Selective Inattention to Interest Rates*

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Abstract

This paper studies whether households are selectively inattentive to interest rates and examines its macroeconomic implications. We first use existing and newly-designed household surveys to establish that households close to durables purchases actively acquire more information about interest rates and have more accurate, less dispersed, and less uncertain interest rate expectations. Next, we use this evidence to calibrate an incomplete markets model with durable consumption and endogenous information acquisition about interest rates through rational inattention. Finally, we quantify how selective inattention changes aggregate consumption responses to interest rates. Relative to exogenous inattention, selective inattention shifts the composition of spending responses to interest rate cuts, accelerates the impact of larger cuts, and generates dampened responses to changes in volatility that are closer to empirical evidence.

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An extensive body of literature in the last couple of decades has leveraged survey data to study households' macroeconomic expectations (Bordalo et al. 2020; Weber et al. 2022). A common finding in this literature is that households' expectations, on average, tend to respond slowly to changes in macroeconomic conditions (Coibion and Gorodnichenko 2012, 2015). This evidence of a high average level of household inattention has motivated quantitative macroeconomic models to incorporate information frictions (McKay and Wieland 2021; Beraja and Wolf 2022), such as sticky or noisy information (Mankiw and Reis 2002; Woodford 2003). These frictions help generate average expectations that are slow-moving and hump-shaped responses to shocks (Carroll et al. 2020; Auclert et al. 2020), both of which are consistent with the data (Christiano et al. 2005).

While the average level of household inattention is clearly high, it is also clear that macroeconomic expectations are much more important for bigger decisions that households make relatively infrequently, such as home purchases, than for smaller decisions that households make more frequently, like buying groceries. This observation that the benefits of attention vary across households' decisions raises two questions. First, to what degree do households *select* into paying attention about macroeconomic variables based on the types of decisions they make? Second, if this *selective inattention* is present at the micro-level, how do its macroeconomic implications differ from exogenous inattention?

This paper addresses these questions by focusing on households' interest rate expectations around durable goods purchases. We begin by using a combination of existing surveys and a newly-designed survey to show that the interest rate expectations of households close to a durables purchase are more accurate, less dispersed, and less uncertain than those with no purchase intentions. Next, we show that these differences in beliefs are also present in information acquisition: households close to a purchase are more likely to actively acquire information about the variables for which their expectations become more accurate. Motivated by this evidence, we then embed endogenous information acquisition about interest rates via rational inattention into a partial equilibrium incomplete markets model with durable consumption. After calibrating the model with our survey evidence, we show how selective inattention changes aggregate consumption responses to interest rates. Relative to exogenous inattention, selective inattention shifts the composition of spending responses to interest rate cuts, accelerates the impact of larger cuts, and generates dampened responses to changes in volatility that are closer to empirical evidence.

Our focus on selective inattention in the context of interest rate expectations and durables purchases, in particular houses and cars, is motivated by two existing findings. First, durables spending plays an important role in business cycle dynamics (Berger and Vavra 2015) and the transmission of monetary and fiscal policy (McKay and Wieland 2021; Beraja and Zorzi 2024). Second, durables purchases have a high intertemporal elasticity: following a temporary rise in interest rates, households can simply postpone their durable spending to future periods when rates normalize, receiving the service flow from existing durables in the meantime (Mankiw 1982; Caballero 1993; Barsky et al. 2007). Given durables purchases are often debt-financed, this large sensitivity makes interest rate expectations the natural set of expectations to study in the durables context.

In the first part of the paper, we use existing surveys of household expectations and a new survey that we design to document several facts that point to the presence of selective inattention to interest rates. We choose to use a combination of existing surveys and our new survey because they are complementary for our purposes. The benefit of existing surveys is that they have high-quality data on expectations over longer samples, while our survey only elicits a single cross-section. However, relative to existing surveys, our survey has the benefit of being designed to precisely identify the households' distances from different forms of durables purchases and patterns in information acquisition. The former is more challenging with existing surveys, while the latter is impossible.

Our first fact is that the interest rate expectations of "decision-makers," meaning households close to a durables purchase, are significantly more accurate than those of non-decision-makers. Using data from the NY Fed Survey of Consumer Expectations (SCE), we find that the absolute nowcast (i.e., current) and forecast errors of mortgage rates for prospective homebuyers are approximately 40% lower than those of households without purchase plans, conditional on a large set of observable characteristics. This difference in expectations accuracy is almost twice as large as the differences between individuals in the top and bottom terciles of the income or education distributions. When we decompose the improvement in forecasting accuracy, we find that most of the gain comes from more accurate nowcasts rather than an improvement in forecasting ability.

The fact that decision-makers have more accurate interest rate expectations is also present when we use the ECB Survey of Consumer Expectations (CES). In the CES, households that are within six months of a mortgage application, which is the only information available about durables purchases, have forecast errors of mortgage rates that 25% lower than those that have not applied for a mortgage. Leveraging the panel dimension of the CES, we show this difference is also present *within*-individual. Given the differences between the SCE and CES in terms format, geographies, and time periods, these findings highlight that decision-makers having more accurate expectations is a robust feature of the data.

Our second fact is that the improvement in expectations accuracy for decision-makers is larger for interest rates than other macroeconomic variables. When we look at inflation forecasts in the SCE, which are the only other set of expectations available in that survey, we find that decision-makers expectations are more accurate, but the accuracy gain is around half as large. For forecasts of unemployment rates and GDP in the CES, we find little evidence of meaningful differences in forecasting accuracy.

Our third fact is that decision-makers' beliefs, in addition to being more accurate, are less dispersed and uncertain. In the SCE, the cross-sectional dispersion (or disagreement) across individuals in expectations about current and future mortgage rates is around 70% lower among decision-makers. In the CES, this lower disagreement is present qualitatively but is smaller quantitatively. Turning to subjective uncertainty, which we elicit in our survey, we find that households within six months of a home purchase report less uncertainty in their interest rate forecasts compared to those very far from a home purchase.

Our final two facts leverage our survey's elicitation of how households acquire information, which builds on Roth et al. (2022). First, decision-makers concentrate their information acquisition around durables purchases: households within six months of a home purchase are twice as likely to actively seek information as those far from a purchase. This relationship is present when we instrument purchase decisions with job-related relocations, suggesting it is not entirely driven by reverse causality. Second, this concentration in information acquisition is present for other decisions, but is concentrated on decision-relevant variables: mortgage rates and home prices for home purchases; car prices and auto loan rates for car purchases; and stock prices and Treasury rates for those close to major financial decisions. In each case, information acquisition is primarily about the current values of these variables rather than future and past values or uncertainty.

In the second part of the paper, we develop a partial equilibrium incomplete markets model with non-durable and durable consumption that contains the necessary ingredients to generate the selective inattention in the data.[1] The model incorporates the standard ingredients in durables models, such collateralized borrowing, adjustment costs, operating and maintenance costs, depreciation, and match-quality shocks, that are necessary to match micro-patterns in durable adjustment and generate realistic interest rate elasticities

[1] Despite only having evidence of improvements in accuracy around home purchases, we choose to model a single durable good for two reasons. First, information acquisition is correlated with belief accuracy, and increases around car purchases. Second, housing is the largest durable for most households.

(Berger and Vavra 2015; McKay and Wieland 2021). Our key innovation is to endogenize households' beliefs about (real) interest rates through rational inattention (Sims 2003). In the model, households optimally acquire information about interest rates to balance the costs of information, which are linear in mutual information (Maćkowiak et al. 2023), against the benefits of having more accurate beliefs when making consumption choices.

We calibrate the marginal cost of information, the key additional parameter in our model, using the difference in information acquisition between decision-makers and non-decision-makers from our survey. This difference is monotonically increasing in the marginal cost of information because the marginal benefits of information are higher in periods of durables adjustments. We find that our model can quantitatively replicate this difference in the data, but also generates novel patterns that are not present in prior quantitative models of rational inattention (e.g., Afrouzi et al. 2024). For example, households acquire information even when they are not adjusting durables and start increasing their information acquisition in anticipation of adjustments, both of which are consistent with our empirical evidence. Despite the presence of selective inattention, our model still generates significant rigidity in aggregate beliefs, consistent with Coibion and Gorodnichenko (2012, 2015).

In the final part of the paper, we use our model to quantify how selective inattention (SI) changes aggregate consumption responses to two different shocks: changes in real interest rates, which capture the effects of monetary policy in reduced-form, and changes in interest rate volatility, which has doubled since the pandemic (see Figure A5) and affects the incentives to acquire information. To highlight the importance of SI, we compare responses in our model with two alternative models: one with exogenous inattention (EI) but the same level of aggregate inattention, and another with rational expectations (RE).

Our first result is that SI preserves the sluggish responses of aggregate beliefs and non-durable consumption to changes in interest rates that is present with EI. In both cases, aggregate beliefs move in the right direction, but they are slow-moving and under-react, consistent with the data (Coibion and Gorodnichenko 2012). Similarly, aggregate non-durable consumption increases following a fall in rates, but the increase on impact is smaller and dampened in both models relative to RE. The dampened response of non-durable consumption with SI reflects the fact that it is primarily determined by households that are not making durables adjustments, who are relatively inattentive.

While SI preserves the sluggish responses of aggregate beliefs and non-durables, it shifts the composition of spending responses to interest rate changes. Under EI, durables spending responds sluggishly to a 25 basis points cut in interest rates, with an increase that is 60% smaller than RE on impact and 25% smaller after two years. In contrast, the increase in durables spending with SI is twice as large as EI on impact and identical to RE after two years. The larger and faster response with SI reflects the fact that a fall in rates stimulates durables adjustments, which induces information acquisition by those making the adjustments and moves their beliefs and choices closer to RE. Nevertheless, this high attention of those making adjustments is offset by the low attention of the remaining households. Because there is a much larger mass of the latter, SI generates a smaller two-year response of non-durable consumption than EI that, combined with the larger durable response, leads an almost identical aggregate spending response. In other words, SI shifts the composition of aggregate spending responses, but not the overall level.

Another consequence of SI is that it accelerates the impact of larger changes in interest rates. For a smaller cut in interest rates (e.g., 25 bps), the response of aggregate beliefs is similar between EI and SI. In contrast, larger cuts (e.g., 100 basis points) increases the incentives for information acquisition by creating larger incentives for durables adjustment and errors in households' prior beliefs. The resulting responses of aggregate beliefs with SI generate faster responses of durable and non-durable consumption to these larger cuts unlike with EI, where inattention does not adjust endogenously to the size of the shock.

Our final result is that SI substantially dampens the effect of changes in interest rate volatility relative to EI. Under RE, doubling interest rate volatility causes a 5% decline in aggregate spending over two years due to precautionary motives. With EI, this effect is even stronger because subjective uncertainty increases by more than the increase in volatility, leading to a spending decline of over 15%. In contrast, with SI, aggregate spending falls by 8% over two years, which is closer than EI to estimates in Cremers et al. (2021). The smaller fall in spending under SI reflects households endogenously increasing information acquisition in response to an increase in volatility, which dampens the large increase in subjective uncertainty that occurs with EI. This same mechanism also makes interest rate cuts relatively more effective as volatility increases with SI compared to EI. Given that increases in volatility can dampen the passthrough from nominal to real rates (Vavra 2014; Afrouzi et al. 2024), this finding suggests that the sign of the effect of volatility on the transmission of monetary policy to consumption may be ambiguous.

Related literature. The primary contribution of this paper is to connect households' belief formation and information acquisition to durables purchases. This contributes to the literature that studies subjective expectations (see Bordalo et al. 2020 and Weber et al. 2022 for reviews) by highlighting how a high level of *average* inattention can mask significant *selective* inattention. Relative to standard models that feature exogenous information frictions (Carroll et al. 2020; Auclert et al. 2020; McKay and Wieland 2021; Beraja and Wolf 2022), our model shows that endogenizing inattention in a way that is quantitatively consistent with the data generates distinct counterfactual predictions, while still generating significant rigidity in average beliefs (Coibion and Gorodnichenko 2012, 2015). The difference between models with exogenous and endogenous inattention is also emphasized by Broer et al. (2022) and Guerreiro (2023), to which we view our results as complementary. Broer et al. (2022) incorporate binary information choice into a Krusell and Smith (1998) model and focus on the macroeconomic implications of heterogeneity in expectations by wealth and employment. Guerreiro (2023) shows that the income beliefs of households that are more exposed to aggregate income shocks, which endogenously pay more attention, play a larger role in aggregate demand responses.

The model that we develop connects models of durables adjustment (Berger and Vavra 2015; McKay and Wieland 2021; Beraja and Wolf 2022; Beraja and Zorzi 2024) with models of rational inattention (Sims 2003; Maćkowiak et al. 2023) by providing the first model, to our knowledge, that combines the two.[2] A closely-related paper that preceded our work is Afrouzi et al. (2024), which incorporates rational inattention into a model of time-dependent price-setting. Their model generates a starker form of selective inattention, which they call selection into information acquisition, than our model: firms only acquire information when they adjust their price, and only the expectations of price-setters matter for monetary non-neutrality. Our model differs in that it has (i) time- *and* state-dependent adjustment of an endogenous variable (durables, in our case, prices, in theirs) and (ii) a second endogenous variable (non-durables) that benefits from information in the presence of inaction. As a result, our model generates information acquisition even when durables are not adjusted, and implies that the beliefs of inactive agents still matter for aggregate outcomes.[3] Another closely-related paper is Alvarez et al. (2012), who show that a model of durable consumption with both adjustment and observation costs is necessary to match individuals' trading behavior. Our model shares this focus on durables and information acquisition, but differs in that it also has non-durables, continuous information choice,

[2]An alternative framework is behavioral inattention (Gabaix 2019). Qualitatively, this framework would generate many of the same predictions for our purposes as our model of information acquisition.

[3]The point that average beliefs may not be relevant when beliefs are heterogeneous has also been made in asset pricing models, where the marginal buyer's or the wealth-weighted average belief can set prices (see e.g., Miller 1977; Simsek 2013; Martin and Papadimitriou 2022).

and time-dependent adjustment. These differences generate richer patterns in information acquisition that are consistent with our survey data, while also being consistent with micro-data on durables purchases (McKay and Wieland 2021).

Finally, this paper contributes to two other related literatures. First, we build on a literature that elicits information acquisition in the field (Coibion et al. 2018; Roth et al. 2022; Mikosch et al. 2024) by showing how these elicitations can be used to identify structural models of information acquisition. Second, by studying the effects of interest rate volatility, this paper is part of the literature that studies the macroeconomic effects of changes in second-moments (Bloom 2014; Vavra 2014; Bloom et al. 2020; Cremers et al. 2021; Ilut et al. 2025). Our contribution is to highlight how the macroeconomic effects of changes in volatility are heavily mediated by endogenous information acquisition.

Outline. The layout of this paper is as follows. Section 1 describes our the existing surveys and new survey that we design. Section 2 presents our five facts from these surveys that point to the presence of selective inattention to interest rates. Section 3 describes our incomplete markets model and our calibration strategy. Section 4 examines patterns in information acquisition and beliefs in the model's steady-state. Section 5 studies how the responses in this model to changes in the level and volatility of interest rates differ from that of rational expectations and exogenous inattention. Section 6 concludes.

1 Data Description

This section describes the data from existing and new surveys that we use. The benefit of existing surveys is that they have high-quality data on expectations over longer samples, while our survey only elicits a single cross-section. However, our survey has the benefit of being designed to precisely identify the households' distances from different forms of durables purchases and patterns in information acquisition.

1.1 Existing Household Surveys

The two existing surveys that we use are the NY Fed's Survey of Consumer Expectations (SCE) and the ECB's Consumer Expectations Survey (CES). We choose these surveys because these are the only household surveys of expectations, to our knowledge, that contain sufficient information for us to determine a household's distance from a durables purchase. These surveys focus on home purchases and have some information on car purchases; in the survey that we conduct, along with detailed information on primary-home purchases, we also study car purchases, other real estate investments (e.g., second homes), and major financial investments.

1.1.1 NY Fed Survey of Consumer Expectations (SCE)

The first existing survey that we use is the SCE, which is conducted by the NY Fed and contains repeated cross-sections starting in 2013. We merge information from the monthly Core module of the SCE with data from the special Credit and Housing modules. To define a household's home purchase decision-making status, we classify respondents into four groups of renters and two groups of homeowners. Our categorization of renters is as follows: (i) renters with no purchase plans, who report zero probability of purchasing a primary residence in the future; (ii) distant renters, who express an intent to purchase in the future but report a low probability of applying for a mortgage within the next 12 months; (iii) close renters, who plan to buy and report a high probability of applying for a mortgage within the next 12 months; (iv) prospective buyers, who have already applied for a mortgage in the previous 12 months. Homeowners are classified based on the timing of their most recent purchase: those who bought a home within the last five years, and those who bought more than five years before the survey date.

We then study households' expectations accuracy about mortgage rates and inflation, which are the two main macroeconomic variables available in the survey. Nowcasts and one-year ahead forecasts of the average US 30-year fixed mortgage rate are elicited once a year in the special Housing module. In particular, respondents are asked to report the perceived current value, and the expected value for the average interest rate on a 30-year fixed-rate mortgage in the US one year from now. We compute nowcast and forecast errors relative to the realized values from Freddie Mac's Primary Mortgage Market Survey. One-year ahead inflation forecasts are taken from the Core module, where respondents are asked every month what level of inflation (or deflation) they expect over the subsequent 12 months in the US. We measure errors relative to the realized values of CPI, but our results are unchanged for inflation if we measure errors relative to the PCE. In all results using these data, we report heteroskedasticity-robust standard errors.

1.1.2 ECB Consumer Expectations Survey (CES)

The second existing survey that we use is the CES, which is a monthly survey that was recently launched by the ECB in 2020. Two key advantages relative to the SCE are that the survey is a panel, which allows us to study within-individual variation, and that it has more precise information on households' distances from a home purchase. The main downside is that the sample is much shorter and covers only the post-COVID period. We restrict the sample to individuals who were renters when they joined the survey panel, and use data from six largest euro area economies that have been present since the beginning of the survey: Belgium, France, Germany, Italy, the Netherlands, and Spain.[4]

To define a household's home purchase decision-making status in the CES, we classify respondents into four mutually exclusive groups based on the timing of their mortgage application relative to the survey wave: those who already applied for a mortgage at the time of the current wave; those who apply within six months of the current wave (including those who applied at the time of the survey); those who apply between seven and twelve months after the current wave; those who apply more than twelve months after the current wave, or not at all while on the survey panel. While the survey is run monthly, this information on mortgage applications is from a module that is only run quarterly.

We study households' forecasts of one-year ahead mortgage rates, inflation, the unemployment rate, and output growth, which are the only macroeconomic expectations available in this survey. We compute errors relative to the corresponding realized values of each of these variables, which vary based on the respondent's country of residence. In particular, mortgage rate errors are computed using realized values of mortgage rates on loans to households for home purchases, as published by the European Central Bank, while errors for inflation, unemployment, and output growth are based on realized values reported by Eurostat. In all results using these data, we report standard errors that are clustered at the country-by-month level.

1.2 New Household Survey

Our third data source is a novel survey of US households that we design and implement. The full questionnaire is available in Appendix B. This survey is designed with three main goals. First, we aim to measure respondents' proximity to purchasing their primary home,

[4]Five smaller countries—Austria, Finland, Greece, Ireland, and Portugal—were added later, but do not yet have enough data for our analysis.

but also other major decisions, such as auto purchases and financial investments. Second, we elicit households' information acquisition about the different sources of macroeconomic information using an approach that builds on the elicitation techniques in Coibion et al. (2018), Roth et al. (2022), and Mikosch et al. (2024). These patterns in information acquisition are used in Section 3 to calibrate our quantitative model. Finally, we want to collect data on macroeconomic expectations, including nowcasts, forecasts, and measures of subjective uncertainty. These measures allow us to benchmark our findings with existing surveys, but also connect our novel measures of information acquisition to beliefs directly.

1.2.1 Sample and Data Quality

We conducted our survey in March 2025 through Prolific, targeting US renters aged 25 to 65 who are currently active in the labor force. We implement two initial screening questions to improve targeting of our sample. First, because our research focuses on household behavior around the time of a first-home purchase, we target respondents who are either currently renting their primary residence and plan to purchase their first home within the next five years, or homeowners who purchased their first home at most in the previous five years. Second, we include only respondents who actively participate in their households' economic and financial decision-making. Our rationale is that respondents with limited decision-making roles have fewer incentives to closely monitor macroeconomic conditions.

The median and average survey completion times are 16 and 19 minutes, respectively. To ensure data quality, we impose several additional restrictions. First, we include an attention check at the beginning of the survey, modeled after Stantcheva (2024), to screen respondents who fail basic attentiveness criteria. Second, an additional attention check is administered midway through the survey to further enhance data quality. Finally, we filter respondents based on their quantitative responses, excluding those who provide more than one answer within the top 5th percentile of extreme values. We adopt this criterion because extreme outlier responses likely indicate poor attention or misunderstanding of the survey questions, but our main results remain robust to the inclusion of this excluded subsample. In all results with these data, we report heteroskedasticity-robust standard errors.

1.2.2 Survey Structure

We now provide an overview of the key sections of our survey. The survey includes one main randomization: half of the respondents are presented with the "Macroeconomic Expectations" and "Information Acquisition" sections first, followed by the "Distance from

Home Purchase" section. The other half of the respondents see these sections in the reverse order. Our results are not influenced by the order in which these blocks are shown.

Distance from home purchase. Initially, survey respondents are classified as renters or homeowners based on preliminary screening questions. Each group is then guided to answer targeted sets of questions specific to their current status.

Renters are first asked when they anticipate finalizing the purchase of their first primary residence. We then inquire whether they intend to finance this purchase through a mortgage or pay in cash. Approximately 15% of respondents indicate plans to purchase with cash. This figure is slightly higher than the current share of first-home cash transactions in the U.S., which stands between 5% and 10% according to the NAR. The slightly larger share in our data is consistent with our sample having higher income and wealth than the national average, and with recent trends in the U.S. housing market showing an increasing share of cash purchases. In the next step, renters are asked if they have undertaken any of the following preparatory actions: searching for a home, gathering mortgage information, obtaining financing details from banks, or preparing their personal finances for the purchase. We then ask how close they are to applying for mortgage pre-approval or pre-qualification (if applicable), whether they are already working with a real estate agent, and their proximity to submitting a mortgage application. For respondents who have applied for or already secured a mortgage, we inquire about the mortgage type (fixed or adjustable) and the requested loan amount.

Homeowners are initially asked how long ago they finalized the purchase of their current primary residence. Subsequently, they indicate whether they currently have an outstanding mortgage, and if so, whether the mortgage rate is fixed or adjustable. We also ask if they have recently refinanced or plan to do so in the near future, including details about the timing of these actions. This section concludes by inquiring about plans to sell their current property or purchase a new one.

Distance from other decisions. In the SCE and the CES, we can only classify households based on their decision-making status with respect to buying a house. In our survey, we also include a set of questions to track whether respondents have recently (i) bought a car or motor vehicle, (ii) made real estate investments other than their primary residence (e.g., business-related properties or second homes), or (iii) made significant financial investments.[5] For (i) and (ii), we also check whether these decisions resulted in the origination of loans or mortgages. Additionally, we ask about plans to undertake any of these actions in the future, by eliciting the expected distance from these purchases and investments.

Information acquisition. This block consists of two parts. In the first, we elicit whether respondents actively searched for information regarding a list of US economic variables in the previous three years. We clarify that by “active search” we mean a deliberate effort to find information which could include searching online, reading news articles or reports, talking to a financial advisor or broker, or any other intentional effort to gather information. The list of variables include: mortgage rates, inflation, home prices, exchange rates, stock market, unemployment rate, GDP, Treasury bill rates, industrial production, auto loan rates, car prices, and federal funds fate. Respondents are shown this list in randomized order.

For each variable that was actively searched for, we ask a follow-up question that directly elicits how many months before the survey the respondent has searched for information. If respondents select either mortgage rates, auto loan rates, or Treasury bill rates, we ask what type of information regarding these variables they were most interested in. They can choose multiple options from a list that includes the current level of the variables, their expected value 1- and 3-years ahead, the uncertainty surrounding their future value, and their past value over the past 5 years. For the same three variables we have an additional follow-up question to investigate the sources they used to obtain information. This list is modeled after a similar question included in the Survey of Consumer Finances.

Macroeconomic expectations. First, we elicit households nowcasts, or expectations of the current value, for three variables: the average mortgage rate on a 30-year fixed-rate mortgage, inflation, and the interest rate on a 1-year Treasury bill. The elicitation closely follows the SCE structure. Second, we elicit one-year ahead forecasts of the average mortgage rate and the 1-year Treasury bill rate as density forecasts using a scenario-based elicitation. The approach follows the recent methodology proposed by Boctor et al. (2024) that is based on Bloom et al. (2020), which substitutes bin-based density forecasts with the elicitation of point forecasts and associated subjective probabilities for three scenarios (low, medium, and high realizations of the forecasted variable). We refer to these papers

[5] Very few respondents that report (ii) at the time of the survey, so we do not analyze these decisions in detail. However, we control for whether a respondent has recently made, or plans to make, such an investment.

for details, but the main advantage is making the elicitation more compact and reducing priming. The scenario-based forecasts also provide a measure of the subjective uncertainty associated with the forecast. Finally, we ask respondents to recall the 30-year fixed-rate mortgage rate and the inflation rate in December 2019, right before the start of the Covid-19 pandemic. These questions allow us to assess whether differences in nowcasting or forecasting performance also manifest in differences in recall.

One concern is that the nowcasts and forecasts about mortgage rates—referring to the average rate for a new 30-year fixed-rate mortgage in the US—might be influenced by the rates respondents think they would obtain. To address this concern, we include a short question that sequentially asks whether the respondent thinks they would qualify for a 30-year fixed-rate mortgage if they applied today, and if so, at what rate. We find that our results are unaffected by controlling for a respondent's perceived eligibility.

Financial situation. This block provides a snapshot of the financial position of the respondent's household by asking a series of detailed questions on assets and liabilities. The elicitation follows a simplified and more compact version of the one used in the Survey of Consumer Finances. Before the full elicitation, we include two short questions to measure the respondent's beliefs about the prevailing economic conditions in the US and the financial situation of the household.

We then collect information on four categories of assets using brackets: short-term savings (e.g., checking accounts), other financial assets that can be easily liquidated (e.g., stocks), financial assets that cannot be easily liquidated (e.g., retirement accounts), and non-financial assets (e.g., cars). Each category is carefully described with a comprehensive list of the assets included. We have two questions on liabilities: one for credit card debts and other consumer loans, and one for outstanding mortgages and auto loans. Finally, we ask for estimates of the monthly rent payment as well as any monthly payments towards the repayment of mortgages, car loans, or student loans. We also ask respondents to report the highest credit score in the respondent's household, using identical brackets to those in the NY Fed SCE. We use these variables to construct synthetic indicators of a respondent's financial position that are included as controls in our analyses.

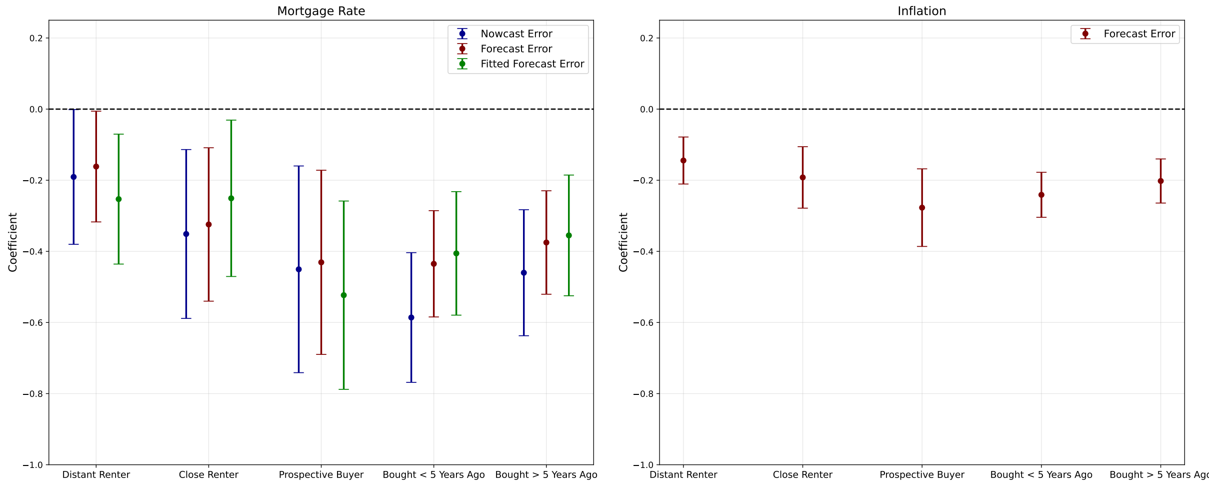
Background characteristics. Finally, we obtain any additional background information about the respondent that was not included in the opening block or the financial situation block. The opening block is the first part of the survey shown to respondents and is designed to filter out respondents who do not meet our sampling criteria and to target quotas. Questions in that block include the respondent's state of residence, age, gender, total household income in 2024, household size, employment status, and race. In this final block, respondents report their education level, field of study, and political affiliation. We also ask whether the household has recently moved or plans to move in the near future, for instance, due to a job relocation. These questions are designed to obtain additional information on a dimension— moving plans—that is often associated with changes in housing status as well as other durables purchases.

Before completing the survey, respondents answer two short questions aimed at measuring their numerical ability. Given the nature of our questionnaire, we selected two questions from the larger set included in the NY Fed SCE that specifically relate to reasoning with percentages and understanding real versus nominal returns (Lusardi and Mitchell 2011). These questions jointly provide information on respondents' ability to reason with numbers, as well as an additional attention check.

1.3 Summary Statistics

We conclude this section by providing some summary statistics from our three surveys, which are provided in Table A1. Our survey has around 820 observations, while the SCE has around 10K and the CES around 570K. The median nowcast error of mortgage rates in our survey is 0.65 percentage points (i.e., reporting 7.65% when the mortgage rate is 7%), close to the value of 0.63 in the SCE. The median forecast error is around 1 percentage point, which is close to the 1.19 in the SCE and 1.36 in the CES. As is standard, average forecast errors would be larger due to the presence of a few outliers. The similarity of errors across these data sets reinforces our confidence in their quality and comparability. Table A2 compares our survey to the SCE across key demographic characteristics. While gender and income distributions are relatively similar in the two surveys, respondents in our sample are slightly younger and more educated. These differences likely reflect our targeting, which focused on renters nearing a home purchase or individuals who recently bought a home.

Figure 1. Decision-Making and Expectation Accuracy in the NY Fed SCE



Notes: This figure shows the estimates of β_s in (1) for different decision-making groups indexed by s. The omitted category are households without any purchase plans. The left panel reports results for mortgage rate nowcasts and one-year ahead forecasts, while the right panel focuses on inflation one-year ahead forecasts. The left panel also presents results for "fitted" forecasts, which are described in the text. Bars correspond to 95% confidence intervals. The samples of absolute nowcast and forecast errors are trimmed at the 5% level.

2 Empirical Evidence of Selective Inattention

2.1 Fact #1: Decision-Makers Have More Accurate Expectations

We begin by studying how households' expectation accuracy varies based on their proximity to a primary home purchase. Using the SCE, we estimate the following regression:

$$\log\left(|\text{Error}_{it}|\right) = \sum_s \beta_s \cdot \mathbf{1}\left(\text{DM Status}_{it} = s\right) + \text{Controls}_{it} + \delta_t + \epsilon_{it}, \tag{1}$$

where $|\text{Error}_{it}|$ denotes the absolute nowcast or forecast error for respondent i in period t and DM Status_{it} indicates the decision-making group based on distances from a home purchase defined in Section 1.1.1. We include a standard set of demographic controls—income, education, age, gender, survey tenure, U.S. region, and an indicator for the household's financial outlook—along with time fixed effects δ_t. The omitted category are renters without purchase plans.

The left panel in Figure 1 shows the estimated coefficients from this regression with mortgage rate nowcasts and forecasts. For households that are far from a home purchase, Distant Renters, we find little evidence of a difference in nowcast and forecast accuracy. In contrast, as households approach the time of the choice, both nowcasts and forecast errors of mortgage rates fall significantly. At the time of the purchase, Prospective Buyers have errors that are around 40% lower than renters without purchase plans (the omitted category). This difference in accuracy is substantial: it is almost twice as large as the differences between individuals in the top and bottom terciles of the income distribution, or in the top and bottom terciles of the education distribution.

A natural question raised by the evidence in Figure 1 is whether the improvement in forecasting performance is simply driven by an improvement in nowcasting, or an actual improvement in forecasting ability. To assess this, we construct "fitted forecast error" by first regressing forecasts onto nowcasts and then computing the error implied by households' nowcasts, holding the relationship between nowcast and forecasts fixed.[6] The left panel of Figure 1 then reports the estimates from (1) with these fitted forecast errors in green. The results show that most of the overall reduction in forecast errors is explained by a reduction in nowcast errors.

Next, we show the patterns in Figure 1 are also present in the CES. Similar to (1) in the SCE, we estimate the following regression:

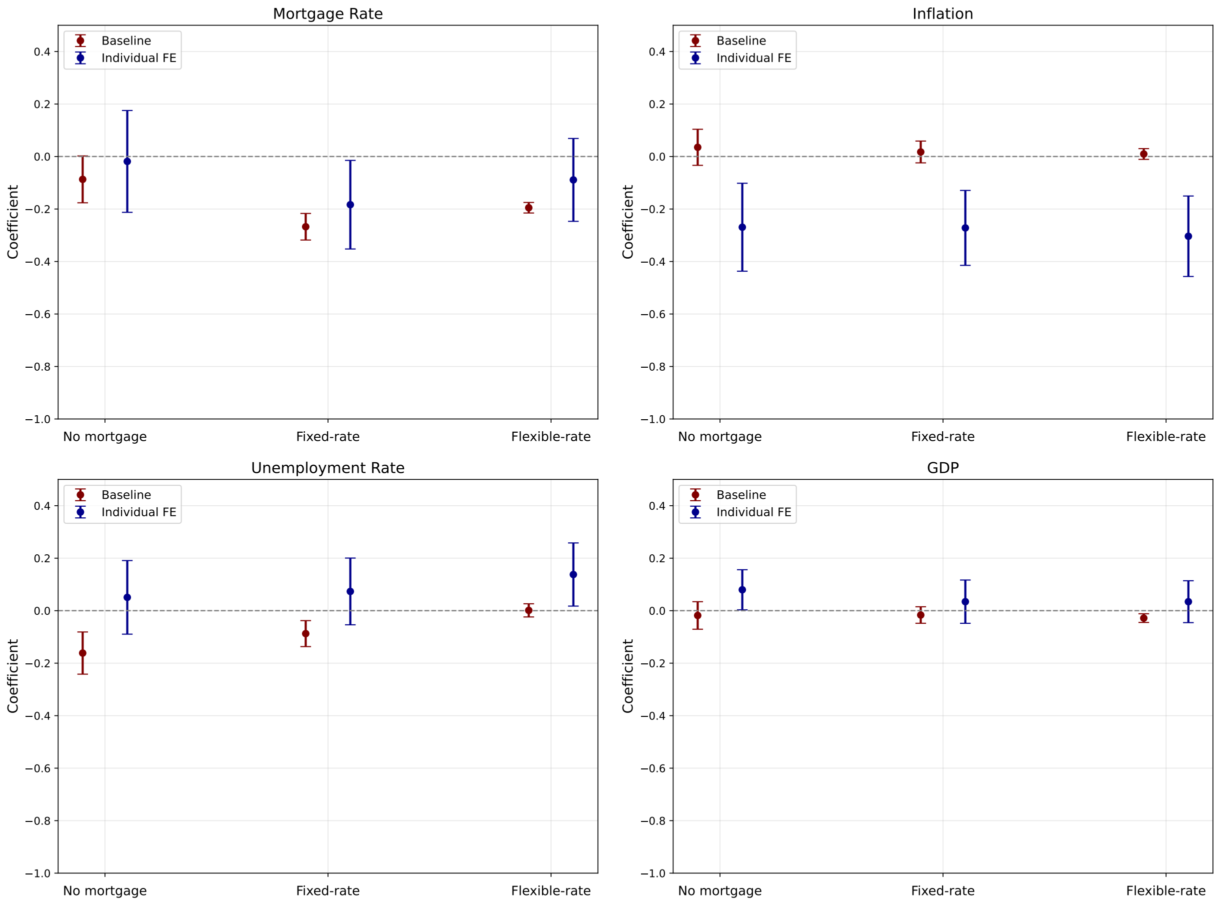
$$\log\left(|\text{Error}_{it}|\right) = \sum_{s} \beta_s \cdot \mathbf{1}\left(\text{DM Status}_{it} = s\right) + \gamma \cdot \text{Tenure}_{it} + \alpha_i + \lambda_{ct} + \varepsilon_{it}, \tag{2}$$

where DM Status_{it} indicates the decision-making group defined based on mortgage application status in Section 1.1.2. We include fixed effects for individuals, α_i, and country-by-survey wave, λ_{ct}. We also control for survey tenure, measured by the number of survey waves in which a respondent has participated. The omitted category is households that apply for a mortgage more than twelve months before the current survey wave or, that do not apply at all during their survey tenure.

The top left panel in Figure 2 shows the estimated coefficients for one-year ahead mortgage rate forecasts with and without individual fixed effects. Without individual fixed effects, we find that households within six months of a mortgage application have 25% lower forecast errors that those more than twelve months from an application. This difference persists post-application, with a slightly smaller magnitude. The size of both of these effects are around half of our estimates from the SCE, but tell the same pattern qualitatively. When we add individual fixed effects, the estimated effects shrink by around a fifth, with the reduction in forecast errors for households within six months of an application estimated at 20%. The standard errors of these estimates are much larger due to the combination of a short panel and the fact that households do not change decision-making groups often.

[6] The R^2 in the regression of forecasts on nowcasts is around 80%.

Figure 2. Decision-Making and Expectation Accuracy in the ECB CES



Notes: This figure shows the estimates of β_s in (2) for different decision-making groups indexed by s. The omitted category are households that apply for a mortgage more than twelve months before the current survey wave or, that do not apply at all during their survey tenure. All panels report results for one-year ahead forecasts with two sets of estimates with and without individual fixed effects. The top left panel uses mortgage rate forecasts, the top right uses inflation forecasts, the bottom left using unemployment forecasts, and the bottom right uses output growth forecasts. Bars correspond to 95% confidence intervals. The sample of absolute forecast errors is trimmed at the 5% level.

Finally, we explore the relationship between home purchases and interest rate expectations accuracy in our new household survey. In this analysis, we have significantly less power because our survey was elicited in one cross-section, for which there is only one corresponding realization of the variable of interest. This is not an issue when we study patterns in information acquisition later, which is the primary purpose of our survey. Nevertheless, we explore this relationship by running the following regression:

$$\log |\text{Error}_i| = \sum_d \beta_d \cdot \mathbf{1}\left(\text{Home Distance}_i = d\right) + \text{Controls}_i + \text{Other Distances}_i + \epsilon_i, \qquad (3)$$

where Home Distance$_i$ is defined as the months from a home purchase. We run this regression among households that are renters and intend to use credit, binning the distance from the purchase: households within 12 to 7 months of a purchase, households within 6 months of a purchase, and all other households that have not yet made a purchase, who are the omitted group. We include controls for a range of observable characteristics in our survey, including income, age, education, net assets, household role, numeracy, gender, FICO score, and employment status. We also control for indicators of whether households are close to making car purchases, other real estate purchases, or large financial investments, as well as if they have recently undertaken any of these actions.

The top panel Figure 3 shows that households who are close to making a home purchase have 55% lower nowcast errors of mortgage rates than households that are far from purchase, close to our estimate from the SCE. This difference is also present when we look at Treasury bill rate nowcasts, for which the reduction is around 40%. This suggests that households become more accurate about interest rates broadly, rather than just mortgage rates. These differences in nowcast accuracy do not reflect differential memory: we find no significant difference in the recall errors of decision-makers for Treasury and mortgage rates. The standard errors of all our estimates are larger than in the SCE and ECB, given the difference in sample size.

The bottom two panels of Figure 3 show the estimates of (3) replacing Home Distance$_i$ with the distance from a car purchase and a major financial investment, respectively.[7] For car purchases, we find no evidence of an improvement in nowcast errors of mortgage or Treasury rates. For major financial investments, we find a large reduction in Treasury rate nowcast errors of around 95%.

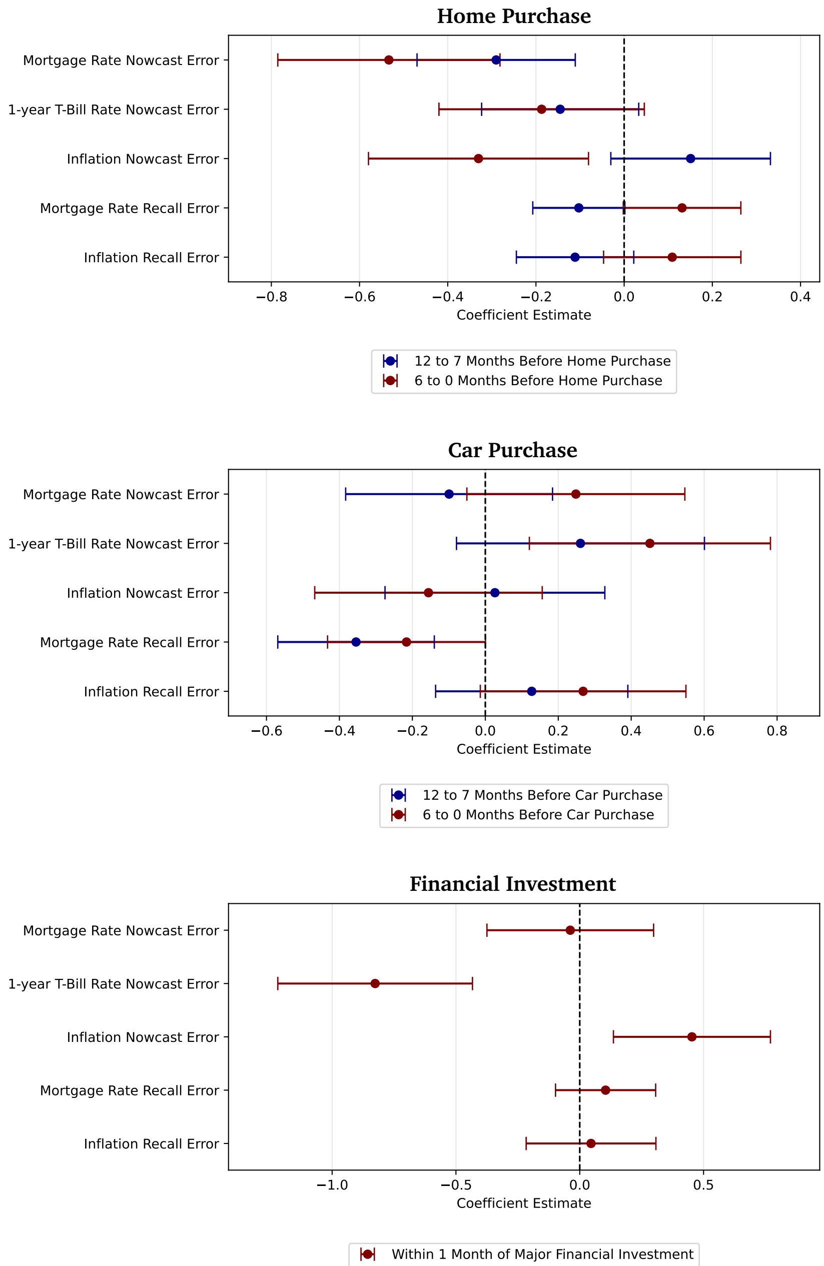
2.2 Fact #2: Improvement in Accuracy is Largest for Interest Rates

Having providing evidence that decision-makers close to a home purchase have more accurate interest expectations, we next explore the accuracy of these households expectations for other variables. In the SCE, the right panel of Figure 1 repeats the analysis in the left panel for one-year ahead inflation forecasts (there are no inflation nowcasts available in the SCE). We find some evidence of a reduction in inflation forecast errors for households that are close to a purchase, but the decline is only around half as large.

In the CES, the remaining panels of Figure 2 repeat the analysis in the top left panel for one-year ahead inflation, unemployment rate, and output growth forecasts. For unemployment rate and output growth forecasts, we find little consistent evidence that

[7] Like in (3), we control all other decisions when focusing on a given decision of interest.

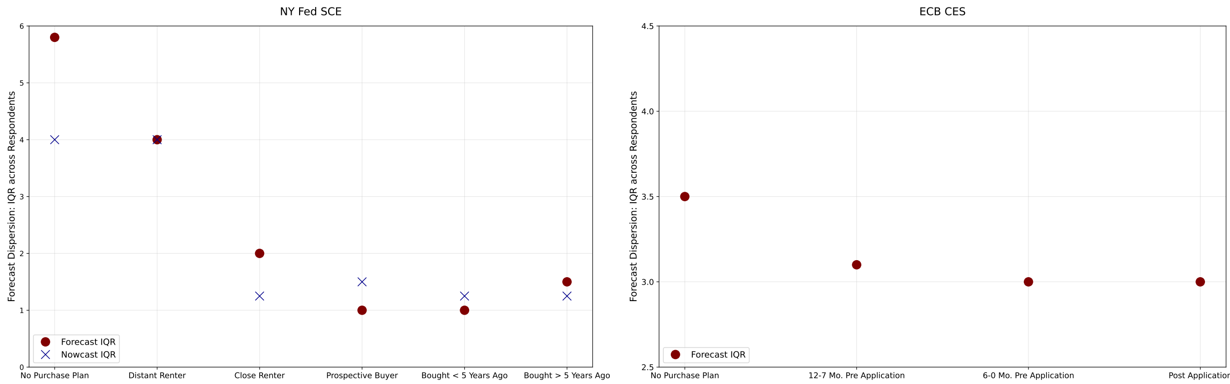
Figure 3. Decision-Making and Expectation Accuracy in New Household Survey



Notes: This figure shows the estimates of β_d in (3) based on the distances from different decisions. The sample is all households that are renters and plan to use credit and the omitted group is all households who are yet to make a home purchase. The top/middle/bottom panel shows the estimates based on the distance from a home purchase/car purchase/major financial investment, where the distances from other decisions are included as controls. Within each panel, each row corresponds to a regression with a different dependent variable. Bars correspond to 95% confidence intervals. The sample of observations is trimmed at the 5% level based on the dependent variable.

decision-makers have more accurate expectations. For inflation, the evidence is less conclusive and depends on whether individual fixed effects are included. An important caveat to the analysis of inflation forecasts in the ECB is that the sample period covers the post-COVID inflation spike, which had large effects on inflation expectations.

Figure 4. Decision-Making and Forecast Dispersion in SCE and CES



Notes: This figure shows the dispersion in mortgage rate expectations by decision-making group, where dispersion is measured using the interquartile range. The left panel uses nowcasts and forecasts from the SCE; the right panel uses forecasts from the CES. The groups of decision-makers the same groups that are used in Figure 1 and Figure 2.

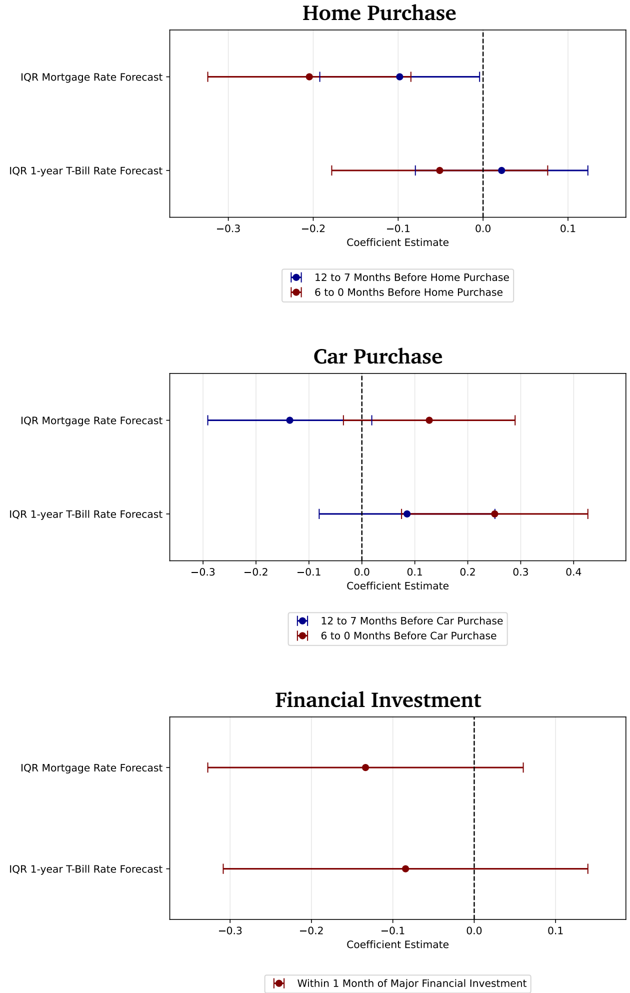
When we look at other variables in our survey, Figure 3 shows that inflation nowcasts are more accurate for households close to a home purchase. Similar to the CES, this might reflect the fact that we ran our survey in March 2025, which is a time period during which inflation was particularly volatile and salient. For car purchases and financial investments, we find no improvement in inflation nowcast accuracy.

2.3 Fact #3: Decision-Makers Have Less Dispersed and Uncertain Expectations

Next, we explore how disagreement varies based on decision-making status. Figure 4 shows the dispersion in mortgage rate expectations, measured using the interquartile range, among households within each of the decision-making groups. In the SCE, the left panel shows that nowcast and forecast dispersion declines by around 70% as households get close to a home purchase, and stays lower after the choice. The right panel shows a similar pattern for forecast dispersion in the CES qualitatively, but it is smaller quantitatively. Part of this difference likely difference stems from the fact that forecast disagreement in the CES is much lower overall than in the SCE.

The combination of an improvement in expectation accuracy and decline in forecast dispersion among decision-makers suggests that they are better informed. To test this more directly, we construct a measure of subjective uncertainty using our scenario-based elicitation. Uncertainty is defined as the difference between the respondent's assigned value for a given variable in the high-value and low-value scenarios, which can be interpreted

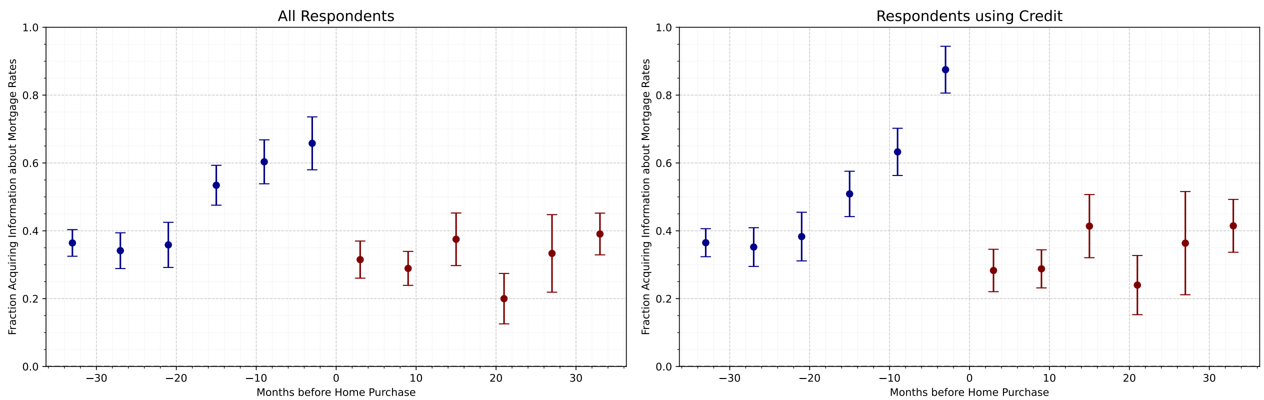
Figure 5. Decision-Making and Subjective Uncertainty in New Household Survey



Notes: This figure shows the estimates of β_d in (3) based on the distances from different decisions, replacing the dependent variable with a measure of subjective uncertainty that is defined as the log difference between the respondent's assigned value for a given variable in the high-value and low-value scenarios. The sample is all households that are renters and plan to use credit and the omitted group is all households who are yet to make a home purchase. The top left/top right/bottom panel shows the estimates based on the distance from a home purchase/car purchase/major financial investment, where the distances from other decisions are included as controls. Within each panel, each row corresponds to a regression with a different dependent variable. Bars correspond to 95% confidence intervals. The sample of observations is trimmed at the 5% level based on the dependent variable.

as an interquartile range. Figure 5 reports the results from estimating (3) with the log of this uncertainty measure as the dependent variable. The results show that uncertainty is lower among households that are closer to a home purchase by about 20% for mortgage rates, and only around 5% lower for Treasury bill rates. Consistent with the absence of a reduction in nowcast errors, we find no change in uncertainty for car purchases. For financial investments, we estimate a reduction in uncertainty of around 10% that is not statistically significantly.

Figure 6. Decision-Making and Information Acquisition in New Household Survey



Notes: This figure plots the share of respondents in our survey who acquired information about mortgage rates during the survey quarter against their distance from a purchase. The left panel presents results for the full sample, while the right panel focuses on respondents who either plan to or have used credit to finance their home. Bars correspond to 95% confidence intervals. We exclude respondents who report more than three outlier nowcasts or forecasts, which corresponds to approximately 5% of the sample.

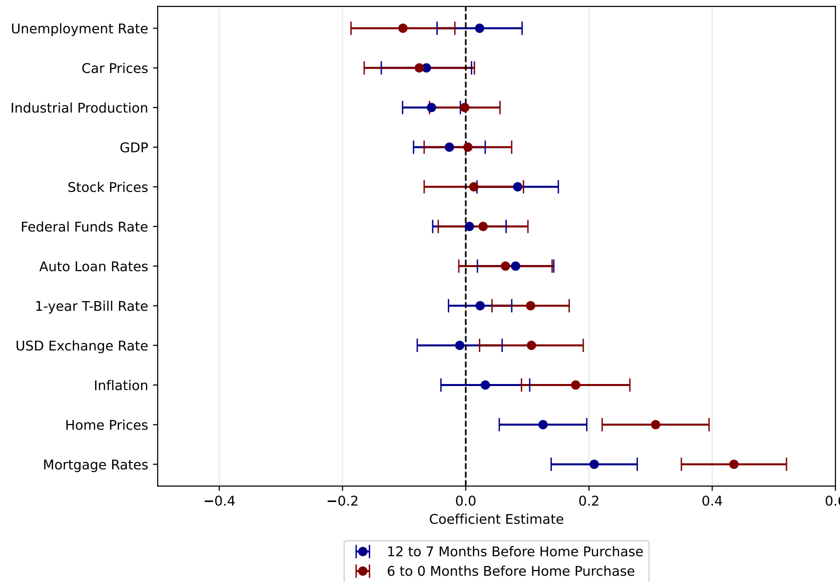
2.4 Fact #4: Concentration in Information Acquisition around Decision-Making

We now turn to our set of facts that leverages our survey's elicitation of patterns in information acquisition. Figure 6 shows the share of respondents that report actively acquiring information about mortgage rates as a function of their distance from a home purchase. The left panel shows results for the full sample, while the right panel restricts to households that plan to or have used credit to finance the purchase.

The results in Figure 6 illustrate three notable patterns. First, a non-trivial fraction of households acquires information in all periods, even when they are not close to a purchase. Second, and more importantly, there is a significant increase in the fraction acquiring information about mortgage rates as households approach the purchase. At the time of the purchase, this share is approximately double what it is among households who are several years from the purchase. As expected, this increase is larger among households that either plan to or have used credit (i.e., a mortgage) to finance the purchase. Finally, the share acquiring information drops immediately after the purchase. Surprisingly, Figure A1 shows that drop in information acquisition after the purchase is present regardless of the type of mortgage that households use or their refinancing plans.

We now test for the relationship between decision-making and information acquisition more formally by estimating (3) with an indicator for reporting active information acquisition in the last three months on the left-hand side. In this regression, the omitted group is

Figure 7. Decision-Making and Information Acquisition by Macroeconomic Variable



Notes: This figure shows results from a series of regressions that estimate (3), replacing the dependent variable with an indicator for reporting active information acquisition about a different macroeconomic variable in each row. The sample in this analysis includes all respondents who either plan to or have used credit. The omitted group is all households who are more than 12 months before a purchase or are after a purchase. Each row reports the point estimates and 95% confidence intervals on the decision-making indicators. We exclude respondents who report more than three outlier nowcasts or forecasts, which corresponds to approximately 5% of the sample.

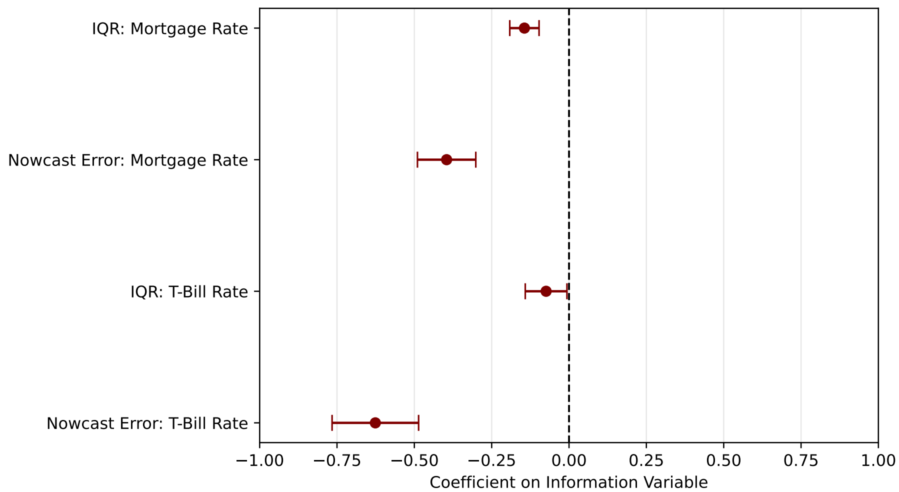
all households who are more than 12 months before or are after a purchase, and we again focus on households that report using credit. The bottom row of Figure 7 shows that the increase in information acquisition prior to the choice is quantitatively similar to Figure 6, even after controlling for all of the demographic, financial, and other decision-making variables in our survey.[8]

One advantage of our survey is that we can directly test whether increased information acquisition is related to beliefs. Figure 8 shows the results from regressions of (log) nowcast errors and subjective uncertainty of interest rates and Treasury bill rates onto indicators for having acquired information about the respective variable in the previous three months, including the set of controls from (3). We find that information acquisition is associated with 40% and 60% reduction in nowcast errors of mortgage and Treasury rates, respectively. For subjective uncertainty, the reductions are between 10 and 20%.

Finally, a concern with our evidence thus far is that the correlation between decision-making status and beliefs may be driven by reverse causality in which decision-making is determined by beliefs. While we allow this causality to go in both directions in our model, in

[8]Figure A2 reproduces Figure 6 among the sample of respondents all respondents, including those that do not use credit. For all variables, the results are quantitatively similar.

Figure 8. Link Between Information Acquisition and Beliefs



Notes: This figure shows the results from regressions of (log) nowcast errors and (log) subjective uncertainty of interest rates and Treasury bill rates an indicator for having acquired information about the respective variable in the previous three months. All regressions include the same set of controls in (3). Each row corresponds to a different regression with the corresponding dependent variable indicated in the row, and the coefficient plotted is the coefficient on the information acquisition indicator for the variable of interest. Bars correspond to 95% confidence intervals. The sample of observations is trimmed at the 5% level based on the dependent variable and includes all individuals regardless of their use of credit.

the data, we leverage the design of our survey to assess whether there is any evidence that decision-making status has causal impact on information acquisition. To do so, we construct an instrument for households being within six months of a home purchase based on whether they are within six months of a job-related relocation. While job-related moves are not entirely exogenous, they likely induce some variation in decision-making that is orthogonal to other determinants of beliefs. Table A3 shows that decision-making induced by these job relocations leads to a significant increase in information acquisition, consistent with there being some causal effect of decision-making on information acquisition. However, we interpret these results as suggestive, given the small sample size and instrument's strength.

2.5 Fact #5: Information Acquisition is about Decision-Relevant Variables

Our final fact is that the increase in information acquisition by decision-makers is specifically about decision-relevant variables. In addition to mortgage rates, Figure 7 shows the increases in information acquisition about other macroeconomic variables for households that are close to a home purchase. The increase is the largest for mortgage rates and home prices, which are the two most relevant macroeconomic variables for the decision. Consistent with the reduction in inflation and Treasury bill forecast errors, we find some evidence of increased information acquisition about these variables as well. In contrast, for other macroeconomic variables, we find little evidence of increase in information acquisition. Notably, the lack of an increase for GDP and unemployment rates is consistent the absence of a difference in expectation accuracy about these variables in Figure 2.

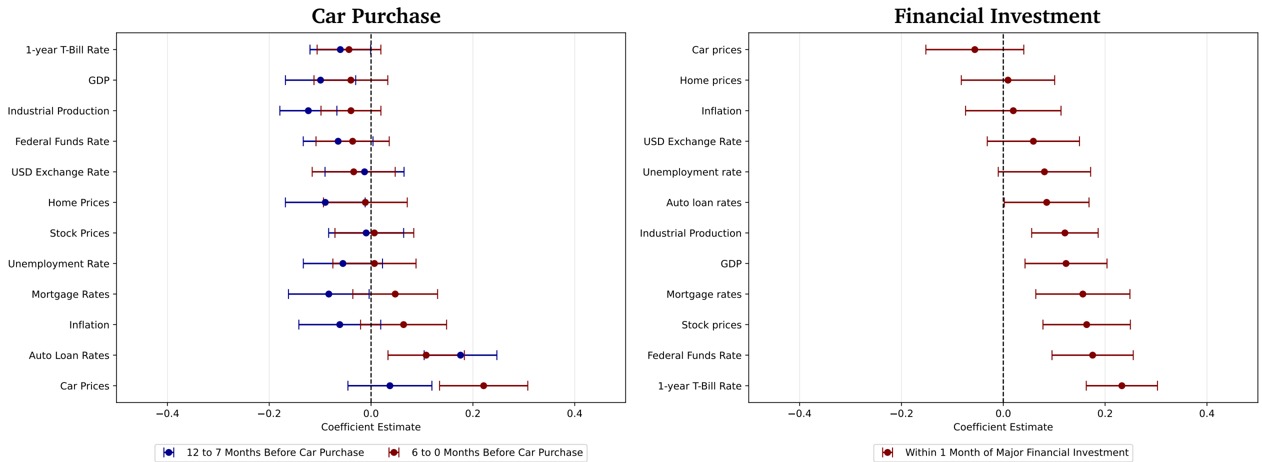
Figure 9 shows that the patterns in Figure 7 change dramatically when you look at other household decisions. The left panel shows that when households are close to car purchase, they acquire significantly more information about car prices and auto loan rates. In contrast, there is no change in information acquisition about Treasury or mortgage rates, consistent with our evidence in Figure 3 that households close to a car purchase do not have more accurate beliefs about these variables. Similarly, the right panel shows that for major financial investments, the increase in information acquisition is largest for the Treasury bill rate—the variable for which nowcasts become more accurate in Figure 3—stock prices, and the federal funds rate. Collectively, these results reinforce the conclusion that information acquisition is decision-specific and relatively sparse á la Gabaix (2014).

Finally, we explore the sources and types of information that households acquire. Figure A3 shows that households primarily acquire information about the main variable of interest—mortgage rates for home purchases, auto loan rates for car purchases, and Treasury bill rates for financial investments—through internet searches, both on general sites (e.g., Google) and specialized sites (e.g., Zillow). Households also report acquiring information from real estate agents and personal connections, such as family and friends, and especially social media for financial investments. Figure A4 shows that this information acquisition is primarily about the current values of variables, rather than future values, past values, or uncertainty. This is consistent with Figure 1, which shows that most of the increase in forecasting accuracy of decision-makers comes from nowcasting, and Figure 3, which shows that decision-makers show no differential accuracy in recall.

2.6 Taking Stock

This section uses a combination of new and existing surveys to document five facts, which collectively establish that households are selectively inattentive to interest rates based on the types of decisions they make. While no individual piece of evidence is perfect, the fact that our conclusions are consistent across three surveys with different formats, geographies, and time periods makes us relatively confident that selective inattention a robust feature of the data. Before turning to our model in Section 3, we conclude this section by discussing

Figure 9. Decision-Making and Information Acquisition: Car Purchases and Financial Investments



Notes: This figure replicates Figure A2 with decision-making defined based on the distance from a car purchase in the left panel, and based on distance from a major financial investment in the right panel.

three specific modeling choices that we make, and how they are informed by the empirical evidence in this section.

First, we model a single composite durable good, despite only presenting evidence that beliefs become more accurate around home purchases. We do not have evidence of improvements in belief accuracy for car purchases because of the lack of an objective measure of auto loan rates that are comparable across people. Nevertheless, given that information acquisition is correlated with belief accuracy and increases around car purchases, we expect accuracy to increase around car purchases as well. However, even if households are only selectively inattentive around house purchases, we do not expect this to change the key implications of our model, given housing is the largest durable for most households.

Second, our model has a single stochastic interest rate with a constant borrowing spread, and this is the only variable about which households have to acquire information. We focus on the implications of endogenous inattention to interest rates because our empirical evidence suggests that they are the variable for which this effect is the strongest. Our choice to have a single time-varying component of the interest rate is made for tractability; we make the interest rate rather than the borrowing spread time-varying because we observe changes in beliefs and information acquisition for mortgage rates and Treasury rates.

Finally, we restrict households in our model to acquiring information about the current values of interest rates. This is primarily done for tractability, but we view it as a reasonable approximation because of two findings in this section: (i) households acquire information primarily about the current values of decision-relevant rates, and (ii) more than half of the improvement in forecasting accuracy comes from the change in nowcasts.

3 Incomplete Markets Model with Selective Inattention

This section describes the model that we develop, which contains the necessary ingredients to generate the selective inattention we observe in the data. The goal of the model is to capture how selective inattention affects the transmission of changes in the level and volatility of interest rates, which we study in the next section. The core of our model is the household block in McKay and Wieland (2021), which is an incomplete markets model with durable consumption. To this model, we add a stochastic and persistent interest rate and, most importantly, dynamic and continuous information acquisition via rational inattention. To isolate the effects of selective inattention on the household side, the model is in partial equilibrium. Therefore, these results should be interpreted as demand-side inputs to general equilibrium analyses, similar to Laibson et al. (2025).

3.1 Model Description

The economy is populated by a continuum of infinitely-lived households that receive utility from non-durable consumption, c, and their stock of durable goods, d'. Time is discrete, and the model period is one quarter. All households have identical time-separable expected utility preferences with (quarterly) discount factor β and flow utility function $U(c, \mathcal{S}(\cdot))$. $\mathcal{S}(\cdot)$ denotes the service flow that households receive from their durables stock, which is described below and depends on the current set of states. Throughout, we drop individual and time subscripts for brevity, and denote the next period value of a state variable x by x'.

Households have rational expectations about all variables in the economy, except the current value of aggregate log interest rate, r. Each period in the model is divided into two subperiods. In the second subperiod, households choose c and d', given their beliefs about r. In the first subperiod, households solve an information acquisition problem to determine their beliefs about r, anticipating the choices they will make in the second subperiod. We now describe the two subperiods of the model in reverse order.

3.1.1 Household Problem, Given Beliefs

Households choose c and d' to maximize the discounted sum of their flow utilities. Households face idiosyncratic risk in their income, y, which follows an exogenous AR1 process. There is a single liquid asset, b, which earns a gross rate of return equal to $\exp(r)$, where r follows an exogenous AR1 process with persistence ρ. Households face a collateralized borrowing constraint that allows them to borrow up to a fraction λ of their durables stock, where λ corresponds to an LTV limit. When borrowing, households pay an exogenous constant borrowing spread of τ_b.

Households' stock of durables depreciates at a rate δ, and a fraction χ of this depreciation must be paid immediately in the form of maintenance costs (Bachmann et al. 2013). These costs capture the maintenance required to continue enjoying the flows from durable consumption, such as fixing broken appliances in a house or a flat tyre. Households must also pay costs of operating their durables that are equal to a fraction ν of their durables stock, which capture expenditures like utilities, taxes, and fuel.

Adjusting the durables stock requires paying a fixed cost f, which is proportional to the durables stock. These costs could be monetary, such as closing costs, or psychological, such as the hassle associated with finding a new car or house. The presence of these fixed costs creates an inaction region where not all households will adjust their durables stock in each period. When we compare the model to the data, these durables adjustments will be our notion of "decision-making".[9]

At this point, durables adjustments in the model would only occur due to income fluctuations, interest rate fluctuations, and depreciation. In reality, households may adjust their durables stocks for other reasons, such as job relocations or changes in family composition. Therefore, we introduce match-quality shocks to capture unmodeled events that drive durables adjustments, which McKay and Wieland (2021) show are important to get an empirically realistic interest rate elasticity of durables demand. These match-quality shocks take the form $\xi \sim \text{Bernoulli}(\bar{\xi})$ and determine the service flow from durables as follows. When $\xi = 0$, households receive a service flow of (approximately) zero if they do not adjust their durables stock. If they adjust when $\xi = 0$ or alternatively $\xi = 1$, they receive a service flow equal to the value of durables that they choose. Because households hit by a match-

[9] There is a slight disconnect between the notion of decision-making in the model versus in the data. In the data, when we look at homeowners, we are comparing recent buyers to renters. Therefore, the correct notion of decision-making would be buying versus renting. However, we choose to omit modeling renting for tractability, which has the added benefit of keeping our model of choices given beliefs close to prior literature.

quality shock are forced to adjust, this model features both state- and time-dependent adjustment, as in Nakamura and Steinsson (2010), Andersen et al. (2020), and de Silva (2025).

Households do not observe the current interest rate and form beliefs over it, given their individual-specific information sets that we denote by $\mathcal{I}$. Households have rational expectations given these information sets, which are endogenized in the first subperiod below. Although households misperceive r, we assume that they know the parameters of its data-generating process.[10] Nevertheless, because households misperceive r, they also misperceive the values of interest rates and their assets in future periods. We require that households satisfy the borrowing constraint given the true value of r.[11]

Given this environment, households' state vector can be written as $\mathbf{x} = (b, d, r, y, \xi, \Omega)$, where Ω is a (multidimensional) state variable that is needed to characterize how households information sets evolve dynamically that we describe below. At a given set of states, households' choices of c and d' are the solution to the following problem:

$$\mathbf{c}(\mathbf{x}), \mathbf{d}'(\mathbf{x}) = \underset{c \geq \underline{c}, d' \geq \underline{d}}{\arg\max}\, U\Big(c, \mathcal{S}(\mathbf{x}, d')\Big) + \beta \mathbb{E}\Big(V(\mathbf{x}') \mid \mathcal{I}\Big) \tag{4}$$

$$\begin{aligned}
&\text{subject to}: \\
&\mathcal{S}(\mathbf{x}, d') = \begin{cases} \underline{d} & \text{if } \xi = 0 \text{ and } d' = (1 - \delta + \delta\chi)d, \\ d' & \text{else}, \end{cases} \\
&c + b' + d' = y + \left[\exp(r) + \tau_b \times \mathbf{1}_{b<0}\right] b + (1-\delta)d\left[1 - f \times \mathbf{1}_{d' \neq (1-\delta+\delta\chi)d}\right] - \nu d, \\
&b' \geq -\lambda d', \\
&r' = (1-\rho)\overline{r} + \rho r + \sigma\eta, \quad \eta \sim N(0,1), \\
&\log y' = \rho_y \log y + \sigma_\epsilon \epsilon, \quad \epsilon \sim N(0,1), \\
&b_0, d_0 \text{ given.}
\end{aligned}$$

In this problem, $V(\cdot)$ denotes households' value function that is defined by a recursive equation in the next section, and $\underline{c}$ and $\underline{d}$ denote floors on non-durable and durable consumption that ensure our solution method is well-behaved. Importantly, households

[10] Ideally, we would allow households to misperceive the DGP as well, but this makes our model intractable. We choose to focus on the case of households misperceiving the current interest rate because of two of our empirical findings: (i) households primarily acquire information about the current value of interest rates, and (ii) most households' improvement in forecast accuracy is coming from improvements in their nowcasts.

[11] An alternative assumption would be that households observe the true value of state variables when they hit the constraint. We choose not to make this assumption because it introduces non-convexities in our information acquisition problem.

compute the expectation of $V(\cdot)$ in (4) using their subjective beliefs, $\mathbb{E}(\cdot \mid \mathcal{I})$, which corresponds to the mathematical expectation given their information set. Appendix C describes how we compute this expectation in more detail. If these beliefs differ from rational expectations, households' choices will not maximize their objective lifetime utility.

3.1.2 Information Acquisition Problem to Determine Beliefs

We endogenize households' beliefs about the current value of the (log) interest rate, r, through rational inattention (Sims 2003; Maćkowiak et al. 2023). To make our model tractable, we impose the following restriction on the set of signals that households can acquire: households can only acquire *Gaussian* signals about the *current* value of r.[12] This assumption is made for tractability, but the restriction to signals about the current rate is consistent with our empirical evidence that households acquire information primarily about the current values of decision-relevant interest rates. The benefit of this assumption is that implies that Ω can be reduced to a two-dimensional vector, (μ, Σ), where μ and Σ correspond to the mean and variance of households' prior beliefs about r upon entering the period, respectively.

A defining feature of models of rational inattention is leaving the signal space unrestricted (Maćkowiak et al. 2023). The reason for this difference is that the existing quantitative models of rational inattention typically work with linear-quadratic decision problems, in which case the signal structure that we assume becomes optimal (Afrouzi and Yang 2024). This is typically achieved through taking a second-order approximation of the objective function (Maćkowiak and Wiederholt 2009, 2015; Afrouzi 2024; Afrouzi et al. 2024).[13] In contrast, our rich incomplete markets model, unlike models of firm price-setting or complete markets models, is not well-approximated by a quadratic objective.[14] Nevertheless, we view our restriction on the signal space as a reasonable approximation that captures the essence of the economic forces we are trying to capture, similar to the justification for taking a quadratic approximation of an objective function.

[12]An alternative model would be one in which observing the current interest rate requires paying an observation cost, similar to Alvarez et al. (2012). Such a model would be inconsistent with the fact that households in our survey that report acquiring information still have zero nowcast errors.

[13]A notable exception is Luo et al. (2017), who solve a general equilibrium incomplete markets model with rational inattention. Luo et al. (2017) restricts the signal space to be Gaussian, like in our model, but obtains analytic tractability through the use of CARA utility and focusing on non-durable consumption.

[14]An alternative approach would be to work with the characterization of the solution to dynamic rational inattention problems in Steiner et al. (2017). However, we found that the discretization that this approach requires led to inaccurate numerical solutions to the incomplete markets block of the model.

Our restriction on the signal space implies that households' beliefs can be characterized by the Kalman filter. Defining $e \sim N(0, \Sigma_e)$ as the additive noise in households' signal about r in the current period, the evolution of μ and Σ can be characterized as follows:

$$\begin{aligned} G &= \frac{\Sigma}{\Sigma + \Sigma_e}, \\ \mu' &= (1-\rho)\overline{r} + \rho\left[(1-G)\mu + G(r+e)\right], \\ \Sigma' &= \rho^2\Sigma(1-G) + \sigma^2, \\ \mu_0 &= \overline{r}, \quad \Sigma_0 = \frac{\sigma^2}{1-\rho^2}. \end{aligned} \tag{5}$$

Given these laws of motion, households' value function is then defined by the following recursive equation, which comes from optimizing their choice of Σ_e:

$$V(\mathbf{x}) = \max_{\Sigma_e \geq 0} \mathbb{E}\left(U\Big(\mathbf{c}(\mathbf{x}), \mathcal{S}(\mathbf{x}, \mathbf{d}'(\mathbf{x}))\Big) + \beta V(\mathbf{x}') \mid \mathbf{x} \right) + \omega \log(1-G). \tag{6}$$

The dependence of the objective function in (6) on Σ_e is implicit, but the key tradeoff is as follows. By acquiring a more accurate signal (lower Σ_e), households will receive a smaller utility loss from $\mathbf{c}(\mathbf{x})$ and $\mathbf{d}'(\mathbf{x})$. This is encoded in (6) in the first term: households evaluate their expected utility given knowledge of $\mathbf{x}$, which includes r, but anticipate that their choices of $\mathbf{c}(\mathbf{x})$ and $\mathbf{d}'(\mathbf{x})$ will depend on their subjective beliefs about r. Therefore, the first term in (6) is maximized when $\Sigma_e = 0$, so that households' have perfect knowledge of r and, therefore, make choices that maximize their objective utility.

The cost that prevents households from always acquiring full information is the second term in (6), which captures the fact that more precise signals are more costly. We make the standard assumption in the literature on rational inattention that the cost of information is linear in mutual information, where ω is the marginal cost of a unit of information and mutual information is defined reduction in entropy about r after receiving the signal $r+e$.[15] Given the assumption of normal signals, mutual information is proportional to $-\log(1-G)$.[16] Therefore, the second term in (6) is maximized when $\Sigma_e = \infty$, creating a tradeoff with the first term.

[15] We define units of information in "nats" by defining entropy using the natural logarithm.

[16] The entropy of a normal random variable with mean zero and variance σ^2 is $0.5\left(1+\log\left(2\pi\sigma^2\right)\right)$. The entropy of the prior distribution about r is therefore $0.5\left(1+\log(2\pi\Sigma)\right)$ while the entropy of the posterior is $0.5\left(1+\log\left(2\pi\Sigma\left(1-G\right)\right)\right)$. Differencing these two gives $-0.5\log(1-G)$.

3.2 Calibration

Simulation procedure. We solve the model by performing value function iteration on (6). This is a computationally-intensive procedure because we have seven state variables, five shocks, and have to solve (4) each time we evaluate the objective function in (6). After solving the model, we simulate 50,000 individuals for 400 periods, discarding the first 200 periods as a burn-in. Because our model is in partial equilibrium, there is no meaningful distinction between idiosyncratic and aggregate variables. Therefore, to minimize the dependence of our results on a particular path of interest rates, we simulate 500 distinct paths of r and assign each individual to one of these paths randomly. In Section 5, when we examine impulse responses to changes in the level and volatility and interest rates, we compute these impulse responses as differences between the realized and counterfactual paths assuming no change occurred, and then report the average of these differences across our simulations.

External calibration. We calibrate a number of parameters externally with values shown in Panel A of Table 1. We set households' flow utility function to CRRA utility over a CES aggregate of durable and non-durable consumption:

$$U(c,s) = \frac{\left[\psi^{\frac{1}{\xi}} c^{\frac{\xi-1}{\xi}} + (1-\psi)^{\frac{1}{\xi}} s^{\frac{\xi-1}{\xi}}\right]^{\frac{\xi(1-\gamma)}{\xi-1}}}{1-\gamma}$$

For the parameters governing preferences and durables, we follow the calibration in McKay and Wieland (2021). This calibration captures a broad notion of durables, including residential housing, autos, and appliances, as in Berger and Vavra (2015). The only exception is γ, which corresponds to relative risk aversion (and the inverse EIS). McKay and Wieland (2021) choose a value of 4, which they consider low but is necessary to match the small response of non-durable consumption in the data. Because we are more interested in matching patterns in information acquisition, for which γ is very relevant, we set choose a value of 2, which is a more standard value in the literature (Berger and Vavra 2015) and is close to the estimates in Choukhmane and de Silva (Forthcoming). Our income process is calibrated following Flodén and Lindé (2001), as is standard in the literature. We calibrate the parameters of the interest rate process using quarterly data on the 10-year Treasury rate, and calibrate the borrowing spread using the average spread between the 10-year Treasury and the average 30-year fixed rate mortgage rate from FRED. Finally, we set the non-durable and durable consumption floors to small values such that they are never

Table 1. Calibrated Parameters

Parameter	Description	Value	Source
Panel A: Externally-Calibrated			
γ	RRA (and inverse EIS)	2	See text
ε	Durables elasticity of substitution	0.5	McKay and Wieland (2021)
$1-\lambda$	Required downpayment	0.2	McKay and Wieland (2021)
δ	Depreciation rate	0.017	McKay and Wieland (2021)
χ	Maintenance share	0.35	McKay and Wieland (2021)
ν	Operating cost	0.012	McKay and Wieland (2021)
ρ_y	Income persistence	0.977	Flodén and Lindé (2001)
σ_ϵ	Income standard deviation	0.058	Flodén and Lindé (2001)
$\overline{r}$	Interest rate mean	0.0143	10-Year Treasury Rate: 1961-2024
ρ	Interest rate persistence	0.979	10-Year Treasury Rate: 1961-2024
σ	Interest rate standard deviation	0.0014	10-Year Treasury Rate: 1961-2024
τ_b	Quarterly borrowing spread	0.4156%	30-Year Fixed Mortgage Rate: 1971-2024
$\underline{c}$	Non-durable consumption floor	10^{-6}	·
$\underline{d}$	Durable consumption floor	10^{-3}	·
Panel B: Internally-Calibrated			
β	Discount factor	0.9829	Asset-to-GDP ratio
ψ	Non-durables exponent	0.627	Durable-to-nondurable consumption ratio
f	Fixed cost	0.11	Adjustment probability
$1-\overline{\xi}$	Match-quality shock probability	0.034	Share of adjustments from MQ shocks
ω	Marginal information cost	$10^{-3.741}$	Concentration in information acquisition

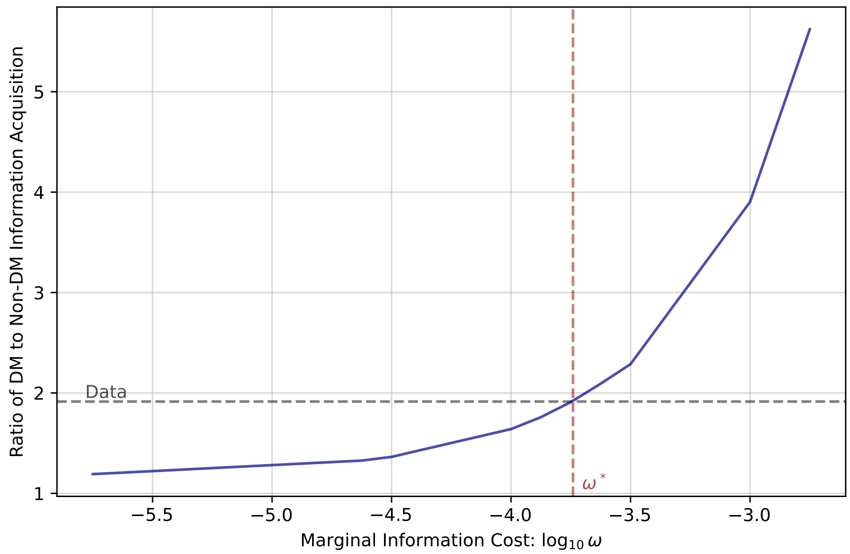
Notes: This table shows the calibrated values of our model parameters. The top half of the table shows parameters that are externally-calibrated. The bottom half of the table shows parameters that are internally-calibrated.

reached, but ensure that individuals' objective functions are never evaluated at values that imply negative consumption.

Internal calibration. We calibrate the remaining parameters in Panel B of Table 1 internally. The first four parameters in the table are calibrated to match moments from the model in McKay and Wieland (2021). We calibrate β to generate a ratio of liquid assets to aggregate spending (GDP) of 0.87, where aggregating spending is defined to include non-durables, operating costs, the change in the non-depreciated durables stock, and adjustment costs (McKay and Wieland 2021). We calibrate ψ to match a ratio of durable to non-durable consumption of 2.64. The fixed cost, f, is calibrated to match a quarterly adjustment probability of 4.75%. Finally, the match-quality shock is calibrated to match a fraction of 75% of durables adjustments coming from match quality shocks.

The final parameter is the key new parameter in our model: the marginal cost of information, ω. We calibrate ω using the concentration in information acquisition around durables purchases from our survey. In particular, we target the ratio of the fraction of households

Figure 10. Concentration in Information Acquisition as a Function of ω



Notes: For various values of ω, this figure plots the ratio of the fraction of households that choose $\Sigma_e < \infty$ in in the contemporaneous quarter of to the fraction that choose choose $\Sigma_e < \infty$ at eight quarters before a durables adjustment. The sample restricts to all individuals making durables adjustments that did not make an adjustment in the previous eight quarters. The dashed horizontal line corresponds to the value that we target, which is computed from our survey.

acquiring information in the quarter prior to the purchase to the fraction acquiring information eight quarters prior, which is around 1.91. In the model, we compute the analogous moment using the fractions of households that choose $\Sigma_e < \infty$ in the contemporaneous quarter of and eight quarters before a durables adjustment. The reason we choose to target ratios of information acquisition instead of raw levels is because this selection into information acquisition based on durables adjustment is the key force we want the model to capture. Another benefit of not targeting raw levels is that they are not directly comparable: acquiring information in the model requires both collecting it and incorporating it into decisions, while the data only measures the latter (Auclert et al. 2020).

Figure 10 shows that the amount of concentration in information acquisition around durables purchases is monotonically increasing in ω. This is because, having calibrated all other parameters in the model, the benefits of information acquisition at each point in the state-space are pinned down. Given these parameters and a value of ω, individuals making a durables adjustment will acquire more information because the marginal benefits of doing so are higher. Therefore, as ω increases, the difference in information acquisition between those who making durables adjustments and those who are not increases because the value of acquiring any information falls below the cost sooner for those only choosing non-durables.

An alternative strategy to calibrating ω would be to use data on beliefs instead of information acquisition. We choose not to do this for three reasons. First, the accuracy of beliefs is sensitive to the path of interest rates that we feed into the model. Second, our model of beliefs is likely misspecified because there are patterns in households' expectations that cannot be explained by our model of information acquisition, such as overreaction (Bordalo et al. 2022). By using moments of information acquisition, which closer to the main mechanism in our model, we hope to minimize the effect of this misspecification on our calibration. Finally, the link between beliefs and actions is often small (Giglio et al. 2021), while our measure of information acquisition (in principle) captures households actually taking an action. This makes it a better target for a model that maps these beliefs into predictions about behavior.

Other benchmark models. In Section 5, we compare our model with selective inattention to two alternative models. The first model is *rational expectations*, which corresponds to the case with $\omega = 0$. The second is *exogenous inattention*, in which we fix households' choices of Σ_e such that that Kalman gain defined in (5) is constant at a value, $\overline{G}$. We then calibrate $\overline{G}$ in this model so that the Coibion and Gorodnichenko (2015) (CG) regression coefficient, which is a standard way of measuring belief rigidity, is identical to in our baseline model. In Section 4.3, we report and discuss the value of this CG regression coefficient. As CG show, this coefficient directly measures belief rigidity in sticky and noisy information models, which are the benchmarks in the literature (Carroll et al. 2020; Auclert et al. 2020).

4 Information Acquisition and Beliefs in the Steady-State

This section explores patterns in households' information acquisition and beliefs in our model's steady-state, before turning to counterfactuals in Section 5.

4.1 Summary Statistics

Table 2 shows summary statistics of key variables from our model's steady state. Households in our model have savings equal to around 3.5 times current income, and choose a durables stock that is around 2.5 times as large as consumption. Most households in the model have a positive durables gap, reflecting the presence of depreciation: most households let their durables stock drift downwards before adjusting. Turning to patterns in

Table 2. Steady-State Summary Statistics

	Mean	SD	P10	P50	P90
Assets/Income: b/y	3.51	4.93	-0.91	1.91	10.27
Durable/Non-Durables: d'/c	2.55	0.40	1.99	2.58	3.01
Durables Gap	0.14	0.17	-0.05	0.11	0.38
Acquired Information	0.23	0.42	0.00	0.00	1.00
Kalman Gain: G	0.10	0.21	0.00	0.00	0.40
Kalman Gain Conditional on IA	0.46	0.21	0.30	0.40	0.80
Normalized Nowcast Error: $\lvert\hat{\mathbb{E}}(r) - r\rvert/\lvert r\rvert$	0.28	8.00	0.02	0.10	0.32
Normalized Prior Variance: Σ/σ_r^2	0.33	0.17	0.13	0.30	0.57

Notes: This table shows summary statistics from our model's steady-state. Each row corresponds to a different variable, and each column corresponds to a different statistic. Each variable is defined in the corresponding row with the following exceptions. Durables Gap equals $\log(d^*/d)$, where d^* is the optimal choice of d' if adjustment were forced to occur. Acquired Information corresponds to an indicator variable that equals one if $\Sigma_e < \infty$. Kalman Gain Conditional on IA reports the distribution of G conditional on $\Sigma_e < \infty$.

information acquisition, the average household does not acquire much information on the extensive or intensive margin. In the steady-state, only around 20% of households acquire information and the average Kalman gain is around 0.1. This results in households having non-trivial nowcast errors of the current interest rate that are around 30% of the current rate on average and 10% at the median.

It is instructive to compare the patterns in Table 2 with Afrouzi et al. (2024), who incorporate rational inattention into a time-dependent model of price-setting. There are two notable differences between these two models. First, our model generates a continuous distribution in the amount of information that households' acquire: the Kalman gain, G, ranges from 0.3 at the 10th percentile to 0.8 at the 90th percentile. As a result, there is a non-trivial distribution in households' subjective variance, Σ, unlike Afrouzi et al. (2024), in which it is always reset to the same value upon information acquisition. Second, as illustrated in the next section, households' acquire information even in the event of no durables adjustment. This is consistent with the data (Figure 6) and reflects the fact that our model features an additional decision, non-durable consumption, that still benefits from having more accurate beliefs about interest rates.

4.2 Selective Inattention at the Micro-Level

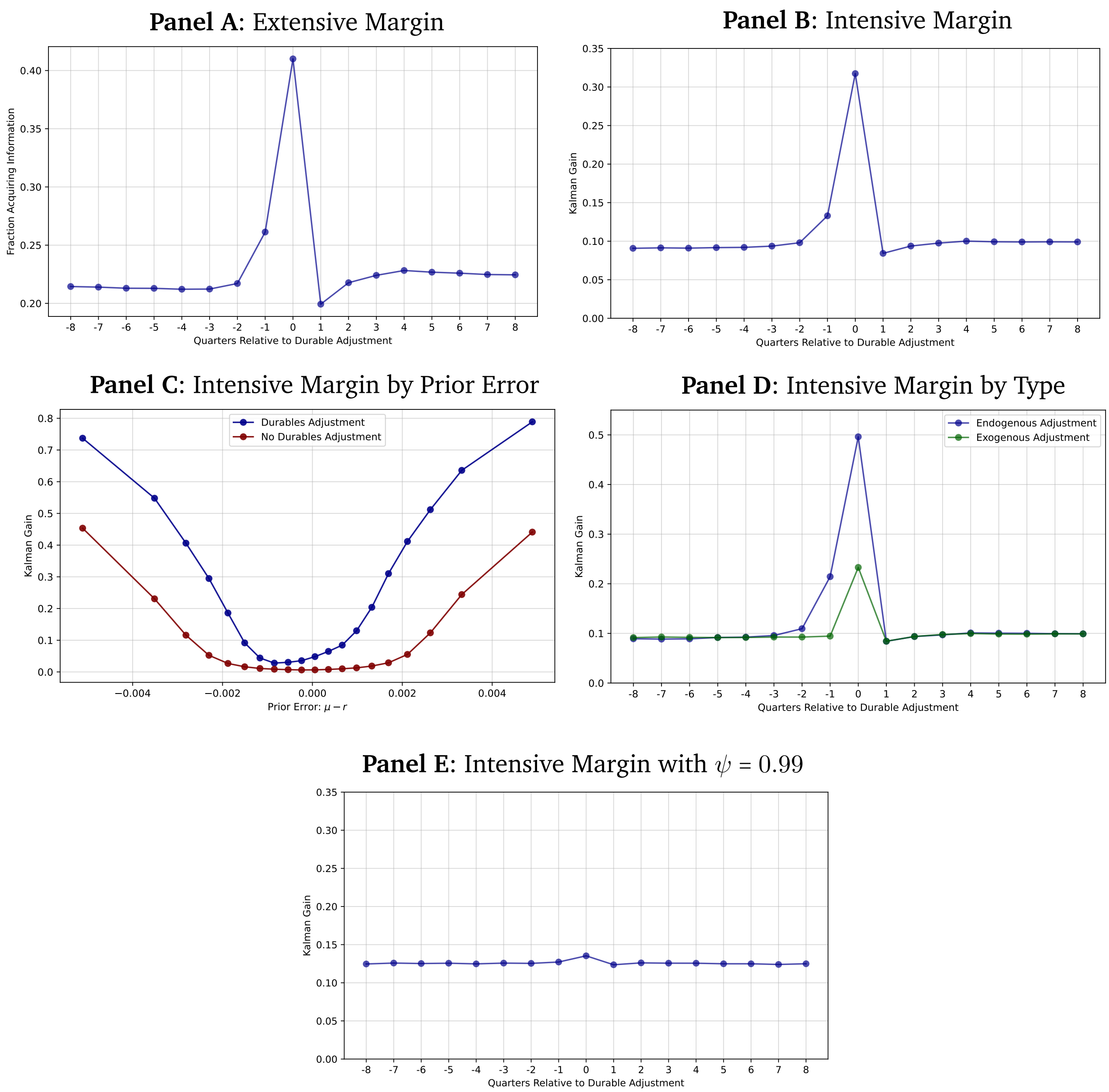
Information acquisition. Next, we explore patterns in households' information acquisition around durables adjustments, which is the key novel pattern that our model generates. Panel A of Figure 11 plots the fraction of households that acquire some positive information in event-time relative to durables adjustments, restricting to households that haven't made a durables adjustment in the prior eight quarters. The ratio of the points at time 0 and -8 is what we targeted to calibrated ω. As illustrated in Panel A, the model generates concentration in information acquisition around durables adjustments, with the fraction of households that acquire information approximately doubling from 22% to 42%. Panel B shows this is even larger on the *intensive* margin: the average Kalman gain increases by over a factor of three from around 0.1 to 0.33.

One way to see the mechanism through which durables adjustments affect information acquisition is by examining how information acquisition varies with prior beliefs. Panel C of Figure 11 shows that the Kalman gain is larger when prior beliefs are less accurate, with information acquisition exhibiting (s, S)–style behavior. This is a natural feature of a model with rational inattention: when beliefs become very inaccurate, the benefits from improving belief accuracy are higher. However, Panel C also shows that durables adjustment effectively shift these (s, S) bands. This is because the utility loss from having incorrect beliefs is larger when a durables adjustments is made, which in turn creates incentives to acquire more information.

Panels A and B of Figure 11 also show that, on both the extensive and intensive margin, information acquisition starts to increase around one quarter in anticipation of the durables adjustment. This finding is qualitatively consistent with our empirical evidence in Figure 6. To understand what drives this result in the model, Panel D shows how the average Kalman gain evolves depending on the type of the durables adjustment. For "exogenous" adjustments that are driven by the match-quality shock, all the increase in information acquisition occurs at the time of the choice. This is the same behavior that occurs in Afrouzi et al. (2024), which only features (time-dependent) exogenous adjustments. However, for "endogenous" adjustments, information acquisition starts to increase around two quarters ahead of the choice, as households collect information in order to help them accurately *time* their durables adjustments. This result highlights an important way in which the model of the adjustment process and information collection interact.

Although our model generates an increase in information acquisition prior to durable adjustments, the timing of this increase is closer to the adjustment than in the data. This is not surprising for two reasons. First, it is a well-known property of rational inattention models that a cost function that is linear in mutual information eliminates any incentives to smooth information collection over time (Maćkowiak et al. 2023). Second and more importantly, the process of making a durables purchase in the data inherently takes much more time than in our model: it requires a search process to find the right good and, in the

Figure 11. Information Acquisition around Durables Adjustments



Notes: This figure shows patterns in information acquisition in event-time relative to durables purchases. The sample restricts to all individuals making durables adjustments that did not make an adjustment in the previous eight quarters. Panel A plots the fraction that acquire a positive amount of information, $\Sigma_e < \infty$. Panel B plots the average Kalman gain defined in (5), G. Panel C plots the average Kalman gain as a function of $\mu - r$ for two groups of individuals: those adjusting their durables stock and those who are not. Panel D reproduces Panel B, splitting individuals based on whether they received a match-quality shock, $\xi = 0$, in the quarter of the durables adjustment. Panel E reproduces Panel B after setting $\psi = 0.99$, holding all other parameters fixed.

case of a home purchase, requires time to secure financing. While a richer model would include these additional features of the adjustment process, we abstract from these issues to keep our model tractable. Nevertheless, we view our model a useful first step to quantifying the impact of selective inattention to interest rates based on durables purchases.

While we calibrated the marginal costs of information based on the concentration in information acquisition around durables adjustments, this concentration is also heavily influence by the *benefits* of information acquisition. To illustrate this, Panel E of Figure 11 shows how the Kalman gain evolves in a model where durables play a much smaller role. In particular, we set $\psi = 0.99$ so that households derive most of their utility from non-durable consumption, consuming very few durables. In this model, the average Kalman gain does not increase prior to or during the choice, despite its average level being similar to Panel B. This is because when $\psi = 0.99$, durables adjustments are less important, so the value of acquiring information to improve these adjustments is lower.

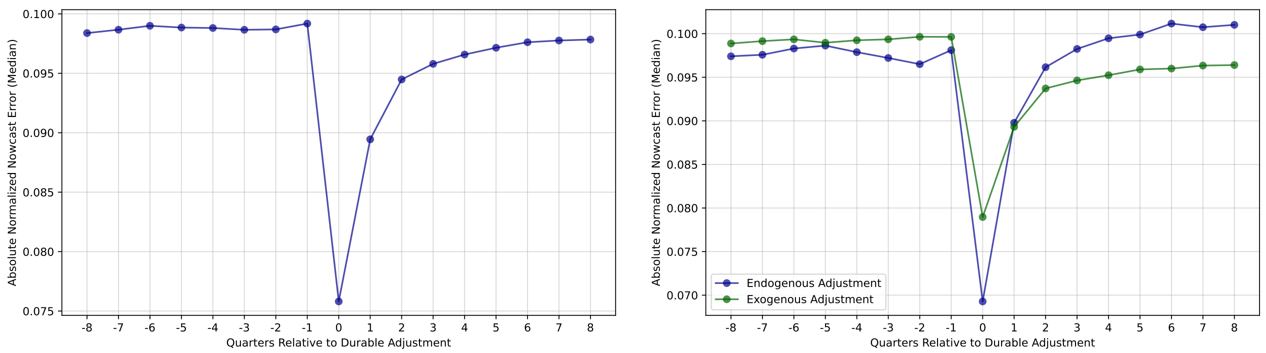
Nowcast errors. Having examined properties in information acquisition around durables adjustments, we now explore patterns in beliefs. Panel A of Figure 12 shows the median nowcast error of interest rates in event-time relative to a durables adjustment. Consistent with the patterns in information acquisition, nowcast errors fall by over 30% in the quarter of adjustment. Panel B shows that these patterns are more pronounced for endogenous adjustments that do not occur because of a match quality shock, with nowcast errors declining earlier before the choice and by a larger amount.

An important difference between the behavior of beliefs and information acquisition is that nowcast errors remain below their pre-adjustment values for several periods after the adjustment. This reflects the fact that beliefs are a "stock" variable that accumulates past "flows" of information acquisition. When we study impulse responses in Section 5, this has important implications because changes in the environment that affect durable adjustments will have persistent effects on beliefs.

Utility losses of inattention. Next, we quantify the welfare losses from inattention in Table A4. We find that the "static" loss from inattention, defined as the utility loss from not having full information in the current period, is equivalent to 0.03 basis points of lifetime consumption on average. The "dynamic" loss, which we define as the lifetime cost of not having rational expectations, is larger at around 2 basis points of lifetime consumption average. Both of these utility losses are small and on the same order of magnitude of the lifetime losses from inattention of 5 basis points from Maćkowiak and Wiederholt (2015) and 6 basis points from Carroll et al. (2020). Despite these small losses from selective inattention at the micro-level, the results in the remainder of the paper highlight that it has

Figure 12. Interest Rate Nowcast Errors around Durables Adjustments

Panel A: All Adjustments **Panel B**: Split by Type



Notes: This figure shows patterns in nowcast errors of interest rates in event-time relative to durables purchases. The sample restricts to all individuals making durables adjustments that did not make an adjustment in the previous eight quarters. Panel A plots the median absolute normalized nowcast error, which is computed as the absolute value of households' expectations of $\exp(r)$ minus the true realization, normalized by the true realization. We convert from nowcasts of r to $\exp(r)$ using the properties of the normal moment-generating function. Panel B reproduces Panel A, splitting individuals based on whether they received a match-quality shock, $\xi = 0$, in the quarter of the durables adjustment.

important macro implications (Akerlof and Yellen 1985).

4.3 Implications of Selective Inattention for Aggregate Beliefs

Before turning to counterfactuals in Section 5, we conclude this section by examining the implications of the micro-level patterns in selective inattention from Section 4.2 for patterns in aggregate beliefs. A well-documented fact is that average household expectations tend to be rigid, responding slowly to changes in macroeconomic conditions. A common way of characterizing this rigidity is to run a Coibion and Gorodnichenko (2015) (CG) regression using consensus expectations. In particular, we run the following regression:

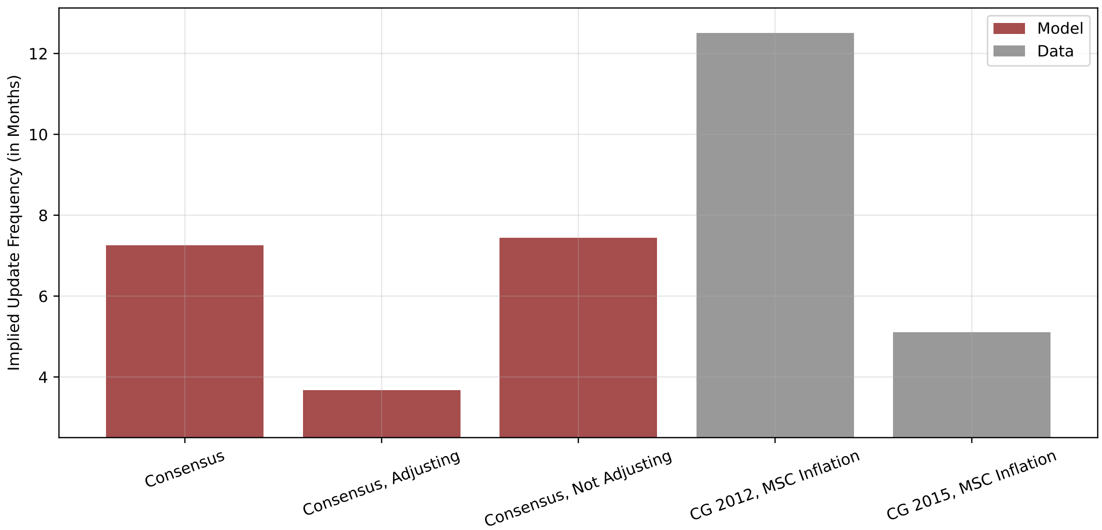
$$r_{t+3} - \overline{F}_t r_{t+3} = \alpha + \beta_{CG} \left(\overline{F}_t r_{t+3} - \overline{F}_{t-1} r_{t+3} \right) + \epsilon_t, \tag{7}$$

where the dependent variable is the forecast error of the three quarter-ahead average expectation and the independent variable is the quarterly revision in that expectation. We then compute the following measure of belief rigidity, which CG show corresponds to the structural update frequency in a model with sticky expectations that is implied by the estimate of β_{CG}:

$$\text{implied update frequency} = \frac{3}{1 - \frac{\beta_{CG}}{1+\beta_{CG}}} \text{ months.} \tag{8}$$

The first column of Figure 13 shows the implied update frequency in our model is around

Figure 13. Belief Rigidity in Model versus Data



Notes: This figure reports the implied update frequency in months of several sets of expectations. Each estimate comes from estimating (7) with the specified set of expectations and then applying (8). The first column uses the cross-sectional average expectation in our model. The second column uses the cross-sectional average expectation among households that are adjusting their durables stock at a given point in time. The third column uses a cross-sectional average among households that are not in the second column. The fourth and fifth columns provide estimates from Coibion and Gorodnichenko (2012) and Coibion and Gorodnichenko (2015) that are based on households' inflation expectations from the Michigan Survey of Consumers. The value in the fourth column is calculated slightly differently: it uses the coefficient from a regression of current onto lagged forecast errors in Coibion and Gorodnichenko (2012).

seven months. This implies aggregate beliefs in our model are quite rigid: households effectively update their expectations less than twice per year. As a comparison, the final two columns show estimates from Coibion and Gorodnichenko (2012) and CG that use three-quarter ahead inflation forecasts from the Michigan Survey of Consumers. We choose these benchmarks because they are often cited as calibration targets, and these values are the only estimates in those papers that use data on household expectations. Our estimate in the first column is in line with these estimates, which range from around five to twelve months.

The second and third columns of Figure 13 show that the relatively high aggregate belief rigidity in our model masks substantial heterogeneity. In particular, estimate the implied update frequency separately among two consensus expectations: one among those making durables adjustments and another among those who are not. The implied update frequency for households making durables adjustments is around four months, close to the three months that would correspond to rational expectations (the model is quarterly). However, only 5% of households make durables adjustments in each quarter, so the update frequency of those not making durables adjustments is close to the average.

5 Counterfactuals: Interest Rate Passthrough with Selective Inattention

Section 4 shows that our model features substantial selective inattention. In this section, we study the quantitative implications of this selective inattention for the passthrough of changes in both the level and volatility of interest rates.

5.1 Effects of Changes in Interest Rates

We begin by studying impulse responses to cuts in the interest rate that has the same persistence as the underlying process. Since our model is in partial equilibrium, this should be interpreted as a reduced-form monetary shock that would be induced by the combination of an innovation to a Taylor rule and nominal rigidities in a general equilibrium model.

5.1.1 Selective Inattention Preserves the Sluggishness of Average Beliefs and Non-Durables

Figure 14 shows impulse responses up to eight quarters after a 25 basis points annualized reduction in interest rates for the three models described in Section 3.2. The top left panel shows responses in interest rate nowcasts, while the right panel shows information acquisition measured using the Kalman gain. Under rational expectations, nowcasts track the value of the of interest rates perfectly. With exogenous inattention, nowcasts respond sluggishly, but eventually converge to the true value after seven quarters. With selective inattention, the cut in interest rates drives an increase in information acquisition, yet the response of nowcasts is still sluggish like with exogenous inattention.

The fact that aggregate beliefs are slightly more sluggish with selective rather than exogenous attention reflects the fact that attention is endogenous to the size of the rate cut, which is only at the 33rd percentile of the distribution of quarterly interest rate changes in the model. Since this is in the lower part of the distribution, households acquire less information than in the exogenous inattention model, which only has the same belief rigidity on average. Nevertheless, the preservation of sluggish average beliefs is a desirable feature of selective inattention, given the sluggishness in beliefs is what motivated models of exogenous inattention.

The middle left panel of Figure 14 shows the cumulative responses of non-durable consumption. With rational expectations, this increase is relatively large on impact at around 0.3%, and grows to over 2% after eight quarters. As expected, exogenous inattention dampens this response significantly on impact by more than half to 0.1%, leading to a lower cumulative change over eight quarters. Relative to exogenous inattention, we find that selective inattention generates a quantitatively similar response on impact. The dampened response of non-durable consumption with SI reflects the fact that it is primarily determined by households that are not making durables adjustments, who are relatively inattentive. We also view this as a desirable feature of the model because non-durable consumption responds sluggishly in the data (Christiano et al. 2005).

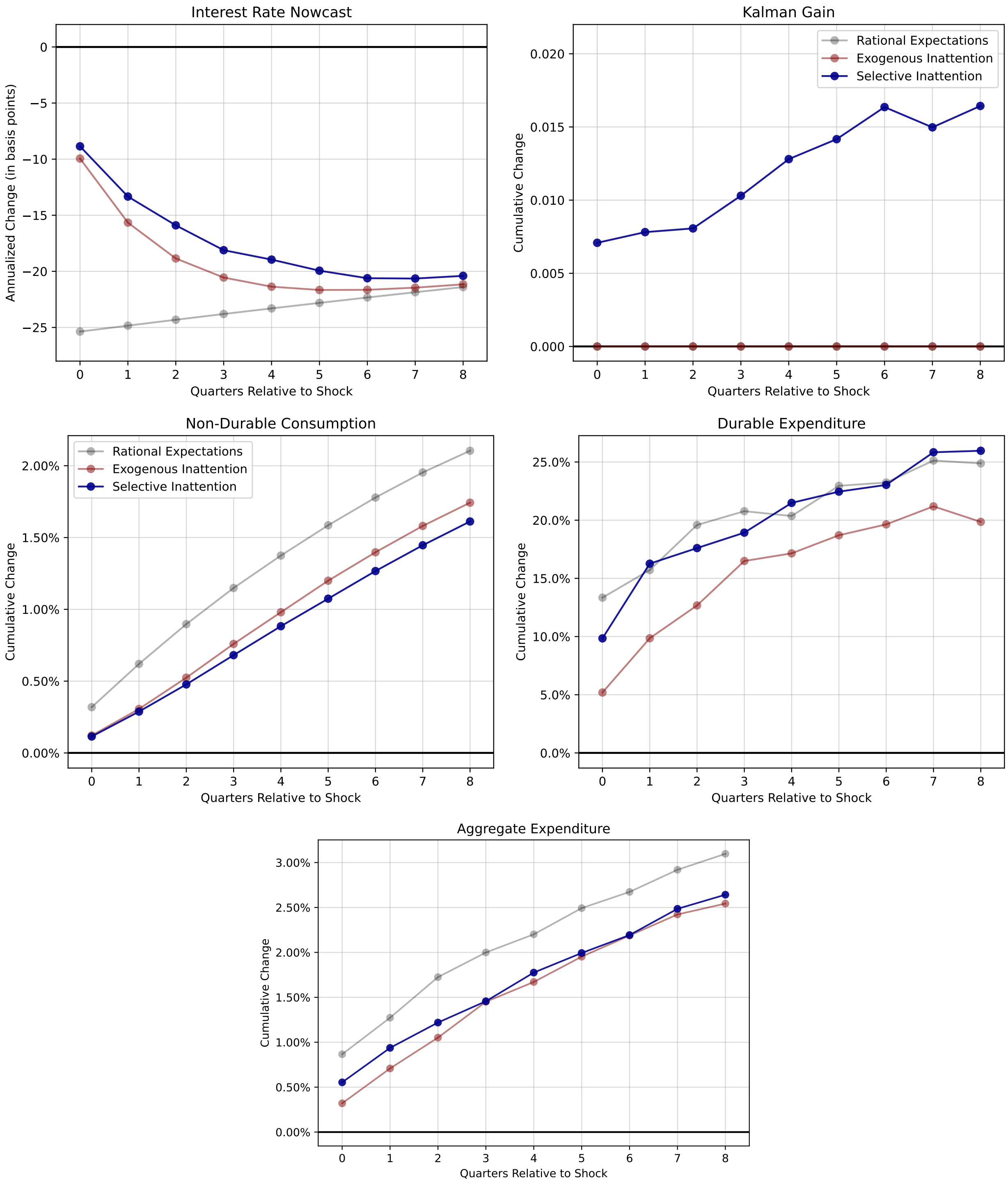
5.1.2 Selective Inattention Shifts the Composition of Spending Responses

The middle right panel of Figure 14 shows that the cumulative responses of durable consumption to the reduction in interest rates. With rational expectations, the increase on impact is large at over 13%, reflecting the high intertemporal elasticity of durables (Mankiw 1982; Caballero 1993). Consistent with McKay and Wieland (2021), exogenous inattention significantly dampens this response, lowering the response on impact to a 5% increase. However, unlike with non-durable consumption, selective inattention generates a quantitatively different response: the increase on impact is twice as large as exogenous inattention at 10%, and converges to that of the rational expectations model.

The reason that selective inattention amplifies durables responses relative to exogenous inattention is precisely because of the endogenous link between beliefs and durables adjustment that the model is designed to capture. When interest rates fall, individuals are more likely to receive signals about interest rates that are lower, suggesting they should update their durables stock. However, as shown in Section 4.2, durables adjustments induce additional information acquisition, which in turn moves their beliefs and durables choices closer to the rational expectations case.

This result suggests that generating a sluggish response of durables spending to interest rates, which is a feature of the data (McKay and Wieland 2021), requires other mechanisms than inattention (or recalibrating other parameters). While identifying this mechanism is outside the scope of our paper, one additional ingredient we find particularly plausible is the fact that durables purchases often require a significant search process that is absent from our model. In addition to generating a sluggish aggregate response, a search process would also help generate a larger increase in information acquisition prior to the actual adjustment, which would be more consistent with our survey evidence.

Figure 14. Impulse Responses to a 25 Basis Points Fall in Interest Rates



Notes: Each panel of this figure shows the impulse response of a variable labeled at the top of the graph to a 25 basis point annualized decline in $\exp(r)$ that occurs at quarter zero with the same persistence as the underlying process. The top left panel plots raw changes. The top right panel plots cumulative changes. The remaining three panels plot cumulative changes as a fraction of the pre-shock steady-state values. Each line corresponds to a different model. Our procedure for computing impulse responses is described in Section 3.2.

The bottom panel of Figure 14 shows aggregate spending responses, which are almost identical between exogenous and selective inattention after two years. This contrasts with the two middle panels, which show that the model with selective inattention has a larger durables response and a smaller non-durables response. Collectively, these results that selective inattention shifts the *composition* of aggregate spending responses relative to exogenous inattention, rather the level.

5.1.3 Selective Inattention Accelerates the Impact of Larger Cuts

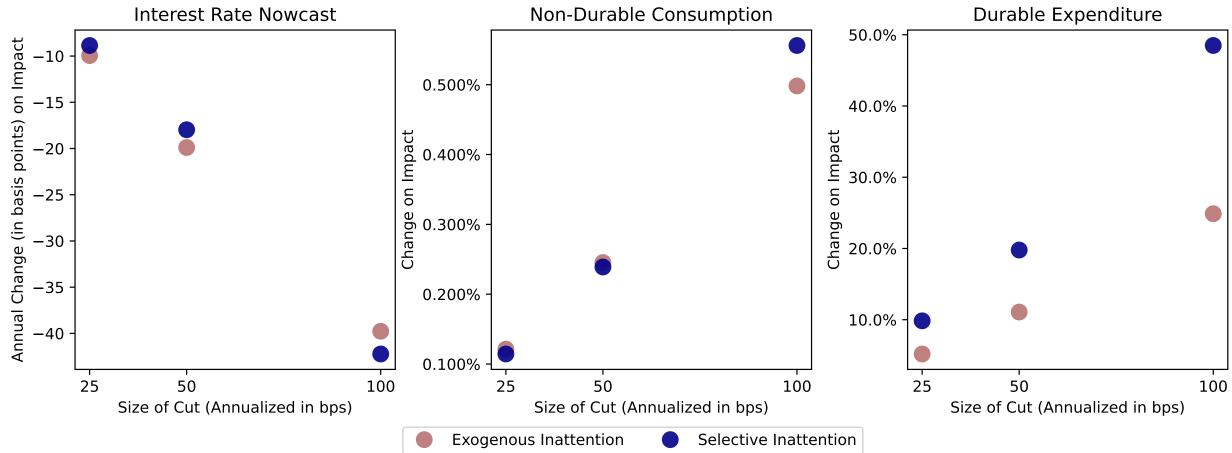
Next, we examine the extent to how the impulse responses to a cut in interest rates vary with the size of the shock. In addition to the 25 basis point cut from the previous section, we also consider larger cuts of 50 and 100 basis points (also annualized). Panel A of Figure 15 shows the impulse responses of interest rate nowcasts, non-durables, and durables on impact. The leftmost graph shows that the result from the previous section that nowcasts are more sluggish with selective rather than exogenous inattention is also present for the 50 basis point shock. However, with the 100 basis points shock, the relationship flips: nowcasts with selective inattention respond more. This is because a larger shock induce a bigger error in households' prior, which, as shown in Section 4.2, creates additional incentives to acquire information.

The center and rightmost graphs in Panel A of Figure 15 show that fact that large shocks generate responses in beliefs with selective inattention that are closer to rational expectations also translates into non-durable and durable consumption. While the difference between the non-durable response with selective and exogenous inattention is similar for 25 and 50 basis point cuts, non-durable consumption responds by more rather than less with selective inattention in response to the 100 basis point cut. Similarly, the right panel shows that the difference between the durables responses grows with the size of the shock.

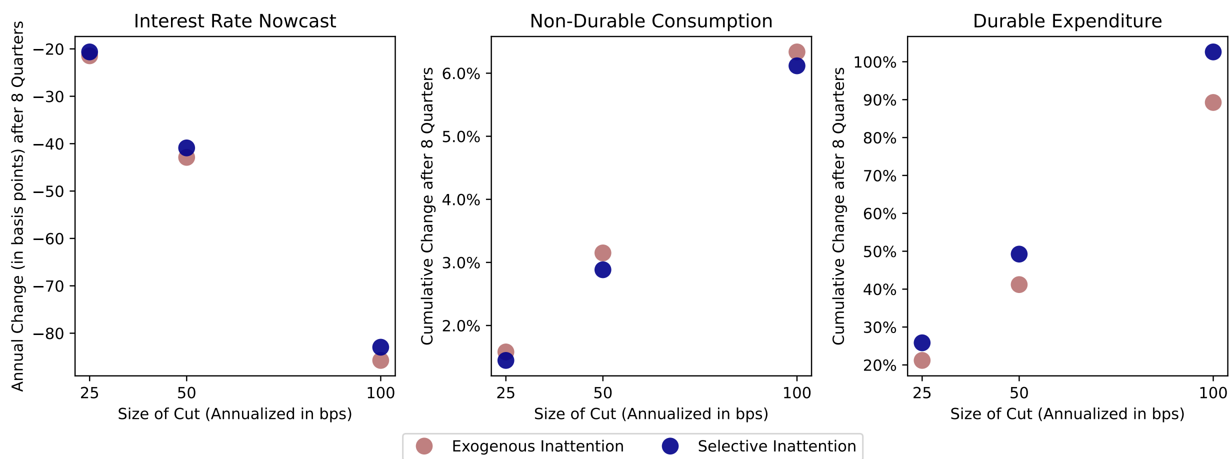
In Panel B of Figure 15, we show the impulse responses after eight quarters. Unlike the results in Panel A, the difference between exogenous and selective inattention is varies much less with respect to the size of the interest rate cuts. Therefore, selective inattention accelerates the impact larger interest rate cuts, rather than increasing their cumulative impact.

Figure 15. Impulse Responses to a Fall in Interest Rates of Different Magnitudes

Panel A: Responses on Impact



Panel B: Responses after Eight Quarters

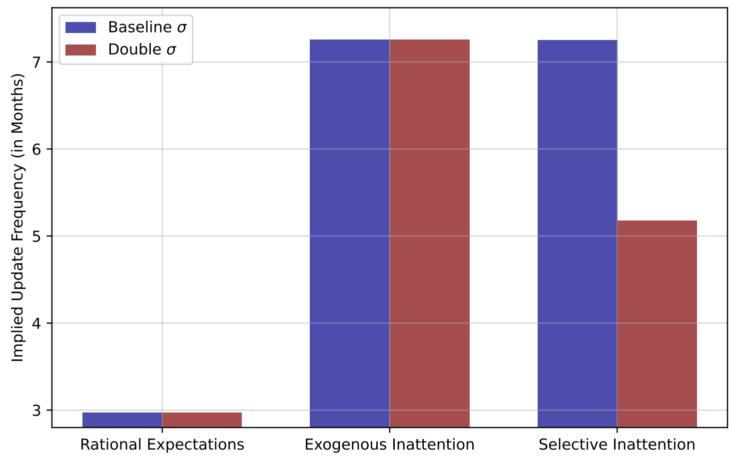


Notes: This figure shows impulse responses declines in $\exp(r)$ of different magnitudes that occurs at quarter zero with the same persistence as the underlying process. Panel A shows responses of various variables on impact; Panel B shows cumulative responses after eight quarters. The plots within each panel correspond to different variables labeled at the top of each plot, and the size of the change in interest rates is denoted on the horizontal axes. The response to interest rate nowcasts is shown in levels, while the other responses are shown as fractions of the pre-shock steady-state values. Each series of dots corresponds to a different model. Our procedure for computing impulse responses is described in Section 3.2.

5.2 Effects of Changes in Interest Rate Volatility

Next, we examine the effects of an increase interest rate volatility. We view this as an interesting counterfactual to study in the context our model for two reasons. First, there has been a significant increase in interest rate volatility over the past few years, with both the realized and implied volatility of Treasury rates approximately doubling (Figure A5). Second, changes in volatility alter the incentives to acquire information, which is precisely

Figure 16. Effects of Doubling Interest Rate Volatility on Belief Rigidity



Notes: This figure plots the implied update frequency for consensus forecasts computed in (8) for the three different benchmark models shown on the horizontal axis. The blue bars on the left correspond to values from our baseline calibration. The red bars on the right correspond to values when σ is increased by a factor of two, but all other parameters are held fixed. The procedure to compute the implied update frequency is the same as for the leftmost bar in Figure 13.

the behavior that our model is designed to capture.

5.2.1 Selective Inattention Increases Information Acquisition

Figure 16 shows the effects of doubling the volatility of innovations in r, σ, relative to Table 1 on aggregate belief rigidity, measured using the implied update frequency in (8).[17] With rational expectations and exogenous inattention, belief rigidity does not adjust to the change in volatility by construction. In contrast, with selective inattention, the frequency with which aggregate beliefs update falls by a third. This reduction in belief rigidity is driven by increased information acquisition on both the extensive and intensive margin: Table A5 shows that the fraction of households acquiring information increases from 23% to 32%, and the average Kalman gain doubles. Although information acquisition increases, Table A5 shows that nowcast errors and prior variances more than double, reflecting additional uncertainty.

5.2.2 Selective Inattention Reduces Fall in Aggregate Spending

Figure 17 shows impulse responses to the increase in interest rate volatility. The top left panel shows the effect on non-durable consumption. With rational expectations, the increase in volatility leads to a decline in aggregate consumption of around 5% over

[17] We choose this shock size based on the evidence in Figure A5 that realized and implied interest rate volatility has doubled in the last few years.

two years through standard precautionary motives: additional volatility in interest rates provides the incentive to accumulate savings to hedge against declines in future interest rates. Similarly, the top right panel shows that durables spending falls by 35%.

The decline in non-durable and durable consumption in response to the increase in volatility is much larger under exogenous inattention than rational expectations: over the following two years, non-durables and durables fall by over 12% and 70%, respectively. These larger responses reflect the fact that subjective uncertainty increases more than one-for-one with the increase in volatility due to inattention, as illustrated by the updating equation for the posterior variance in (5). In contrast, with selective inattention, non-durable and durable consumption decline by only 7% and 50% over two years. These smaller declines reflect the increase in information acquisition shown in Figure 16. This additional information acquisition leads to a larger Kalman gain, which through (5), dampens the increase in posterior variance that happens with exogenous inattention.

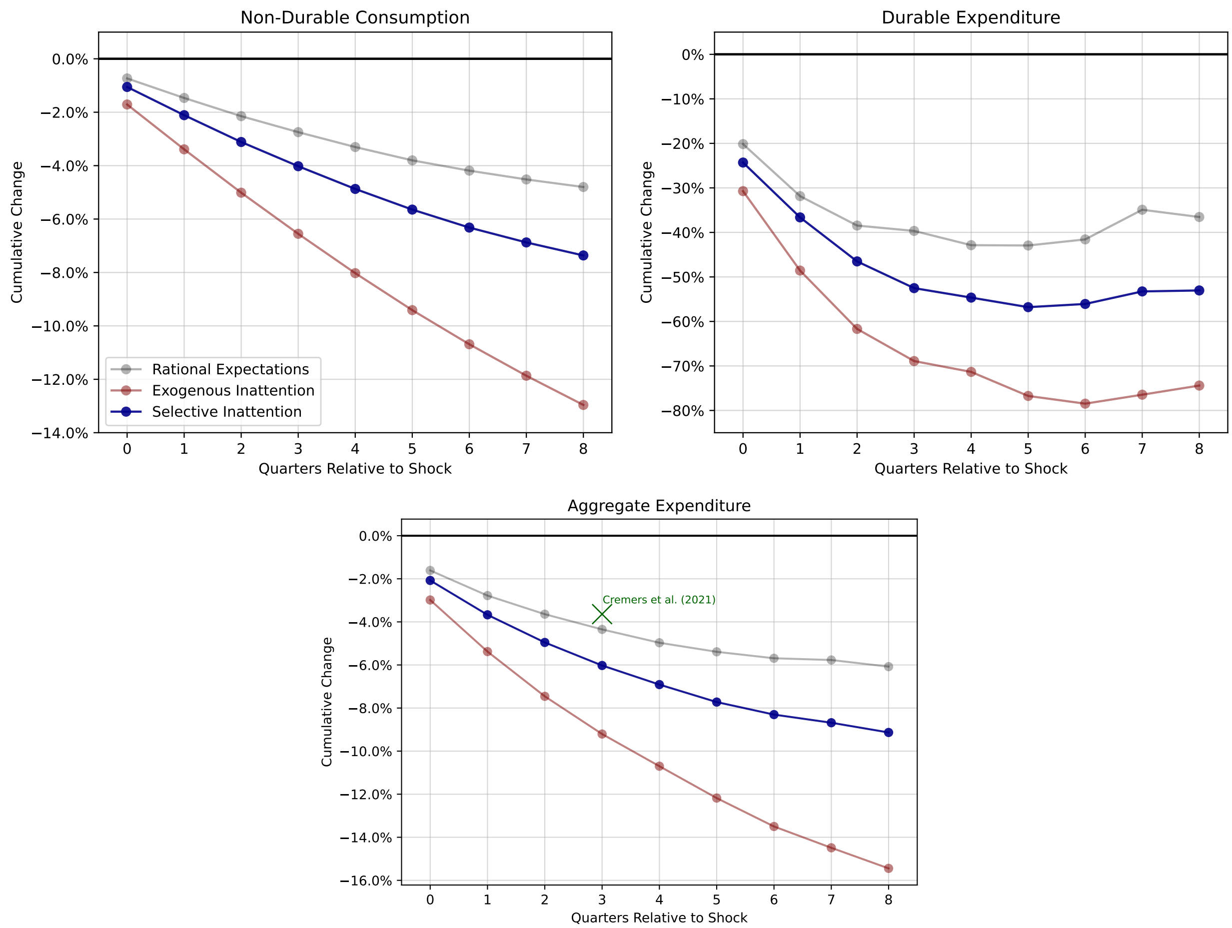
The bottom panel in Figure 17 shows that the model with selective inattention generates a fall in aggregate spending that is much lower than exogenous inattention and closer to rational expectations. Importantly, this panel also shows the empirical estimate from Cremers et al. (2021), who estimate impulse responses to changes in interest rate volatility. As evident from the figure, the model with selective inattention is quite a bit closer to the data than the model with exogenous inattention. While the model with rational expectations provides the closest fit, this model cannot capture the micro- and macro-level patterns in beliefs documented in previous sections.

5.2.3 Selective Inattention Reduces State-Dependence on Volatility

Finally, we explore the extent to which selective inattention affects the state-dependence of interest rate cuts based on volatility. Figure 18 shows how the impulse responses from steady-state to a 25 basis points annualized cut in interest rates differ depending on the underlying volatility, σ. Panel A shows the responses on impact; Panel B shows the responses after eight quarters. With exogenous inattention, beliefs update by the same amount regardless of the underlying volatility. However, because a 25 basis point cut is a smaller shock in a higher volatility environment, the increases in non-durable and durable consumption are over 30% smaller on impact. After two years, the increase in non-durable consumption is half as large.

Under selective inattention, the additional information acquisition with higher volatility

Figure 17. Impulse Responses to Doubling in Interest Rate Volatility

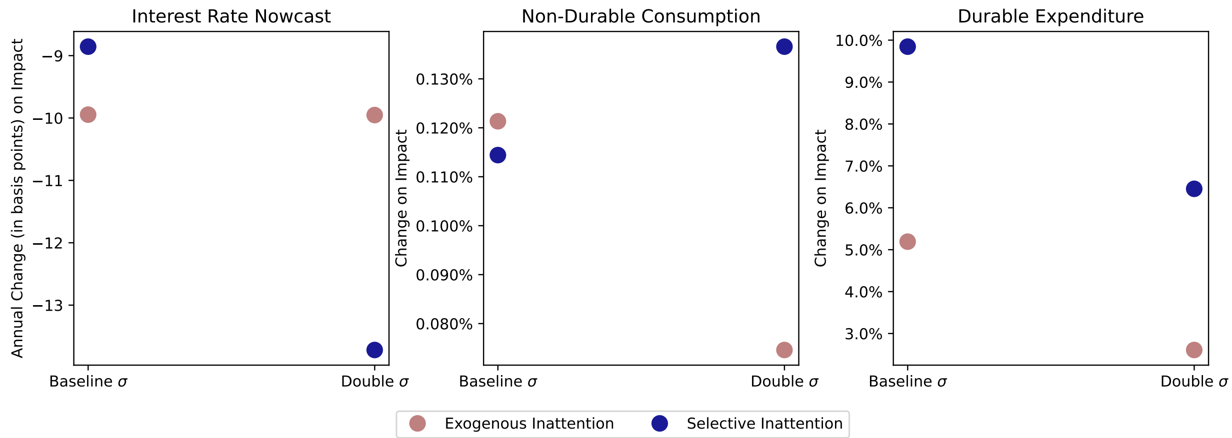


Notes: Each panel of this figure shows the impulse response of a variable labeled at the top of the graph to an unexpected and permanent doubling of σ that occurs at quarter zero. All panels plot cumulative changes as a fraction of the pre-shock steady-state values. Each line corresponds to a different model. Our procedure for computing impulse responses is described in Section 3.2. The green cross corresponds to an estimate from Cremers et al. (2021): they estimate that increasing interest rate volatility by 1.17% leads to a fall in 1.26% fall in the PCE over the next year. Using the fact that the standard deviation of their measure of implied volatility is 3.38%, this corresponds to a $1.26*3.38/1.17=3.64\%$ decline, which is the value plotted in the graph. We choose to compare this effect on the PCE with aggregate expenditure in our model, given the former includes some spending on durable goods.

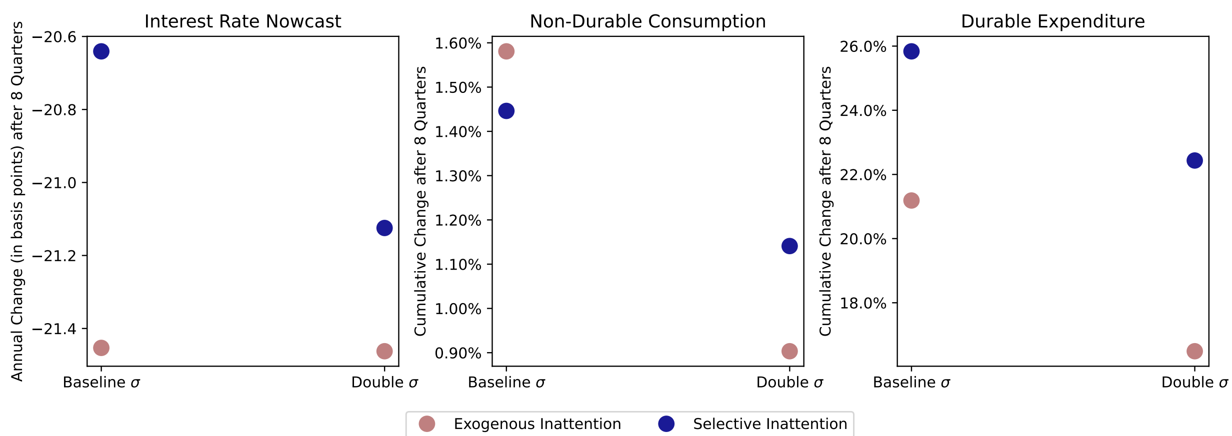
causes beliefs to update significantly more in response to the same 25 basis point cut. On impact, Panel A of Figure 18 shows that the average nowcast updates by 14 bps compared to under 9 bps. As a result, non-durable consumption increase by more on impact when volatility is higher, in contrast with exogenous inattention (where it increases by less). This is because, even though a 25 basis point cut is effectively a smaller shock in a higher volatility environment, the endogenous response of information acquisition causes it to be more accurately perceived. For the same reason, durables spending falls by less (in percentage terms) than with exogenous inattention. Panel B shows similar patterns are present two years after the shock: selective inattention causes the increases of non-durable and durable consumption in response to an interest rate cut become less dependent on

Figure 18. Responses to a 25 Basis Points Fall in Interest Rate as a Function of Volatility

Panel A: Impulse Responses on Impact



Panel B: Impulse Responses after 8 Quarters



Notes: This figure shows impulse responses a 25 basis points annualized decline in $\exp(r)$ that occurs at quarter zero with the same persistence as the underlying process. Each figure shows the results in the steady-states of the baseline model and the model in which σ is increased by a factor of two. Panel A shows responses of various variables on impact; Panel B shows cumulative responses after eight quarters. The plots within each panel correspond to different variables labeled at the top of each plot, and the size of the change in interest rates is denoted on the horizontal axes. The response to interest rate nowcasts is shown in levels, while the other responses are shown as fractions of the pre-shock steady-state values. Each series of dots corresponds to a different model. Our procedure for computing impulse responses is described in Section 3.2.

volatility.

In this analysis, we have taken as given a real interest rate cut of the same size for different levels of volatility. In general equilibrium, it is likely that, in the presence of higher volatility, a larger nominal rate change is required to achieve the same real rate change. For example, Vavra (2014) shows that in a (s, S) model of price-setting, firms are more likely to adjust prices when the volatility of (aggregate) productivity is high, which in turn reduces monetary non-neutrality. Afrouzi et al. (2024) deliver the same result through a different mechanism that is similar to ours but on the firm side: when the volatility of (individual) marginal costs are high, firms pay more attention to current information and monetary shocks. Collectively, this suggests that the sign of the effect of volatility on the transmission of monetary policy to consumption is ambiguous because more volatility causes a smaller passthrough from nominal to real rates, but a large passthrough from real rates to consumption.

6 Conclusion

This paper argues that households select into paying attention to interest rates when making durable goods purchases. Using a combination of existing and new surveys, we show that households close to durables purchases actively acquire more information about interest rates and have more accurate, less dispersed, and less uncertain interest rate expectations. We then embed information acquisition about interest rates through rational inattention into a partial equilibrium incomplete markets model with durable consumption. After calibrating the model using our survey evidence, we use the model to study the determinants of selective inattention at the micro-level and its implications at the macro-level. Like exogenous inattention, selective inattention generates slow-moving aggregate beliefs and sluggish responses of aggregate non-durable consumption to interest rate cuts. However, unlike exogenous inattention, selective inattention shifts the composition of spending responses to interest rate cuts, accelerates the impact of larger cuts, and generates impulse responses to changes in volatility that are closer to the data. Collectively, our findings suggest that a high level of aggregate household inattention can mask substantial selective inattention that can be measured, modeled, and has different implications.

Our findings raise several questions for future work. First, our conclusions echo the results in Afrouzi et al. (2024), who study patterns in firm attention around price adjustments. This naturally leads to the question of how endogenous attention on the firm and household side interact in general equilibrium (Maćkowiak and Wiederholt 2015), especially in the presence of changes in aggregate volatility. Second, while our findings suggest that households become significantly more informed around durables purchases, these expectations are still far from rational. Studying the microeconomic and macroeconomic implications of endogenous inattention in otherwise non-rational models of belief formation, which are necessary to match other patterns in expectations (Bordalo et al. 2022), represents an important task for future work.

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Internet Appendix for "Selective Inattention to Interest Rates"

For Online Publication Only

Contents

Appendix A. Additional Figures and Tables

A.1 Results Discussed in Section 2

Table A1. Summary Statistics: Nowcasts and Forecasts for Mortgage Rates

	New Survey	NY Fed SCE	ECB CES
Median nowcast error mortgage rate	0.650	0.660	—
Median forecast error mortgage rate	1.000	1.190	1.360
Sample years	2025	2014–2023	2020–2024
Observations	824	11,177	569,260

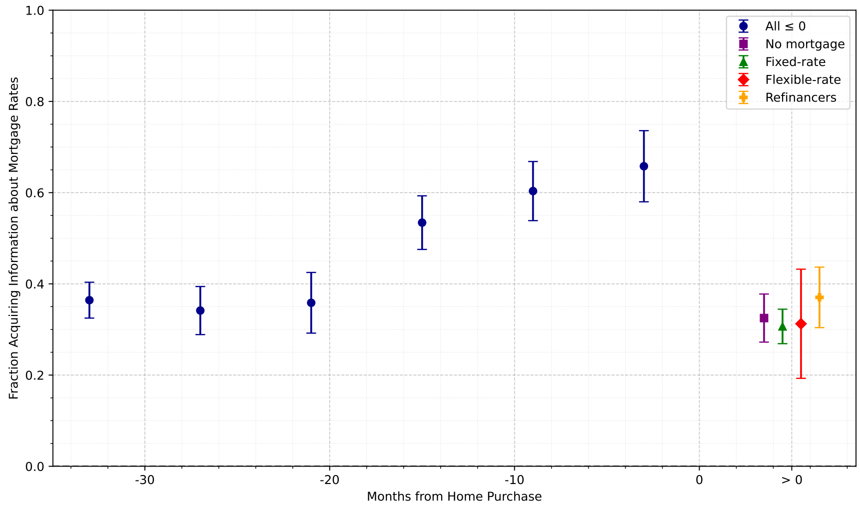
Notes: This table shows a few selected statistics for the nowcasts and forecasts of the mortgage rate in the three samples we use. All respondents in all surveys are included.

Table A2. Summary Statistics: Main Demographics

	New Household Survey	**NY Fed SCE**
Income		
Below $50,000	18.9%	35.0%
Between $50,000 and $100,000	37.9%	35.7%
Above $100,000	43.2%	29.4%
Age		
Under 40	64.0%	28.5%
Between 40 and 60	32.2%	39.0%
Over 60	3.9%	32.5%
Education		
High school	8.6%	11.5%
Some college	14.1%	32.6%
College	77.3%	55.9%
Gender		
Male	46.6%	51.7%
Female	52.8%	48.3%
Other	0.6%	0.0%

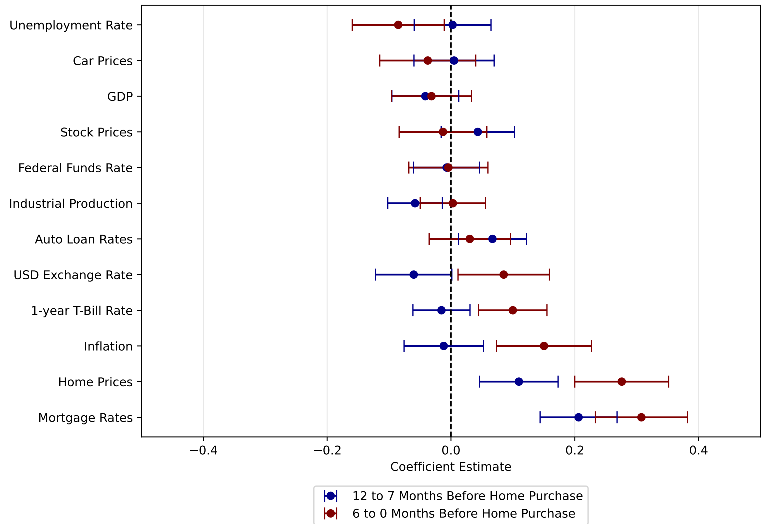
Notes: This table shows the demographic composition in our new survey and the NY Fed SCE. All respondents in all surveys are included.

Figure A1. Decision-Making and Information Acquisition: Heterogeneity among Owners



Notes: This figure replicates the analysis in the left panel of Figure 6 for households prior to the home purchase. For households after the home purchase, this figure plots averages based on households' mortgage status, averaging across all periods after the choice.

Figure A2. Decision-Making and Information Acquisition by Macroeconomic Variable



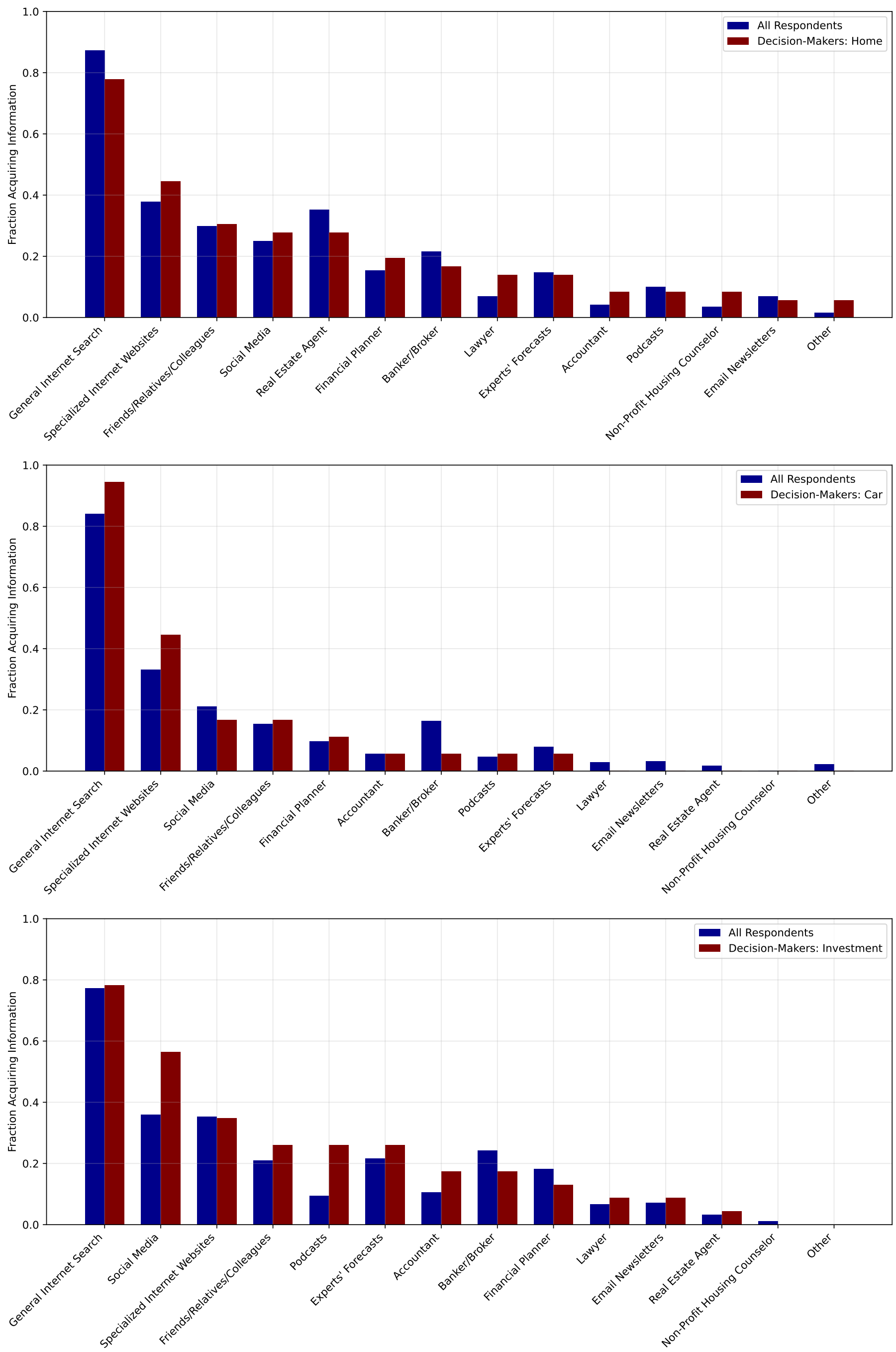
Notes: This figure reproduces Figure 7 within the full sample of households within our survey, including those that do not report using credit, as in the left panel of Figure 6.

Table A3. Regressions of Information Acquisition onto Decision-Making with IV

Variable	OLS	First Stage	IV	OLS	First Stage	IV
Home Decision-Maker	0.30***		0.89***	0.30***		0.96***
	(0.07)		(0.34)	(0.06)		(0.34)
Job Relocation		0.23***			0.23***	
		(0.07)			(0.07)	
N	787	787	787	787	787	787
Controls				✓	✓	✓
F-stat		10.51			3.57	

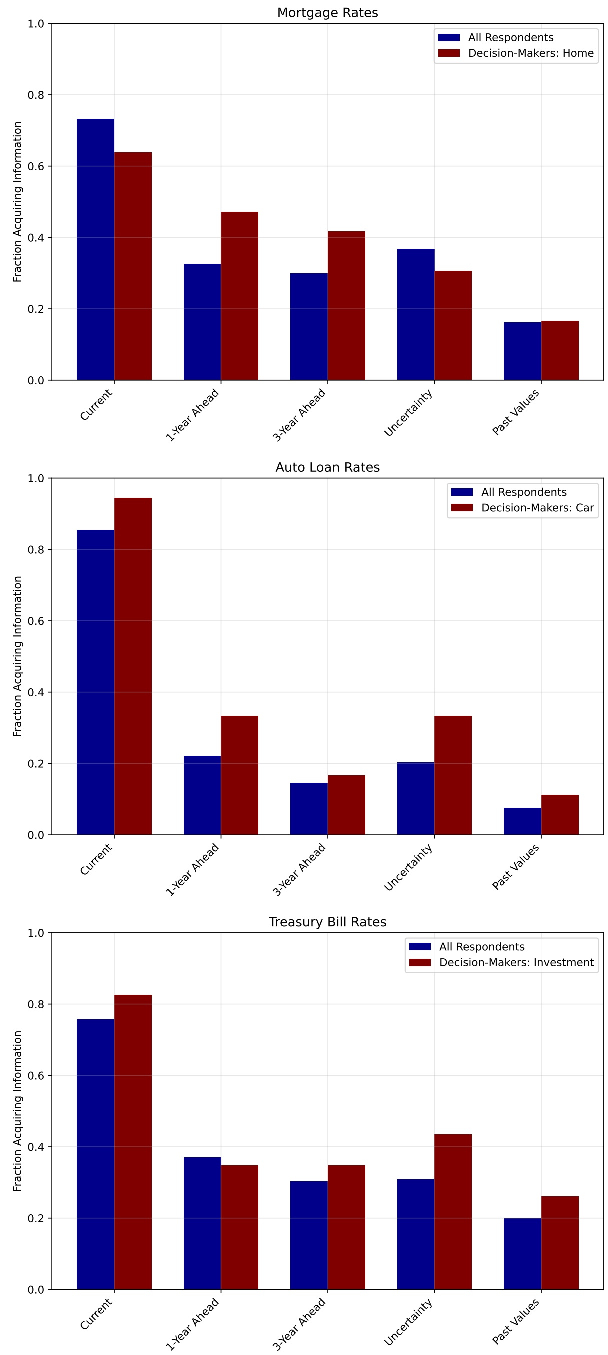
Notes: This first column of this table shows results from a regression of an indicator for whether households have acquired information about mortgage rates in the past three months onto an indicator for whether they are within six months of a home purchase. The second column shows the first-stage of an IV regression, instrumenting the independent variable in the first column with an indicator variable based on whether households report being within six months of a job-related relocation. The third column show shows the second stage of the IV. The next three columns repeat the first three columns, after including the set of controls from (3). The sample includes all individuals regardless of their use of credit. We exclude respondents who report more than three outlier nowcasts or forecasts, which corresponds to approximately 5% of the sample.

Figure A3. Sources of Information Acquisition



Notes: Each panel of this figure shows, among the households that report acquiring information about a given variable, the fraction report acquiring information about the variable of interest from a particular source. The sample includes all households in our survey, including those that do not report using or intending to use credit. The first panel focuses on information acquisition about mortgage rates among the full sample and those that are close to a home purchase. The second panel focuses on information acquisition about auto loan rates among the full sample and those that are close to a car purchase. The final panel focuses on information acquisition about Treasury bill rates among the full sample and those that are close to a major financial investment.

Figure A4. Types of Information Acquisition



Notes: Each panel of this figure shows, among the households that report acquiring information about a given variable, the fraction report acquiring information about a particular characteristic of the variable of interest. The sample includes all households in our survey, including those that do not report using or intending to use credit. The first panel focuses on information acquisition about mortgage rates among the full sample and those that are close to a home purchase. The second panel focuses on information acquisition about auto loan rates among the full sample and those that are close to a car purchase. The final panel focuses on information acquisition about Treasury bill rates among the full sample and those that are close to a major financial investment.

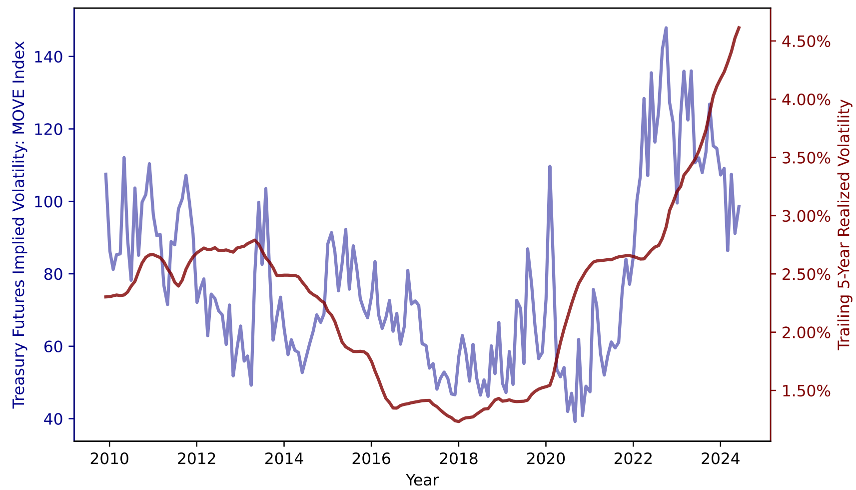
A.2 Results Discussed in Section 5

Table A4. Utility Losses from Inattention in Basis Points of Lifetime Consumption

	Static	Dynamic
Mean	0.03	2.17
Median	0.02	1.9

Notes: This table shows the utility losses in the baseline model relative to rational expectations in basis points of the lifetime consumption aggregate. The static loss corresponds to the average loss from not having rational expectations in a single period, which is computed by calculating the increase in individuals' value function that comes from setting $\Sigma_e = 0$ and $\omega = 0$. The dynamic loss corresponds to the average lifetime cost of not having rational expectations. This is computed by evaluating $U(\cdot, \cdot)$ at individuals' choices of c and d' over the entire simulation and discounting them using β. The differences in these discounted utilities for our baseline model and the model with rational expectations ($\omega = 0$) are then translated into consumption-equivalent losses by computing that value of g such that if c and d' were increased by g at every state and every date, individuals would be indifferent.

Figure A5. Motivating Evidence: Rise in Interest Rate Volatility



Notes: This figure shows measures of interest rate volatility over time. The blue line plotted on the left axis is the ICE BofAML MOVE Index, which is an index based on the implied volatility from options on Treasury futures. The red line plotted on the right axis is the annualized standard deviation of the 10-Year Treasury Rate computed using trailing five-year windows and daily data.

Table A5. Steady-State Summary Statistics

	Mean	SD	P10	P50	P90
Assets/Income: b/y	6.10	7.92	-1.15	3.28	18.18
Durable/Non-Durables: d'/c	2.57	0.46	1.97	2.58	3.12
Durables Gap	0.13	0.18	-0.07	0.10	0.38
Acquired Information	0.32	0.47	0.00	0.00	1.00
Kalman Gain: G	0.19	0.31	0.00	0.00	0.80
Kalman Gain Conditional on IA	0.60	0.24	0.30	0.80	0.90
Normalized Nowcast Error: $\lvert\hat{\mathbb{E}}(r) - r\rvert/\lvert r\rvert$	0.72	16.84	0.02	0.13	0.67
Normalized Prior Variance: Σ/σ_r^2	0.82	0.55	0.28	0.66	1.61

Notes: This table produces the same summary statistics as in Table 2 from our baseline model in which σ is increased by a factor of two. See the notes to Table 2 for additional details.

Appendix B. New Household Survey

This section shows the format of the new household survey that we conduct and describe in Section 1. The survey was administered via Qualtrics; we reproduce the questions in text format below.

B.1 Introduction and Consent

This is a survey for academic research purposes. It will take approximately 10 minutes to complete. The purpose of this survey is for us to understand how the economic expectations of U.S. households are formed. To this end, we will ask you a few questions about your household's circumstances, and your expectations about the U.S. economy.

You will be compensated for this interview conditional upon completing the survey. Please note that it is very important for the success of our research that you answer honestly and read the questions very carefully before answering.

You should know the following: Whether or not to take part is up to you. Your participation is completely voluntary. You can choose not to take part. You can agree to take part and later change your mind. Your decision will not be held against you. Your refusal to participate will not result in any consequences or any loss of benefits that you are otherwise entitled to receive. You can ask all the questions you want before you decide. As part of this research design, you may not be told or may be misled about the purpose or procedures of this research. However, the purpose or procedures of the research will be disclosed to you following your participation.

If you have questions, concerns, or complaints, or think the research has hurt you, contact the research team at macroeconomysurvey@gmail.com.

All of the answers you provide will remain anonymous and be treated with absolute confidentiality. The data are only used for research purposes, and the research is non-partisan. Anonymous data collected from this study will be publicly available in an online repository.

Do you agree to participate?

- Yes
- No

B.2 Initial Screening

Housing Ownership

Q1. Do you own or rent your current primary residence?

- Own
- Rent
- Other

Q2. Have you ever owned another house in the past used as a primary residence?

- Yes
- No

Q3. For how many years have you owned your current primary residence?

- Less than 1 year
- 1–3 years
- More than 3 years
- Don’t know

Q4. At what point in the future do you think you will buy a primary residence?

- Less than 1 year
- Less than 2 years
- Less than 3 years
- More than 3 years
- I don’t plan to buy
- Don’t know

Financial Decision-Making

Q5. Which of the following best describes financial decision-making in your household?

- Someone else makes all decisions
- Someone else makes most decisions
- Shared equally
- I make most decisions
- I make all decisions

Demographics

Q6. In which state do you currently reside?

Q7. What is your gender?

- Man
- Woman
- Other (please specify): ____________________

Q8. What is your age?

Q9. What is your current employment status?

- Full-time employee
- Part-time employee
- Self-employed or business owner
- Unemployed and looking
- Temporarily laid off
- Student
- Not working and not looking
- Retiree

Q10. How many people currently belong to your household (including yourself)?

Q11. What is your household's pre-tax income for 2024?

Q12. How would you describe your ethnicity/race?

- White
- African American/Black
- Hispanic/Latino
- Asian/Asian American
- Mixed race
- Other (specify): ____________________

B.3 Attention Check 1

Q13. It is very important for us that you do not get distracted throughout the survey. This question is to check whether you are not getting distracted. To proceed, please select the definition of ”dog” from the following options.

- A yellow and black flying insect that makes honey and can sting you.
- A large, strong bird with a curved beak that eats meat and can see very well.
- A large wild animal of the cat family with yellowish-orange fur with black lines.
- A very large sea mammal that breathes air through a hole at the top of its head.
- A common animal with four legs, kept by people as a pet, or to guard things.

B.4 Macroeconomic Knowledge

Introduction
We will now ask you a few short questions about the U.S. economy. Please answer to the best of your knowledge, and do not use any outside sources.

Q14. What do you think is the current average interest rate to obtain a new 30-year fixed-rate mortgage in the U.S.?

____

Q15. What do you think is the current interest rate on a 1-year Treasury Bill in the U.S.?

____

Q16. Over the past 12 months, do you think there was inflation or deflation in the U.S.?

- Inflation
- Deflation
- Don’t know

Q17. Over the past 12 months, what do you think the rate of inflation was in the U.S.?

____

Q18. Over the past 12 months, what do you think the rate of deflation was in the U.S.?

____

Q19. 12 months from now, what approximate average interest rate on a new 30-year fixed-rate mortgage would you assign to the following scenarios?

- LOW: ______________________________
- MEDIUM: ______________________________
- HIGH: ______________________________

Please distribute 100 points to the percentage changes you just entered, to indicate how likely you think it is that each mortgage rate will happen. The sum of the points you allocate should total to 100.

- LOW: ____
- MEDIUM: ____
- HIGH: ____
- Total: ____

Q20. 12 months from now, what approximate interest rate on a 1-year Treasury Bill would you assign to the following scenarios?

- LOW: ______________________________
- MEDIUM: ______________________________
- HIGH: ______________________________

Please distribute 100 points to the percentage changes you just entered, to indicate how likely you think it is that each mortgage rate will happen. The sum of the points you allocate should total to 100.

- LOW: ____
- MEDIUM: ____
- HIGH: ____
- Total: ____

Q21. What do you think the average interest rate on a new 30-year fixed-rate mortgage was in December 2019?

____

Q22. What do you think the rate of inflation was in December 2019?

____

Q23. Suppose today you needed to apply for a 30-year fixed-rate mortgage. Do you think you would qualify?

- Yes
- No
- Don't know

Q24. What interest rate do you think you would qualify for today?

____

B.5 Information Acquisition

Introduction
We will now ask you a few short questions about how you stay informed about the U.S. economy. Please answer based on your own experience.

Q25. In the last 3 years, did you actively search for information about any of the following economic variables in the U.S.? Please indicate Yes or No for each:

- Mortgage rates
- Inflation
- Home prices
- Dollar exchange rate
- Stock market
- Unemployment rate
- Gross domestic product (GDP)
- Treasury Bill rates
- Industrial production
- Auto loan rates
- Car prices

- Federal Funds rate

Q26. How many months ago did you last actively search for information about mortgage rates?

____

Q27. What type of information about mortgage rates were you mostly interested in?

- Their value when you checked
- What their value would be in 1 year
- What their value would be in 3 years
- The uncertainty surrounding their future value
- Their value in the previous 5 years
- Other: ______________________________

Q28. Which of the following sources did you use to obtain more information about mortgage rates? (Select all that apply)

- General internet search
- Social media
- Specialized websites
- Friends/relatives/colleagues
- Lawyer
- Accountant
- Banker/broker
- Financial planner
- Email newsletters
- Podcasts
- Real estate agent
- Non-profit housing counselor
- Experts' forecasts
- Other: ______________________________

Q29. How many months ago did you last actively search for information about Treasury Bill rates?

____

Q30. What type of information about Treasury Bill rates were you mostly interested in?

- Their value when you checked
- What their value would be in 1 year
- What their value would be in 3 years
- The uncertainty surrounding their future value
- Their value in the previous 5 years
- Other: ______________________________

Q31. Which of the following sources did you use to obtain more information about Treasury Bill rates? (Select all that apply)

- General internet search
- Social media
- Specialized websites
- Friends/relatives/colleagues
- Lawyer
- Accountant
- Banker/broker
- Financial planner
- Email newsletters
- Podcasts
- Real estate agent
- Non-profit housing counselor
- Experts' forecasts
- Other: ______________________________

B.6 Home-Related Decisions (Owners)

Q32. How many months ago did you finalize the purchase of your current primary residence?

____

Q33. Do you have an outstanding mortgage on your current primary residence?

- Yes
- No
- Don't know

Q34. Is the mortgage fixed- or adjustable-rate?

- Fixed rate
- Adjustable rate
- Don't know

Q35. Have you ever refinanced your mortgage?

- Yes, less than 1 year ago
- Yes, 1–3 years ago
- Yes, more than 3 years ago
- Never refinanced it
- Don't know

Q36. How many months ago did you refinance your mortgage?

____

Q37. Are you planning to refinance your mortgage in the near future?

- Yes, within the next 12 months
- Yes, but more than 12 months from now
- No, I am not planning it now
- Don't know

Q38. How many months from now are you planning to refinance your mortgage?

____

Q39. Are you planning to sell your primary residence in the near future?

- Yes, within the next 12 months
- Yes, between 2 and 5 years from now
- Yes, more than 5 years from now
- No, I am not planning it now

- Don't know

Q40. How many months from now are you planning to sell your primary residence?

____

Q41. Currently, are you actively trying to sell your primary residence?

- Yes
- No

Q42. Are you planning to buy a new primary residence as you are selling the current one?

- Yes
- No
- Don't know

Q43. Currently, are you actively searching for the new home?

- Yes
- No

B.7 Home-Related Decisions (Renters)

Q44. How many months from now do you expect the closing on your primary residence purchase?

____

Q45. How do you think you will buy your primary residence?

- Financed with a mortgage
- Cash purchase
- Other: ____________________

Q46. Have you started searching for a home to buy as primary residence?

- Yes
- No

Q47. Have you started preparing your finances to buy a home as primary residence?

- Yes

- No

Q48. Have you started considering the mortgage rates offered by banks?

- Yes
- No

Q49. Have you started considering the conditions applied by different banks to obtain a mortgage?

- Yes
- No

Q50. How many months ago did you begin taking the initial steps in preparation for purchasing your primary residence?

____

Q51. Have you already obtained a mortgage pre-qualification or pre-approval?

- No
- No, but I plan to apply in the near future (less than 2 years)
- Yes, I obtained the pre-qualification already
- Yes, I obtained the pre-approval already
- No, I don't plan to obtain it
- Don't know

Q52. How many months from now are you planning to apply for mortgage pre-qualification or pre-approval?

____

Q53. Are you currently working with one or more real-estate agents to find a primary residence to buy?

- Yes
- No
- Don't know

Q54. Have you already applied for a mortgage to buy your primary residence?

- No
- No, but I plan to apply in the near future (less than 2 years)
- Yes, I applied and I am waiting for the approval
- Yes, I applied and obtained it
- Yes, I applied but got rejected
- No, I will not get a mortgage to buy it
- Don't know

Q55. How many months from now are you planning to apply for a mortgage to buy your primary residence?

____

Q56. Have you already locked the interest rate on your mortgage?

- Yes
- No
- Don't know

Q57. Could you provide an estimate of the dollar amount you requested for your mortgage?

____

Q58. Have you applied for a fixed- or an adjustable-rate mortgage?

- Fixed-rate
- Adjustable-rate
- Don't know

B.8 Car-Related Decisions

Q59. Did you recently buy any cars, motorcycles, or other motor vehicles?

- Yes, less than 1 year ago
- Yes, 1–3 years ago
- Yes, 3–5 years ago
- Yes, more than 5 years ago

- No, not recently
- Don't know

Q60. How many months ago did you finalize this purchase?

____

Q61. Do you have one or more outstanding loans that you used to buy it/them?

- Yes
- No
- Don't know

Q62. Are these loans fixed- or adjustable-rate?

- Fixed rate
- Adjustable rate
- Some fixed, some adjustable
- Don't know

Q63. Are you planning to buy any new car, motorcycle, or other motor vehicle in the near future?

- Yes, in less than 1 year
- Yes, in 1–2 years
- Yes, in 3–5 years
- No, I am not planning it now
- Don't know

Q64. How many months from now do you expect to finalize this purchase?

____

Q65. Have you started searching for a car, motorcycle, or other motor vehicle to buy?

- Yes
- No

Q66. Have you started considering the auto loan rates currently offered?

- Yes

- No

Q67. Will you buy the new car/motorcycle/other motor vehicle with a loan?

- Yes
- No
- Don't know

Q68. Have you applied already for a loan to buy the new car/motorcycle/other motor vehicle?

- No
- No, but I will apply in the near future (less than 1 year)
- Yes, I applied and I am waiting for the approval
- Yes, I applied and I obtained it
- Yes, I applied but I was rejected
- No, I will not get a loan to buy it
- Don't know

B.9 Other Financial Decisions

Q69. Did you buy any real estate properties other than a primary residence (e.g. commercial, investment, or second home) in the past?

- Yes, less than 1 year ago
- Yes, 2–5 years ago
- Yes, more than 5 years ago
- No, never
- Don't know

Q70. Do you have any outstanding mortgages on these other real estate properties?

- Yes
- No
- Don't know

Q71. Are you planning to buy any real estate properties other than your primary residence in the future?

- Yes, in less than 1 year
- Yes, in 2–5 years
- Yes, in more than 5 years
- No, I am not planning it now
- Don't know

Q72. Did you make any major financial investment recently?

- No
- Yes, less than 1 month ago
- Yes, 2–6 months ago
- Yes, 6–12 months ago
- Yes, more than 1 year ago
- Don't know

Q73. Are you planning to make any major financial investment in the near future?

- No
- Yes, in less than 1 month
- Yes, in 2–6 months
- Yes, in 6–12 months
- Yes, in more than 1 year
- Don't know

B.10 Attention Check 2

Q74. This is a question to check whether you are still paying attention and reading the questions carefully. Please select both "Somewhat unfair" and "Very fair" to continue.

- Very unfair
- Somewhat unfair
- Somewhat fair
- Very fair

B.11 Sentiment

Q75. Do you think you/your household are financially better off or worse off today than you were 12 months ago?

- Much worse off
- Somewhat worse off
- About the same
- Somewhat better off
- Much better off

Q76. Do you think that the U.S. economy is doing better or worse today than 12 months ago?

- Much worse
- Somewhat worse
- About the same
- Somewhat better
- Much better

B.12 Household's Balance Sheet

Introduction
You are close to the end of the survey. We will now ask you a few short questions about your household's financial situation[1].

Q77. How much money did your household have in short-term savings on the day before the last regular paycheck arrived?

Q78. How much money did your household have in other financial assets that are easy to sell?

Q79. How much money did your household have in other financial assets you can't easily sell?

Q80. What do you think is the current value of non-financial assets of your household?

Q81. Could you provide an estimate of the current total amount of your household's credit card balances and other outstanding debts?

[1]Each of the following questions in this block uses multiple-choice options, allowing respondents to choose from specified brackets.

Q82. Could you provide an estimate of the current total value of your household's outstanding mortgages and auto loans?

Q83. What is the monthly rent your household pays for your primary residence?

Q84. What is your household's monthly repayment amount for mortgages, auto, and student loans?

Q85. What is the highest credit score in your household?

B.13 Background (General)

Q86. Has the size of your household changed recently, or will it change in the near future? (Select all that apply)

- Yes, it recently got larger
- Yes, it recently got smaller
- Yes, it will get larger soon
- Yes, it will get smaller soon
- No, it did not change recently and will not change soon

Q87. How many months ago did it get larger?

____

Q88. How many months ago did it get smaller?

____

Q89. How many months from now will it get larger?

____

Q90. How many months from now will it get smaller?

____

Q91. Did you/your household have to relocate to a different neighborhood/city/state for a new job recently, or will you relocate in the near future? (Select all that apply)

- Yes, I/we moved recently

- Yes, I/we will move in the near future
- No, I/we did not move recently and will not move soon

Q92. How many months ago did you move?

____

Q93. How many months from now will you move?

____

Q94. What is your highest level of education?

- Eighth grade or lower
- Some High School
- High School degree/GED
- Some College
- 2-year College Degree
- 4-year College Degree
- Master's Degree
- Doctoral Degree
- Professional Degree (e.g., JD or MD)
- I don't know
- I prefer not to say

Q95. What is/was your field of study in college? If multiple degrees apply, please select the field corresponding to your last degree.

Q96. You selected 'other' for field of study. Please specify below:

____

Q97. Generally speaking, do you usually think of yourself as a Republican, a Democrat, or an Independent?

- Republican
- Democrat
- Independent
- Prefer not to say

B.14 Feedback

Introduction
Before concluding the survey, please answer the following two short questions about how people use numbers in everyday life.

Q98. Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After one year, how much would you be able to buy with the money in this account?

- More than today
- Exactly the same
- Less than today

Q99. The chances of winning a lottery prize worth $10 are 1%. What is your best guess about how many people would win a $10 prize if 1,000 people each buy a single lottery ticket?

____

Q100. Please feel free to give us any feedback or impressions on this survey.

____

____

____

____

____

B.15 Debrief

Thank you for your participation in our research study. To submit your answers, click on the red arrow at the bottom of this page.

In case you are interested, we would like to discuss with you in more detail the study you just participated in and to explain exactly what we were trying to study.

Before we tell you about all the goals of this study, however, we want to explain why it is necessary in some kinds of studies not to tell people all about the purpose of the study before they begin.

As you may know, scientific methods sometimes require that participants in research studies are not given complete information about the research until after the study is completed. Although we cannot always tell you everything before you begin your participation, we do want to tell you everything when the study is completed.

We do not always tell people everything at the beginning of a study because we do not want to influence their responses. If we tell people what the purpose of the study is and what we predict about how they will react, then their reactions would not be a good indication of how they would react in everyday situations.

The main goal of this study is to understand how American households form expectations about the US economy when making large decisions. For this purpose, you were asked about large decisions you might have made such as buying a house or other durable goods (e.g. cars), or about your future purchasing plans. You were also asked to think about some economic variables in the US.

If other people knew the true purpose of the study, it might affect how they behave/answer questions, so we are asking you not to share the information we just discussed.

We hope you enjoyed your experience and we hope you learned some things today. If you have any questions later please feel free to contact us on the email provided in the consent form (macroeconomysurvey@gmail.com). Do you have any other questions or comments about anything you did today or anything we have talked about? Please leave them in the box below.

Thank you again for your participation.

Click on the arrow to be redirected back to Prolific and register your submission.

Appendix C. Model Appendix

C.1 Discretization of State Variables

We have six continuous state variables that we discretize when solving the model. Durables, d, are placed onto a power grid with 37 points that range from 0.5 to 8 and curvature parameter 0.8.[2] Income, y, is discretized using Rouwenhorst's method (Kopecky and Suen 2010) with 7 points. The log interest rate, r, is placed on an equally-spaced grid with 11 points and lower and upper points equal to the stationary mean minus and plus twice the stationary standard deviation, respectively. The prior mean, μ, is placed on the same grid as r. The prior variance, Σ, is placed on an equally-spaced grid with 11 points and lower and upper points that are equal to σ_η^2 and the stationary variance of r, which it is bounded between theoretically.

Finally, the grid for assets, b, is adaptive and depends on the values of d, r, and y. We use an adaptive grid to ensure that the value function is well-defined on all possible values of the grid, which is not guaranteed since it may not be possible to satisfy all the required constraints at a given state. For each of the $37 \times 11 \times 7$ possible discretized values of d, r, and y, b is discretized onto a power grid with 37 points that range between $\underline{b}$ and 25 with curvature parameter of 0.8. Given the values of other state variables, $\underline{b}$ is computed as the minimum value of b such that the borrowing constraint binds and consumption equals the floor, $\underline{c}$. For any values of b below $\underline{b}$, the value function is not well-defined because the necessary constraints cannot be satisfied. The fact that both the borrowing constraint and the consumption floor become easier to satisfy as b increases implies that we can compute $\underline{b}$ as follows. First, we assume that the borrowing constraint and consumption floor bind and plug them into the budget constraint. This delivers:

$$\underline{c} - \lambda d' = y + \left[\exp(r) + \tau_b \times \mathbf{1}_{b<0}\right] b + (1-\delta) d \left[1 - f \times \mathbf{1}_{d' \neq (1-\delta+\delta\chi)d}\right] - \nu d - d',$$

Solving for b, this yields:

$$b = \frac{\underline{c} - \lambda d' - y - (1-\delta) d \left[1 - f \times \mathbf{1}_{d' \neq (1-\delta+\delta\chi)d}\right] + \nu d + d'}{\exp(r) + \tau_b \times \mathbf{1}_{b<0}}.$$

Given values of d, r, and y, the only remaining unknown to compute this value of b is d'. Since we are interested in finding the minimum possible value of b, we can minimize the right-hand side of this expression of d'. This expression is strictly decreasing in d', which implies that the minimum

[2]A power grid for an array of values x is a grid that is evenly spaced on the unit interval for the function $x^{k^{-1}}$, where k is the curvature parameter. The grid is adjusted from the unit interval based on the specified lower and upper grid points.

value of b is achieved when $d' = \underline{d}$ or $d' = (1-\delta+\delta\chi)d$. Therefore, we compute $\underline{b}$ as follows:

$$\underline{b} = \min\left\{\frac{\underline{c}-(1-\lambda)\underline{d}-y-(1-\delta)d\,(1-f)+\nu d}{\exp(r)+\tau_b}, \frac{\underline{c}-(1-\lambda)(1-\delta+\delta\chi)d-y-(1-\delta)d\,(1-f)+\nu d}{\exp(r)+\tau_b}\right\}.$$

The only remaining state variable is ξ. This variable does not need to be discretized because can only take values of 0 or 1. The total number of points in our discretized state space is over 25 million.

C.2 Numerical Integration and Interpolation

Evaluating the objective function in (4) requires computing households' expected value function under their subjective beliefs. We denote the CDF of the joint distribution of exogenous shocks—η, y', and ξ'—by $F(\cdot)$ and the CDF of their beliefs about r, which is a normal random variable with mean $(1-G)\mu + G(r+e)$ and variance $\rho\Sigma(1-G)$, by $F_r(\cdot)$, Using this notation, we can rewrite this expectation as follows:

$$\mathbb{E}\Big(V\left(\mathbf{x}'\right)\mid\mathcal{I}\Big) = \int\int V\Big(b'+\Delta_b(\tilde{r}), d', r'+\Delta_r(\tilde{r}), y', \xi', \mathcal{I}'\Big)dF(\eta, y', \xi')dF_r(\tilde{r}). \tag{9}$$

In the previous equation, $\Delta_r(\tilde{r})$ and $\Delta_b(\tilde{r})$ correspond to households' misperceptions about the evolution of interest rates and their assets. These misperceptions depend on $\tilde{r}$—the dummy variable when integrating over $F_r(\cdot)$—and take the following form:

$$\Delta_r(\tilde{r}) = \rho\left(\tilde{r}-r\right), \quad \Delta_b(\tilde{r}) = b\Big(\exp(\tilde{r})-\exp(r)\Big).$$

To evaluate (9) numerically, we integrate over y' using the transition matrix over the possible values given y from the Rouwenhorst discretization. Integrating over ξ' is straightforward because it has a Bernoulli distribution. To integrate over ν and the subjective distribution of r, we use Gauss–Hermite quadratures with 5 and 3 nodes, respectively.

To evaluate the objective function in (6), we rewrite it as follows:

$$\int\Big[U(\mathbf{c}(\mathbf{x}), \mathcal{S}(\mathbf{x}, \mathbf{d}'(\mathbf{x}))) + \beta\int V(\mathbf{x}')dF(\eta, y', \xi')\Big]dH(e) + \omega\log(1-G), \tag{10}$$

where $H(\cdot)$ denotes the CDF of e, which is a normal random variable with mean 0 and variance Σ_e. We evaluate the inner integral in (10) over the exogenous states using the same procedure used to integrate over these states in (9). To evaluate the outer integral over e, we use a Gauss–Hermite quadrature with 5 nodes.

When solving the model, we do not discretize the choice variables, c and d', which substantially improves the accuracy of our solution. However, this implies that when we evaluate the value function at the next period's states, we interpolate it over the grid of the discretized state variables using multidimensional linear interpolation. Since the grid for b is adaptive, we first use a bisection algorithm to find the coordinates of the remaining state variables. Then, we use these coordinates to select the grid of b that we interpolate over. Importantly, we work with the Epstein–Zin recursive generalization of our CRRA value function, as in Guvenen (2009). This substantially reduces the curvature of the value function in wealth, making linear interpolation substantially more accurate (Carroll 2020). We do not allow choices of c and d' that lead to next-period states that require extrapolation, and we choose the endpoints of our grid so that the extreme values of each state variable in simulations are far from the grid endpoints.

C.3 Solution Algorithm

We solve the model by performing value function iteration on (6). This is a computationally intensive procedure because we have seven state variables, five shocks, and have to solve the optimization problem in (4) each time we evaluate the objective function in (6), which also needs to be optimized. Our value function iteration proceeds as follows. First, we initialize the value function in each state, assuming that $\omega = 0$, durables are not adjusted, and individuals consume half of the available cash on hand. Second, we continue assuming $\omega = 0$ and iterate on the value function until convergence, which corresponds to the rational expectations solution. Finally, we use the value function from this prior iteration as an initial guess and perform value function iteration with $\omega > 0$ until convergence. In both cases, convergence is defined as the maximum percent difference between the subsequent value function across all possible states being less than 0.01.

Within each step of value function iteration, at each state, we solve for the optimal values of c and d' in (4) using a Nelder–Mead algorithm. We start the optimization from four different starting points and use whichever solution delivers the highest objective. We also perform a Golden-Section search over just consumption, assuming durables are not adjusted, and use this solution if it delivers a higher objective than the Nelder–Mead results. We then find the optimal value of Σ_e in (6) using a Nelder–Mead algorithm from two different starting points. To make this latter optimization problem better behaved, we optimize instead over the Kalman gain, G, and then compute the implied value of Σ_e using (5). We require that $G \in [G_{tol}, 1 - G_{tol}]$, where $G_{tol} = 10^{-4}$ to avoid numerical issues associated with setting $G = 0$ or $G = 1$. When we solve the model with exogenous information, we impose $G = \overline{G}$, where $\overline{G}$ is calibrated as described in Section 3.2.

C.4 Simulation Procedure

We simulate 50,000 individuals starting from the initial condition $b_0 = d_0 = 2$, which are close to the steady-state values in the calibrated model. We draw the initial value of y from the stationary distribution of the Rouwenhorst discretization. The simulation lasts for 400 periods, but we discard the first 200 periods as a burn-in.[3] In each period, we draw η, e, ξ, y from their respective distribution using a fixed random seed. Because our model is in partial equilibrium, there is no meaningful distinction between idiosyncratic and aggregate variables. Therefore, to minimize the dependence of our results on a particular path of interest rates, we simulate 500 distinct paths of r and randomly assign each individual to one of these paths. In Section 5, all realizations of the underlying shocks are identical in both realized and counterfactual simulations after any change.

C.5 Internal Calibration

After externally calibrating the parameters described in Section 3.2, our internal calibration proceeds as follows. Calibrating all remaining five parameters jointly is not computationally feasible, so we implement a two-step procedure. In the first step, we set $\omega = 0$ and calibrate β, ψ, f, and $\overline{\xi}$ to match the moments from McKay and Wieland (2021) described in the main text. We have found that ω has essentially no effect on these moments, which is why we use this shortcut of calibrating these parameters separately. This is substantially faster computationally because solving the model with $\omega = 0$ is several orders of magnitude faster than when $\omega > 0$. In a second step, we calibrate ω using the moment described in Section 3.2. Since this moment is monotonically increasing in ω, as shown in Figure 10, we can match the data exactly. When calibrating ω in the second stage, we reduce the number of distinct paths of r and the total number of individuals simulated by a factor of 5 for computational efficiency.

C.6 Software and Hardware

The code to solve and estimate the model is compiled with version 12.4.0 of the GNU Fortran compiler. All floating point variables are stored in double precision. We parallelize the value function iteration across states and simulation across individuals using MPI. At the calibrated parameter values, solving the model and simulating from it takes around one day when parallelized across 1000 CPUs on Stanford's Sherlock computing cluster. The number of simulations is chosen to be as large as possible while still being able to fit the necessary outputs in double precision in RAM of each CPU, which is 6GB.

[3]We have experimented with longer burn-in periods and have found that our model reaches a steady state after around 150 periods.