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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 limited-information rational expectations (LIRE) 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 associations. 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 learning and memory limitations. 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 limited information rational expectations (LIRE) and its possible violations.

[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.

The null hypothesis of LIRE generalizes full information rational expectations (FIRE) and applies to a broad class of models in which people form Bayesian forecasts using limited information, including limited availability of information, rational inattention, or memory constraints (e.g., da Silveira et al., 2020). People may violate LIRE if they are excessively sensitive to the informational content of household-level events. Such excess sensitivity can arise from overconfidence/over-precision bias (e.g., Scheinkman and Xiong, 2003; Broer and Kohlhas, 2022) and misperceived correlation between different macroeconomic variables (e.g., Kamdar, 2019; Candia et al., 2020). It can also arise from selective recall, as in theories of diagnostic expectations due to the representativeness heuristic (Bordalo et al., 2018, 2022; Bianchi et al., 2023) and in theories of non-Bayesian inference from associative memory (e.g., Mullainathan, 2002; Bordalo et al., 2023, 2024). That is, positive (negative) household-level events cue recall of positive (negative) memories, and people who take these recalled memories at face value become overly optimistic (pessimistic) about the economy. Finally, there may be 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.*

We start by investigating how inflation forecasts and actual inflation covary with recent changes in total household income, as well as related variables such as labor income. Under the assumption that recent household income changes are in respondents' information sets, LIRE implies that a regression of actual inflation on recent household income changes and a regression of forecasted inflation on recent household income changes should produce identical coefficients. 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 income changes and inflation expectations. The data provide a stark rejection of LIRE because the coefficient of recent income changes in the first regression is a tightly estimated near-zero, while the coefficient of recent income changes in the second regression is significantly different from zero, and negative. The results are robust to varying sets of controls and to alternative measures of income changes. We also show that our empirical results are inconsistent with LIRE in the more general case where recent income changes are not (fully) in respondents' information sets.

This result is robust to a number of different subsamples: high- versus low-income respondents, respondents who do not experience unemployment, marriage, or retirement transitions, respondents with income changes that are 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. Thus, an association between people's prior biases about inflation and income growth trajectories cannot explain this set of regressions 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. Under innocuous regularity assumptions, LIRE then predicts that regressing actual and forecasted inflation, respectively, on the survey responses will yield identical coefficients. Instead, and analogous to the first test, we find that the coefficient in the first regression is tightly estimated to be effectively zero, while the coefficient in the second 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 forecasted and actual inflation on realized household future income changes. A key challenge in relating such regression results to formal tests of rational expectations is that realized future income changes are not plausibly in people's information sets. Thus, LIRE does not imply that the coefficients of future income changes in the two regressions 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 degree to which household-level income changes are idiosyncratic rather than correlated. Empirically, we find that this bound is an order of magnitude smaller than the difference between the estimated coefficients of future income changes in the two regressions. Thus, people's inflation forecasts appear to be excessively sensitive also to news about their future income changes.

In the second part of the paper, we investigate mechanisms for the excess sensitivity of inflation forecasts to recent and expected income changes, focusing on the role of selective recall. This analysis 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 estimate regression models that are analogous to the ones 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 household-level variables generate tightly estimated near-zero coefficients, respondents' recollections of past inflation are significantly negatively associated with the household-level variables. In fact, we find that inflation backcasts are more strongly associated with our measures of household-level income changes than are forecasts. 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 investigate the possibility that an important channel through which household-level events influence memory is *affective associations*: negative (positive) household-level events trigger recall of price increases (decreases), because people perceive price increases as negatives and price decreases as positives. 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 propensity to visit the ER, respondents who are randomly asked to take the survey in the month of an ER visit have higher inflation backcasts and forecasts. Moreover, ER visits have significantly larger effects on backcasts than on forecasts, consistent with the hypothesis that memory plays a mediating role in respondents' forecasts.

While there is a large and growing literature rejecting FIRE,[2] less is known about how much of this is due to limited information versus systematic deviations from Bayesian updating. Our paper contributes to the smaller literature that studies how economic forecasts deviate from Bayesian updating. Bordalo et al. (2020) show that, at the household level, revisions in forecasts about macroeconomic variables can predict forecast errors of these variables. This finding rules out LIRE 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 LIRE violations.

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, 2023). The scope of our paper is broader because we also study the impact of news about household-level events, and because we provide

[2]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).

evidence of imperfect recall and affective associations as a mechanism.[3] Additionally, we expand this literature by (i) developing and implementing formal tests of LIRE, (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,[4] and (iv) studying how experiences in one domain affect economic expectations in a different domain (see also Cenzon, 2023, for concurrent work on cross-domain extrapolation).

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; Bordalo et al., 2018; da Silveira et al., 2020; Zimmermann, 2020; Gagnon-Bartsch et al., 2021; Huffman et al., 2022; Afrouzi et al., 2023; Sial et al., 2023; Bordalo et al., 2023; Enke et al., 2024; Bordalo et al., 2024; Salle et al., 2024; Graeber et al., forthcoming). 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 and 4 contain our main tests about how recent and expected future income changes relate to inflation forecasts. Section 5 analyzes backcasts and investigates the role of selective recall and affect in explaining forecast biases. Section 6 concludes.

1 Data, Sample Selection, and Variable Construction

1.1 Survey Data

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

[3] In recent work, Link et al. (2024) find that past adverse inflation experiences lead to more attention to inflation, which is also consistent with associative memory.

[4] 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 LIRE tests that are robust to potential noise and by leveraging administrative tax data where any potential reporting error is minimal.

from the registry of the Danish Civil Registration System (CPR Registret).[5] Sampled individuals receive a link to participate in the online survey through the Danish Digital Post system. Each Danish resident receives a unique account to the Digital Post system at the age of 15 and can use it as a secure way to communicate with all public authorities. Individuals who cannot receive digital mail are contacted through physical letters. Non-respondents first receive reminders and, if there is no follow-up, Statistics Denmark attempts a final contact through telephone interviews. Individuals are classified as non-respondents whenever they do not reply by the closing date of the survey wave—two days before the publication of the Statistical Newsletter. Overall, the official, Government-branded means of contact and persistent follow-ups lead to high response rates. The average monthly response rate is 64%.

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

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

[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.

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:

> *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 the household's financial position:

> *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

[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.

[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?"*.

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] 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.[11]

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.[12]

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.[13] In Appendices B.3.4 and B.4.6, we demonstrate

[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.

[11] 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 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).

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

[13] 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.

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;[14] (ii) if they declined to answer any of the key survey forecast or backcast questions mentioned above;[15] (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, recent changes in the household's log nominal income are constructed as the log nominal income of year $t-1$ minus that of year $t-2$. This measure captures the recent changes in households' log nominal income that occurred before the interview.[16] Similarly, we measure future log nominal income changes by comparing log nominal incomes in years $t+1$ versus $t-1$.[17] In the appendix, we show that our findings remain valid when focusing on recent changes in households' log real income. We provide similar robustness checks for future income changes.

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 fluctuations in households' economic situation affect inflation expectations. Finally, we trim all income changes at the 2.5 and 97.5 percentiles.[18]

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

[15] 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).

[16] 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 LIRE test developed in Section 3.

[17] 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.

[18] 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

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 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 income changes relate to beliefs about inflation, this section presents the notation we use throughout the paper, defines limited-information rational-expectations (LIRE) benchmark, and discusses the possible LIRE violations that could be consistent with our empirical results.

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 from 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 that we will consider are recent household income changes $X_{i,t(\tau)^-}$ and future household income changes $X_{i,t(\tau)^+}$, where $t(\tau)$ is the year that includes 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 LIRE 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,

before trimming the income changes). For analyses studying wealth changes, we trim the changes analogously.

and to any macroeconomic variable Y and household-level variable X_i.

In our formal tests, we also distinguish people's subjective beliefs and their survey reports of those beliefs. We let $\tilde{F}_i Y$ denote respondent i's report of their subjective belief $\mathbb{F}_i[Y|I_i]$, with the potential difference being due to random elicitation noise. We let Z_i denote survey responses that don't have a clear cardinal interpretation, such as the 1-5 Likert scale assessments of future household financial situation that are elicited in the Danish survey.

We define the null hypothesis of (limited-information) rational-expectations as follows.

Definition 1 (LIRE)**.** The subjective belief of person i about Y is given by

$$\mathbb{F}_i[Y|I_i] = \mathbb{E}[Y|I_i],$$

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.

LIRE encompasses the standard approach to modeling belief formation. It generalizes FIRE, which is the special case in which the information set I_i incorporates all available information in the economy. However, 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). Our definition of LIRE allows for survey response noise, as it is a condition on $\mathbb{F}_i$, not on $\tilde{F}_i Y$.

One goal of our empirical analysis will be to provide evidence for LIRE violations that involve *excessive sensitivity to information* in the household-level variable X_i (e.g., recent changes in household income). That is, the person's subjective belief about Y is more sensitive to information in X_i than its Bayesian counterpart. Formally:

Definition 2 (Excessive sensitivity to information)**.** Person i's subjective belief about Y is excessively sensitive to information in X_i if

$$\left|\bar{\mathbb{F}}_i[Y|X_i] - \bar{\mathbb{F}}_i[Y|X_i^{'}]\right| \geq \left|\mathbb{E}[Y|X_i] - \mathbb{E}[Y|X_i^{'}]\right| \quad \text{for} \quad X_i \neq X_i^{'}, \tag{1}$$

where $G(\cdot|X_i)$ is the distribution of I_i conditional on X_i, and $\bar{\mathbb{F}}_i[Y|X_i] := \int \mathbb{F}_i[Y|I_i] dG(I_i|X_i)$ is the average subjective belief conditional on X_i.

Excessive sensitivity to information can arise from commonly studied theories of quasi-Bayesian updating, such as overconfidence and misperceived correlations between different macroeconomic variables. To illustrate, suppose that the household-level variable is given by $X_i = X + \nu_i$, a sum of an aggregate component X that is related to Y and an idiosyncratic component ν_i that is independent of Y. Overconfidence implies that the person's perceived variance of the noise (the idiosyncratic component), $\text{Var}^p(\nu_i)$, is lower than its actual variance $\text{Var}(\nu_i)$. As a result, the person is excessively sensitive to information in X_i because they perceive X_i as a more informative signal about Y than it actually is. Excessive sensitivity to information can also arise from misperceived correlation between different macroeconomic variables, which means that the person has an incorrect perception of the correlation between the aggregate component X and the macro variable Y. For example, such misperceived correlation can arise because the person has a "supply-side" view of inflation (Kamdar, 2019; Candia et al., 2020); i.e., that the person perceives inflation as being driven by negative supply shocks (e.g., supply chain shortages) that decrease economic activity and household income, and ignore the fact that at least in some cases inflation is driven by positive demand shocks (e.g., accommodative monetary and fiscal policies that increase economic activity and household income).

Excessive sensitivity to information can also arise from selective recall, as emphasized in theories of diagnostic expectations and the representativeness heuristic (Bordalo et al., 2018, 2022; Bianchi et al., 2023), and in theories of associative memory (e.g., Mullainathan, 2002; Bordalo et al., 2023, 2024). These theories consist of two components. The first is how X_i cues recall of certain types of events. For example, negative household events may cue the recall of negative events, such as large increases in the prices of commonly-purchased groceries. We refer to this specific type of association as affective association, a hypothesis we will also explore. The second component is how people utilize the recalled information. The theories of selective recall cited above posit that people do not incorporate the influence of X_i on recall in a fully Bayesian manner. To take an example, if a negative household shock leads a person to recall a large price increase but the person does not appreciate that this recall is influenced by the negative shock, then this person will perceive recent price increases as more representative of the economy than they actually are, and thus overestimate the extent of recent inflation. This, in turn, can lead to inflation forecasts that are too high, if the person (correctly) believes inflation to be strongly autocorrelated. Thus, if people do not fully incorporate the influence of X_i on recall in a fully Bayesian manner, then both their backcasts and forecasts will be excessively sensitivity to X_i. Alternatively, if people fully account for the relationship between X_i and the recalled events, and form beliefs about past and present in a Bayesian manner, then backcasts, and consequently forecasts, will satisfy LIRE and will *not* be excessively sensitive to X_i. For example, if a person understands that price increases are coming to mind more readily due to a negative household event, then this person will appropriately down-weight the influence of recalled price increases when forming an assessment of past or future economic conditions.[19]

Another possible source of LIRE violations is what we call *prior bias* (Patton and Timmermann,

[19]In somewhat more formal notation, consider the case in which the person's information at the time of forecast is given by $I_i = \{X_i, \boldsymbol{m_i}(X_i)\}$, where $\boldsymbol{m_i}(X_i)$ captures the recalled events cued by the household variable X_i. Rational people understand the dependence of $\boldsymbol{m_i}(X_i)$ on X_i. As a result, their subjective beliefs are still given by $\mathbb{F}_i[Y|I_i] = \mathbb{E}[Y|I_i] = \mathbb{E}[Y|X_i]$. The recalled events do not affect their subjective forecast, and people's forecasts still satisfy LIRE as in Definition 1. On the other hand, if people do not understand the dependence of $\boldsymbol{m_i}(X_i)$ on X_i when forming subjective forecasts, or directly make forecasts based on "simulation" given $\boldsymbol{m_i}$ (Bordalo et al., 2024), then their forecasts will not satisfy LIRE.

2010; Das et al., 2020; Farmer et al., 2023). For example, people's subjective forecasts may be given by $\mathbb{F}_i[Y|I_i] = \mathbb{E}[Y|I_i] + a_i$, where a_i captures the person being persistently overly pessimistic or optimistic, independent of available information. Empirically, to distinguish excess sensitivity from prior bias, we need to rule out the possibility that a_i is associated with X_i, which we pursue in some of our analyses. For example, we will rule out that prior bias is related to households' income growth trajectories, which will suggest that excessive sensitivity to information explain forecast biases.

3 Inflation Forecasts and Recent Changes in Household Income

In this section, we study the association between inflation forecasts and recent changes in household income and related variables. The analysis is guided by a formal test of LIRE, which dictates how the association between recent income changes and forecasted inflation should compare to the association between recent income changes and actual inflation. We begin by providing a general formulation of the test for any household-variable X_i and any macroeconomic variable Y and its forecasts $\tilde{F}_i Y$. We then proceed to implement the test in our data.

3.1 Testing LIRE Using Variables in People's Information Sets

Our formal test of rational expectations requires two assumptions.

Assumption 1. *The survey elicitation of $\mathbb{F}_i[Y|I_i]$ is given by*

$$\tilde{F}_i Y = \mathbb{F}_i[Y|I_i] + \eta_i \quad \textit{where} \quad \eta_i \perp I_i, \ \eta_i \perp Y. \tag{2}$$

Assumption 2. *The household-level variable X_i is in person i's information set:*

$$\mathbb{E}[X_i|I_i] = X_i \quad \forall I_i.$$

The first assumption is relatively innocuous: it states that any noise or measurement error in the survey elicitation of subjective beliefs is idiosyncratic, though not necessarily mean-zero. The second assumption only plausibly applies to recent, consequential, and salient household-level variables, such as recent changes in household income. We also develop an approach that allows us to utilize weaker assumptions than Assumption 2, which we summarize later in this section and expand in Section 4.3.

Test 1. *If Assumptions 1 and 2 hold, then LIRE implies that the forecast error $Y - \tilde{F}_i Y$ is uncorrelated with X_i: $Cov\left(Y - \tilde{F}_i Y, X_i\right) = 0$. Equivalently, in linear regressions of Y and $\tilde{F}_i Y$ on X_i,*

$$Y = \beta_0^X + \beta_1^X X_i + \epsilon_i^X \quad v.s. \quad \tilde{F}_i Y = \tilde{\beta}_0^X + \tilde{\beta}_1^X X_i + \tilde{\epsilon}_i^X, \quad where \ Cov\left(\epsilon_i^X, X_i\right) = Cov\left(\tilde{\epsilon}_i^X, X_i\right) = 0, \tag{3}$$

LIRE implies that $\beta_1^X = \tilde{\beta}_1^X$.

Intuitively, Test 1 leverages the implication that, with rational expectations, information is used efficiently and thus the forecast error $Y - \mathbb{E}[Y|I_i]$ cannot be predicted by anything within the information set, so $\beta_1^X - \tilde{\beta}_1^X = 0$. In particular, in a regression of the forecast error $Y - \mathbb{E}[Y|I_i]$ on X_i, the coefficient of X_i is $\beta_1^X - \tilde{\beta}_1^X$, and LIRE implies that this coefficient is zero. Idiosyncratic survey response noise does not alter this prediction, and neither does pooling across people with different information sets. 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. Last, 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, described below.

The variable X_i is related to Y through time-series variation, and it is related to $\tilde{F}_i Y$ through both time-series variation and household-level (informational) differences in the cross-section. (As discussed in Section 2, we drop the time subscripts from those variables to simplify notation and exposition). One concern is that if our sample does not include sufficiently many years, our estimate of the relationship between Y and X_i, which are related to each other only through time-series variation, could be biased. In particular, this could generate a downward bias in our estimate of $\left|\beta_1^X\right|$, as illustrated by considering the extreme case where we have survey data from only a single month. In this case, the macroeconomic variable Y is constant in this sample, while X_i still varies across households in this sample, and thus the estimates of β_1^X are mechanically zero in this sample. Fortunately, 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 the tests that follow are tests on the joint distribution of $\left(X_i, Y, \tilde{F}_i Y\right)$. A particular causal interpretation, such as changes in household income X_i *causing* changes in beliefs $\mathbb{F}[Y|I_i]$, 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. Test 1 also does not require any functional form assumptions, such as $\mathbb{E}[Y|X_i]$ being linear in X_i; the test applies to any pair of regressions, irrespective of the curvature of the conditional expectation functions.

If Assumption 2 is violated, then Test 3 from Section 4.3, which does not require the household-level variable to be in the person's information set, implies the bound $|\beta_1^X - \tilde{\beta}_1^X| \leq 0.01$ for recent income changes.[20] Intuitively, because most of the variation in X_i is idiosyncratic, both β_1^X and $\tilde{\beta}_1^X$ have to be close to zero under LIRE, and thus X_i cannot have significant predictive power for Y.

3.2 Main Empirical Results

To implement Test 1, we regress realized inflation (Y) and forecasted inflation ($\tilde{F}_i Y$) over the 12 months following the survey response on recent changes in household's log nominal income (X_i). As discussed in Section 1, recent changes in the households' log nominal 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.

Table 1 and Figure 1 present our main results. Column 1 of Table 1 presents a regression of realized inflation on recent changes in households' log nominal 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. 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 3-5 of Table 1 present regressions of inflation forecasts on recent changes in households' log nominal income, with varying sets of controls, further discussed below. All three regressions find large and negative associations between recent changes in household income and inflation forecasts, starkly rejecting the null hypothesis that $\tilde{\beta}_1^X = \beta_1^X$. Figure 1 provides a binned scatter plot of the relationship between inflation forecasts and recent household income changes, based on the column 4 specification.[21]

The uncontrolled regression in column 3 can in principle be consistent with excessive sensitivity or the possibility that prior bias a_i is associated with income growth trajectories and thus recent income changes. For example, inflation forecasts are known to differ with demographics such as income level, gender, and education (e.g., Das et al., 2020, D'Acunto et al., 2021a and D'acunto et al., 2023a; see Appendix Table B.4 for replication in our data), and income growth trajectories may differ along those demographics as well. To begin differentiating between excess sensitivity and prior bias, in column 4 we include the following 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

[20] Note that in Section 4.3 we instead focus on the bound for regressions on future income changes, which has a slightly different value.

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

[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.

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. The coefficient of recent income changes increases rather than decreases in magnitude when such controls are included. To further investigate the possibility that prior bias a_i is associated with income growth trajectories, 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 $t-10$.[24] 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 a_i is not associated with income growth trajectories.

In column 5, we additionally include calendar-month fixed effects, as it is done in some related work (e.g., Gennaioli et al., 2016; Kuchler and Zafar, 2019). 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 LIRE. 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.

The magnitudes in columns 3 to 5 are comparable to known associations between inflation forecasts and household income, education level, or gender—see Appendix Table B.4 for a replication in our data.

3.3 Additional Results and Robustness

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

[24] 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 $t-6$.

(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 might see a different association for respondents whose incomes are not subject to local shocks.[25] 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.[26] 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

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

[26]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.

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?[27] 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.[28]

Appendix Table B.7 further extends Table 1 by considering other ways in which the household financial situation changed in the recent past: changes in liquid assets and changes in total 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.[29]

Appendices B.3.4 and B.3.5 include several other robustness checks, replicating our main results. First, we include the years 2008-2011, covering the Great Recession, where inflation was more volatile. Second, we consider real income change rather than nominal income changes.

4 Inflation Forecasts and Expected Future Household Income Changes

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 changes in expected future household income? The answer to this question is a priori unclear. There are reasons why inflation forecasts may associate less strongly with expected future 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 changes in household income can be salient as well, and people may perceive a closer relationship between future inflation and future rather than past household income changes.

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

[28]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.

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

Our analysis in this section consists of two sets of tests, corresponding to two types of proxies for changes in expected future household income. First, we consider how inflation forecasts relate to qualitative survey forecasts of household financial situation changes (which are shown are highly informative of future household income changes). Second, we consider how inflation forecasts relate to the actual future income changes that we measure in administrative tax data.

4.1 Forecastability of Future Income Changes

As a preliminary step, we first show that people possess information about future household income changes 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 highly informative of future household income changes. Panel (a) presents the distributions of future changes in households' log nominal income (between the year after the survey response versus the year before), 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 households' log nominal 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 households' log nominal income. Appendix Table B.10 presents regressions, with various sets of controls, that quantify the patterns in Figure 2. Importantly, Appendix Table B.10 shows that recent income changes are in fact negatively autocorrelated with future income changes and that the predictive power of the survey proxy is unaltered when recent income changes are included as a control. Appendix Figure B.2 and Appendix Table B.15 show that these results are robust to alternatively using real income.

4.2 Inflation Forecasts and Forecasted Household Financial Situation Changes

4.2.1 Formal Test

The analysis in this subsection is guided by a formal test of LIRE, which dictates how the association between inflation forecasts and the survey proxy of expected future income changes (forecasted changes in household financial situation) should compare to the association between actual inflation and the same survey proxy. We begin by providing a general formulation of the test for any survey response Z_i and any macroeconomic variable Y and its forecasts $\tilde{F}_i Y$. We then proceed to implement the test in our data. Relative to our first test, we utilize the following additional assumption, in conjunction with Assumption 1.

Assumption 3. *The survey response Z_i is independent of the random noise in the survey elicitation*

$\tilde{F}_i Y = \mathbb{F}[Y|I_i] + \eta_i$*:*

$$Z_i \perp \eta_i.$$

Additionally, the survey response Z_i contains no information about Y beyond the information set I_i. That is, conditional on I_i, Z_i is independent of Y:

$$Z_i \perp Y|I_i.$$

The first part of Assumption 3 is particularly plausible when the elicitation format for Z_i is different from the elicitation format for Y. In our case, Z_i is a response on a 5-point Likert scale, while $\tilde{F}_i Y$ is a quantitative response in percentage point units. Thus, survey noise in the elicitation of Z_i is unlikely to be associated with survey noise in the elicitation $\tilde{F}_i Y$. The second part of Assumption 3 is arguably close to tautological, as it simply requires that people's survey responses do not contain any more information than the information people actually have. Our next test leverages this assumption as follows.

Test 2. *Consider linear regressions of Y and $\tilde{F}_i Y$ on the survey response Z_i:*

$$Y = \beta_0^Z + \beta_1^Z Z_i + \epsilon_i^Z \quad v.s. \quad \tilde{F}_i Y = \tilde{\beta}_0^Z + \tilde{\beta}_1^Z Z_i + \tilde{\epsilon}_i^Z, \quad where\ Cov\left(\epsilon_i^X, Z_i\right) = Cov\left(\tilde{\epsilon}_i^X, Z_i\right) = 0. \quad (4)$$

If Assumptions 1 and 3 hold, then LIRE implies that $\beta_1^Z = \tilde{\beta}_1^Z$.

Similar to Test 1, the intuition for Test 2 is based on the implication that the rational expectations forecast error $Y - \mathbb{E}[Y|I_i]$ cannot be predicted by anything within the person's information set because rational expectations require agents to use their information efficiently. The implications of this intuition are powerful, as the test requires minimal structure on Z_i. For example, consider the case where Z_i is people's qualitative forecasts about their financial situation changes, given by $Z_i = h\left(\mathbb{E}[X_i|I_i]\right) + \eta_i^Z$—a transformation of expected future household income changes $\mathbb{E}[X_i|I_i]$ together with random noise η_i^Z, where X_i now captures future changes in household income. Assumption 3 then reduces to η_i^Z being independent of η_i, and conditionally independent of Y (conditional on I_i). No additional assumptions about the function h are required. For example, the result holds for any function that maps $\mathbb{E}[X_i|I_i]$ to an integer between 1 and 5, and where the addition of η_i^Z generates a garbling of this mapping.

4.2.2 Implementation and the Main Result

To implement Test 2, we regress realized inflation (Y) and forecasted inflation ($\tilde{F}_i Y$) on qualitative survey forecasts of future household financial situation changes (Z_i).

Table 4 and Figure 3 present our main results. Figure 3 plots forecasted and actual inflation for each of the five values that Z_i takes on. Table 4 presents regressions of actual and forecasted inflation on Z_i, where we simply treat Z_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 2 permits us to regress on any transformation of Z_i, as well as on dummy variables for each of the possible values of Z_i (analogous to Figure 3). Despite the clear nonlinear relationship between $\tilde{F}_i Y$ and Z_i shown in figure 3, we regress directly on Z_i for the sake of simplicity—to reduce dimensionality and to ease comparability of coefficients across different regressions.

Both Table 4 and Figure 3 show that while forecasts of households' future financial situation changes contain effectively no information about inflation, survey respondents' inflation forecasts are nevertheless significantly negatively associated with their forecasts of their own financial situation changes. 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.

The results thus far can in principle be explained solely by prior bias. People who are more optimistic about lower inflation may also be more optimistic about their future income, 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.[30] The question in the Michigan survey is *"do you think that a year from now you will be better off financially, or worse off, or just about the same as now?."* Appendix Figure B.1 and Appendix Table B.14 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 forecasted changes in household financial situations is dampened, but still remains highly significant when respondent fixed effects are included. This implies that beliefs about inflation are excessively sensitive to news about the future household income changes. At the same time, the dampening of the coefficient of Z_i implies that some of the relationship between inflation forecasts and Z_i is driven by across-respondent differences in how optimistic (pessimistic) they are about both inflation and their household finances changes.

4.3 Inflation Forecasts and Realized Future Changes in Household Income

An alternative proxy for expected future household income changes is the actual realization of the 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 3.2 and Appendix Table B.5). Second, while the survey forecasts Z_i are informative about future income changes, the somewhat vague phrasing of "financial position of your household" leaves open the possibility that responses to this question reflect beliefs about variables other than future income. This, in turn, could be consequential because it leaves open the possibility that some of the association between inflation

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

forecasts and Z_i could be driven by the beliefs about other variables that Z_i reflects. By contrast, because X_i corresponds to realized future changes in household income, an association between $\tilde{F}_i Y$ and X_i would imply that $\tilde{F}_i Y$ is associated with actual signals that people receive about X_i.

4.3.1 Formal Test

The test involves regressing realized inflation (Y) and forecasted inflation ($\tilde{F}_i Y$) on *realized* future changes in household income (X_i). However, because realized future income changes are not plausibly fully contained in individuals' information sets, the implications of LIRE for such regressions are more nuanced. Specifically, consider linear regressions of Y and $\tilde{F}_i Y$ on future realized income changes X_i:

$$Y = \beta_0^X + \beta_1^X X_i + \epsilon_i^X \text{ v.s. } \tilde{F}_i Y = \tilde{\beta}_0^X + \tilde{\beta}_1^X X_i + \tilde{\epsilon}_i^X, \text{ where } Cov\left(\epsilon_i^X, X_i\right) = Cov\left(\tilde{\epsilon}_i^X, X_i\right) = 0. \quad (5)$$

LIRE no longer implies that $\beta_1^X = \tilde{\beta}_1^X$. As a simple example, suppose that $Cov\left(Y, X_i\right) = 0$, and thus $\beta_1^X = 0$. However, individuals' information sets are given by $I_i = \{Y + X_i\}$, so that the law of total covariance implies that

$$\begin{aligned} Cov\left(\mathbb{E}\left[Y|I_i\right], X_i\right) &= Cov\left(Y, X_i\right) - \mathbb{E}\left[Cov\left(Y, X_i|I_i\right)\right] \\ &= -\mathbb{E}\left[Cov\left(Y, X_i|I_i\right)\right] \\ &> 0, \end{aligned}$$

where the last line follows because by definition of I_i, Y and X_i are negatively correlated conditional on I_i. Thus, $\tilde{\beta}_1^X = {}^{Cov(\mathbb{E}[Y|I_i], X_i)}/_{Var(X_i)} > 0$. Similarly, $Cov\left(\mathbb{E}\left[Y|I_i\right], X_i\right)$ and thus $\tilde{\beta}_1^X$ will be negative if $I_i = \{Y - X_i\}$.

More generally, the difference between $Cov\left(\mathbb{E}\left[Y|I_i\right], X_i\right)$ and $Cov\left(Y, X_i\right)$ is difficult to quantify or even sign when, roughly speaking, the signals that people receive about X_i are correlated with Y *conditional on* X_i. To develop our third test, we thus impose additional structure on the information sets, ruling out the problematic case where signals about X_i may be conditionally correlated with Y. We formalize this below.

Assumption 4. *Suppose that X_i is given by an aggregate and an idiosyncratic component:*

$$X_i = X + \nu_i \quad \textit{with} \quad \nu_i \perp X, Y,$$

where $\mathbb{E}[\nu_i] = 0$. Information sets consist of three components

$$I_i = \{s_i, I_i^{'}, I_i^{\nu}\},$$

where:

1. *s_i is a signal about X_i, satisfying $s_i \perp Y|(X_i, I_i^{'}, I_i^{\nu})$;*
2. *I_i^{ν} is a vector of signals about ν_i, satisfying $I_i^{\nu} \perp X$, $I_i^{\nu} \perp Y$;*

3. $I_i^{'}$ is a vector of signals about aggregates X and Y, satisfying $I_i^{'} \perp \nu_i$, $I_i^{'} \perp I_i^{\nu}$;

4. All signals and variables are jointly normally distributed.

In words, we consider an information structure with three types of signals: information about future household income changes X_i (s_i), information about macroeconomic variables ($I_i^{'}$), and information about purely idiosyncratic factors affecting the future (I_i^{ν}). The key assumption, which rules out examples like the one above, is that s_i is independent of Y conditional on $X_i, I_i^{'}, I_i^{\nu}$. We show in Appendix C.2 that Assumption 4 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 3. *Consider linear regressions of Y and $\tilde{F}_i Y$ on future realized income changes X_i, as given in (5). Define $\rho := Corr\left(X_i - \mathbb{E}[X_i|I_i^{'}, I_i^{\nu}], s_i - \mathbb{E}[s_i|I_i^{'}, I_i^{\nu}]\right)$. If Assumption 1 and Assumption 4 hold, then LIRE implies that*

$$\left|\tilde{\beta}_1^X - \beta_1^X\right| \leq \left(1 - \rho^2\right) \frac{\sqrt{Var\,(Y)\,Var\,(X)}}{Var\,(X_i)} \tag{6}$$

The intuition for the bound in equation (6) is as follows. First, note that $\rho = 1$ implies that X_i is in the person's information set I_i. In this case, we obtain the Test 1 implication that $\tilde{\beta}_1^X = \beta_1^X$. More generally, the closer ρ is to 1, the more information about X_i is contained in I_i, and thus the closer we are to the limit case of the Test 1 implication. Second, note that when $Var\,(X) = 0$ and all variation in X_i is idiosyncratic, we again have $\tilde{\beta}_1^X = \beta_1^X = 0$. This reflects the intuition that when X_i carries no information about macroeconomic variables, it cannot be associated with either Y or $\mathbb{E}\,[Y|I_i]$. Although we have shown that this seemingly intuitive conclusion does not hold when signals about X_i are conditionally associated with Y (e.g., the example where $I_i = \{Y + X_i\}$), Assumption 4 provides the additional structure that does guarantee this conclusion. The bound in equation (6) generalizes this logic by showing that $\tilde{\beta}_1^X$ and β_1^X will not differ much 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 $0.021 \cdot (1 - \rho^2) \leq 0.021$. The bound in (6) can be further tightened when ρ is close to zero; see Appendix C.3 for details.

4.3.2 Implementation and Main Result

To implement Test 3, we regress realized inflation (Y) and forecasted inflation ($\tilde{F}_i Y$) on the difference in household log income between the years $t+1$ and $t-1$ (X_i), where t denotes the year of survey response.

Table 5 and Figure 4 present our main results. Again, there is no association between realized inflation and X_i, but there is a strong negative association between inflation forecasts and X_i. This is robust to the inclusion of different sets of controls, including recent changes in log nominal income. In fact, the coefficient of X_i 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 future income changes and inflation forecasts. In all specifications, $\left|\tilde{\beta}_1^X - \beta_1^X\right|$ far exceeds the bounds provided in Test 3.

4.4 Additional Results and Robustness

We provide additional analyses, analogous to those described in Section 3.3, but for survey-reported expected income changes and for realized future income changes. Appendix Table B.11 presents subsample analysis for forecasted family financial situation changes while Appendix Table B.12 presents results for realized future income changes. Qualitatively, the results are analogous to the results for recent income changes in Section 3.3. Table B.13 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.17 and B.18 show that the results are robust to starting in 2008. Table B.16 shows that using real rather than nominal future income changes does not alter our results.

Across two different types of analyses, we again find stark violations of LIRE for expected future income changes. Proxies of expected future income changes are strongly negatively related to inflation forecasts but have effectively no predictive power for actual realizations of inflation. As in our analysis of recent income changes, excessive sensitivity to information plays an important role.

5 Extensions and Mechanisms

In this section, we investigate the role that selective memory and affect may play in the excessive sensitivity of forecasts. The first set of results is facilitated by a unique feature of the Danish Consumer Survey: elicitation of survey participants' recollections of inflation in the past 12 months ("backcasts").[31] The next set of results is facilitated by establishing a novel link between the survey and data on emergency room (ER) visits. Our results are consistent with the hypothesis that associative memory, with the associations influenced by affect, shapes inflation forecasts.

5.1 Inflation Backcasts Predict Forecast Errors

Figure 5a shows that inflation backcasts themselves are strongly associated with inflation forecast errors, where we define an error as the difference between the actual realization and the respondent's report. Because inflation backcasts plausibly satisfy the properties of Z_i in Test 2, LIRE (with limited memory) would instead imply no relationship between backcasts and forecast errors. Thus,

[31]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.

Figure 5a constitutes another rejection of LIRE. Figure 5b also shows the converse to Figure 5a: inflation forecasts are strongly associated backcast errors.

Collectively, these results provide initial evidence that memory is imperfect and, more suggestively, that the systematic imperfections in memory may explain some of the forecasting errors. Appendix Tables B.20 and B.21 present regressions that quantify the patterns in Figure 5.

5.2 Inflation Backcasts and Changes in Household Income

We now turn to LIRE Tests 1 – 3, with 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 corresponding binned scatterplots. The results for backcasts are similar to those for forecasts. As with actual inflation over the next twelve months, actual inflation over the past twelve month does not covary with recent income changes, the survey proxy of expected future income changes, and realized future income changes. However, inflation backcasts covary strongly and negatively with these household-level variables.

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 the results in Section 5.1 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). As discussed in Section 2, under this assumption, the recalled events are just a part of people's information sets, and Tests 1 – 3 characterize the implications of LIRE for predictions about past events.

Third, the Table 6b,c results on the association between inflation backcasts and expected future income changes 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 6b,c.

In sum, Table 6 shows that recall is influenced by household-level events. This is consistent with associative memory (e.g., Mullainathan, 2002; Enke et al., 2024; Bordalo et al., 2023, 2024). In fact, and consistent with the possibility that the impact of household-level events on people's forecasts is at least partly mediated by associative memory, 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 LIRE tests, indicating that backcasts are more sensitive than forecasts to information in household-level income changes.

Additionally, Table 7 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, Table 7 and Figure 7 thus rule out the possibility that our income change measures are associated with backcasts simply because people's backcasts reflect their forecasts.[32] Instead, our results 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.

5.3 Affective Association

What is the channel through which our household-level income change measures influence people's recall? One plausible hypothesis is affective association: that the association occurs through affect, 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, prompting the recall of other memories associated with negative affect, such as memories of disappointingly large price increases. If agents then believe that inflation is strongly autocorrelated (as it is in reality), then recall of recent price increases would lead them to also forecast future price increases.

If affect is an important channel for how household-level events influence backcasts and consequently 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 households with the same number of ER visits and the same demographics, but with the difference being that one household was asked to take the survey right around the ER visit, while the other household was asked to take the survey further away from an 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 household was approached to take the survey near the ER visit while the other

[32] Formally, suppose that backcasts $\tilde{F}_i Y^-$ are related to forecasts $\tilde{F}_i Y^+$ via the model $\tilde{F}_i Y^- = \alpha_0 + \alpha_1 \tilde{F}_i Y^+ + \epsilon_i$, where $\epsilon_i \perp \tilde{F}_i Y^+$ and $\epsilon_i \perp X_i$, meaning that the income change measure X_i is related to backcasts only through forecasts. Because empirically $\alpha_1 < 1$ (backcasts and forecasts are not perfectly correlated), 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, with the ratio of the coefficients given by $1/\alpha_1$. Second, it predicts that in regressions of forecasts on backcasts and X_i, the coefficient of X_i will always remain significantly negative, contrary to the column 6 results.

one was not. Thus, this generates a plausibly clean natural experiment.

There are several key properties of ER visits that make them well-suited for our analysis. First, ER visits plausibly proxy for negative events that lead to negative affect. At the same time, ER visits are plainly not related to inflation. Second, ER visits are sufficiently common that we have enough statistical power to examine the impact of an 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 ER visits is that they might induce selection into survey non-response, but Appendix Table B.29 shows this is not the case in our sample.[33]

Our analysis utilizes the available data on ER visits over 11 years, ranging from 2008 to 2018.[34] 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 an ER visit close to the survey date. Under the null hypothesis of rational expectations, a respondent's inflation forecast or backcast should have no relationship to a proximate ER visit. Similarly, because there is no reason why 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.30 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.32 and B.31 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 an ER visit in the survey month, including our standard set of demographic controls, calendar month fixed effects, and also controlling for total number of ER visits in our sample period with varying flexibility: linearly, quadratically, and non-parametrically via fixed effects.[35] Table 8 presents the results. Columns (1) through (5) pool inflation backcasts

[33] A second issue might be that ER shocks have direct economic implications for the household. Emergency room care is completely free for all Danish citizens and permanent residents.

[34] 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.

[35] 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 LIRE. 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

and forecasts.[36] In columns (6) and (7) we include an interaction term with an indicator for forecasts to assess if ER visits have larger effects on backcasts than forecasts.

Columns (1) through (5) show a significant and robust effect of an ER visit in the survey month on inflation backcasts and forecasts. Controlling for total number of ER visits slightly lowers the estimate relative to column (1), but as column (2) shows, the association with one additional ER visit in the sample period is only 0.045, while the impact of an ER visit in the survey month is approximately five times larger. Controlling more flexibly for the total number of ER visits, as we do in columns (3)-(5), has no impact on the results. Column (5) has the most flexible controls for total ER visits: we include fixed effects for total number of 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 8 study the differential impact of an ER visit in the survey month on forecasts versus backcasts. Column (6) controls for total number of ER visits 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 7: an ER visit in the survey month has a much larger impact on backcasts than forecasts, consistent with the hypothesis that affective consequences of an ER visit in the survey month is channeled through associative memory.

Finally, one hypothesis might be that the channel through which 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.33 and B.34 show that when controlling for our measures of recent or future income changes, the impact of an ER visit on inflation forecasts and backcasts is, if anything, slightly higher.

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 future income

expectations, conditional on the calendar month. We include calendar month fixed effects to increase precision. Excluding them has no impact on our results.

[36]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.

changes. We establish additional results that suggest that associative memory 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 limited-information 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)).[37] 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.

[37]Broer et al. (2021) explore the implications of differences in subjective forecasts due to information frictions in a model of endogenous information choice within LIRE. 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)
Recent Log Nominal Income Change	0.008 (0.022)	0.034** (0.016)	-0.655*** (0.140)	-0.674*** (0.140)	-0.563*** (0.137)
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
Responses	35050	62449159	35050	35050	35050

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" denotes regressions where we use the full Danish population. 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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

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

(a) Realized inflation

	Realized Inflation next 12m											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Recent Log Nominal Income Change	0.014 (0.024)	0.007 (0.027)	0.020 (0.027)	0.005 (0.025)	-0.004 (0.029)	0.011 (0.024)	-0.009 (0.030)	0.022 (0.022)	-0.009 (0.035)	0.011 (0.027)	0.006 (0.025)	-0.033 (0.038)
Demog. Controls	No	No	No	No	No	No	No	No	No	No	No	No
Sample Restriction	Income Change Restricted	No Unemp. or Leave	Some Unemp. or Leave	No Marriage or Retirement Transitions	> Median Avg Past Income	< Median Avg Past Income	College Educated	Non-College Educated	Simple Income	Net Saver	Net Borrower	Public Employee
Responses	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*** (0.186)	-0.710*** (0.181)	-0.365* (0.219)	-0.742*** (0.154)	-0.555*** (0.207)	-0.741*** (0.194)	-0.308 (0.203)	-0.899*** (0.186)	-0.843*** (0.249)	-0.842*** (0.190)	-0.500** (0.238)	-0.570* (0.289)
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
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

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)	(0.097)	(0.202)	(0.257)
Demog. Controls	No	No	No	Yes	Yes	Yes
Sample	Respondents	Simple Income	Respondents	Respondents	Respondents	Simple Income
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 4: Inflation Forecasts and Forecasted Family Finances Changes

	Realized Inflation next 12m	Forecasted Inflation next 12m			
	(1)	(2)	(3)	(4)	(5)
Forecasted Family Finances Change	-0.009* (0.005)	-0.341*** (0.027)	-0.320*** (0.027)	-0.318*** (0.027)	-0.285*** (0.025)
Recent Log Nominal Income Change				-0.638*** (0.138)	
Demog. Controls	No	No	Yes	Yes	Yes
Month FE	No	No	No	No	Yes
Responses	35050	35050	35050	35050	35050

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. 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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

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)
Future Log Nominal Income Change	-0.027	0.062^{***}	-0.405^{***}	-0.358^{***}	-0.445^{***}	-0.268^{**}
	(0.020)	(0.018)	(0.106)	(0.104)	(0.106)	(0.105)
Recent Log Nominal Income Change					-0.762^{***}	
					(0.144)	
Demog. Controls	No	No	No	Yes	Yes	Yes
Month FE	No	No	No	No	No	Yes
Sample	Respondents 2012 - 2019	Population 1991 - 2019	Respondents 2012 - 2019	Respondents 2012 - 2019	Respondents 2012 - 2019	Respondents 2012 - 2019
Responses	35050	62449159	35050	35050	35050	35050

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" denotes regressions where we use the full Danish population. 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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

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)
Recent Log Nominal Income Change	-0.011	0.039**	-0.858***	-0.862***	-0.725***
	(0.022)	(0.015)	(0.209)	(0.201)	(0.188)
Demog. Controls	No	No	No	Yes	Yes
Month FE	No	No	No	No	Yes
Sample	Respondents 2013 - 2019	Population 1991 - 2019	Respondents 2013 - 2019	Respondents 2013 - 2019	Respondents 2013 - 2019
Responses	30752	62449159	30752	30752	30752

(b) Inflation Backcasts and Forecasted Family Finances Changes

	Realized Inflation past 12m	Backcasted Inflation past 12m			
	(1)	(2)	(3)	(4)	(5)
Forecasted Family Finances Change	0.002	-0.337***	-0.312***	-0.310***	-0.277***
	(0.004)	(0.035)	(0.034)	(0.034)	(0.031)
Recent Log Nominal Income Change				-0.831***	
				(0.200)	
Demog. Controls	No	No	Yes	Yes	Yes
Month FE	No	No	No	No	Yes
Responses	30752	30752	30752	30752	30752

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

	Realized Inflation past 12m		Backcasted Inflation past 12m			
	(1)	(2)	(3)	(4)	(5)	(6)
Future Log Nominal Income Change	0.014	-0.026*	-0.563***	-0.510***	-0.624***	-0.413***
	(0.020)	(0.014)	(0.128)	(0.131)	(0.132)	(0.135)
Recent Log Nominal Income Change					-0.985***	
					(0.204)	
Demog. Controls	No	No	No	Yes	Yes	Yes
Month FE	No	No	No	No	No	Yes
Sample	Respondents 2013 - 2019	Population 1991 - 2019	Respondents 2013 - 2019	Respondents 2013 - 2019	Respondents 2013 - 2019	Respondents 2013 - 2019
Responses	30752	62449159	30752	30752	30752	30752

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" denotes regressions where we use the full Danish population. 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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 7: 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*** (0.140)	-0.195* (0.109)				
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*** (0.104)	0.073 (0.083)
Demog. Controls	Yes	Yes	Yes	Yes	Yes	Yes
Responses	35050	35050	35050	35050	35050	35050

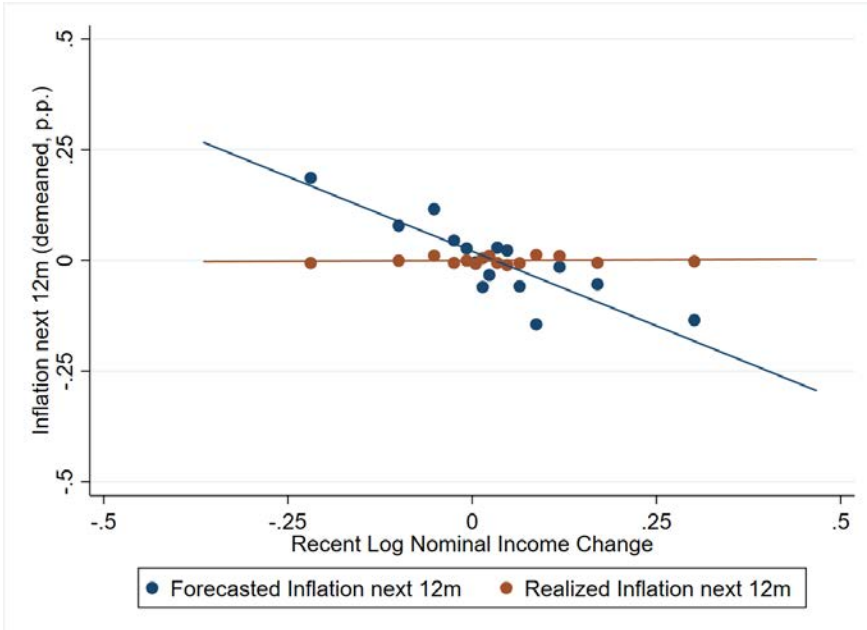
Notes: This table presents regressions of forecasted inflation in recent log nominal income change (Columns 1 and 2), forecasted family finances change (Columns 3 and 4), and future log nominal income change (Columns 5 and 6). Columns (2), (4), and (6) also control for inflation backcasts. Inflation 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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table 8: Impact of 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***	0.210**	0.210**	0.211**	0.211**	0.321***	0.321***
	(0.085)	(0.086)	(0.086)	(0.086)	(0.086)	(0.108)	(0.107)
# of ER visits		0.045***	0.048**			0.045***	
		(0.007)	(0.019)			(0.007)	
# of ER visits sq.			-0.001				
			(0.003)				
I(Forecast) x I(Fam. ER visit)						-0.228**	-0.228**
						(0.101)	(0.101)
I(Forecast)						-0.877***	-0.877***
						(0.099)	(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
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

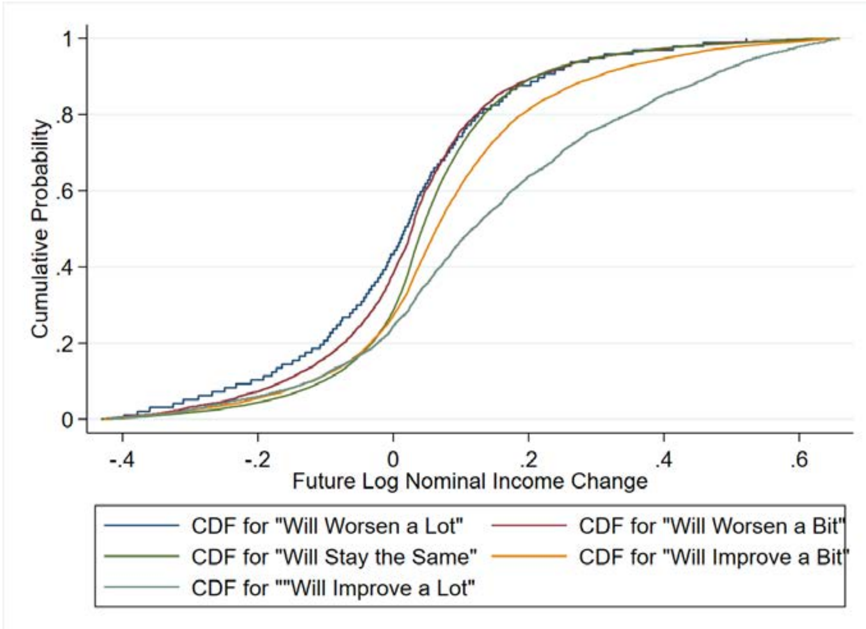
Figure 1: Realized and Forecasted Inflation and Recent Changes in Household Income



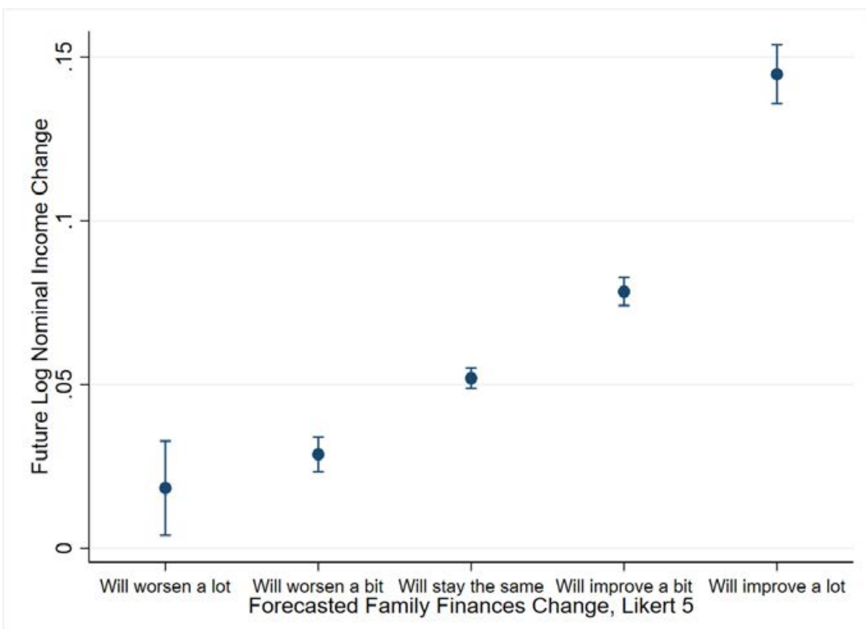
Notes: This figure presents the relationship between realized future and forecasted inflation over the 12 months following the survey response and recent log nominal income change. The relationship is plotted after partialling out demographic controls. The units of inflation and inflation forecasts are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

Figure 2: Informativeness of Forecasted Family Finances Change

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

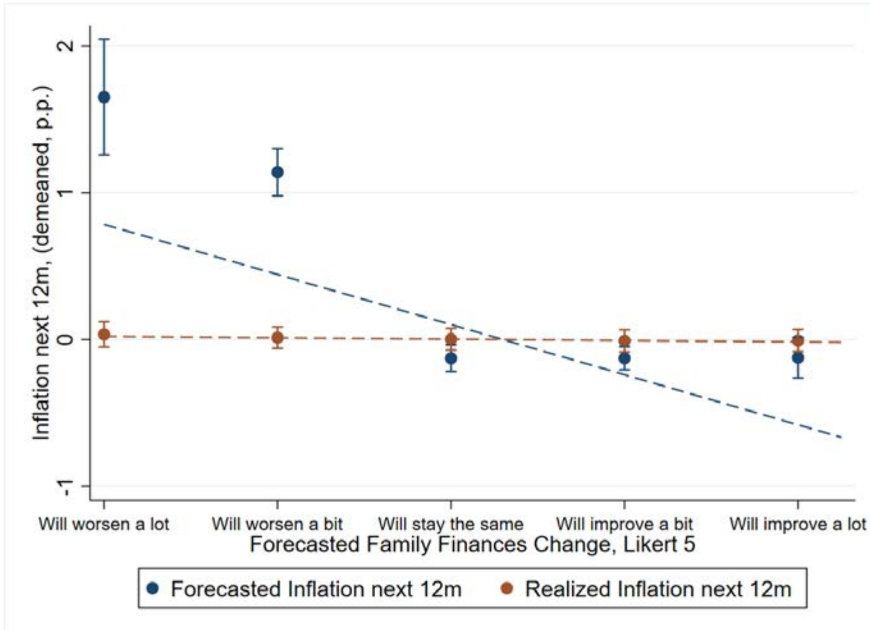


(b) Mean Future Log Nominal Income Change, by Survey Response



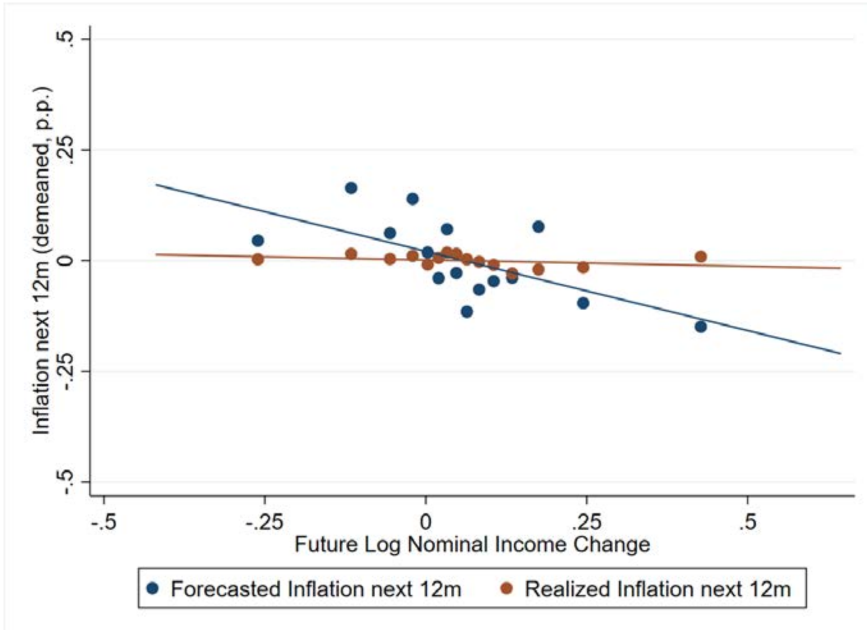
Notes: Panel (a) presents empirical CDFs of future log nominal income changes by responses to the survey question about forecasts of the future family financial situation. Panel (b) presents average future log nominal income change by responses to the same survey question. We do not add any demographic controls for this analysis. Future changes in households' log nominal income are calculated based on the log nominal income of the year $t+1$ minus the log nominal income in the year $t-1$, with t denoting the year of the survey response. Forecasted family finances changes are elicited on a 5-point Likert scale. The confidence intervals in panel (b) are based on robust standard errors, clustered by month. 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 Survey Proxy of Forecasted Family Finances Change



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.

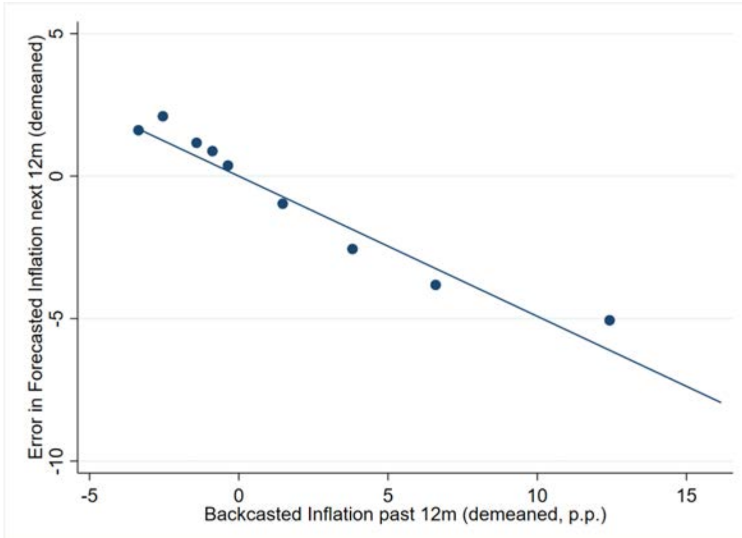
Figure 4: Realized and Forecasted Inflation and Realized Future Income Changes



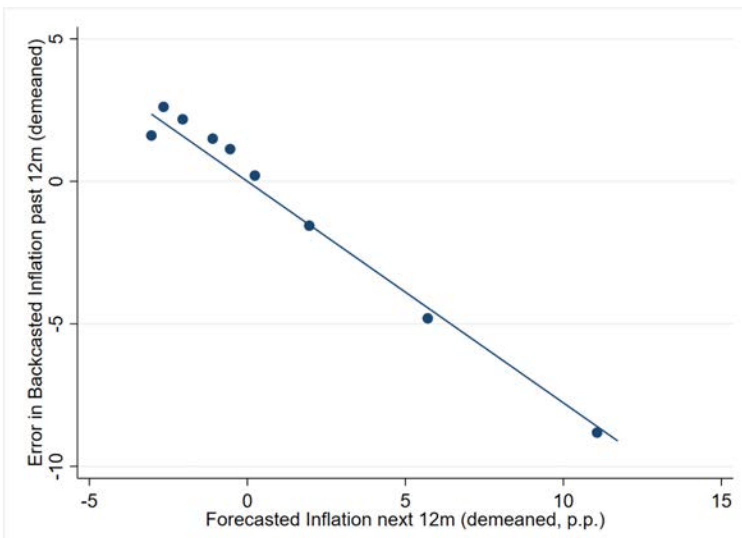
Notes: This figure presents the relationship between realized future and forecasted inflation over the 12 months following the survey response and future realized log nominal income change. The relationship is plotted after partialling out demographic controls. The units of inflation and inflation forecasts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



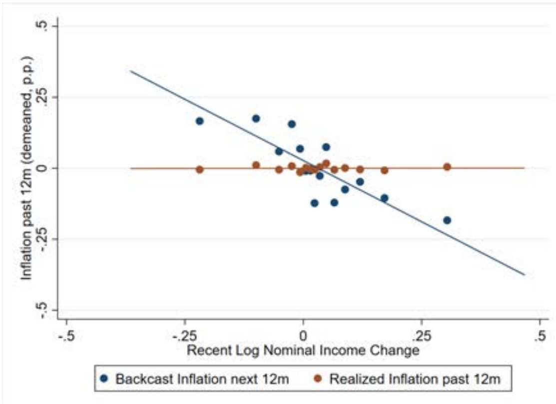
(b) Inflation Forecasts and Inflation Backcast Errors



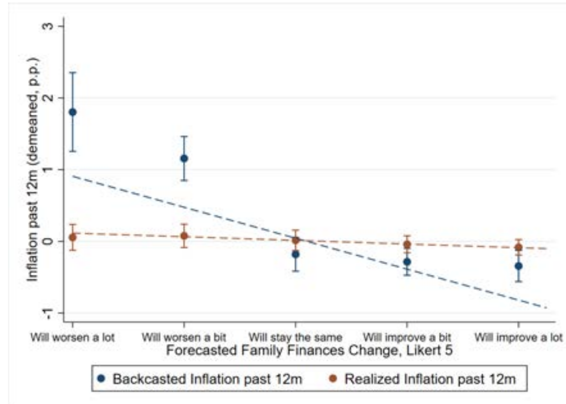
Notes: Panel (a) presents the relationship between the error in backcasted inflation over the 12 months preceding the survey response and forecasted inflation over the 12 months following the survey response. Forecast errors in inflation are calculated by subtracting the realized inflation over the 12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

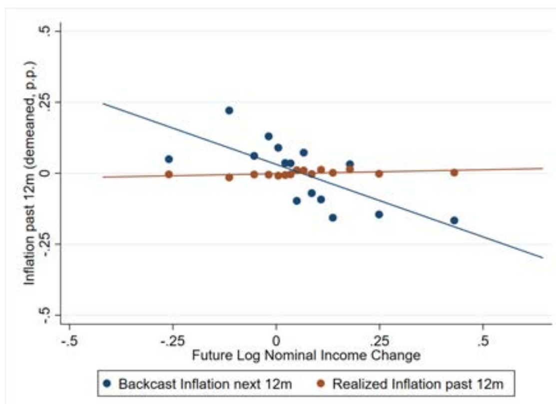
(a) Inflation Backcasts and Recent Changes in Household Income



(b) Inflation Backcasts and Survey Proxy of Expected Future Changes in Household Income

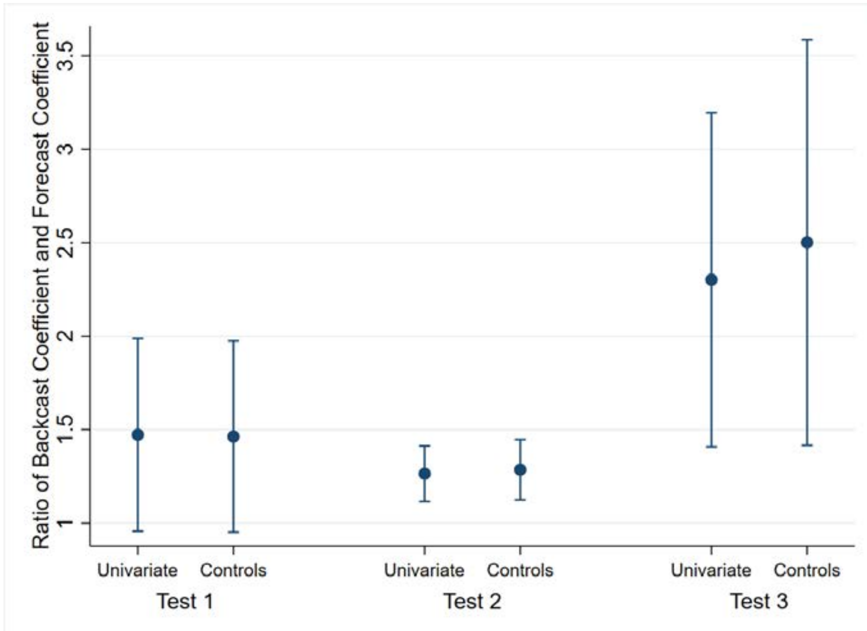


(c) Inflation Backcasts and Future Changes in Household Income



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 by month. 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.

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.[38] 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 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

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

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.[39] 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.

[39] 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 tax 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 Survey Questions

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).

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
Responses	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
Responses	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***			-0.740***
	(0.046)			(0.047)
Female Indicator		0.201***		0.239***
		(0.032)		(0.033)
College Educated			-0.473***	-0.317***
			(0.038)	(0.039)
Year FE	Yes	Yes	Yes	Yes
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

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

(b) Forecasted Inflation

	Forecasted Inflation next 12m			
	(1)	(2)	(3)	(4)
Placebo Income Change	-0.010 (0.100)	0.097 (0.078)	-0.104 (0.070)	-0.009 (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
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

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***	0.444***		
	(0.005)	(0.005)		
Future Log Nominal Labor Income Change			0.448***	0.440***
			(0.006)	(0.006)
Demog. Controls	No	Yes	No	Yes
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

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 (0.031)		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*** (0.167)
Demog. Controls	No	No	No	Yes	Yes	Yes
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

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*** (0.133)	-0.499*** (0.130)	-0.538*** (0.119)
Demog. Controls	No	Yes	Yes
Month FE	No	No	Yes
Sample	Respondents 2008 - 2019	Respondents 2008 - 2019	Respondents 2008 - 2019
Responses	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" denotes regressions where we use the full Danish population. 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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

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	-0.060***	-0.855***	-0.864***	-0.578***
	(0.036)	(0.019)	(0.149)	(0.149)	(0.141)
Demog. Controls	No	No	No	Yes	Yes
Month FE	No	No	No	No	Yes
	Respondents	Population	Respondents	Respondents	Respondents
Sample	2012 - 2019	1991 - 2019	2012 - 2019	2012 - 2019	2012 - 2019
Responses	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" denotes regressions where we use the full Danish population. 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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

B.4 Auxiliary Results to Section 4

B.4.1 Forecastability of Future Income Changes

Table B.10: 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
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

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

Table B.11: 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** (0.005)	-0.011 (0.007)	-0.004 (0.004)	-0.010* (0.005)	-0.009 (0.006)	-0.010* (0.005)	-0.004 (0.006)	-0.014** (0.005)	-0.011 (0.007)	-0.009 (0.006)	-0.010** (0.005)	-0.001 (0.007)
Demog. Controls	No	No	No	No	No	No	No	No	No	No	No	No
Sample Restriction	Income Change Restricted	No Unemp. or Leave	Some Unemp. or Leave	No Marriage or Retirement Transitions	> Median Avg Past Income	< Median Avg Past Income	College Educated	Non-College Educated	Simple Income	Net Saver	Net Borrower	Public Employee
Responses	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*** (0.028)	-0.346*** (0.034)	-0.288*** (0.036)	-0.315*** (0.028)	-0.281*** (0.036)	-0.348*** (0.034)	-0.268*** (0.030)	-0.351*** (0.036)	-0.308*** (0.042)	-0.351*** (0.033)	-0.312*** (0.036)	-0.350*** (0.055)
Demog. Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample Restriction	Income Change Restricted	No Unemp. or Leave	Some Unemp. or Leave	No Marriage or Retirement Transitions	> Median Avg Past Income	< Median Avg Past Income	College Educated	Non-College Educated	Simple Income	Net Saver	Net Borrower	Public Employee
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.12: 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
	(0.031)	(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
Responses	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**
	(0.139)	(0.155)	(0.146)	(0.111)	(0.146)	(0.152)	(0.145)	(0.144)	(0.186)	(0.153)	(0.150)	(0.208)
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
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

B.4.3 Inflation Forecast and Future Labor Income Changes

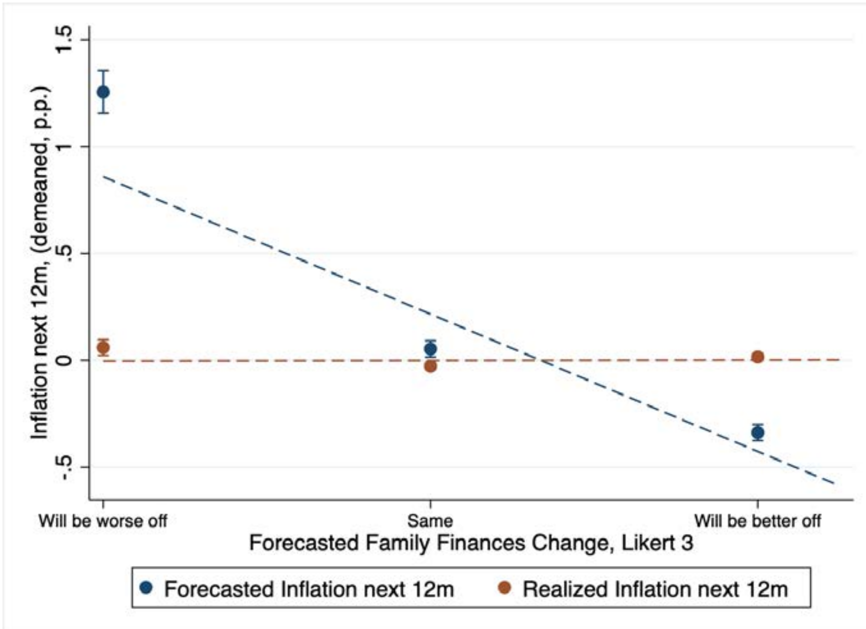
Table B.13: Inflation Forecasts and Realized Future Changes in Household Labor Income

	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)	(0.074)	(0.074)	(0.155)	(0.185)
Demog. Controls	No	No	No	Yes	Yes	Yes
Sample	Respondents	Simple Income	Respondents	Respondents	Respondents	Simple Income
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

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 at the calendar month level.

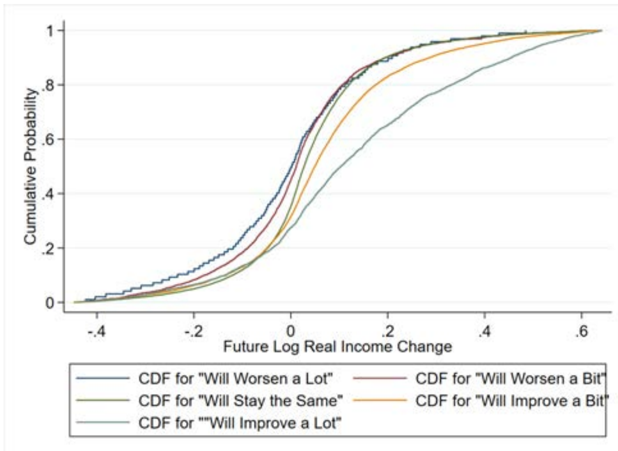
Table B.14: Inflation Forecasts and Forecasted Family Finances Change: Michigan

	Realized Inflation next 12m	Forecasted Inflation next 12m				
	(1)	(2)	(3)	(4)	(5)	(6)
Forecasted Family Finances Change	0.006 (0.009)	-0.630*** (0.023)	-0.601*** (0.022)	-0.491*** (0.022)	-0.257*** (0.030)	-0.188*** (0.029)
Demog. Controls	No	No	Yes	Yes	No	No
Resp. FE	No	No	No	No	Yes	Yes
Month FE	No	No	No	Yes	No	Yes
Responses	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, clustered by respondent, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

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.15: Informativeness of Survey Proxy of Forecasted Family Finances Change (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
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.16: 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)	(0.110)	(0.107)	(0.111)	(0.102)
Recent Log Real Income Change				-0.962***	
				(0.155)	
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
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

B.4.6 Forecastability of Income, Inflation Forecast and Future Income Changes: Years 2008 to 2019

Table B.17: Inflation Forecasts and Forecasted Family Finances Change (Years 2008-2019)

	Forecasted Inflation next 12m			
	(1)	(2)	(3)	(4)
Forecasted Family Finances Change	-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	Yes	Yes	Yes
Month FE	No	No	No	Yes
Obs.	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.18: 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***	-0.214**	-0.285***	-0.183**
	(0.095)	(0.096)	(0.096)	(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
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.19: 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
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

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.20: 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
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.21: 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
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

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

Table B.22: 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 (0.032)	-0.019 (0.027)	-0.001 (0.030)	-0.029 (0.046)
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
Responses	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*** (0.237)	-0.857*** (0.243)	-0.652* (0.352)	-1.020*** (0.220)	-0.502* (0.275)	-1.104*** (0.256)	-0.548** (0.255)	-1.028*** (0.277)	-0.739** (0.316)	-1.007*** (0.258)	-0.697** (0.273)	-1.105** (0.439)
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
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.23: 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
Responses	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^{***} (0.046)	-0.310^{***} (0.045)	-0.282^{***} (0.041)	-0.326^{***} (0.046)	-0.281^{***} (0.048)	-0.384^{***} (0.045)	-0.277^{***} (0.049)	-0.348^{***} (0.070)
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
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.24: Inflation Backcasts and Future Changes in Household Income: Subsamples

(a) Realized inflation

	Realized Inflation past 12m											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Future Log Nominal Income Change	0.038 (0.029)	0.003 (0.021)	0.015 (0.023)	0.014 (0.025)	0.009 (0.030)	0.028 (0.022)	0.018 (0.027)	0.008 (0.021)	0.051 (0.041)	-0.013 (0.024)	0.047* (0.025)	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
Responses	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** (0.192)	-0.355** (0.172)	-0.597*** (0.192)	-0.448*** (0.151)	-0.019 (0.191)	-0.854*** (0.202)	-0.181 (0.194)	-0.680*** (0.176)	-0.331 (0.216)	-0.325* (0.181)	-0.728*** (0.197)	-0.071 (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
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

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

Table B.25: 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**
	(0.015)	(0.031)	(0.132)	(0.133)	(0.259)	(0.310)
Demog. Controls	No	No	No	Yes	Yes	Yes
Sample	Respondents	Simple Income	Respondents	Respondents	Respondents	Simple Income
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.26: 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)	(0.197)	(0.210)
Demog. Controls	No	No	No	Yes	Yes	Yes
Sample	Respondents	Simple Income	Respondents	Respondents	Respondents	Simple Income
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

B.5.4 Additional Results to Section 5.3

Table B.27: 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***				
	(0.193)	(0.187)				
I(Forecast) × Recent Log Nominal Income Change	0.310**	0.310**				
	(0.151)	(0.151)				
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***
					(0.115)	(0.115)
I(Forecast)	-0.333***	-0.333***	-0.619***	-0.619***	-0.354***	-0.354***
	(0.076)	(0.076)	(0.133)	(0.133)	(0.078)	(0.078)
Demog. Controls	No	Yes	No	Yes	No	Yes
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

B.5.5 Additional Results to Section 5.4

Table B.28: 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.29: 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)	(0.009)
# 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
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.30: Impact of 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** (0.128)	0.220* (0.128)	0.219* (0.128)	0.222* (0.129)	0.217 (0.130)	0.361** (0.164)	0.363** (0.164)
# of ER visits		0.037*** (0.011)	0.055* (0.031)			0.037*** (0.011)	
# of ER visits sq.			-0.003 (0.005)				
I(Forecast) x I(Fam. ER visit)						-0.283* (0.153)	-0.283* (0.153)
I(Forecast)						-0.350*** (0.084)	-0.350*** (0.084)
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
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.31: Impact of 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*** (0.120)
# 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
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.32: Impact of 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** (0.078)	0.140* (0.079)	0.139* (0.079)	0.139* (0.079)	0.139* (0.079)	0.234** (0.100)	0.234** (0.100)
# of ER visits		0.039*** (0.005)	0.061*** (0.016)			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*** (0.099)	-0.883*** (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
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.33: Impact of 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***	0.242***	0.242***	0.242***	0.244***	0.326***	0.326***
	(0.089)	(0.090)	(0.090)	(0.090)	(0.090)	(0.111)	(0.111)
# of ER visits		0.045***	0.046**			0.045***	
		(0.007)	(0.019)			(0.007)	
# of ER visits sq.			-0.000				
			(0.003)				
I(Forecast) x I(Fam. ER visit)						-0.173	-0.173
						(0.107)	(0.107)
I(Forecast)						-0.882***	-0.882***
						(0.100)	(0.100)
Recent Log Nominal Income Change	-0.273***	-0.271***	-0.271***	-0.271***	-0.269***	-0.270***	-0.270***
	(0.071)	(0.071)	(0.071)	(0.071)	(0.071)	(0.071)	(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
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

Table B.34: Impact of 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*** (0.090)	0.238*** (0.090)	0.239*** (0.090)	0.241*** (0.090)	0.322*** (0.111)	0.323*** (0.111)
# 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 (0.107)	-0.173 (0.107)
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
Responses	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, clustered by calendar month, in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

C Mathematical Results

C.1 Proofs

Proof of Test 1. From (3) and Assumption 1, we have:

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

Using the definition of LIRE in Definition 1 to substitute $\mathbb{E}[Y|I_i]$ for $\mathbb{F}[Y|I_i]$, we have:

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

where we use the law of total covariance for the second equality. Using Assumption 2 to substitute X_i for $\mathbb{E}[X_i|I_i]$, we have:

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

Proof of Test 2. From (4), Assumption 1, and the first part of Assumption 3, we have:

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

Using the definition of LIRE in Definition 1 to substitute $\mathbb{E}[Y|I_i]$ for $\mathbb{F}[Y|I_i]$, we have:

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

Using the law of total covariance and the second part of Assumption 3, we have:

$$\tilde{\beta}_1^Z = \frac{Cov\left(Y, Z_i\right)}{Var\left(Z_i\right)} = \beta_1^Z.$$

Proof of Test 3. We use $\hat{}$ over a variable to denote its residual after conditioning on I_i' and I_i^ν, e.g., $\hat{s}_i := s_i - \mathbb{E}\left[s_i|I_i', I_i^\nu\right]$. From Assumption 4, we have:

$$\begin{aligned}
\hat{X}_i &:= X_i - \mathbb{E}\left[X_i|I_i', I_i^\nu\right] = X - \mathbb{E}\left[X|I_i'\right] + \nu_i - \mathbb{E}\left[\nu_i|I_i^\nu\right], \\
\hat{Y}_i &:= Y - \mathbb{E}\left[Y|I_i', I_i^\nu\right] = Y - \mathbb{E}\left[Y|I_i'\right].
\end{aligned}$$

Because $s_i \perp Y|(X_i, I_i', I_i^\nu)$ in Assumption 4, we have:

$$Cov\left(\hat{s}_i - E\left[\hat{s}_i|\hat{X}_i\right], \hat{Y}_i - E\left[\hat{Y}_i|\hat{X}_i\right]\right) = 0 \Longrightarrow Cov\left(\hat{s}_i, \hat{Y}_i\right) = \frac{Cov\left(\hat{X}_i, \hat{s}_i\right) Cov\left(\hat{X}_i, \hat{Y}_i\right)}{Var\left(\hat{X}_i\right)}. \tag{7}$$

Because the variables follow a multivariate normal distribution,

$$\mathbb{E}\left[X_i|I_i\right]=\mathbb{E}\left[X|I_i^{'},I_i^{\nu}\right]+\mathbb{E}\left[\nu_i|I_i^{'},I_i^{\nu}\right]+\frac{Cov\left(\hat{X}_i,\hat{s}_i\right)}{Var\left(\hat{s}_i\right)}\hat{s}_i=\mathbb{E}\left[X|I_i^{'}\right]+\mathbb{E}\left[\nu_i|I_i^{\nu}\right]+\frac{Cov\left(\hat{X}_i,\hat{s}_i\right)}{Var\left(\hat{s}_i\right)}\hat{s}_i. \tag{8}$$

From (5), Assumption 1, and the definition of LIRE in Definition 1 to substitute $\mathbb{E}[Y|I_i]$ for $\mathbb{F}[Y|I_i]$, we have:

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

Using the law of total covariance and (8), we have:

$$\begin{aligned}\tilde{\beta}_1^X&=\frac{Cov\left(Y,\mathbb{E}\left[X_i|I_i\right]\right)}{Var\left(X_i\right)}=\frac{Cov\left(Y,\mathbb{E}\left[X|I_i^{'}\right]\right)}{Var\left(X_i\right)}+\frac{Cov\left(\hat{X}_i,\hat{s}_i\right)Cov\left(\hat{s}_i,Y\right)}{Var\left(\hat{s}_i\right)Var\left(X_i\right)}\\&=\frac{Cov\left(Y,\mathbb{E}\left[X|I_i^{'}\right]\right)}{Var\left(X_i\right)}+\frac{Cov\left(\hat{X}_i,\hat{s}_i\right)Cov\left(\hat{s}_i,\hat{Y}_i\right)}{Var\left(\hat{s}_i\right)Var\left(X_i\right)}.\end{aligned}$$

Using (7), we have

$$\tilde{\beta}_1^X=\frac{Cov\left(Y,\mathbb{E}\left[X|I_i^{'}\right]\right)}{Var\left(X_i\right)}+\frac{Cov^2\left(\hat{X}_i,\hat{s}_i\right)}{Var\left(\hat{s}_i\right)Var\left(\hat{X}_i\right)}\frac{Cov\left(X-\mathbb{E}\left[X|I_i^{'}\right]+\nu_i-\mathbb{E}\left[\nu_i|I_i^{\nu}\right],Y-\mathbb{E}\left[Y|I_i^{'}\right]\right)}{Var\left(X_i\right)}.$$

Set $\rho:=Corr\left(X_i-\mathbb{E}[X_i|I_i^{'},I_i^{\nu}],s_i-\mathbb{E}[s_i|I_i^{'},I_i^{\nu}]\right)=\frac{Cov^2\left(\hat{X}_i,\hat{s}_i\right)}{Var(\hat{s}_i)Var\left(\hat{X}_i\right)}$. Using Assumption 4, we have

$$\begin{aligned}\tilde{\beta}_1^X&=\frac{Cov\left(Y,\mathbb{E}\left[X|I_i^{'}\right]\right)}{Var\left(X_i\right)}+\rho^2\frac{Cov\left(X-\mathbb{E}\left[X|I_i^{'}\right],Y-\mathbb{E}\left[Y|I_i^{'}\right]\right)}{Var\left(X_i\right)}\\&=\frac{Cov\left(Y,\mathbb{E}\left[X|I_i^{'}\right]\right)}{Var\left(X_i\right)}+\rho^2\frac{Cov\left(X-\mathbb{E}\left[X|I_i^{'}\right],Y\right)}{Var\left(X_i\right)}\\&=\left(1-\rho^2\right)\frac{Cov\left(Y,\mathbb{E}\left[X|I_i^{'}\right]\right)}{Var\left(X_i\right)}+\rho^2\frac{Cov\left(Y,X\right)}{Var\left(X_i\right)}.\end{aligned}$$

From (5) and Assumption 4, we have

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

As a result,

$$\begin{aligned}\left|\tilde{\beta}_1^X - \beta_1^X\right| &\leq \left(1-\rho^2\right)\left|\frac{Cov\left(Y, X - \mathbb{E}\left[X|I_i'\right]\right)}{Var\left(X_i\right)}\right| \\ &\leq \left(1-\rho^2\right)\frac{\sqrt{Var\left(Y\right)Var\left(X - \mathbb{E}\left[X|I_i'\right]\right)}}{Var\left(X_i\right)} \\ &\leq \left(1-\rho^2\right)\frac{\sqrt{Var\left(Y\right)Var\left(X\right)}}{Var\left(X_i\right)},\end{aligned}$$

where we use the law of total variance for the last inequality. This is the bound (6) in Test 3.

C.2 Processes Satisfying Assumption 4

Here we show how Assumption 4 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 $\nu_{i,t}^{\text{level}}$, and a transitory idiosyncratic component $\omega_{i,t}$. $X_t^{\text{level}}, \nu_{i,t}^{\text{level}}$, and the macro variable (e.g., inflation) Y_t all follow an AR(1) process:

$$X_{i,t}^{\text{level}} = X_t^{\text{level}} + \nu_{i,t}^{\text{level}} + \omega_{i,t}, \tag{9}$$

$$X_t^{\text{level}} = \rho_x X_{t-1}^{\text{level}} + \varepsilon_t^x, \tag{10}$$

$$\nu_{i,t}^{\text{level}} = \rho_\nu \nu_{i,t-1}^{\text{level}} + \varepsilon_{i,t}^\nu, \tag{11}$$

$$Y_t = \rho_y Y_{t-1} + \varepsilon_t^y, \tag{12}$$

where $\rho_x, \rho_\nu, \rho_y \in [-1, 1]$, $\omega_{i,t}$ and $\varepsilon_{i,t}^\nu$ are i.i.d. across i, t, and ε_t^x and ε_t^y are i.i.d. across t. Moreover, the processes $\{\omega_{i,t}\}$ and $\left\{\varepsilon_{i,t}^\nu\right\}$ are independent of $\left\{X_t^{\text{level}}, Y_t\right\}$ and each other. This income process is akin to the one in Guvenen and Smith (2014), abstracting from deterministic life-cycle components.

The household's realized future income change, its aggregate component, and the macro variable in Test 3 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 agent perfectly knows about past household income levels and past macro variables, following the standard assumption in macroeconomics. They also receive a signal $s_{i,t}$ about its future income level $X_{i,t+1}^{\text{level}}$. That is, agent i's information I_i is given by

$$I_i = I_{i,t} = \left\{ s_{i,t} = X_{i,t+1}^{\text{level}} + \varepsilon_{i,t}^s, \left\{X_{i,t-l}^{\text{level}}\right\}_{l=0}^{+\infty}, \left\{X_{t-l}^{\text{level}}, Y_{t-l}\right\}_{l=0}^{+\infty} \right\}. \tag{13}$$

Note that I_i in (13) is equivalent to $I_i = \{s_i, I_i', I_i^\nu\}$, where $s_i = s_{i,t}, I_i^\nu = \left\{\nu_{i,t-l}^{\text{level}} + \omega_{i,t-l}\right\}_{l=0}^{\infty}$ and

$I_i' = \left\{X_{t-l}^{\text{level}}, Y_{t-l}\right\}_{l=0}^{\infty}$, which satisfies Assumption 4.

In fact, this example can be extended to cases where the person has perfect knowledge of past household income levels and macro variables up to a finite number of lags. That is, information I_i is given by

$$I_i = I_{i,t} = \left\{s_{i,t} = X_{i,t+1}^{\text{level}} + \varepsilon_{i,t}^{s}, \left\{X_{i,t-l}^{\text{level}}\right\}_{l=0}^{L}, \left\{X_{t-l}^{\text{level}}, Y_{t-l}\right\}_{l=0}^{L_{agg}}\right\}, \tag{14}$$

and $L_{agg} \geq L \geq 0$. Note that I_i in (14) is equivalent to $I_i = \{s_i, I_i', I_i^{\nu}\}$, where $s_i = s_{i,t}, I_i^{\nu} = \left\{\nu_{i,t-l}^{\text{level}} + \omega_{i,t-l}\right\}_{l=0}^{L}$ and $I_i' = \left\{X_{t-l}^{\text{level}}, Y_{t-l}\right\}_{l=0}^{L_{agg}}$, which satisfies Assumption 4.

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 5.2. Now we consider an alternative example where the person only perfectly knows about past household income levels (but not past macro variables) and Assumption 4 still holds.

Example 2: Now consider the case that the persistent idiosyncratic component $\nu_{i,t}^{\text{level}}$ follows a random walk. That is, consider the process in (9) – (12) with $\rho_\nu = 1$. 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

$$I_i = I_{i,t} = \left\{s_{i,t} = X_{i,t+1}^{\text{level}} + \varepsilon_{i,t}^{s}, \left\{X_{i,t-l}^{\text{level}}\right\}_{l=0}^{L}, \left\{\omega_{i,t-l}\right\}_{l=0}^{L_\omega}\right\}. \tag{15}$$

Note that I_i in (15) is equivalent to $I_i = \left\{s_i, I_i', I_i^{\nu}\right\}$, where

- If $L \geq L_\omega : s_i = s_{i,t}, I_i' = \left\{\left\{X_{t-l}^{\text{level}} + \nu_{i,t-l}^{\text{level}}\right\}_{l=0}^{L_\omega}, \left\{X_{i,t-l}^{\text{level}}\right\}_{l=L_\omega+1}^{L}\right\}$ and $I_i^{\nu} = \{\omega_{i,t-l}\}_{l=0}^{L_\omega}$;
- If $L < L_\omega : s_i = s_{i,t}, I_i' = \left\{\left\{X_{t-l}^{\text{level}} + \nu_{i,t-l}^{\text{level}}\right\}_{l=0}^{L}\right\}$ and $I_i^{\nu} = \{\omega_{i,t-l}\}_{l=0}^{L_\omega}$.

Both cases satisfy Assumption 4. To see this, note that

$$X_i^{+} = \underbrace{X_{t+1}^{\text{level}} - X_t^{\text{level}}}_{X^{+} \text{ in Assumption 4}} + \underbrace{\omega_{i,t+1} - \omega_{i,t} + \varepsilon_{i,t+1}^{\nu}}_{\nu_i \text{ in Assumption 4}}, \tag{16}$$

and $I_i' \perp \left(\omega_{i,t+1} - \omega_{i,t} + \varepsilon_{i,t+1}^{\nu}\right)$ and $I_i' \perp I_i^{\nu}$.

Finally, it is worth commenting on the role of several elements in the income process and information assumptions above. First, the transitory idiosyncratic component $\omega_{i,t}$ in the income level introduces a force that leads to negative autocorrelation in income changes, consistent with our empirical evidence. Second, the key challenge for Assumption 4 to hold is that knowledge of past household income levels serves as signals for both aggregates and idiosyncratic components.

In Example 1, knowledge of past aggregates means that knowledge of past household income levels is equivalent to knowledge of past idiosyncratic components, satisfying Assumption 4. In Example 2, because the persistent idiosyncratic component $\nu_{i,t}^{\text{level}}$ follows a random walk, knowledge of past income levels is informative only about aggregates, again satisfying Assumption 4.

C.3 An additional bound for Test 3.

It is worth noting that the bound in equation (6) is not a tight bound because it attains its highest value when $\rho = 0$, which is the case in which all information about X_i is contained in signals solely about macroeconomic aggregates and in signals solely about the idiosyncratic component ν_i. In this case, however, it can be shown that $Cov\left(\mathbb{E}[Y|I_i], X_i\right) = Cov\left(\mathbb{E}[Y|I_i], X\right)$, and thus LIRE implies that

$$\tilde{\beta}_1^X = \frac{Cov\left(\tilde{F}_i Y, X\right)}{Var\left(X_i\right)} = \frac{Cov\left(\tilde{F}_i Y, X\right)}{Var\left(X\right)} \cdot \frac{Var\left(X\right)}{Var\left(X_i\right)}$$

That is, $\tilde{\beta}_1^X$ must equal the regression coefficient of inflation forecasts on the (national) *average* income change, multiplied by the share of X_i variation that is aggregate. We now generalize this fact, showing that when ρ is small, $\tilde{\beta}_1^X$ has to be close to $\frac{Cov\left(\tilde{F}_i Y, X\right)}{Var(X_i)}$.

Proposition 1. *Consider linear regressions of Y and $\tilde{F}_i Y$ on future realized income changes X_i, as given in (5). Define $\rho := Corr\left(X_i - \mathbb{E}[X_i|I_i', I_i^\nu], s_i - \mathbb{E}[s_i|I_i', I_i^\nu]\right)$. If Assumption 1 and Assumption 4 hold, then LIRE implies that*

$$\left|\tilde{\beta}_1^X\right| \leq \left|\frac{Cov\left(\tilde{F}_i Y, X\right)}{Var\left(X\right)} \cdot \frac{Var\left(X\right)}{Var\left(X_i\right)}\right| + \left(\rho^2 + |\rho|\right) \frac{\sqrt{Var\left(Y\right) Var\left(X\right)}}{Var\left(X_i\right)} \tag{17}$$

Proof. For the bound in (17), note that Assumption 4 implies

$$\mathbb{E}\left[X_i|I_i\right] = \mathbb{E}\left[X|I_i\right] + \mathbb{E}\left[\nu_i|I_i\right] = \mathbb{E}\left[X|I_i\right] + \mathbb{E}\left[\nu_i|I_i^\nu\right] + \frac{Cov\left(\hat{\nu}_i, \hat{s}_i\right)}{Var\left(\hat{s}_i\right)} \hat{s}_i,$$

where $\hat{s}_i := s_i - \mathbb{E}\left[s_i|I_i', I_i^\nu\right]$ and $\hat{\nu}_i := \nu_i - \mathbb{E}\left[\nu_i|I_i', I_i^\nu\right] = \nu_i - \mathbb{E}\left[\nu_i|I_i^\nu\right]$. Similar to above,

$$\begin{aligned}
\tilde{\beta}_1^X &= \frac{Cov\left(Y, \mathbb{E}\left[X_i|I_i\right]\right)}{Var\left(X_i\right)} = \frac{Cov\left(Y, \mathbb{E}\left[X|I_i\right]\right)}{Var\left(X_i\right)} + \frac{Cov\left(Y, \hat{s}_i\right) Cov\left(\hat{\nu}_i, \hat{s}_i\right)}{Var\left(X_i\right) Var\left(\hat{s}_i\right)} \\
&= \frac{Cov\left(Y, \mathbb{E}\left[X|I_i\right]\right)}{Var\left(X_i\right)} + \frac{Cov\left(\hat{Y}_i, \hat{s}_i\right)}{Var\left(X_i\right)} \left(\frac{Cov\left(\hat{X}_i, \hat{s}_i\right)}{Var\left(\hat{s}_i\right)} - \frac{Cov\left(X - \mathbb{E}\left[X|I_i'\right], \hat{s}_i\right)}{Var\left(\hat{s}_i\right)}\right).
\end{aligned}$$

Using (7), we have

$$\tilde{\beta}_1^X = \frac{Cov\left(Y, \mathbb{E}\left[X|I_i\right]\right)}{Var\left(X_i\right)} + \frac{Cov\left(\hat{X}_i, \hat{Y}_i\right)}{Var\left(X_i\right)} \left(\frac{Cov^2\left(\hat{X}_i, \hat{s}_i\right)}{Var\left(\hat{X}_i\right) Var\left(\hat{s}_i\right)} - \frac{Cov\left(\hat{X}_i, \hat{s}_i\right) Cov\left(X - \mathbb{E}\left[X|I_i'\right], \hat{s}_i\right)}{Var\left(\hat{X}_i\right) Var\left(\hat{s}_i\right)} \right)$$

$$= \frac{Cov\left(\mathbb{E}\left[Y|I_i\right], X\right)}{Var\left(X_i\right)} + \frac{Cov\left(X - \mathbb{E}\left[X|I_i'\right], Y\right)}{Var\left(X_i\right)} \left(\rho^2 - \rho \frac{Cov\left(X - \mathbb{E}\left[X|I_i'\right], \hat{s}_i\right)}{\sqrt{Var\left(\hat{X}_i\right) Var\left(\hat{s}_i\right)}} \right),$$

where we use the law of total covariance and Assumption 4 for the second equality. As a result,

$$\left|\tilde{\beta}_1^X\right| \leq \left| \frac{Cov\left(\mathbb{E}\left[Y|I_i\right], X\right)}{Var\left(X_i\right)} \right| + \frac{\sqrt{Var\left(Y\right) Var\left(X\right)}}{Var\left(X_i\right)} \left(\rho^2 + |\rho| \sqrt{\frac{Var\left(X - \mathbb{E}\left[X|I_i'\right]\right)}{Var\left(\hat{X}_i\right)}} \right)$$

$$\leq \left| \frac{Cov\left(\tilde{F}_i Y, X\right)}{Var\left(X\right)} \cdot \frac{Var\left(X\right)}{Var\left(X_i\right)} \right| + \left(\rho^2 + |\rho|\right) \frac{\sqrt{Var\left(Y\right) Var\left(X\right)}}{Var\left(X_i\right)},$$

where we use Assumption 1 and the definition of LIRE in Definition 1 in the last step. This is the bound (17) in Test 3.