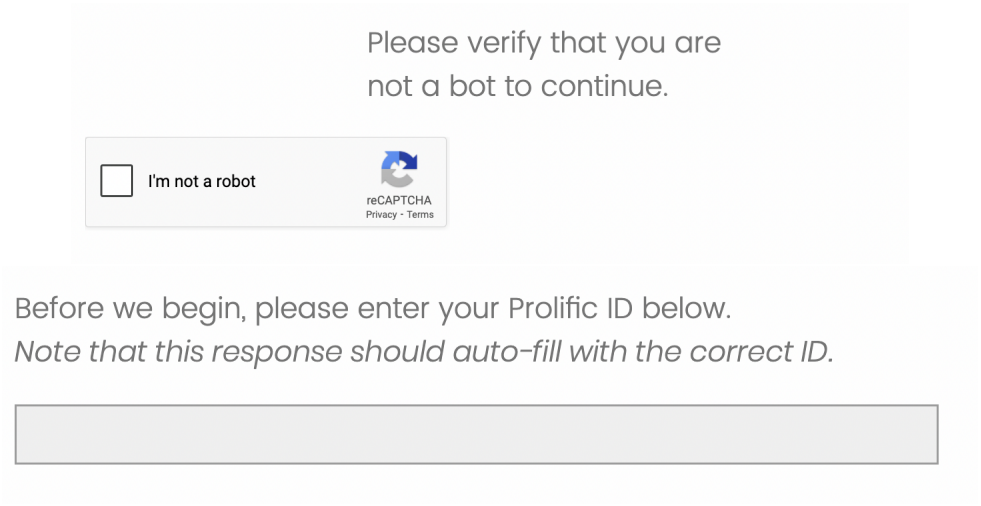
A.4 Prolific Survey: Questionnaire

In this section we outline questions from the survey we conducted through Prolific.

A.4.1 Introduction and Consent

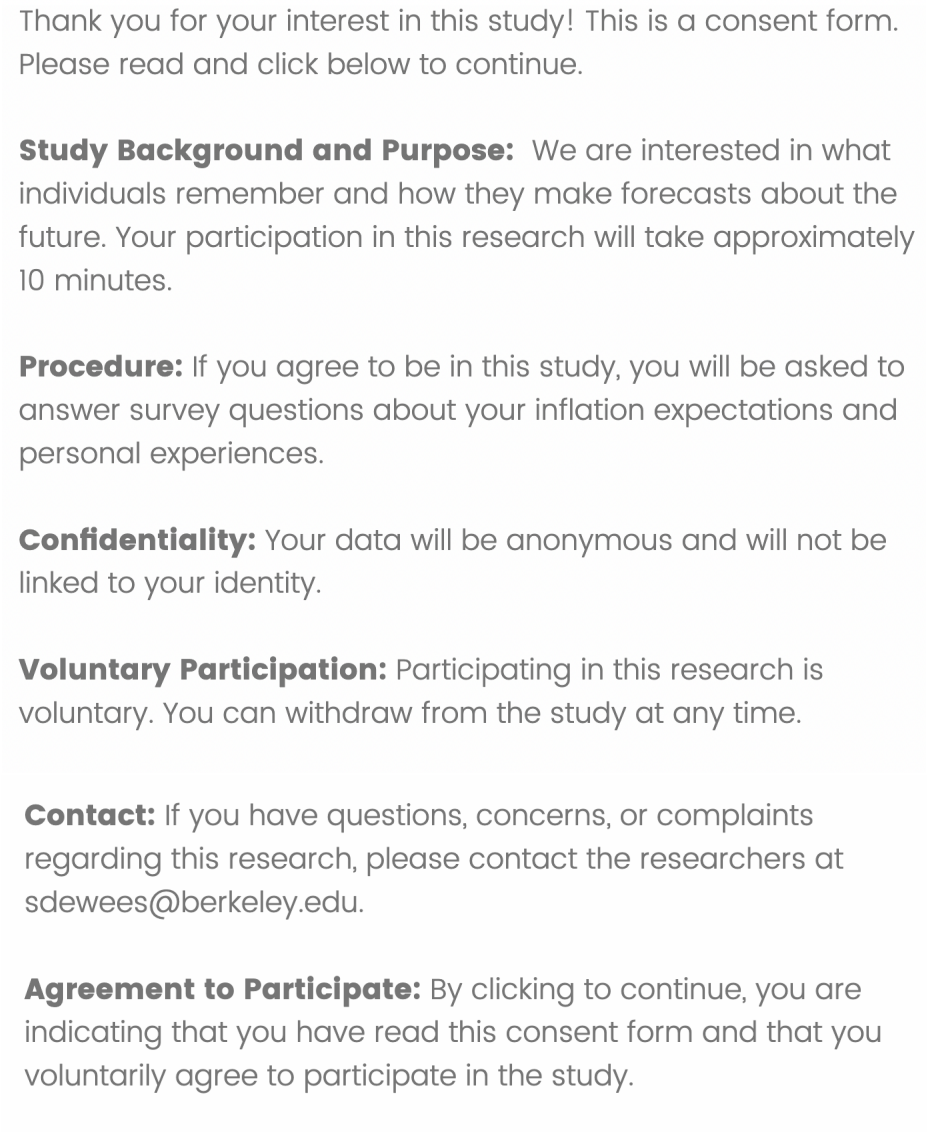
Individuals 18 years or older and living in the U.S. were recruited through Prolific to participate in a study that involved "Making Forecasts About the Future". A web link to the study opened the Qualtrics survey. Respondents were first asked to complete CAPTCHA identification and fill in their unique Prolific ID.

Figure A1: CAPTCHA Identification and Prolific ID Entry



They were then presented with the following consent screen.

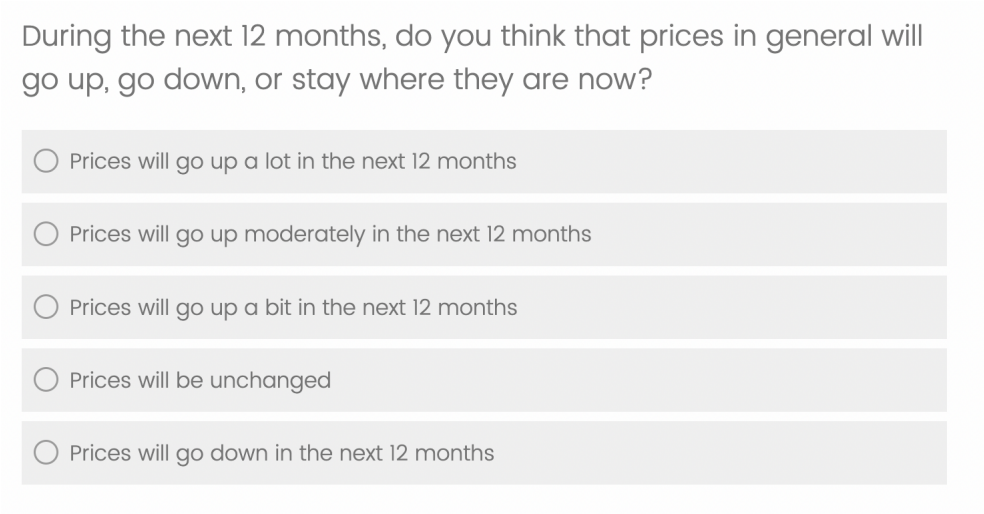
Figure A2: Consent Page



A.4.2 Inflation Elicitations

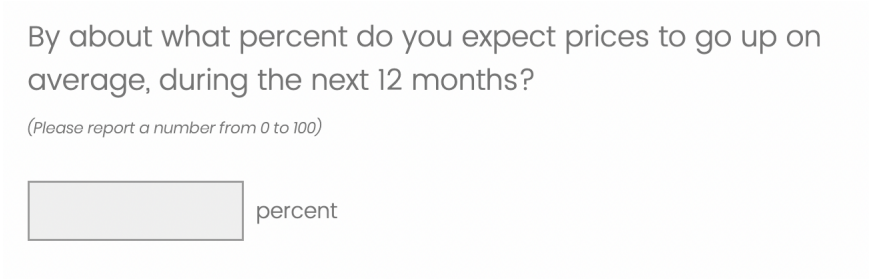
Participants were then asked to predict how much they thought inflation would change over the next 12 months.

Figure A3: Inflation Forecast



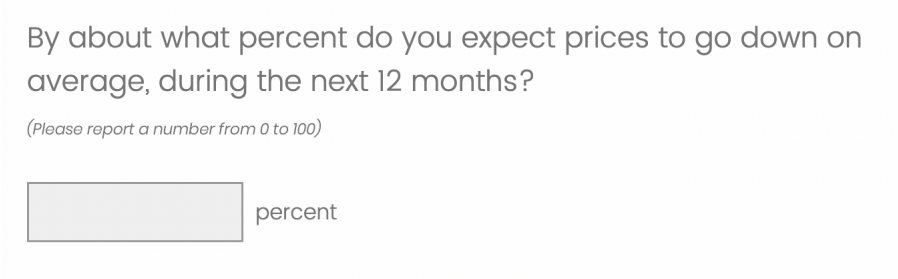
If they selected "Prices will go up a lot in the next 12 months", "Prices will go up moderately in the next 12 months", or "Prices will go up a bit in the next 12 months", they were asked to provide the percent they expected prices to increase.

Figure A4: Price Increase



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



Next, participants were asked to indicate how much each of the provided factors influenced their

inflation forecast.

Note 1: The first line in Figure 6 "You previously wrote that you thought that prices will..." displayed the answer respondents provided on the previous page.

Note 2: 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.

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
- 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
- Workers' wages changing due to labor market conditions in the United States
- Politicians' management of the economy
- Household spending in the United States
- Change in the value of the U.S. dollar

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

Figure A6: Factors Influencing Inflation Forecast



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?

Note: The options for this question were randomized such that participants were shown 5 "Non-fiancial" and 5 "Financial" options from a list of 10 affective and 10 financial options. Each option had both a positive and a negative version. Participants were randomly shown either the positive or negative version. The options are provided 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 I expect my household income to increase \ **Negative:** When I expect my household income to decrease
- **Positive:** When my household income has recently increased \ **Negative:** When my household income has recently decreased

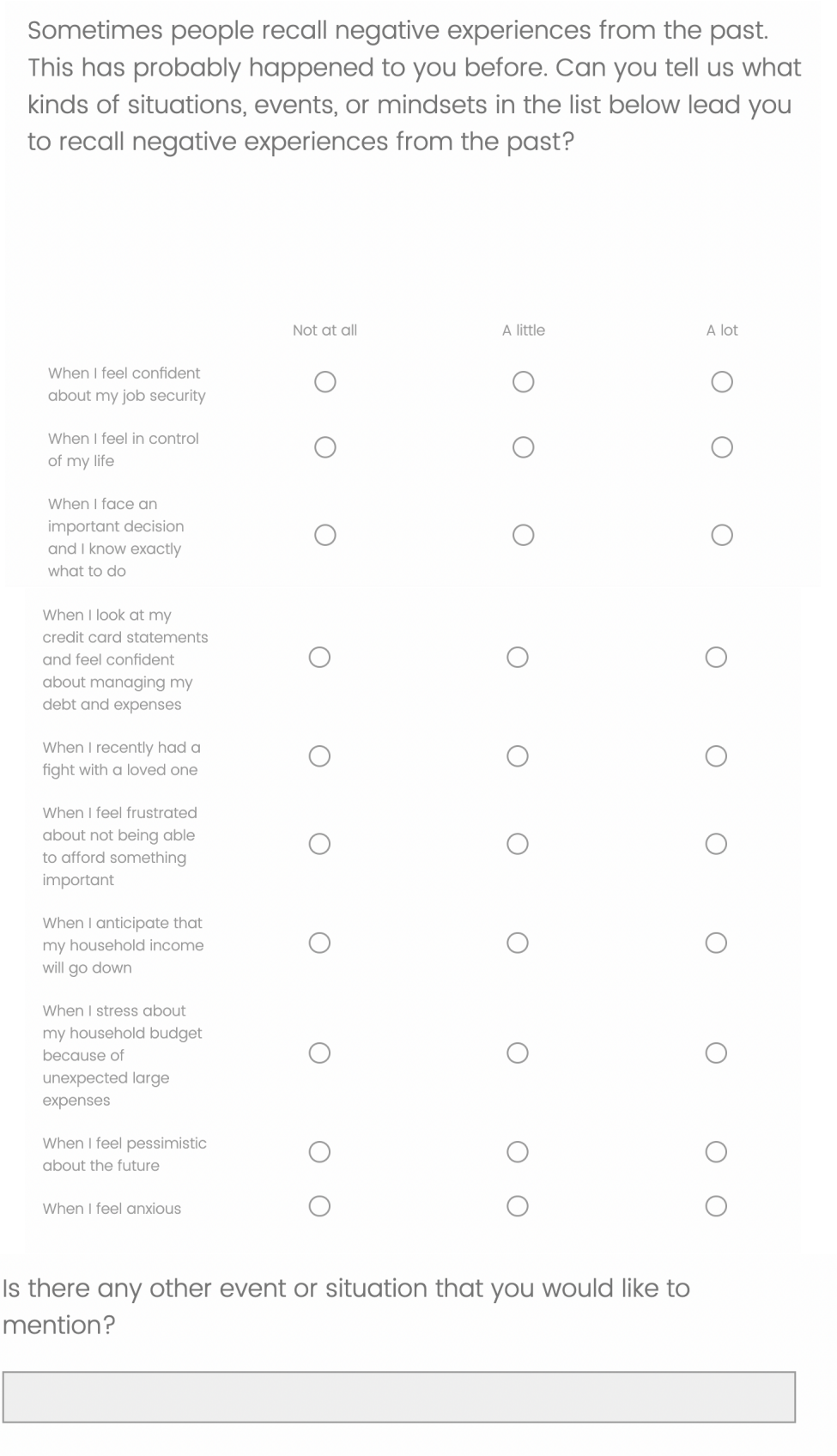
- **Positive:** When I feel good about my household budget due to lower-than-normal expenses \ **Negative:** When I feel pressured by my household budget due to unexpectedly high expenses
- **Positive:** When I look at my bank statements and feel confident that I can manage my debt and expenses \ **Negative:** 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
- **Positive:** When my wealth has recently increased \ **Negative:** When my wealth has recently decreased

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

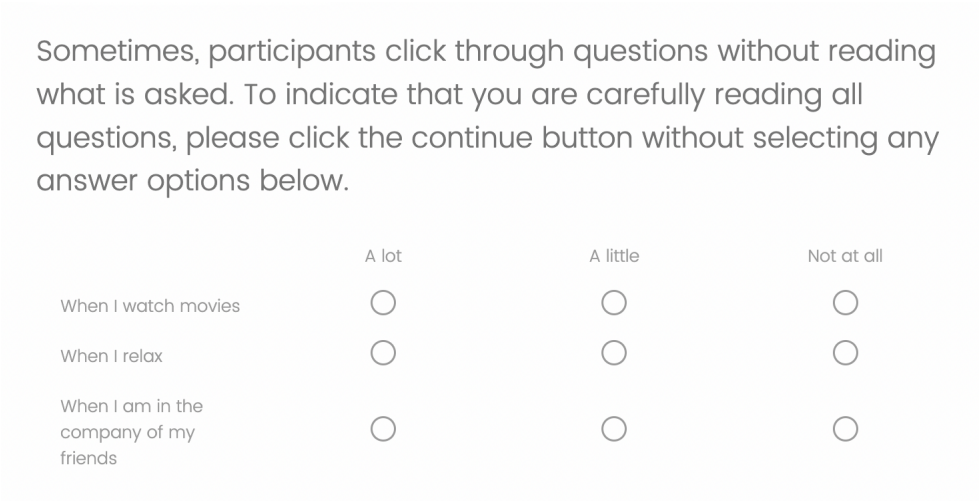
Figure 7 provides an example of what a respondent might have seen when taking the survey.

Figure A7: Recall of Past Experiences



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

Figure A8: Attention Check



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 7 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 7 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 7.

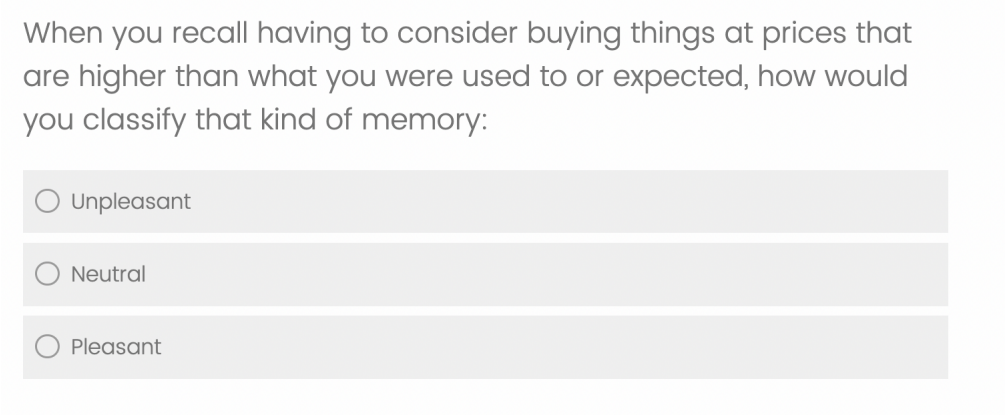
Figure 9 displays an example of what participants might have seen when taking the survey.

Figure A9: Price Fluctuations



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

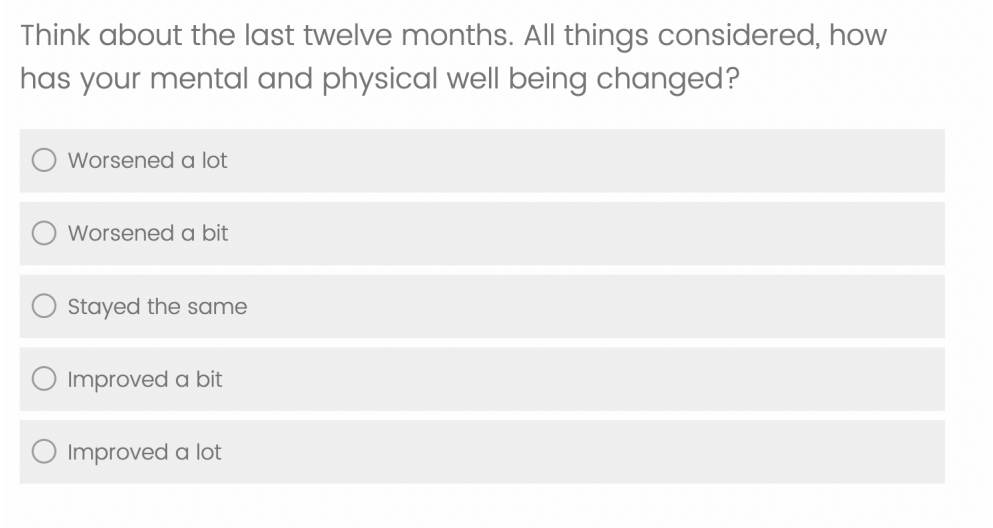
Figure A10: Memory of Buying Things at Higher Prices



A.4.4 Additional Questions and Demographics

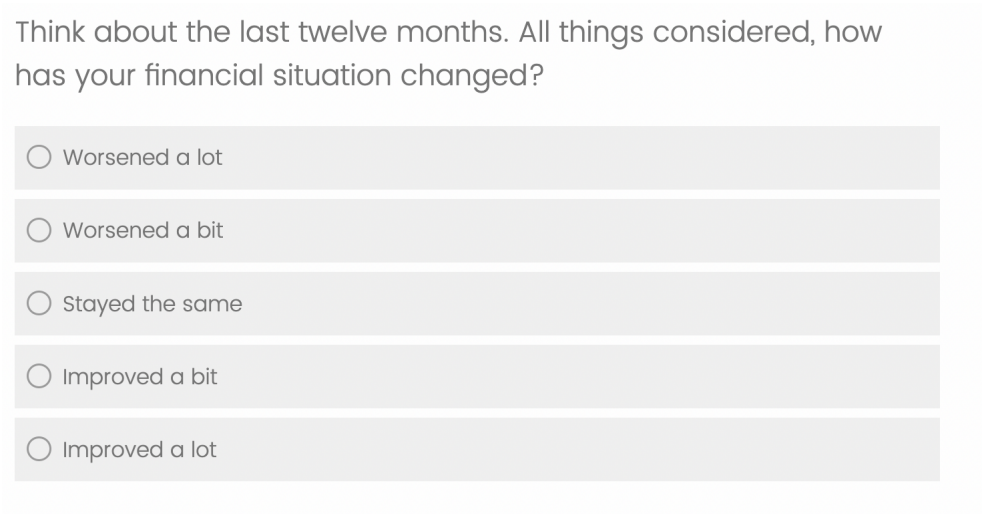
They then were asked how their mental and physical wellbeing changed over the past 12 months.

Figure A11: Mental and Physical Wellbeing Last 12 Months



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

Figure A12: Financial Situation Last 12 Months



Finally, participants were asked to provide demographic information.

Figure A13: Demographics Introduction



Figure A14: Age

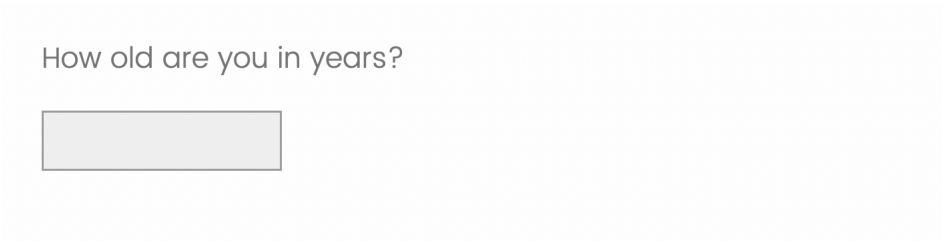


Figure A15: Gender

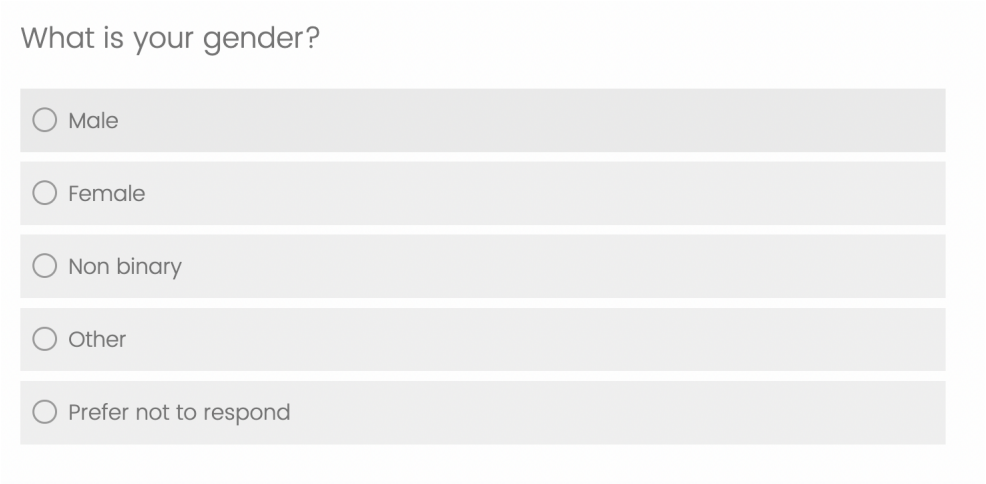


Figure A16: Highest Level of Education

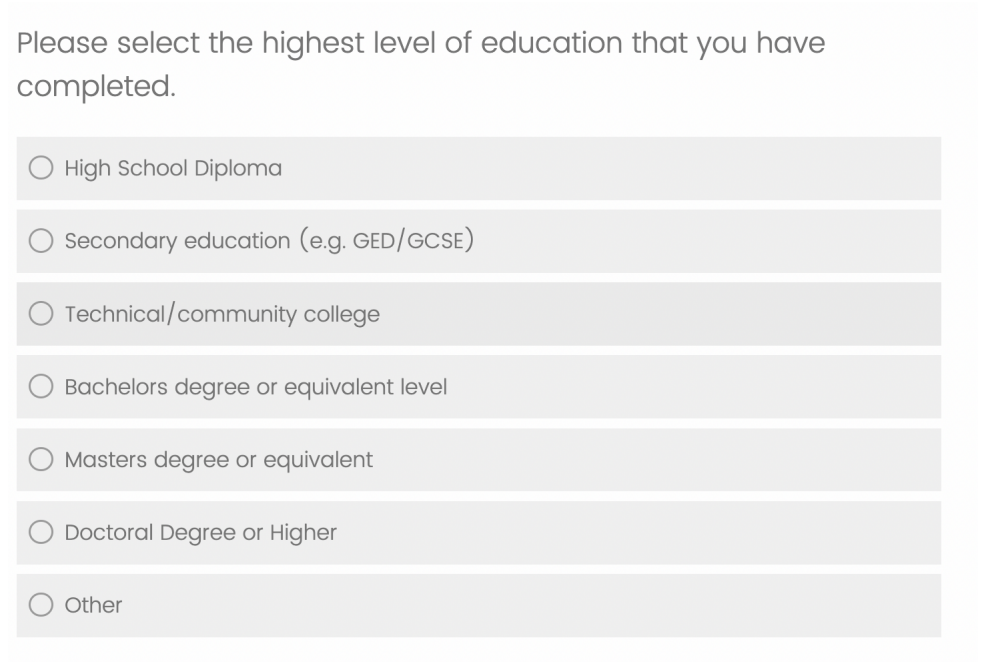


Figure A17: Marital Status

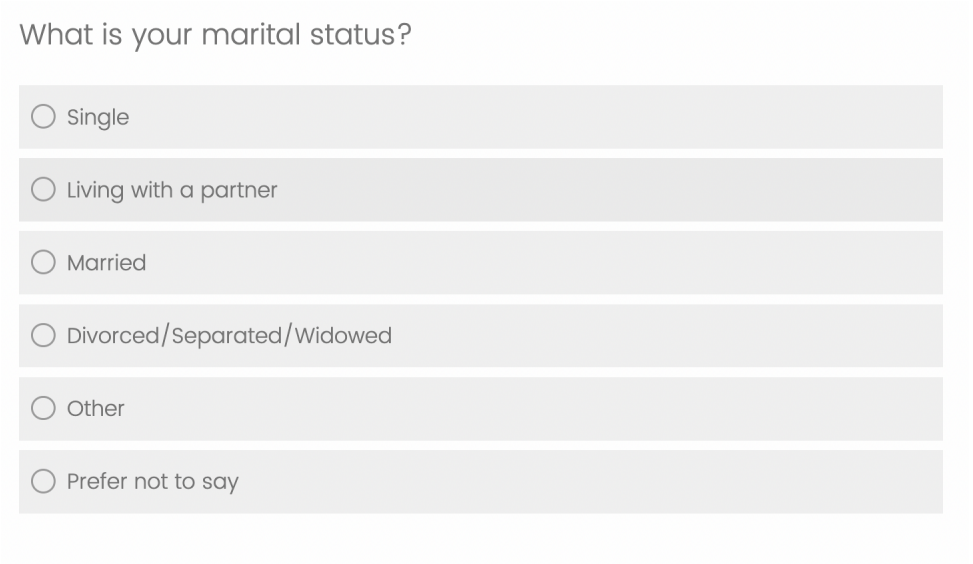


Figure A18: Employment Status

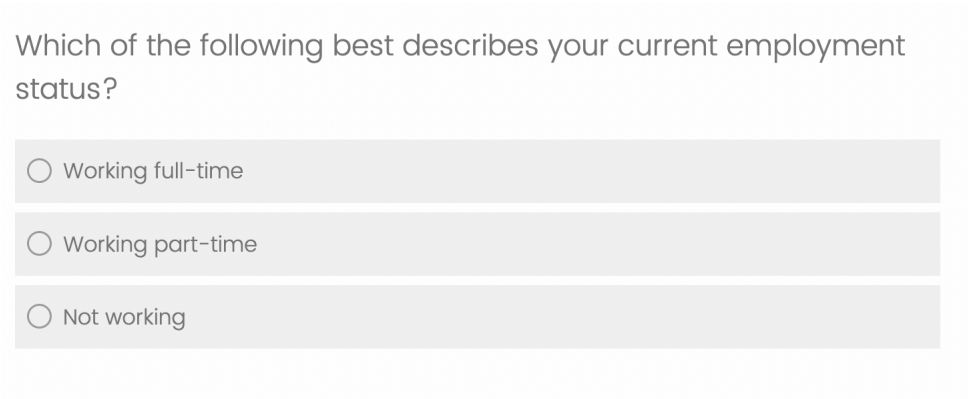
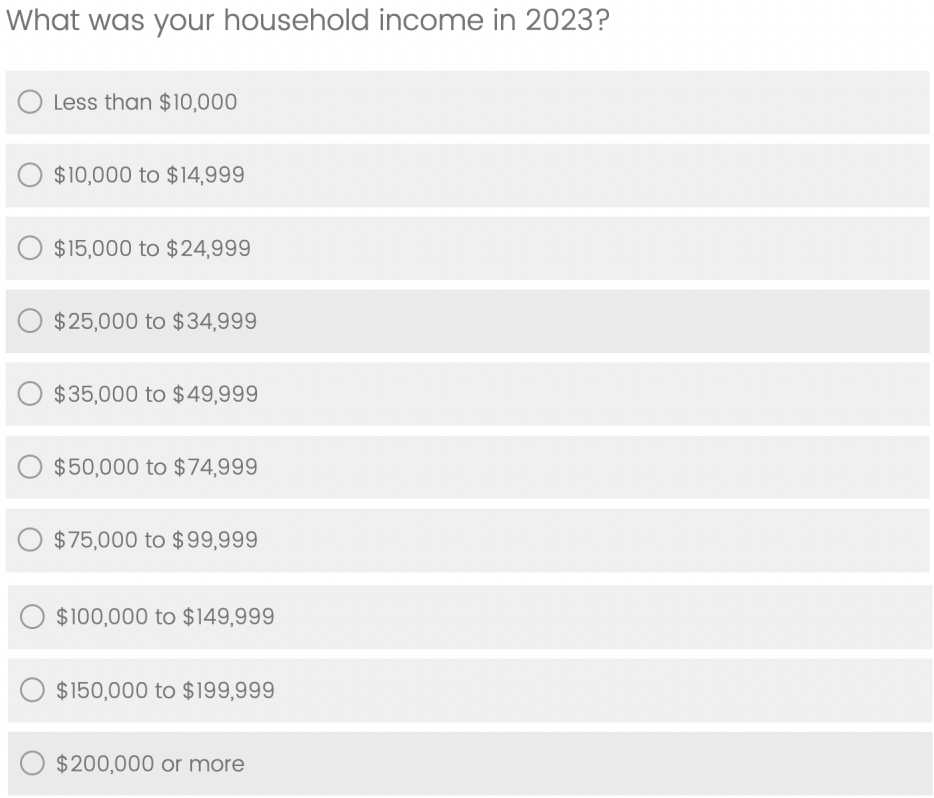


Figure A19: Income



B Supplementary Empirical Results

B.1 Summary Statistics and Representativeness of Survey Respondents

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 Sample
Demographics	
Age	48.6
Female (%)	51.0
Single (%)	25.1
No. of Children in Household	0.77
Highest Education	
Primary or Lower Secondary (%)	21.7
Upper Secondary (%)	44.1
Bachelor or Higher (%)	34.2
Household Income	
Real Household Income	336,570
Observations	103634

Notes: This table presents statistics related to demographics, education, and income for the survey respondses 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

	Forecasted Inflation next 12m			
	(1)	(2)	(3)	(4)
Log Nominal Income Level	-0.867*** (0.046)			-0.740*** (0.046)
Female Indicator		0.201*** (0.032)		0.239*** (0.033)
College Educated			-0.473*** (0.038)	-0.317*** (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 numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

B.3 Auxiliary Results to Section 3

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	0.019	-0.042***	-0.028**	-0.029**
	(0.019)	(0.016)	(0.014)	(0.012)
Placebo Timing	t-6 vs t-7	t-6 vs t-8	t-6 vs t-9	t-6 vs t-10
Observations	33316	32722	32146	31558

(b) Forecasted Inflation

	Forecasted Inflation next 12m			
	(1)	(2)	(3)	(4)
Placebo Income Change	-0.010	0.097	-0.104	-0.009
	(0.100)	(0.078)	(0.070)	(0.066)
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	33316	32722	32146	31558

Notes: These tables present regressions of realized (panel a) and forecasted (panels 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). 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 numerically equivalent to clustering by calendar month alone for the survey sample. * $p<0.10$ ** $p<0.05$ *** $p<0.01$.

B.3.2 Additional Results for Recent Labor Income Changes

Table B.6: 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***	0.442***		
	(0.005)	(0.005)		
Future Log Nominal Labor Income Change			0.448***	0.436***
			(0.006)	(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 log nominal labor 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 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 Wealth Changes

Table B.7: Inflation Forecasts and Recent Changes in Liquid Assets and Total Wealth

	Realized Inflation next 12m			Forecasted Inflation next 12m		
	(1)	(2)	(3)	(4)	(5)	(6)
Recent Asinh Liquid Assets (000's DKK) Change	-0.007 (0.005)		-0.009* (0.005)	-0.023 (0.030)		0.002 (0.031)
Recent Asinh Total Wealth (000's DKK) Change		0.001 (0.002)	0.002 (0.002)		-0.026** (0.013)	-0.025* (0.013)
Recent Log Nominal Income Change			0.014 (0.023)			-0.513*** (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 wealth, and total wealth changes. Recent changes in households' asinh liquid assets and total 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 numerically equivalent to clustering by calendar month alone for the survey sample. * $p<0.10$ ** $p<0.05$ *** $p<0.01$.

B.3.4 Recent Income Change: Years 2008 to 2019

Table B.8: Inflation Forecasts and Recent Changes in Household Income (Years 2008-2019)

	Forecasted Inflation next 12m		
	(1)	(2)	(3)
Recent Log Nominal Income Change	-0.523*** (0.132)	-0.499*** (0.129)	-0.538*** (0.119)
Demog. Controls	No	Yes	Yes
Month FE	No	No	Yes
Sample	Respondents 2008 - 2019	Respondents 2008 - 2019	Respondents 2008 - 2019
Observations	53365	53365	53365

Notes: This table presents regressions of 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 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. Demographic controls include age, highest education, gender, number of children, and average past income level. 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. Robust standard errors are clustered two ways: by calendar month and by unique respondent. * $p<0.10$ ** $p<0.05$ *** $p<0.01$.

B.3.5 Recent Income Change: Real Income Changes

Table B.9: Inflation Forecasts and Recent Real Changes in Household Income

	Realized Inflation next 12m		Forecasted Inflation next 12m		
	(1)	(2)	(3)	(4)	(5)
Recent Log Real Income Change	0.010 (0.036)	-0.060*** (0.019)	-0.855*** (0.148)	-0.864*** (0.148)	-0.578*** (0.140)
Demog. Controls	No	No	No	Yes	Yes
Month FE	No	No	No	No	Yes
Sample	Respondents 2012 - 2019	Population 1991 - 2019	Respondents 2012 - 2019	Respondents 2012 - 2019	Respondents 2012 - 2019
Observations	35014	62449159	35014	35014	35014

Notes: This table presents regressions of realized and forecasted inflation over the 12 months following the survey response on recent log real income change. 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. To compute real income levels in years t 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. "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. 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 numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

B.3.6 Recent Income Change: Net-of-Tax Income Changes

Table B.10: Inflation Forecasts and Recent Changes in Net-of-Tax Income

	Realized Inflation next 12m	Forecasted Inflation next 12m		
	(1)	(2)	(3)	(4)
Recent Log Nominal Net-of-Tax Income Change	-0.061** (0.025)	-0.727*** (0.152)	-0.743*** (0.153)	-0.630*** (0.150)
Demog. Controls	No	No	Yes	Yes
Month FE	No	No	No	Yes
	Respondents	Respondents	Respondents	Respondents
Sample	2012 - 2019	2012 - 2019	2012 - 2019	2012 - 2019
Observations	35049	35049	35049	35049

Notes: This table presents regressions of realized and forecasted inflation over the 12 months following the survey response on recent log nominal net-of-tex income change. The units of inflation and inflation forecasts are expressed in percentage points. Log Nominal Net-of-Tax Income is computed by subtracting the total household tax bill for a given fiscal year. 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 numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

B.4 Auxiliary Results to Section 4

B.4.1 Forecastability of Future Income Changes

Table B.11: 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. 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 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 Finance Changes and Future Income Changes: Sub-sample analysis

Table B.12: 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)
Forecasted Family Finances Change	-0.011**	-0.011	-0.004	-0.010*	-0.009	-0.010*	-0.004	-0.014***	-0.011	-0.009	-0.010**	-0.001
	(0.005)	(0.007)	(0.004)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.007)	(0.006)	(0.005)	(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	21965	13085	29959	18447	16603	15489	19561	17843	19849	15200	9791

(b) Forecasted inflation

	Forecasted Inflation next 12m											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Forecasted Family Finances Change	-0.340***	-0.346***	-0.288***	-0.315***	-0.281***	-0.348***	-0.268***	-0.351***	-0.308***	-0.351***	-0.312***	-0.350***
	(0.028)	(0.034)	(0.036)	(0.027)	(0.036)	(0.034)	(0.030)	(0.036)	(0.041)	(0.033)	(0.036)	(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	21965	13085	29959	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 recent log nominal income change less than the absolute value of 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 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. The "Simple Income" sample restricts to individuals for whom at least ninety percent of income is labor income in the years $t+1$ to $t-2$. "Net Saver" restricts to the subsamples with positive total net assets. "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 numerically equivalent to clustering by calendar month alone for the survey sample. * $p<0.10$ ** $p<0.05$ *** $p<0.01$.

Table B.13: 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**	0.022	-0.043**	-0.038*	-0.041	-0.021	-0.037	-0.019	-0.072*	-0.019	-0.035	-0.024
	(0.030)	(0.021)	(0.022)	(0.022)	(0.028)	(0.024)	(0.027)	(0.020)	(0.041)	(0.023)	(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	21965	13085	29959	18447	16603	15489	19561	17843	19849	15200	9791

(b) Forecasted inflation

	Forecasted Inflation next 12m											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Future Log Nominal Income Change	-0.290**	-0.236	-0.421***	-0.311***	0.004	-0.602***	-0.297**	-0.335**	-0.283	-0.183	-0.568***	-0.425**
	(0.138)	(0.154)	(0.145)	(0.111)	(0.146)	(0.151)	(0.145)	(0.143)	(0.185)	(0.152)	(0.149)	(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	21965	13085	29959	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 recent log nominal income change less than the absolute value of 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. The "Simple Income" sample restricts to individuals for whom at least ninety percent of income is labor income in the years $t+1$ to $t-2$. "Net Saver" restricts to the subsamples with positive total net assets. "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 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

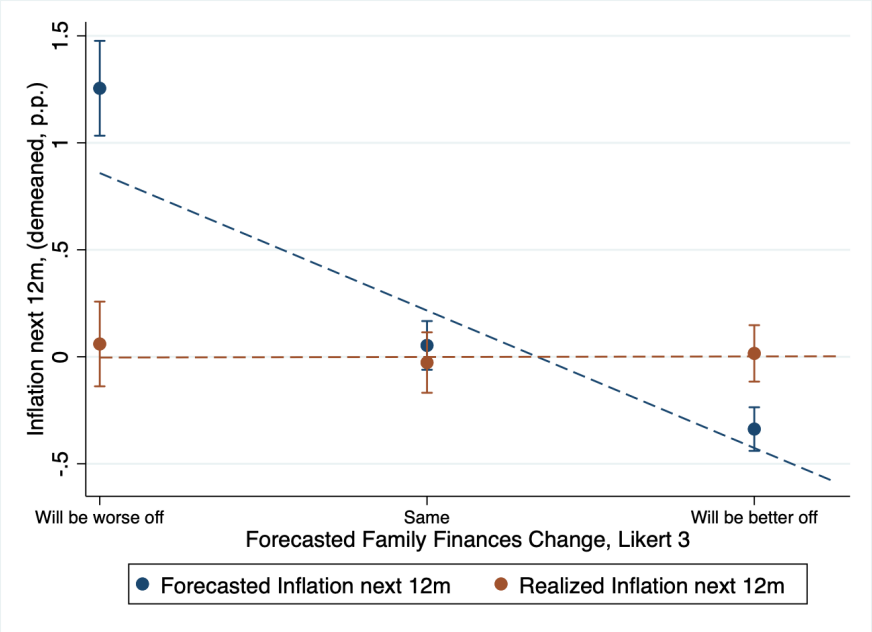
Table B.14: Inflation Forecasts and Realized Future Changes in Household Labor Income

	Realized Inflation next 12m		Forecasted Inflation 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 $t+1$ to $t-2$. 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 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.

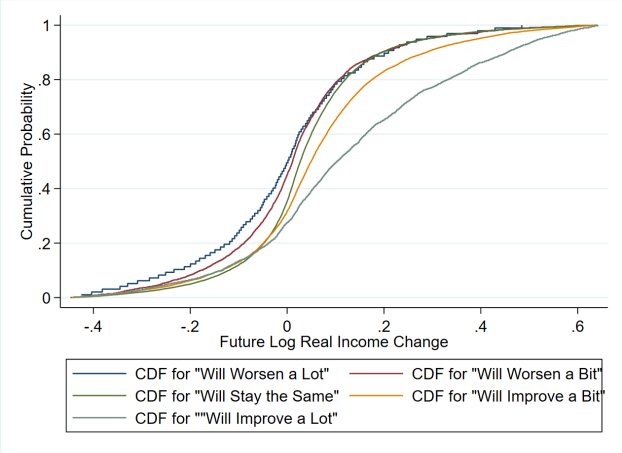
Table B.15: Inflation Forecasts and Forecasted Family Finances Change: Michigan

	Realized Inflation next 12m	Forecasted Inflation next 12m				
	(1)	(2)	(3)	(4)	(5)	(6)
Forecasted Family Finances Change	0.006	-0.630***	-0.601***	-0.491***	-0.257***	-0.188***
	(0.023)	(0.033)	(0.032)	(0.025)	(0.031)	(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	104128	104128	104128	104128	104128	104128

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.4.5 Forecastability of Income, Inflation Forecast and Future Income Changes: Real Income Changes

Figure B.2: Cumulative Density Functions (CDFs) of Future Log Real Income Changes, by Survey Response



Notes: This figure presents empirical CDFs of future log real income changes by responses to the survey question about forecasts of the future family financial situation. 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 $t-1$, 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. The figure is based on data from 2012-2019. 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 A.1.4.

Table B.16: 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. 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 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 Forecasts and Future Real Changes in Household Income

	Realized Inflation next 12m	Forecasted Inflation next 12m			
	(1)	(2)	(3)	(4)	(5)
Future Log Real Income Change	-0.065***	-0.468***	-0.417***	-0.522***	-0.255**
	(0.023)	(0.109)	(0.107)	(0.111)	(0.102)
Recent Log Real Income Change				-0.962***	
				(0.154)	
Demog. Controls	No	No	Yes	Yes	Yes
Month FE	No	No	No	No	Yes
Sample	Respondents 2012 - 2019	Respondents 2012 - 2019	Respondents 2012 - 2019	Respondents 2012 - 2019	Respondents 2012 - 2019
Observations	35014	35014	35014	35014	35014

Notes: This table presents regressions of realized and forecasted inflation over the 12 months following the survey response on future log real income change. The units of inflation and inflation forecasts are expressed in percentage points. 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. "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. 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 numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

B.4.6 Inflation Forecast and Future Income Changes: Net-of-tax Income Changes

Table B.18: Inflation Forecasts and Future Changes in Net-of-tax Income

	Realized Inflation next 12m	Forecasted Inflation next 12m		
	(1)	(2)	(3)	(4)
Future Log Nominal Net-of-Tax Income Change	-0.013 (0.026)	-0.496*** (0.126)	-0.423*** (0.121)	-0.338*** (0.123)
Demog. Controls	No	No	Yes	Yes
Month FE	No	No	No	Yes
Sample	Respondents 2012 - 2019	Respondents 2012 - 2019	Respondents 2012 - 2019	Respondents 2012 - 2019
Observations	35048	35048	35048	35048

Notes: This table presents regressions of realized and forecasted inflation over the 12 months following the survey response on future log nominal net-of-tax income change. The units of inflation and inflation forecasts are expressed in percentage points. Log Nominal Net-of-Tax Income is computed by subtracting the total household tax bill for a given fiscal year. 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 numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

B.4.7 Forecastability of Income, Inflation Forecast and Future Income Changes: Years 2008 to 2019

Table B.19: Inflation Forecasts and Forecasted Family Finances Change (Years 2008-2019)

	Realized Inflation Next 12mos	Forecasted Inflation next 12m			
	(1)	(2)	(3)	(4)	(5)
Forecasted Family Finances Change	-0.036*** (0.009)	-0.390*** (0.023)	-0.359*** (0.023)	-0.359*** (0.023)	-0.315*** (0.021)
Recent Log Nominal Income Change				-0.484*** (0.127)	
Demog. Controls	No	No	Yes	Yes	Yes
Month FE	No	No	No	No	Yes
Observations	53365	53365	53365	53365	53365

Notes: This table presents regressions of forecasted inflation over the 12 months following the survey response on forecasted family finances 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 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. 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. 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.20: Inflation Forecasts and Future Changes in Household Income (Years 2008-2019)

	Forecasted Inflation next 12m			
	(1)	(2)	(3)	(4)
Future Log Nominal Income Change	-0.345*** (0.095)	-0.214** (0.096)	-0.285*** (0.096)	-0.183** (0.091)
Recent Log Nominal Income Change			-0.559*** (0.130)	
Demog. Controls	No	Yes	Yes	Yes
Month FE	No	No	No	Yes
Sample	Respondents 2008 - 2019	Respondents 2008 - 2019	Respondents 2008 - 2019	Respondents 2008 - 2019
Observations	53365	53365	53365	53365

Notes: This table presents regressions of 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 log nominal 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. "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 incomes 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. 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.21: Informativeness of Forecasted Family Finance Change (Years 2008-2019)

	Future Log Nominal Income Change				
	(1)	(2)	(3)	(4)	(5)
Will worsen a lot	-0.042***	-0.045***	-0.046***	-0.045***	
	(0.007)	(0.007)	(0.007)	(0.007)	
Will worsen a bit	-0.027***	-0.028***	-0.029***	-0.029***	
	(0.002)	(0.002)	(0.002)	(0.002)	
Will stay the same	-	-	-	-	
Will improve a bit	0.022***	0.010***	0.010***	0.009***	
	(0.002)	(0.002)	(0.002)	(0.002)	
Will improve a lot	0.080***	0.051***	0.051***	0.050***	
	(0.004)	(0.004)	(0.004)	(0.004)	
Recent Log Nominal Income Change			-0.211***	-0.212***	-0.210***
			(0.007)	(0.008)	(0.008)
Demog. Controls	No	Yes	Yes	Yes	Yes
Month FE	No	No	No	Yes	No
Observations	53365	53365	53365	53365	53365

Notes: This table presents regressions of future log nominal income change on the discrete forecasted family finances change variable. 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. 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. 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. 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 Auxiliary Results to Section 5

B.5.1 Inflation Backcasts Correlate with Forecast Errors and Inflation Forecasts Correlate with Inflation Backcast Errors

Table B.22: Inflation Backcasts and Inflation Forecast Errors

	Error in Forecasted Inflation next 12m		
	(1)	(2)	(3)
Backcasted Inflation past 12m, Likert 5	-1.570*** (0.032)	-1.539*** (0.033)	-1.554*** (0.028)
Demog. Controls	No	Yes	Yes
Month FE	No	No	Yes
Observations	35050	35050	35050

Notes: This table presents the relationship between the error in forecasted inflation over the 12 months following the survey response and backcasted inflation over the 12 months preceding the survey response. Forecast errors in inflation are calculated by subtracting the inflation forecasts for the next 12 months from the time of the survey response from the realized inflation over these 12 months. The units are expressed in percentage points. 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 numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.23: Inflation Forecasts and Inflation Backcast Errors

	Error in Backcasted Inflation past 12m		
	(1)	(2)	(3)
Forecasted Inflation next 12m, Likert 5	-0.720*** (0.036)	-0.748*** (0.036)	-0.791*** (0.032)
Demog. Controls	No	Yes	Yes
Month FE	No	No	Yes
Observations	35050	35050	35050

Notes: This table presents the relationship between the error in backcasted inflation over the 12 months preceding the survey response and forecasted inflation over the 12 months following the survey response. Backcast errors in inflation are calculated by subtracting the inflation forecasts for the past 12 months from the time of the survey response from the realized inflation over these 12 months. The units are expressed in percentage points. 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 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.24: 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)	-0.019 (0.023)	-0.004 (0.035)	-0.002 (0.025)	-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	22926	5655	27009	16530	14222	13698	17054	15649	17360	13391	8587

(b) Backcast inflation

	Backcast Inflation past 12m											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Recent Log Nominal Income Change	-0.846*** (0.236)	-0.857*** (0.241)	-0.652* (0.349)	-1.020*** (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	22926	5655	27009	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 less than the absolute value of 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. The "Simple Income" sample restricts to individuals for whom at least ninety percent of income is labor income in the years $t+1$ to $t-2$. "Net Saver" restricts to the subsamples with positive total net assets. "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 numerically equivalent to clustering by calendar month alone for the survey sample. * $p<0.10$ ** $p<0.05$ *** $p<0.01$.

Table B.25: 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)
Forecasted Family Finances Change	0.003 (0.005)	0.005 (0.006)	-0.001 (0.004)	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	18935	11817	26353	16530	14222	13698	17054	15649	17360	13391	8587

(b) Backcast inflation

	Backcast Inflation past 12m											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Forecasted Family Finances Change	-0.297*** (0.039)	-0.331*** (0.046)	-0.287*** (0.042)	-0.308*** (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	18935	11817	26353	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 recent log nominal income change less than the absolute value of 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, 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. The "Simple Income" sample restricts to individuals for whom at least ninety percent of income is labor income in the years $t+1$ to $t-2$. "Net Saver" restricts to the subsamples with positive total net assets. "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 numerically equivalent to clustering by calendar month alone for the survey sample. * $p<0.10$ ** $p<0.05$ *** $p<0.01$.

Table B.26: 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	0.003	0.015	0.014	0.009	0.028	0.018	0.008	0.051	-0.013	0.047*	0.024
	(0.029)	(0.021)	(0.023)	(0.024)	(0.029)	(0.022)	(0.027)	(0.021)	(0.041)	(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	18935	11817	26353	16530	14222	13698	17054	15649	17360	13391	8587

(b) Backcast inflation

	Backcast Inflation past 12m											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Future Log Nominal Income Change	-0.468**	-0.355**	-0.597***	-0.448***	-0.019	-0.854***	-0.181	-0.680***	-0.331	-0.325*	-0.728***	-0.071
	(0.191)	(0.171)	(0.191)	(0.150)	(0.189)	(0.201)	(0.193)	(0.175)	(0.215)	(0.180)	(0.196)	(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	18935	11817	26353	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 recent log nominal income change less than the absolute value of 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. The "Simple Income" sample restricts to individuals for whom at least ninety percent of income is labor income in the years $t+1$ to $t-2$. "Net Saver" restricts to the subsamples with positive total net assets. "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 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.27: Inflation Backcasts and Recent Changes in Household Labor Income

	Realized Inflation past 12m		Backcasted Inflation 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 $t+1$ to $t-2$. 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 numerically equivalent to clustering by calendar month alone for the survey sample. * $p<0.10$ ** $p<0.05$ *** $p<0.01$.

Table B.28: Inflation Backcasts and Future Changes in Household Labor Income

	Realized Inflation past 12m		Backcasted Inflation 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 $t+1$ to $t-2$. 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 numerically equivalent to clustering by calendar month alone for the survey sample. * $p<0.10$ ** $p<0.05$ *** $p<0.01$.

B.5.4 Inflation Backcasts: Net-of-Tax Income Changes

Table B.29: Inflation Backcasts and Recent Changes in Net-of-Tax Income

	Realized Inflation past 12m	Backcasted Inflation past 12m		
	(1)	(2)	(3)	(4)
Recent Log Nominal Net-of-Tax Income Change	-0.010 (0.023)	-0.964*** (0.243)	-0.955*** (0.237)	-0.801*** (0.220)
Demog. Controls	No	No	Yes	Yes
Month FE	No	No	No	Yes
Sample	Respondents 2013 - 2019	Respondents 2013 - 2019	Respondents 2013 - 2019	Respondents 2013 - 2019
Observations	30751	30751	30751	30751

Notes: This table presents regressions of realized and backcasted inflation over the 12 months preceding the survey response on recent log net-of-tex income change. The units of inflation and inflation backcasts are expressed in percentage points. Log Nominal Net-of-Tax Income is computed in two steps. First, we measure the total household income minus income coming from the rental of owned real estate properties. We then subtract the total household tax bill for a given fiscal year with the exclusion of real estate and land value taxes. 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 numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.30: Inflation Backcasts and Future Changes in Net-of-Tax Income

	Realized Inflation past 12m	Backcasted Inflation past 12m		
	(1)	(2)	(3)	(4)
Future Log Nominal Net-of-Tax Income Change	0.080*** (0.024)	-0.628*** (0.148)	-0.527*** (0.151)	-0.485*** (0.154)
Demog. Controls	No	No	Yes	Yes
Month FE	No	No	No	Yes
Sample	Respondents 2013 - 2019	Respondents 2013 - 2019	Respondents 2013 - 2019	Respondents 2013 - 2019
Observations	30750	30750	30750	30750

Notes: This table presents regressions of realized and backcasted inflation over the 12 months preceding the survey response on future log net-of-tax income change. The units of inflation and inflation backcasts are expressed in percentage points. Log Nominal Net-of-Tax Income is computed by subtract the total household tax bill for a given fiscal year with the exclusion. 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 numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

B.5.5 Additional Results to Section 5.3

Table B.31: Association Between Inflation Forecasts and Income Change Measures when Controlling for Backcasts

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

Notes: This table presents regressions of forecasted inflation in 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 numerically equivalent to clustering by calendar month alone for the survey sample. * $p<0.10$ ** $p<0.05$ *** $p<0.01$.

Table B.32: Inflation Beliefs Correlates with Income Changes and Forecasted Family Finances Changes – Forecasts and Backcasts Coefficient Comparison

	Forecasted/Backcasted Inflation					
	(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)				
Forecasted Family Finances Change			-0.432***	-0.406***		
			(0.038)	(0.038)		
I(Forecast) × Forecasted Family Finances Change			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
Observations	35050	35050	35050	35050	35050	35050

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 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 $t-1$. 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. Since only 467 respondents answer the survey more than once, this is numerically equivalent to clustering by calendar month alone for the survey sample. * $p<0.10$ ** $p<0.05$ *** $p<0.01$.

B.5.6 Additional Results to Section 5.4

Table B.33: Empirical Distribution of Household ER Events

	Freq.	Percent
0	24536	23.68
1	20325	19.61
2	15625	15.08
3	11134	10.74
4	7956	7.68
5	5943	5.73
6	4203	4.06
7	3255	3.14
8	2430	2.34
9	1794	1.73
=10 or more	6433	6.21
Total	103634	100.00

Notes: This table shows the frequency and empirical probability mass functions 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.34: Family ER Visits and Survey Participation

	I(Survey Participation)				
	(1)	(2)	(3)	(4)	(5)
I(Fam. ER visit in survey month)	-0.013	-0.014	-0.014*	-0.014*	-0.015*
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
# of ER visits		0.000	0.010***		
		(0.001)	(0.002)		
# of ER visits sq.			-0.002***		
			(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	149689	149689	149689	149689	149689

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 "# 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 B.35: Impact of Family ER Visit in Survey Month on Inflation Forecasts and Backcasts (Year and Sample Restrictions from Baseline Specification)

	Inflation Forecasts and Backcasts						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
I(Fam. ER visit in survey month)	0.271**	0.220*	0.219*	0.222*	0.217*	0.361**	0.363**
	(0.127)	(0.128)	(0.128)	(0.128)	(0.130)	(0.163)	(0.163)
# of ER visits		0.037***	0.055*			0.037***	
		(0.010)	(0.030)			(0.010)	
# of ER visits sq.			-0.003				
			(0.005)				
I(Forecast) x I(Fam. ER visit)						-0.283*	-0.283*
						(0.152)	(0.152)
I(Forecast)						-0.350***	-0.350***
						(0.083)	(0.083)
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	2012-2018	2012-2018	2012-2018	2012-2018	2012-2018	2012-2018	2012-2018
Observations	26441	26441	26441	26441	26441	26441	26441

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. Inflation forecasts and backcasts are expressed in percentage points. The control variables "# of ER visits" and "# 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. We further restrict the sample by using data from 2012-2018 and applying the sample restrictions from our baseline specification. 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 numerically equivalent to clustering by calendar month alone for the survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.36: Impact of Family ER Visit in Survey Month on Inflation Forecasts and Backcasts (Max 5 ER Events)

	Inflation Forecasts and Backcasts						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
I(Fam. ER visit in survey month)	0.314*** (0.096)	0.267*** (0.097)	0.267*** (0.097)	0.267*** (0.097)	0.268*** (0.097)	0.393*** (0.120)	0.393*** (0.119)
# of ER visits		0.044*** (0.008)	0.047* (0.024)			0.044*** (0.008)	
# of ER visits sq.			-0.001 (0.005)				
I(Forecast) x I(Fam. ER visit)						-0.259** (0.116)	-0.259** (0.116)
I(Forecast)						-0.872*** (0.099)	-0.872*** (0.099)
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
Observations	84348	84348	84348	84348	84348	84348	84348

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. Inflation forecasts and backcasts are expressed in percentage points. The control variables "# of ER visits" and "# 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 5 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 B.37: Impact of Family ER Visit in Survey Month on Inflation Forecasts and Backcasts (Max 9 ER Events)

	Inflation Forecasts and Backcasts						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
I(Fam. ER visit in survey month)	0.203*** (0.077)	0.140* (0.079)	0.139* (0.079)	0.139* (0.078)	0.139* (0.078)	0.234** (0.099)	0.234** (0.099)
# of ER visits		0.039*** (0.005)	0.061*** (0.015)			0.039*** (0.005)	
# of ER visits sq.			-0.003 (0.002)				
I(Forecast) x I(Fam. ER visit)						-0.195** (0.095)	-0.194** (0.095)
I(Forecast)						-0.883*** (0.098)	-0.883*** (0.098)
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
Observations	95829	95829	95829	95829	95829	95829	95829

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. Inflation forecasts and backcasts are expressed in percentage points. The control variables "# of ER visits" and "# 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 9 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 B.38: Impact of Family ER Visit in Survey Month on Inflation Forecasts and Backcasts, Controlling for Recent Income Shocks

	Inflation Forecasts and Backcasts						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
I(Fam. ER visit in survey month)	0.304*** (0.088)	0.242*** (0.090)	0.242*** (0.090)	0.242*** (0.089)	0.244*** (0.089)	0.326*** (0.110)	0.326*** (0.110)
# of ER visits		0.045*** (0.007)	0.046** (0.019)			0.045*** (0.007)	
# of ER visits sq.			-0.000 (0.003)				
I(Forecast) x I(Fam. ER visit)						-0.173 (0.106)	-0.173 (0.106)
I(Forecast)						-0.882*** (0.100)	-0.882*** (0.100)
Recent Log Nominal Income Change	-0.273*** (0.071)	-0.271*** (0.071)	-0.271*** (0.071)	-0.271*** (0.071)	-0.269*** (0.071)	-0.270*** (0.070)	-0.270*** (0.071)
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
Observations	82591	82591	82591	82591	82591	82591	82591

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. Inflation forecasts and backcasts are expressed in percentage points. The control variables "# of ER visits" and "# 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. 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 $t-5$. 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 B.39: Impact of Family ER Visit in Survey Month on Inflation Forecasts and Backcasts, Controlling for Future Income Shocks

	Inflation Forecasts and Backcasts						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
I(Fam. ER visit in survey month)	0.301*** (0.088)	0.238*** (0.089)	0.238*** (0.089)	0.239*** (0.089)	0.241*** (0.089)	0.322*** (0.110)	0.323*** (0.110)
# of ER visits		0.045*** (0.007)	0.046** (0.019)			0.045*** (0.007)	
# of ER visits sq.			-0.000 (0.003)				
I(Forecast) x I(Fam. ER visit)						-0.173 (0.106)	-0.173 (0.106)
I(Forecast)						-0.882*** (0.100)	-0.882*** (0.100)
Future Log Nominal Income Change	-0.216*** (0.062)	-0.215*** (0.062)	-0.215*** (0.062)	-0.215*** (0.062)	-0.213*** (0.062)	-0.215*** (0.062)	-0.215*** (0.062)
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
Observations	82591	82591	82591	82591	82591	82591	82591

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. Inflation forecasts and backcasts are expressed in percentage points. The control variables "# of ER visits" and "# 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. 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 $t-5$. 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. * $p<0.10$ ** $p<0.05$ *** $p<0.01$.

B.6 Additional Results to Section 6

B.6.1 Attention Check and Summary Statistics

Overall, 77 respondents failed the attention check. We present summary statistics for the main analysis sample.

Table B.40: Prolific Survey: Summary Statistics

	Mean	SD
Price Percent Change Next 12m	4.05	10.90
Duration (Minutes)	6.06	4.21
Age	38.95	12.32
Married (%)	41.04	49.21
Bachelors or Higher (%)	0.58	0.49
Respondents	1523	

Notes: This table displays summary statistics for our Prolific survey sample. "Price Percent Change Next 12m" refers to responses to 12 months ahead inflation forecast elicitation, units in percentage point. "Duration" refers to total survey completion time. "Age", "married", and "bachelor or higher" refer to self-reported demographic information in our survey.

B.6.2 Additional Survey Results: Main Elicitations

Table B.41: Factors Influencing Inflation Expectations — Summary Statistics by Factor

	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 survey elicitation "You previously wrote that you thought that prices will increase 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 little" (Column 1) and "a lot" (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).

Table B.42: Factors Influencing Recall of Positive/Negative Events and Framing of the Recall — Regression Table

	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

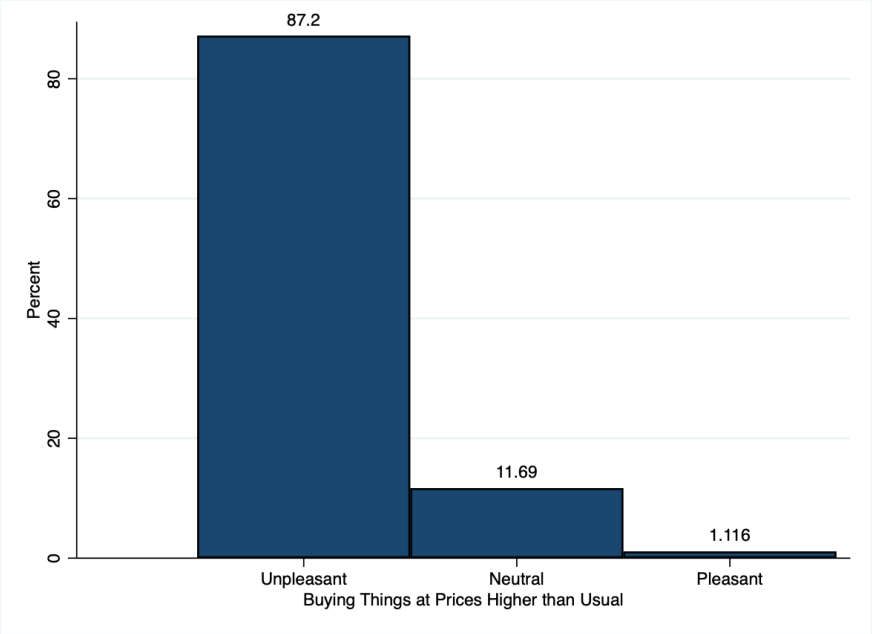
Notes: This table analyzes responses to survey question eliciting which cues are influence recall of positive/negative experiences. We break down responses by the the sub-variants of the elicitation. Colum (1) and (2) present results for the baseline elicitation "Sometimes people recall [negative/positive] 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) presents 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?"
. We display linear regressions of 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. In the first and second columns, we only consider respondents who classify inflation as an unpleasant experience. In the third and fourth columns we restrict to respondents who do not consider inflation an unpleasant experience. Robust standard errors, clustered two-ways (Cameron et al., 2011) at the respondent and cue level, in parentheses. Results are based on the Prolific survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.43: Factors Influencing Recall of High/Low Inflation (By Perceived Valence of Inflation) — Regression Table

	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. We display linear regressions of 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. In the first and second columns, we only consider respondents who classify inflation as an unpleasant experience. In the third and fourth columns we restrict to respondents who do not consider inflation an unpleasant experience. Robust standard errors, clustered two-ways (Cameron et al., 2011) at the respondent and cue level, in parentheses. Results are based on the Prolific survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Figure B.3: Affective Valence of Price Increase — Histogram



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". Results are based on the Prolific survey sample.

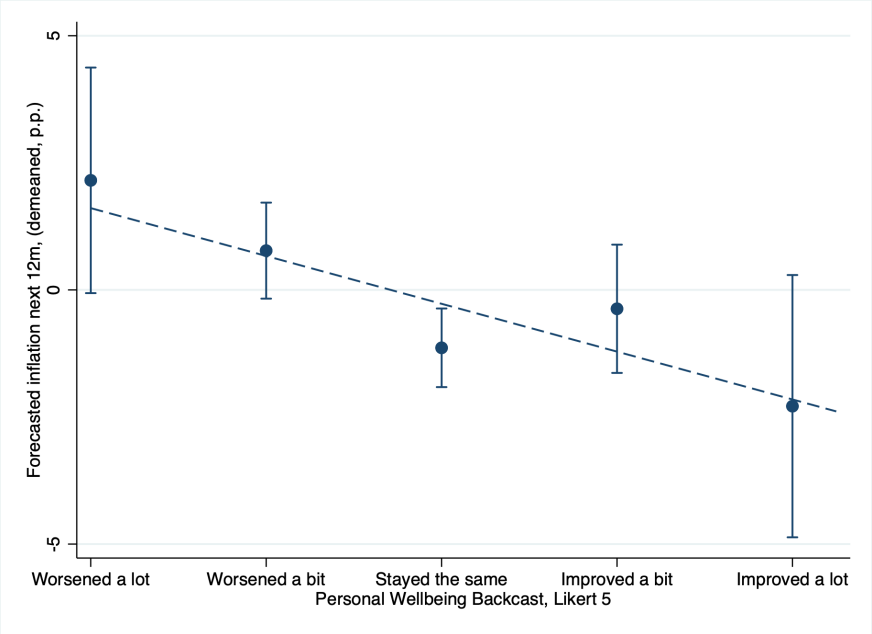
B.6.3 Additional Survey Results: Self-Reported Mood and Inflation Forecasts

Table B.44: Inflation Forecasts and Backcasted Wellbeing Change – Regression Table

	Forecasted inflation next 12m					
	(1)	(2)	(3)	(4)	(5)	(6)
Personal Wellbeing Backcast, Likert 5	-0.941** (0.300)	-0.791** (0.304)			-0.721* (0.326)	-0.632 (0.328)
Backcast Family Finances Changes, Likert 5			-0.738** (0.271)	-0.596* (0.280)	-0.403 (0.292)	-0.311 (0.301)
Demog. Controls	No	Yes	No	Yes	No	Yes
Respondents	1523	1523	1523	1523	1523	1523

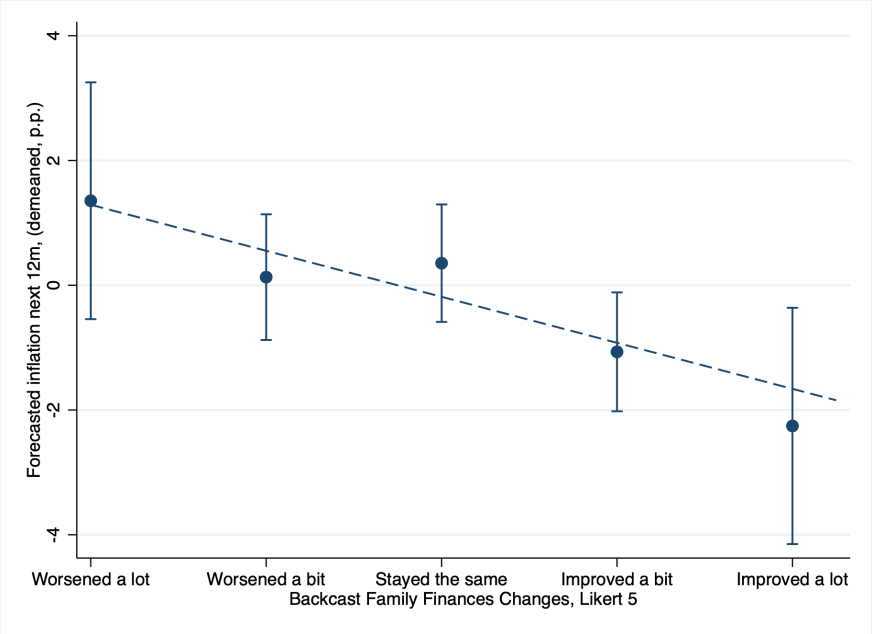
Notes: This table displays a regression of inflation expectations over the 12 months following the survey response on backcasted personal wellbeing and backcasted financial family situation change. We measure backcasted personal wellbeing by asking respondents to select how their mental and physical 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 backcasted financial family situation 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 years of education, age, gender, an indicator for being married, and income. Robust standard errors are in parentheses. Results are based on the Prolific survey sample. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Figure B.4: Inflation Forecasts and Backcasted Wellbeing Change – Figure



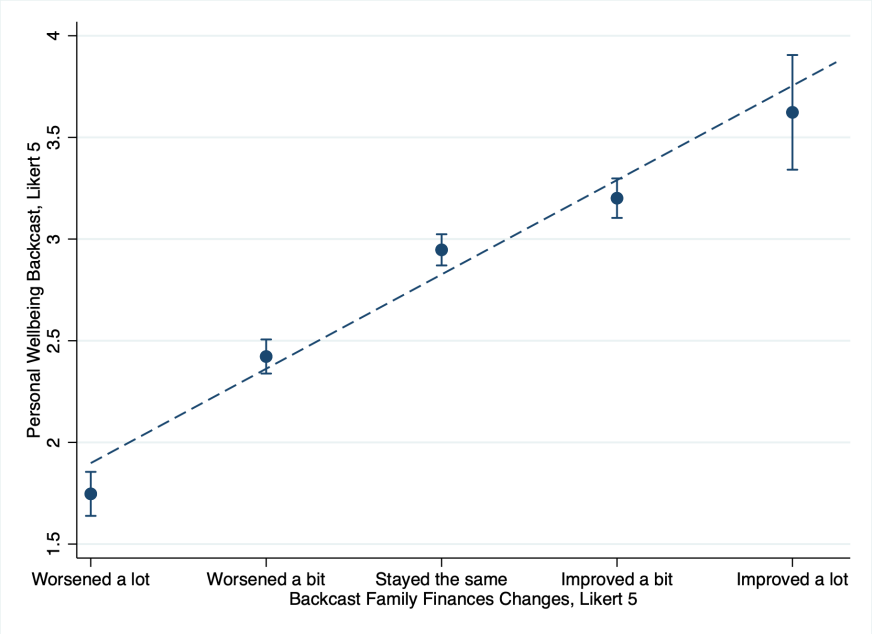
Notes: This figure presents the relationship between forecasted inflation over the 12 months following the survey response and backcasted personal wellbeing. We measure backcasted personal wellbeing by asking respondents to assess how their mental and physical wellbeing has changed over the 12 months 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 Backcasted Wellbeing Change elicitation. Bars denote 95% confidence intervals, constructed using robust standard errors. The fitted line is derived from a regression of forecasted inflation on backcasted personal wellbeing. Results are based on the Prolific survey sample.

Figure B.5: Inflation Forecasts and Backcasted Family Finances Changes – Figure (Prolific Sample)



Notes: This figure presents the relationship between realized inflation and backcasted inflation over the 12 months preceding the survey response and backcasted financial family situation change. We measure backcasted financial family situation 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 Backcasted Financial Situation Change elicitation. Bars denote 95% confidence intervals, constructed using robust standard errors. The fitted line is derived from a regression of realized inflation on backcasted financial family situation change. Results are based on the Prolific survey sample.

Figure B.6: Backcasted Wellbeing Change and Backcasted Family Finances Changes – Figure



Notes: This figure presents the relationship between backcasted personal wellbeing and backcasted financial family situation change. We measure backcasted personal wellbeing 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 backcasted financial family situation change 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 Self-Reported Backcasted Wellbeing Change elicitation. Bars denote 95% confidence intervals, constructed using robust standard errors. The fitted line is derived from a regression of backcasted personal wellbeing on backcasted financial family situation change. Results are based on the Prolific survey sample.

C Mathematical Results

C.1 Proofs

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

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

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 $\mathbb{E}[Y|I_i]$:

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

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,

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

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

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

Because Assumption 1 guarantees that $\mathbb{E}\left[Y|s_i\right]$ is linear in the signal s_i, it follows that[48]

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

and thus

$$\begin{aligned} \frac{Cov\left(\mathbb{E}[Y|I_i], X_i\right)}{Var\left(X_i\right)} &= \frac{Cov\left(s_i, Y\right) Cov\left(s_i, X_i\right)}{Var\left(s_i\right) Var\left(X_i\right)} \\ &= \frac{Cov\left(Z_i + \alpha Y, Y\right) Cov\left(Z_i + \beta Y, Z_i + \alpha Y\right)}{\left(Var\left(Z_i + \alpha Y\right) + Var\left(\delta_i\right)\right) Var\left(X_i\right)} \\ &= \frac{Cov\left(Z + \alpha Y, Y\right) \left(Cov\left(Z + \beta Y, Z + \alpha Y\right) + Var\left(\omega_i\right)\right)}{\left(Var\left(Z + \alpha Y\right) + Var\left(\omega_i\right) + Var\left(\delta_i\right)\right) Var\left(X_i\right)}, \end{aligned} \tag{9}$$

[48] 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.

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+\beta 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+\beta Y, Z+\alpha Y\right)+Var\left(\omega_i\right)}{Var\left(X_i\right)}\right| \\
&= \frac{1}{Var\left(X_i\right)}\Bigg|Cov\left(Z+\beta Y, Y\right) \\
&\quad - \frac{\left(Cov\left(Z+\beta Y, Y\right) - Cov\left(\left(\beta-\alpha\right)Y, Y\right)\right)\left(Cov\left(\left(\beta-\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)}\Bigg| \\
&= \frac{1}{Var\left(X_i\right)}\Bigg|Cov\left(Z+\beta 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) \\
&\quad + \left(\beta-\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)}\Bigg| \\
&= \frac{1}{Var\left(X_i\right)}\Bigg|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) \\
&\quad + \left(\beta-\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)}\Bigg| \\
&\leq \frac{\left|Cov\left(X, Y\right)\right|}{Var\left(X_i\right)} + \frac{\left|\beta-\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\beta-\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\beta-\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\beta-\alpha\mid Var\left(Y\right)}{Var\left(X_i\right)}
\end{aligned}$$

Derivations of formulas in Section 5.2. As $Y_-|I_i$ is Normally distributed, its probability density function can be written as

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

Based on the formula of the similarity function $\mathcal{S}\left(Y_-, I_i\right)$ in (4) ,and the definition of subjective probability density function $f_\theta\left(Y_-|I_i\right)$ in (5), we have

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

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

where

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

which is the subjective inflation backcast in (6).

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

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

Based on the formula of $f_\theta\left(Y_-|I_i\right)$ above and the definition of subjective probability density function $h_\theta\left(Y|I_i\right)$ in (7), we have

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

where

$$\mathbb{F}_i\left[Y|I_i\right] = \rho_Y \mathbb{F}_i\left[Y_-|I_i\right] + \rho_I \mathbb{E}\left[Y|Y_- = 0, I_i\right],$$

and ρ_Y and ρ_I parametrize the Bayesian conditional mean $\mathbb{E}\left[Y|Y_-, I_i\right]$:

$$\mathbb{E}\left[Y|Y_-, I_i\right] = \int g\left(Y|Y_-, I_i\right) dY = \rho_Y Y_- + \rho_I \mathbb{E}\left[Y|Y_- = 0, I_i\right].$$

Analogously, the Bayesian counterpart $\mathbb{E}\left[Y|I_i\right]$ can be written as

$$\mathbb{E}\left[Y|I_i\right] = \rho_Y \mathbb{E}\left[Y_-|I_i\right] + \rho_I \mathbb{E}\left[Y|Y_- = 0, I_i\right].$$

Together,

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

which is the subjective inflation forecast in (8).

C.2 Additional results related to Test 2.

Bound in (3) for the third case 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. This case can be nested within Assumption 1 with $s_i = Z_i = X_{i,1}$, $\alpha = \delta_i = 0$, and $\beta = \gamma_2$. 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 $X = \int X_i di = \left(\gamma_1 + \gamma_2\right) Y$, we have $Var\left(X\right) = \left(\gamma_1 + \gamma_2\right)^2 Var\left(Y\right)$, or $\sqrt{Var(Y)} = \sqrt{Var(X)}/|\gamma_1 + \gamma_2|$, and thus

$$\begin{aligned}\left|\gamma_2\right| Var(Y) &= \left|\gamma_2\right| \sqrt{Var(Y)} \cdot \sqrt{Var(Y)} \\ &= \frac{\left|\gamma_2\right|}{\left|\gamma_1 + \gamma_2\right|} \sqrt{Var(Y)} \cdot \sqrt{Var(X)},\end{aligned}$$

from which it follows that

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

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

A tighter bound when X_i is purely idiosyncratic. Consider a variant of Assumption 1 where the household-level variable X_i is purely idiosyncratic.

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: $X_i = Z_i + \nu_i$, $s_i = Z_i + \alpha Y + \delta_i$, and $Z_i = \omega_i$, where $\nu_i, \delta_i, \omega_i$ are mean-zero,*[49] *and independent of both Y and Z.*

Compared to Assumption 1, this case sets $\beta = 0$ and $Z \equiv 0$, guaranteeing that X_i is purely idiosyncratic, and thus $X_i \perp Y$. We now establish a tighter bound compared to (3).[50]

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

$$\left|\tilde{\beta}_1^X - \beta_1^X\right| \leq \left|\frac{\alpha Var\left(Y\right)}{\alpha^2 Var\left(Y\right) + Var\left(X_i\right)}\right|, \tag{10}$$

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

Proof of Test 3. From (2) and Assumption 2, we have: $\beta_1^X = 0$. By (1),we have:

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

Equation (9) continues to hold, so

$$\begin{aligned}\frac{Cov\left(\mathbb{E}[Y|I_i], X_i\right)}{Var\left(X_i\right)} &= \frac{Cov\left(s_i, Y\right) Cov\left(s_i, X_i\right)}{Var\left(s_i\right) Var\left(X_i\right)} \\ &= \frac{\alpha Var\left(Y\right) Var\left(\omega_i\right)}{\left(\alpha^2 Var\left(Y\right) + Var\left(\omega_i\right) + Var\left(\delta_i\right)\right) Var\left(X_i\right)},\end{aligned}$$

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

[50] Based on (3), we know that rational expectations in (1) imply that $\left|\tilde{\beta}_1^X - \beta_1^X\right| \leq \frac{|\alpha| Var(Y)}{Var(X_i)}$, a bound looser than 10.

where we use the forms of X_i, s_i, and Z_i from Assumption 2 for the final equality. Because $\beta_1^X = 0$,

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

where we use the fact that $Var\left(\omega_i\right) \leq Var\left(X_i\right)$ from Assumption 2. Exact equality holds when $Var\left(\nu_i\right) = Var\left(\delta_i\right) = 0$, meaning that $s_i = X_i + \alpha Y$.

C.3 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: $X_i = Z_i + \beta Y + \nu_i$, $s_i = Z_i + \alpha Y + \delta_i$, 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.*[51]

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 (3) 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*

$$\left|\tilde{\beta}_1^X - \beta_1^X\right| \leq \frac{\sqrt{Var\left(X\right) Var\left(Y\right)}}{Var\left(X_i\right)} + \frac{\left|\beta - \alpha\right| Var\left(Y\right)}{Var\left(X_i\right)}, \tag{11}$$

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

[51] 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 $X = \int X_i di = Z + \beta Y$ 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

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

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 2,

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+\beta 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. \\
&\left. + \mathbb{E}_{I_i'}\left[\left(\beta-\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| \\
&\leq \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{|\,\beta-\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| \\
&\leq \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{|\beta-\alpha|\,\mathbb{E}_{I_i'}\left[Var\left(Y|I_i'\right)\right]}{Var\left(X_i\right)} \\
&\leq \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{|\beta-\alpha|\,\mathbb{E}_{I_i'}\left[Var\left(Y|I_i'\right)\right]}{Var\left(X_i\right)} \qquad (12) \\
&\leq \frac{\sqrt{Var\left(X\right)Var\left(Y\right)}}{Var\left(X_i\right)} + \frac{|\beta-\alpha|\,Var\left(Y\right)}{Var\left(X_i\right)} \qquad (13)
\end{aligned}$$

where (12) follows from the Cauchy–Schwarz inequality and (13) 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 $\xi_{i,t}$.[52] $X_t^{\text{level}}, \eta_{i,t}^{\text{level}}$, and the macro variable (e.g., inflation) Y_t all follow an AR(1) process:

$$X_{i,t}^{\text{level}} = X_t^{\text{level}} + \eta_{i,t}^{\text{level}} + \xi_{i,t}, \qquad (14)$$

$$X_t^{\text{level}} = \rho_x X_{t-1}^{\text{level}} + \varepsilon_t^x, \qquad (15)$$

$$\eta_{i,t}^{\text{level}} = \rho_\eta \eta_{i,t-1}^{\text{level}} + \varepsilon_{i,t}^\eta, \qquad (16)$$

$$Y_t = \rho_y Y_{t-1} + \varepsilon_t^y, \qquad (17)$$

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 independent. This income process is akin to the one in Guvenen and Smith (2014), abstracting from deterministic life-cycle components.

[52] 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.

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 ($L, L_\xi, L_{agg} \in [0, \infty]$). 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

$$\begin{aligned} I_{i,t} &= \left\{ s_{i,t}^{\text{level}} = X_{i,t+1}^{\text{level}} + \delta_{i,t}, \left\{ X_{i,t-l}^{\text{level}} \right\}_{l=0}^{L}, \left\{ X_{t-l}^{\text{level}}, Y_{t-l} \right\}_{l=0}^{L_{agg}}, \{\xi_{i,t-l}\}_{l=0}^{L_\xi} \right\} \\ &= \left\{ s_{i,t} = X_{i,t+1}^{\text{level}} - X_{i,t}^{\text{level}} + \delta_{i,t}, \left\{ X_{i,t-l}^{\text{level}} \right\}_{l=0}^{L}, \left\{ X_{t-l}^{\text{level}}, Y_{t-l} \right\}_{l=0}^{L_{agg}}, \{\xi_{i,t-l}\}_{l=0}^{L_\xi} \right\}, \end{aligned} \tag{18}$$

where $\delta_{i,t}$ is i.i.d. across i, t and indepenent of $\left\{ \varepsilon_t^x, \varepsilon_t^y, \xi_{i,t}, \varepsilon_{i,t}^\eta \right\}$ and I 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 2. 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

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

Becasue $\varepsilon_{i,t}^{\eta+1}$, $\xi_{i,t+1}$, 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 1 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 (14) – (17) 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 ($L, L_\omega \in [0, \infty]$). 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

$$\begin{aligned} I_{i,t} &= \left\{ s_{i,t}^{\text{level}} = X_{i,t+1}^{\text{level}} + \delta_{i,t}, \left\{ X_{i,t-l}^{\text{level}} \right\}_{l=0}^{L}, \{\xi_{i,t-l}\}_{l=0}^{L_\xi} \right\} \\ &= \left\{ s_{i,t} = X_{i,t+1}^{\text{level}} - X_{i,t}^{\text{level}} + \delta_{i,t}, \left\{ X_{i,t-l}^{\text{level}} \right\}_{l=0}^{L}, \{\xi_{i,t-l}\}_{l=0}^{L_\xi} \right\}, \end{aligned} \tag{19}$$

where $\delta_{i,t}$ is i.i.d. across i, t and indepenent of $\left\{ \varepsilon_t^x, \varepsilon_t^y, \xi_{i,t}, \varepsilon_{i,t}^\eta \right\}$ and I 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 2. 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

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

Becasue $\varepsilon_{i,t+1}^\eta$, $\xi_{i,t+1}$, 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.